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A TIME SERIES APPROACH TO ECONOMETRIC MODELS OF TAIWAN'S ECONOMY

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Abstract: Using quarterly Taiwan economic data, we demonstrate that deeper understanding of relations between variables and substantial gains in forecasting can be obtained by applying econometric and statistical tools to the traditional macro-econometric models. The improvement in forecasting accuracy is illustrated by out-of-sample forecasts, and the models employed in the comparison include univariate time series models, macro-econometric models and combined models in which time series techniques are used to describe the dynamic structure of the residual series of econometric models. The paper also considers various issues related to forecasting such as aggregation and model misspecification.

Key words and phrases: ARIMA, out-of-sample forecast, outlier, residual dynamic, structural model, Taiwan macro-econometric time series model.

1. Introduction

Macro-econometric models are constructed based on economic theory and estimated with time series observations. In empirical analyses, it is often found that the error terms in an estimated macro-econometric model are serially correlated. In addition, economic time series are frequently affected by unexpected events and consequently contain various types of outliers. Therefore, one must consider these characteristics in order to improve the efficacy of the model. The main purpose of this study is to develop a systematic procedure to improve the performance of econometric models with the use of statistical and econometric tools to incorporate important empirical characteristics into the theoretically specified macro-econometric models. The procedure will be applied to the macro-econometric models for Taiwan.

The first macro-econometric model for Taiwan was built in 1964 by the late Ta-Chung Liu for the design of its four-year economic plan. Econometric modeling in Taiwan has been under development ever since. The Directorate-General of Budget, Accounting, and Statistics (DGBAS) has built and maintained an annual and a quarterly econometric models for forecasting and budgeting. More recently, the Council of Economic Planning and Development (CEPD) has built models for the design of a six-year economic plan. The Institute of Economics, Academia Sinica and Chung-Hua Institution for Economic Research have also maintained several models and publish economic forecasts on a regular basis. In addition, economists in Taiwan have used various econometric models as analytical tools in their research. See Yu and Lee (1978) for a review of econometric modeling in Taiwan.

Although Taiwan's economy is basically a free market economy, the government plays an important role. The CEPD has used its model to help design the six-year plan which redirects resources into specifically chosen sectors from other sectors. The DGBAS model is officially used to conduct policy evaluation and to forecast some major economic variables, such as the real GNP, private consumption, private and public investment, exports and imports, unemployment rate, and the general price index. Economic policies are formed and executed based on these forecasts and on policy evaluations together with experts' judgment. Therefore, a better econometric model would improve forecast precision and help design more effective policies.

Basically there are two main ways to improve the performance of econometric models: (i) a deeper understanding of the interrelationships between economic variables and (ii) the use of statistical and econometric tools to incorporate important empirical characteristics. While the latter aspect will be the main focus of this paper, major improvements usually come as a result of an iterative process of model building between theory and applications. Indeed, although our main goal is to improve the efficacy of the quarterly DGBAS model via time series techniques which properly account for the dynamic structure of the error terms, we have in the process made a number of changes in the model which we believe enhance understanding of relations between economic variables and better reflect information in the data.

Similar to other existing econometric models, the quarterly DGBAS model relies heavily on economic theory for relations between variables while assuming that the residuals are either white noise or, at most, generated by a first-order autoregressive process. Such a formulation often fails to take into proper account the dynamic structure of the system which, in turn, can have adverse effects on the validity of estimation and, more importantly, can lead to suboptimal forecasts. On the other hand, the autocorrelation structure remaining in the residuals provides useful information which can be extracted to improve model specification and forecast accuracy. In what follows we present the results of applying time series techniques to model the dynamic structure of the error term of each individual behavioral equation of the original quarterly DGBAS model given in Ho (1992). We also discuss the changes that have been made in the relations between economic variables in a number of the equations. Our modified model provides much more accurate out-of-sample forecasts than the original one and that the improvement can be seen as a direct result of the interplay between the use of economic theory and statistical methods.

The rest of the paper is organized as follows. Section 2 describes the basic structure and discusses main features of the modified DGBAS model. In Section 3 we employ data to construct

- the modified DGBAS macro-econometric model assuming the residuals are white noise,
- the macro-econometric model adjusted for the autocorrelation structure in the residuals and for outliers in behavioral variables,
- univariate time series models for individual behavioral variables.

Out-of-sample forecasts for these three models and for Ho's model (1992) are then compared in Section 4. The univariate time series results are obtained to serve as a benchmark, as is often done in economic forecast comparisons. Ho's model is used to demonstrate improvements in forecasting accuracy achieved by the proposed procedure. In Section 5 we construct two-way tables showing the relations and directions between behavioral variables as outputs and behavioral (including lagged values) and exogenous variables as inputs. Finally, conclusions and discussions are given in Section 6.

2. Block Structure & Main Features of the Modified DGBAS Model

2.1. Conventional macro-econometric model

Conventional macro-econometric models take the form of a system of simultaneous equations. Such a system has the structural form

$$\begin{aligned} \boldsymbol{y}_t &= \boldsymbol{f}(\boldsymbol{y}_t, \boldsymbol{y}_{t-}, \boldsymbol{X}_t; \boldsymbol{\eta}) + \boldsymbol{u}_t \qquad && \text{(behavioral equations)} \\ \boldsymbol{g}_t &= \boldsymbol{g}(\boldsymbol{y}_t, \boldsymbol{y}_{t-}, \boldsymbol{X}_t) && \text{(identities)} \end{aligned} \tag{1}$$

In (1), $\boldsymbol{\eta}$ represents a set of unknown parameters, $\boldsymbol{y}_t$ is a vector of behavioral variables, $\boldsymbol{y}_{t-}$ is a vector of lagged values of $\boldsymbol{y}_t$, $\boldsymbol{X}_t$ is a vector of inputs and their lagged values, and $\boldsymbol{u}_t$ is a vector of error terms of the behavioral equations. For the identities, the elements of the vector $\boldsymbol{g}$ are known functions of $(\boldsymbol{y}_t, \boldsymbol{y}_{t-}, \boldsymbol{X}_t)$. Thus, ignoring for the moment the error term $\boldsymbol{u}_t$, (1) describes a system of general nonlinear relationships among elements of $(\boldsymbol{y}_t, \boldsymbol{y}_{t-}, \boldsymbol{X}_t)$. Elements of $\boldsymbol{X}_t$ are often called exogenous variables and those of $(\boldsymbol{y}_t, \boldsymbol{g}_t)$ endogenous variables. In practice, $\boldsymbol{f}$ is often assumed linear in the parameters $\boldsymbol{\eta}$. The probabilistic structure of the error vector $\boldsymbol{u}_t$ will be specified later.

2.2. The macro-econometric model for Taiwan's economy

The model considered here is a modified version of the original DGBAS quarterly model of Taiwan's economy in Ho (1992). We shall denote the modified model as Macro-econometric model (MEM). It assumes the form of equation

(1), consisting of 116 variables, of which 90 are endogenous and 26 are exogenous. There are 41 behavioral equations and 49 identities in a simultaneous equation system for the 90 endogenous variables. A list of the 116 endogenous and exogenous variables is given in Table 1. Details of the 41 behavioral equations are given in Table 2(a) where the error terms are ignored. For each equation, the behavioral variable is shown in the second column, and the corresponding entry in the third column lists all the independent variables which are functions of the endogenous and exogenous variables in the system. The jth lagged value of a variable Y is denoted as $\mathrm{Y}(-j)$. Each equation contains a constant term. All the 49 identities are given in Table 2(b). Note that the behavioral variables, equations and identities in Tables 1 and 2 are organized in sectors to facilitate the discussion below.

The model is designed primarily for short-term forecasting of Taiwan's economy. It is basically a Keynesian model, with an IS-LM and AD-AS system. It can be decomposed into goods market, financial market, labor market, and full-employment output. However, since short-term movements in output are primarily determined by changes in aggregate demand (AD) in the MEM model, aggregate supply (AS) is then described by the full-employment or potential output.

2.3. Block structure of MEM

The behavioral equations of the model are organized by blocks as shown in Exhibit 1. The first three blocks contain the demand functions for purchase of goods and services. The fourth block contains the tax and public monopoly revenues from wines and tobacco. These four blocks comprise a disaggregated IS structure or equivalently, they construct the goods market equilibrium.

The money market equilibrium (LM) is represented by the fifth block. In this model, money supply is treated as exogenous. The market interest rate is thus determined when the money market is in equilibrium. This block also includes an exchange rate reaction function. Exchange rate is mainly determined by the market after 1986, but the Central Bank of China still plays an influential role. The whole block constructs the financial market equilibrium.

Through the IS-LM system, in the sixth block, the equilibrium output is determined. However, this output is from the demand side. In addition, agricultural, industrial, and service products are also contained in this block.

Aggregate supply is modeled in the seventh and eighth blocks. Block 7 comprises the labor market. In this model, import price is used as a proxy for the import material market. Block 8 determines the potential output. Then, through the AD-AS system, all prices are determined in the ninth and final block.

Table 1. Description of variables

(a) Endogenous Variables (Behavioral Equations)

No.	Variable	Description
Private Consumption		
C1	CF	Private Food Consumption
C2	CO	Private Nonfood Consumption
Private Capital Formation		
I1	IBF	Private Fixed Investment
I2	J	Change in Inventory
I3	D	Depreciation
International Trade		
T1	MG	Imports of Goods
T2	MS	Imports of Services
T3	XG	Exports of Goods
T4	XS	Exports of Services
T5	TVMUSA	Imports of Goods from U.S.A.
T6	TVMJAP	Imports of Goods from Japan
T7	TVMHK	Imports of Goods from Hong Kong
T8	TVMOTH	Imports of Goods from Other Areas
T9	TVXUSA	Exports of Goods to U.S.A.
T10	TVXJAP	Exports of Goods to Japan
T11	TVXHK	Exports of Goods to Hong Kong
T12	TVXOTH	Exports of Goods to Other Areas
Government		
G1	TAXTTN	Nominal Government Total Tax Revenue
Financial Market		
F1	MKRM	Nominal Market Interest Rate
F2	TDR1Y	Nominal One-year Time Deposit Rate
F3	MQM	Quasi Money
F4	E	Exchange Rate
Demand		
D1	GDPAGR	GDP of Agriculture Sector
D2	GDPIND	GDP of Industry Sector
Labor		
L1	U	Unemployment Rate
L2	NF	Labor Force
L3	PWM	Manufacture Wage Income Index
Supply		
S1	QF/K88	Potential GDP per Capital Stock
Price		
P1	PM	Import Price Deflator
P2	WPI	Wholesale Price Index
P3	CPI	Consumer Price Index
P4	PCF	Private Food Consumption Price Deflator
P5	PCO	Private Nonfood Consumption Price Deflator
P6	PCG	Government Consumption Price Deflator
P7	PFIA	Factor Income from Abroad Price Deflator
P8	PIBF	Private Fixed Investment Price Deflator
P9	PIG	Government Fixed Investment Price Deflator
P10	PIPC	Public Enterprise Fixed Investment Price Deflator
P11	PJ	Change in Inventory Price Deflator
P12	PD	Depreciation Price Deflator
P13	PX	Export Price Deflator

Table 1. (continued)

(b) Endogenous Variables (Identities)

No.	Variable	Description
Private Consumption		
IC1	CFN	Nominal Private Food Consumption
IC2	CON	Nominal Private Nonfood Consumption
IC3	CN	Nominal Private Consumption
IC4	C	Private Consumption
Private Capital Formation		
II1	IBFN	Nominal Private Fixed Investment
II2	JN	Nominal Change in Inventory
II3	DN	Nominal Depreciation
International Trade		
IT1	TVM	Imports of Goods
IT2	TVX	Exports of Goods
IT3	M	Imports of Goods and Services
IT4	X	Exports of Goods and Serviecs
IT5	XM	Trade Surplus
IT6	MN	Nominal Imports of Goods and Services
IT7	XN	Nominal Exports of Goods and Serviecs
IT8	XMN	Nominal Trade Surplus (NT$)
IT9	XMND	Nominal Trade Surplus (US$)
Government		
IG1	TAXTT	Government Total Tax Revenue
IG2	CG	Government Consumption
IG3	IG	Government Fixed Invesment
IG4	IPC	Public Enterprise Fixed Investment
Financial Market		
IF1	MKRMR	Real Market Interest Rate
IF2	TDR1YR	Real One-year Time Deposit Rate
IF3	MON	Real Money Demand
IF4	MQMN	Nominal Quasi Money
IF5	IRR	Real Interest Rate (ex post)
Demand		
ID1	FIA	Factor Income from Abroad
ID2	I	Domestic Fixed Investment
ID3	IN	Nominal Fixed Investment
ID4	K88	Fixed Capital Stock
ID5	GDP	Gross Domestic Product
ID6	GDPN	Nominal Gross Domestic Product
ID7	CGDP	Annual Growth Rate (in GDP)
ID8	GDPSER	GDP of Service Sector
ID9	GNP	Gross National Product
ID10	GNPN	Nominal Gross National Product
ID11	CGNP	Annual Growth Rate (in GNP)
ID12	TD	Total Demand
ID13	TDN	Nominal Total Demand
ID14	YDD	Disposable Income
ID15	YDDN	Nominal Disposable Income
Labor		
IL1	NEP	Total Employment
Supply		
IS1	QF	Potential GDP
IS2	PDT	Potential GDP per capita
Price		
IP1	PC	Private Consumption Price Deflator
IP2	PI	Fixed Investment Price Deflator
IP3	PGDP	Gross Domestic Product Price Deflator
IP4	PGNP	Gross National Product Price Deflator
IP5	CPGDP	Annual Inflation Rate (in PGDP)
IP6	CPGNP	Annual Inflation Rate (in PGNP)

(c) Exogenous Variables

No.	Variable	Description
E1	MONN	Nominal Money Supply
E2	CGN	Nominal Government Consumption
E3	IGN	Nominal Governmnet Fixed Investment
E4	IPCN	Nominal Public Enterprise Fixed Investment
E5	FIAN	Nominal Factor Income from Abroad
E6	IR	Nominal Rediscount Rate
E7	N	Population
E8	PXUSA	Export Price Deflator for U.S.A.
E9	IGNPUSA	Index of GNP for U.S.A.
E10	WPIUSA	Wholesale Price Index for U.S.A.
E11	PXJAP	Export Price Deflator for Japan
E12	IGNPJAP	Index of GNP for Japan
E13	WPIJAP	Wholesale Price Index for Japan
E14	EJAP	Exchange Rate for Japanese Yen to US $
E15	GNPHK	GNP for Hong Kong
E16	PHK	Index of Price for Hong Kong
E17	EHK	Exchange Rate for Hong Kong $ to US $
E18	POILSAR	Oil Price from Saudi Arabia
E19	TIME	Time (1950:1=1)
E20	Q1	Dummy Variable (the 1st quarter=1, others=0)
E21	Q2	Dummy Variable (the 2nd quarter=1, others=0)
E22	Q3	Dummy Variable (the 3rd quarter=1, others=0)
E23	D1	Dummy Variable (1973:3–1995:2=1, others=0)
E24	D2	Dummy Variable (1979:2–1995:2=1, others=0)
E25	D3	Dummy Variable (1987:2–1995:2=1, others=0)
E26	D4	Dummy Variable(1984:4–1994:3=1, others=0)

Table 2. Structure of models

(a) 41 Behavioral Equations

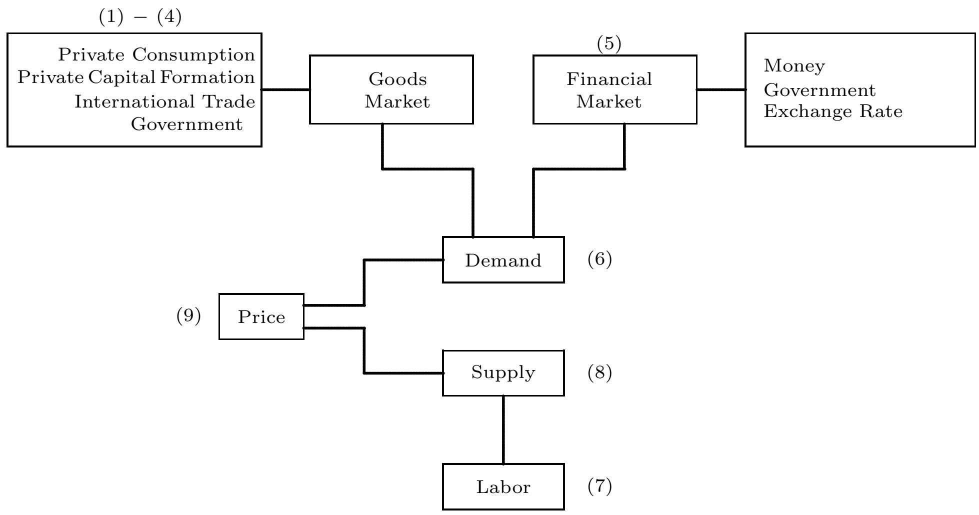
		Macro-econometric Model **MEM**	Macro-econometric Time-Series Model **METSM**		
No.	Dep. Var.	Indep. Var.	Indep. Var.	AR Lags	MA Lags
Private Consumption					
C1	ln(CF)	ln(YDD),ln(CF(-1)),Q1,Q2,Q3	ln(YDD)	1;4	1
C2	ln(CO)	ln(YDD),ln(MON+MQM),ln(CO(-1)),Q1,Q2,Q3	ln(YDD),ln(MON+MQM),ln(CO(-1)), Q1,Q2,Q3	4	1
Private Capital Formation					
I1	ln(IBF)	ln(K88(-1)),MKRMR,ln(GDP)-ln(GDP(-1)), ln(IBF(-4)),Q1,Q2,Q3	c*,ln(K88(-1)),MKRMR, ln(GDP)-ln(GDP(-1)),Q1,Q2,Q3	1;4	
I2	J	GDP-GDP(-1),CPGDP,Q1,Q2,Q3	c,GDP-GDP(-1),CPGDP,Q1,Q3		
I3	D	K88(-1),Q1,Q2,Q3	c,K88(-1)	1;4	2
International Trade					
T1	MG	TVM	c,TVM		6
T2	MS	GNP,MS(-1),Q1,Q2,Q3	c,GNP,Q2,Q3		1,2,3,4
T3	XG	TVX	TVX		2,3,4,8
T4	XS	IGNPUSA,IGNPJAP,XS(-1),Q1,Q2,Q3	c,IGNPUSA,IGNPJAP	1	
T5	TVMUSA	TD,TVMUSA(-1),TVMJAP(-4), (PXUSA*E)/WPI,Q1,Q2,Q3	c,TD,TVMJAP(-4),(PXUSA*E)/WPI, Q1,Q2,Q3	1	
T6	TVMJAP	TD,TVMJAP(-1),(PXJAP*E/EJAP)/WPI, Q1,Q2,Q3	c,TD,(PXJAP*E/EJAP)/WPI, Q1,Q2,Q3	1	2,4
T7	ln(TVMHK)	ln(TD),ln(TVMHK(-1)),ln(TVMJAP(-4)), Q1,Q2,Q3	c,ln(TD),ln(TVMJAP(-4))	1	1
T8	TVMOTH	TD,TVMOTH(-1),PM/WPI,Q1,Q2,Q3	TD,PM/WPI	1	1,3
T9	TVXUSA	IGNPUSA,TXVUSA(-1),PX/WPIUSA*E, D3*IGNPUSA,D3,Q1,Q2,Q3	c,IGNPUSA,PX/WPIUSA*E,D3, D3*IGNPUSA,Q1,Q2,Q3		1,2,3,4
T10	TVXJAP	IGNPJAP,TVXJAP(-1),PX/(WPIJAP*E/EJAP), Q1,Q2,Q3	c,IGNPJAP, PX/(WPIJAP*E/EJAP)	1 to 5	
T11	TVXHK	GNPHK,TVXHK(-1),PX/(PHK*E/EHK), Q1,Q2,Q3	GNPHK,PX/(PHK*E/EHK),Q2	1	1 to 5
T12	$\sqrt{\text{TVXOTH}}$	IGNPUSA,IGNPJAP, $\sqrt{\text{TVXOTH}}$(-1),PX/E, Q1,Q2,Q3	c,IGNPUSA,IGNPJAP, PX/E		1,2,3,4
Government					
G1	ln(TAXTTN)	ln(GNPN),Q1,Q2,Q3	c,ln(GNPN),Q1,Q2	4	
Financial Market					
F1	MKRM	ln(MON),ln(GNP),Q1,Q2,Q3	ln(MON),ln(GNP)	1	1,2,4
F2	TDR1Y	MKRM,IR,Q1,Q2,Q3	c,MKRM,IR	1	1
F3	ln(MQM)	ln(GNP),TDR1Y,Q1,Q2,Q3	ln(GNP),TDR1Y,Q1	1	1,2,4
F4	E	XMND+XMND(-1)+XMND(-2),E(-1),Q1,Q2,Q3	XMND+XMND(-1)+XMND(-2)	1,2	
Demand					
D1	GDPAGR	ln(CF),Q1,Q2,Q3	c,ln(CF),Q1,Q2,Q3	3	4
D2	ln(GDPIND)	ln(TD-X),ln(X),Q1,Q2,Q3	c,ln(TD-X),ln(X)	1;4	3,4
Labor					
L1	U	U(-1),ln(PWM/PDT),Q1,Q2,Q3	U(-1),ln(PWM/PDT),Q3		2,4
L2	NF	N,PWM/PDT,Q1,Q2,Q3	c,N,PWM/PDT,Q1,Q2,Q3	2,4	1,9
L3	ln(PWM)	ln(PDT),U(-1),ln(PWM(-4)),Q1,Q2,Q3	ln(PDT)	1;4	2,6,8,12
Supply					
S1	ln(QF/K88)	ln(NF/K88),TIME,POILSAR,EJAP,Q1,Q2,Q3	ln(NF/K88),TIME,POILSAR,EJAP	4	1,2,3
Price					
P1	PM	POILSAR,PXUSA*E, PXJAP*E/EJAP,Q1,Q2,Q3	c,POILSAR,PXUSA*E, PXJAP*E/EJAP,Q1,Q2,Q3	1	3,4
P2	WPI	WPI(-1),PM,PWM/PDT,GDP/QF,D1,D2, D4*PWM/PDT,D4,Q1,Q2,Q3	c,WPI(-1),PM,GDP/QF,PWM/PDT, D1,D2,D4*PWM/PDT,D4		
P3	CPI	CPI(-1),PWM/PDT,D1,D2,Q1,Q2,Q3	c,CPI(-1),PWM/PDT,D1,D2,Q1		1,4,8
P4	PCF	CPI,Q1,Q2,Q3	CPI,Q1,Q3	1	4
P5	PCO	CPI,Q1,Q2,Q3	CPI,Q1,Q2,Q3	1	4,8
P6	PCG	CPI,Q1,Q2,Q3	CPI	4	1,2,3,5
P7	PFIA	CPI,Q1,Q2,Q3	c,CPI	1	
P8	PIBF	WPI,D4*WPI,D4,Q1,Q2,Q3	WPI,D4*WPI,D4	1	2,3,4
P9	PIG	WPI,D4*WPI,D4,Q1,Q2,Q3	WPI,D4*WPI,D4,Q1	1;4	2
P10	PIPC	WPI,D4*WPI,D4,Q1,Q2,Q3	WPI,D4*WPI,D4	1	1,4,5
P11	PJ	WPI,Q1,Q2,Q3	WPI	1	6
P12	PD	WPI,D4*WPI,D4,Q1,Q2,Q3	WPI,D4*WPI,D4,Q1,Q2,Q3	1	2,4,6
P13	PX	WPI,Q1,Q2,Q3	WPI,Q1		1,2,8

* c : constant term remains in the equation; without c the constant is dropped.

Table 2. (b) 49 Identities

No.	Identity
IC1	CFN = CF*PCF/100.
IC2	CON = CO*PCO/100.
IC3	CN = CFDN+CON
IC4	C = CF+CO
II1	IBFN = IBF*PIBF/100.
II2	JN = J*PJ/100.
II3	DN = D*PD/100.
IT1	TVM = TVMUSA+TVMJAP+TVMHK+TVMOTH
IT2	TVX = TVXUSA+TVXJAP+TVXHK+TVXOTH
IT3	M = MG+MS
IT4	X = XG+XS
IT5	XM = X-M
IT6	MN = M*PM/100.
IT7	XN = X*PX/100.
IT8	XMN = XN-MN
IT9	XMND = (XMN)/E
IG1	TAXTT= TAXTTN/PGDP*100.
IG2	CG = CGN/PCG*100.
IG3	IG = IGN/PIG*100.
IG4	IPC = IPCN/PIPC*100.
IF1	MKRMR = MKRM-CPGDP
IF2	TDR1YR = TDR1Y-CPGDP
IF3	MON = MONN/PGDP*100.
IF4	MQMN = MQM*PGDP/100.
IF5	IRR = IR-CPGDP
ID1	FIA = FIAN/PFIA*100.
ID2	I = IBF+IPC+IG
ID3	IN = IBFN+IPCN+IGN
ID4	K88 = K88(-1)+I-D
ID5	GDP = C+CG+I+J+X-M
ID6	GDPN = CN+CGN+IN+JN+XN-MN
ID7	CGDP = (GDP/GDP(-4)-1.)*100.
ID8	GDPSER = GDP-GDPAGR-GDPIND
ID9	GNP = GDP+FIA
ID10	GNPN = GDPN+FIAN
ID11	CGNP = (GNP/GNP(-4)-1.)*100.
ID12	TD = GDP+M
ID13	TDN = GDPN+MN
ID14	YDD = GNP-TAXTT-D
ID15	YDDN = GNPN-TAXTTN-DN
IL1	NEP = NF*(1.-.01*U)
IS1	QF = K88*(QF/K88)
IS2	PDT = QF/NEP
IP1	PC = CN/C*100.
IP2	PI = IN/I*100.
IP3	PGDP = GDPN/GDP*100.
IP4	PGNP = GNPN/GNP*100.
IP5	CPGDP = (PGDP/PGDP(-4)-1.)*100.
IP6	CPGNP = (PGNP/PGNP(-4)-1.)*100.

Exhibit 1. Block structure of the macro-econometric model (MEM)



Block	Equation No.
(1) Private Consumption	C1 − C2
(2) Private Capital Formation	I1 − I3
(3) International Trade	T2 − T12
(4) Government	G1
(5) Financial Market	F1 − F4
(6) Demand	D1 − D2
(7) Labor	L1 − L3
(8) Supply	S1
(9) Price	P1 − P3

2.4. Main features of the MEM model

The MEM model has Keynesian features characterized by different markets. We shall now provide a brief description of the main characteristics of each market. We begin with the behavioral equations in the goods and financial markets, then consider the labor markets and production, and finally deal with price equations.

2.4.1. The goods market

There are four main sectors in the demand side of the goods market: private consumption, private capital formation including business investment and inventory investment, international trade, and government expenditure. (See Tables 1(a,b) and 2(a).) Government expenditure is treated as a policy variable. It consists of three items: public consumption, government investment, and public enterprise investment. In this model, private consumption is composed of food and nonfood consumption. Food consumption CF is mainly determined by private disposable income YDD which is just GNP minus taxes and physical capital depreciation. Nonfood consumption CO depends on YDD and private wealth. Money MON and quasi money MQM, which is the definition of money supply M2, are used as a proxy for private wealth. Both food and nonfood consumptions also depend on their own lagged-one-quarter values which capture the habit persistence.

In the private capital formation sector, private fixed investment IBF is explained by the change in output GDP-GDP(-1), real market interest rate MKRMR and the existing capital stock K88(-1). Inventory investment J depends on the change in output and the inflation rate. Depreciation of physical capital D is just proportional to the existing capital stock.

In the international trade sector, imports are divided into goods MG and service MS imports. Goods import (data from DGBAS) is proportional to the total import value TVM (data from Customs), while service import MS depends on GNP and the lagged-one-quarter service import. The TVM can be categorized according to geographical regions into TVMUSA, TVMJAP, TVMHK and TVMOTH. More generally, international trade between Taiwan and the United States, Japan, Hong Kong, and other areas of the world explains most of the import and export values. Imports from each region depend on domestic total demand TD, terms of trade and lagged-one-quarter import value of each region. Imports from the U.S. and Hong Kong can also be explained by lagged-four-quarter imports from Japan because Taiwan imports machines mainly from Japan and raw materials from the U.S. and Hong Kong (mainly Mainland China after 1986) and there is roughly a four-quarter lag between them. Exports are also divided into commodity and service categories. Goods export XG (data from DGBAS) is proportional to the total export value TVX (data from Customs) while service export XS depends on foreign countries' GNP, mainly the U.S. and Japan, and lagged-one-quarter service export. The regional export values depend on each area's GNP and terms of trade. The lagged-one-quarter export value in each area also affects the export value in each area.

Total output is decomposed into three components: agriculture, industry, and service. Since total output is demand-determined, only two sectors' equations are specified in the demand sector. Agricultural output GDPAGR depends on food consumption CF as well as its lagged-one-quarter value. The industrial product GDPIND is a function of domestic sales and export demand. Finally, in the government sector, total taxes and monopoly revenues from the public enterprises TAXTTN are proportional to aggregate demand, i.e., nominal GNP.

2.4.2. Financial markets

Financial markets are composed of money, short-term assets, long-term assets (the government bond market), and foreign exchange markets. In this model, money supply is treated as a policy variable, so the nominal market interest rate MKRM is endogenously determined by money stock MON and GNP. The market interest rate is a weighted average of the curbed market interest rate and one month time deposit interest rate. The nominal one year time deposit interest rate TDR1Y depends on the market interest rate and nominal rediscount rate IR. Quasi money demand MQM consists mainly of the short-term asset demand of bank deposit and short-term bills issued by the Central Bank. It depends on GNP and TDR1Y. By the wealth identity, the long-term asset market is excluded from the model. The exchange rate is determined by accumulated balance of payments XMND as well as its lagged-one-quarter value.

2.4.3. Labor markets and production

There are three equations to represent the labor market. The unemployment rate U depends on its lagged-one-quarter value. It also depends on the ratio of manufacture wage income index PWM to potential labor productivity PDT (i.e., unit labor cost). Labor force NF, on the other hand, is a function of population N and real wage rate. The PWM is a function of PDT and lagged-four-quarter PWM. The wage function explains the labor market equilibrium. The potential GDP, denoted as QF, is constructed under the assumption of constant return to scale of the production function. It is determined by NF, total capital stock K88, technology, as well as materials. Since a vast quantity of machinery comes from Japan and most oil imports from Saudi Arabia, the exchange rate of the Japanese Yen to the US dollar EJAP and the oil price POILSAR affect the material demand and therefore the potential output. A time variable TIME is added to represent technology improvement in QF.

2.4.4. Price formation

The price sector includes 13 price equations. Import price deflator PM is different from other price indexes since it depends on other countries' economies. Import materials come mainly from Japan, the U.S. and Saudi Arabia. Therefore, PM depends on export prices of Japan PXJAP, the U.S. PXUSA and the oil price of Saudi Arabia POILSAR. Since no behavioral equation is formulated for material market price in this model, import price can be seen as a proxy for it. The other two important price indexes are the wholesale price index WPI and consumer price index CPI. WPI is determined by the PM, the unit labor cost PWM/PDT and demand pressure which is approximated by the ratio of

GDP to QF. CPI is a weighted average of retail prices and can be explained through the input cost mark-up. Both WPI and CPI include the lagged price level to account for the effects of expectations of other firms' and retailers' price decisions on actual decisions, respectively. Two dummy variables D1 and D2 are added to WPI and CPI to try to pick up possible level-shift effects of the two oil crises in 1973 and 1979. The other price function depends on either CPI and WPI. Private and public consumption prices depend on CPI, while prices of investment, inventory, depreciation and export are determined by WPI. The price deflator of income from abroad PFIA is determined by CPI because income from foreign countries is part of household income. Finally, it should be noted that with two exceptions, seasonal indicators Q1,Q2 and Q3 are added to individual behavioral equations to represent seasonal effects in the data.

2.5. Main differences between the original and the modified DGBAS model

In the process of our study, a number of modifications have been made to the original DGBAS model in Ho (1992), with respect to relations between economic variables in the simultaneous equation system. The aim of these revisions is to enhance both the understanding of the system and the performance of the prediction. The main differences between the original and current model are listed below:

- *Equations in the price sector.* Important changes have been made to the behavioral equations of CPI and WPI, which are basic to most of the other price equations. In the original model, CPI is related to current and lagged-four-quarter value of WPI, the ratio PWM/PDT and the ratio MON(-1)/GDP of lagged-one-quarter value of money demand to GDP. In our revised model, the last ratio is dropped because we have found that it has essentially no explanatory power, and we have also replaced the WPI's by the lagged-one-quarter value of CPI itself. In addition, as mentioned earlier, we have added two dummy variables to account for potential effects of the oil crises in 1973 and 1979. With respect to the WPI equation, in the original model it depends only on the price of import and the ratio of GDP to potential GDP. A number of new variables has been added to this equation, as described earlier in Section 2.4.4. These changes have resulted in substantial improvements in the forecast performance of the entire price sector, as will be seen later in Section 4.
- *Money market behavioral equations.* In the original model, the money demand and quasi money demand equations represent the money market. Therefore, interest rate is treated as exogenous and money supply is determined endogenously by money demand. After dropping money demand from the equation

for CPI, as discussed above, we have found that money plays no role in the modified model. This seems counter intuitive. To better reflect the features of the money market, we have revised the money market block by dropping the money demand equation but adding two behavioral equations: the market interest rate and one year time deposit rate. There are then three equations for money market in the modified model. The market interest rate function implies that the money market is in equilibrium. The one year time deposit rate connects market interest rate and rediscount rate to quasi money demand. Quasi money demand remains in the model.

- *Removal of six behavioral equations.* In the modified model, six equations have been dropped: index of import unit value, index of export unit value, index of export competition, index of world trade, nominal government bonds and nominal foreign assets of the Central Bank of China. Our empirical analysis has indicated that these six variables are not significantly associated with any other variables of interest in the system. If, for any reasons, some of these variables are of interest by themselves, they can be added back easily without changing the solutions of other variables.
- *Data transformation.* In the original model, only one dependent variable has been logarithmically transformed. A careful examination of the data shows that a number of variables exhibit nonhomogeneous pattern in variation associated with changes in level. This calls for log or square-root transformations. In sum, we have applied the log transformation to nine dependent variables and the square-root transformation to one variable. Several independent variables in the behavioral equations have also been similarly transformed. Details are given in Table 2(a).
- *Addition and removal of independent variables.* We have added or dropped independent variables for a number of equations based on empirical findings. We only report two cases with substantial changes here. In the original model, the average tariff rate affects the behavioral variables nonfood consumption CO and import price PM. From a theoretical point of view, this is proper. However, empirically the effects are not significant and the estimated coefficients do not support the direction of relationship expected from the theory for both equations. We drop it as an independent variable from both equations, which in turn rules out the nominal tariff revenue as an exogenous variable. The equation for change in inventory J depends on sales TD-J, real interest rate and the existing inventory stock in the original model. Empirically, we have revised the equation with change in output and inflation rate as independent variables because they provide a much better fit, although forecasting performance of change in inventory is not greatly improved with the new model.

3. Estimation, Time Series Modeling and Forecasting Procedures

In this section, we give details of the univariate time series models for the behavioral variables, estimation of the MEM model, and the time series models used to account for the dynamic structure of the behavioral equations. We then present forecast comparisons of the different models in the next section.

3.1. Univariate time series models

Let $\{y_t\}$ be an observed time series. The univariate time series model considered here is of the following autoregressive-integrated-moving average (ARIMA) form (Box and Jenkins (1976)):

$$\phi(B)(1-B^4)^{d_s}(1-B)^d y_t = c + \theta(B)a_t, \tag{2}$$

where B is the backward shift operator such that $By_t = y_{t-1}$, $\phi(B) = 1-\phi_1 B - \cdots - \phi_p B^p$ and $\theta(B) = 1-\theta_1 B - \cdots - \theta_q B^q$ are polynomials in B having all zeros lying outside the unit circle and with no common zeros, c is a constant, d and d_s are nonnegative integers, and the $a_{t's}$ are identically and independently distributed as $N(0,\sigma_a^2)$. In the above $(1-B)$ is the regular difference operator and $(1-B^4)$ the seasonal difference operator (for quarterly data). For each of the behavioral variables, the model building approach proposed by Box and Jenkins (1976) is applied individually to specify an empirically appropriate model from the above class. The diagnostic tools include the autocorrelation function, the partial autocorrelation function, the extended autocorrelation function, Tsay and Tiao (1984), and some portmanteau statistics. The model is estimated by the maximum likelihood estimation method. The diagnostic and estimation steps are repeated until a satisfactory model is found. The resulting model will then be used to produce forecasts which are based solely on its own past values. We denote the models and associated forecasts by the heading "UTS". Employing quarterly data over the period 1966:1 to 1995:2, the forms of the specified ARIMA models for the 41 behavioral variables are given in Table 3(a).

3.2. Estimation of the model MEM

In (1), if the error term $\{\boldsymbol{u}_t\}$ is a sequence of independent multivariate $N(\mathbf{0},\boldsymbol{\Sigma})$ random variables and $\boldsymbol{f}$ has a given functional form, then, at least in principle, one can write down the joint likelihood function for $\boldsymbol{\eta}$ and $\boldsymbol{\Sigma}$ and compute the corresponding maximum likelihood estimates. However, in practice, due to the limited sample size and large number of unknown parameters, this is usually not feasible. When $\boldsymbol{f}$ is assumed linear in the parameters $\boldsymbol{\eta}$ as in our MEM in Table 2(a), then for forecasting purposes, the parameters of each behavioral equation are often estimated individually by ordinary least squares (OLS). The estimated equations are then used jointly in (1) to produce forecasts for future values of the endogenous variables.

Table 3. Univariate time series models **UTS**

(a) 41 Behavioral Variables

No.	Variable	Difference Order	AR Lags	MA Lags	Constant
Private Consumption					
C1	ln(CF)	1	1,2,3,4		Y
C2	ln(CO)	1,4	1		
Private Capital Formation					
I1	ln(IBF)	4	1	1;4	Y
I2	J	4		1;4	
I3	D	4	1,4	4	
International Trade					
T1	MG	1	4	1	Y
T2	MS	4	1	4	Y
T3	XG	4		1,2,3	Y
T4	XS	1		5	Y
T5	TVMUSA	1		1	Y
T6	TVMJAP	1	1,2,4		Y
T7	ln(TVMHK)	1		1,2	
T8	TVMOTH	1		1,3	Y
T9	TVXUSA	4	1	4	
T10	TVXJAP	1	1	1	Y
T11	TVXHK	1,4	4	4	
T12	sqrt(TVXOTH)	1	1,2,3,4		Y
Government					
G1	ln(TAXTTN)	1,4		1;4	
Financial Market					
F1	MKRM	1		1	
F2	TDR1Y		1	1	
F3	ln(MQM)	1	1,3,4,5		Y
F4	E	1		1,2,3	
Demand					
D1	GDPAGR	4	1,3,4		Y
D2	ln(GDPIND)	1,4		4	
Labor					
L1	U	4	1,2,3	4	Y
L2	NF	4		1,2,3	Y
L3	ln(PWM)	4	1,3,5		
Supply					
S1	ln(QF/K88)	4		1,2,3,4	
Price					
P1	PM	1	2,3,4		Y
P2	WPI	1	1		Y
P3	CPI	1	1		Y
P4	PCF	1	4		Y
P5	PCO	1	4	2	Y
P6	PCG	1	1,2,3,4		Y
P7	PFIA	1	2,4		Y
P8	PIBF	1	1,3,4		Y
P9	PIG	1	4	6	Y
P10	PIPC	1	1	1,4	Y
P11	PJ	1	1,2,3		Y
P12	PD	1	3	4	Y
P13	PX	1	3,4	1	Y

Table 3. (b) 18 Exogenous Variables

No.	Variable	Difference Order	AR Lags	MA Lags	Constant
E1	MONN	1	4	1,2,3,4	Y
E2	CGN	1	1,2,3,4		Y
E3	IGN	1,4	4	1,3	
E4	IPCN	1,4	1	4	
E5	FIAN	1	1,2,3	6,8,10	Y
E6	IR	1		1,2	
E7	N	1,4	1	2,4	Y
E8	PXUSA	1	1	4	Y
E9	IGNPUSA	1	1	8,12	Y
E10	WPIUSA	1	1	6	Y
E11	PXJAP	1		1	Y
E12	IGNPJAP	1	2		Y
E13	WPIJAP	1	1		
E14	EJAP	1		1	Y
E15	GNPHK	1,4	4	4,5,9,10	
E16	PHK	1	1,2,4	6	
E17	EHK	1		1,2	
E18	POILSAR	1		1,4	

In theory, the predicted value of a future y_{t+h} has to be solved from the reduced form since the structural form (1) cannot be used to forecast as there are unknown endogenous variables on the right hand side of each equation. In practice the reduced form is often too complicated to have an analytical solution, especially when there are many identities and nonlinear variable transformations. As a result, we turn to numerical approximations. Given the parameter estimates and exogenous variables at time $t+h$, the predicted values of y_{t+h} are obtained by solving the systems of nonlinear equations (1) numerically using the Gauss-Seidel algorithm. This, in fact, is equivalent to forecasting from the reduced system numerically. See Fair (1984), Ch. 7, for example.

3.3. Macro-econometric time series model (METSM)

In the above formulation, the assumption of a vector white noise model for the error term $\boldsymbol{u}_t$ ignores the possibility of dynamics in the residuals. Auto- and cross-correlations often arise in the error term due to model misspecification, missing variables and other causes. Failure to take the dynamic structure of the errors into account can have appreciable effects on the precision of the OLS estimates and lead to inefficient forecasts (see, e.g. Box and Newbold (1971)). In general, dynamic structures in $\boldsymbol{u}_t$ can be usefully represented by vector ARMA models of the form

$$\boldsymbol{\Phi}(B)\boldsymbol{u}_t = \boldsymbol{c} + \boldsymbol{\Theta}(B)\boldsymbol{a}_t, \tag{3}$$

where $\boldsymbol{c}$ is a vector, $\boldsymbol{\Phi}(B) = \boldsymbol{I} - \boldsymbol{\Phi}_1 B - \cdots - \boldsymbol{\Phi}_p B^p$, $\boldsymbol{\Theta}(B) = \boldsymbol{I} - \boldsymbol{\Theta}_1 B - \cdots - \boldsymbol{\Theta}_q B^q$, $\boldsymbol{\Phi}_i$ and $\boldsymbol{\Theta}_j$ are matrices such that all zeros of the determinants $|\boldsymbol{\Phi}(B)|$ and $|\boldsymbol{\Theta}(B)|$

are on or outside the unit circle, and the $\boldsymbol{a}_t$ are i.i.d. $N(\boldsymbol{O}, \boldsymbol{\Sigma})$. The matrix polynomials $\boldsymbol{\Phi}(B)$ and $\boldsymbol{\Theta}(B)$ are assumed to have no left-common factors. For model building procedures of vector ARMA models, see Tiao and Box (1981) and Tiao and Tsay (1989).

Due to data limitation and the size of the system of behavioral equations for the modified DGBAS model, it would not be feasible to contemplate a vector model of full generality in the $\boldsymbol{\Phi}_i$ and $\boldsymbol{\Theta}_j$ to modify these behavioral equations. In this paper, we shall adjust the error term of each behavioral equation individually using an univariate ARIMA model of the form (2). Specifically, each individual behavior equation will take the form

$$\begin{aligned} y_t &= f(\boldsymbol{y}_t, \boldsymbol{y}_{t-}, \boldsymbol{X}_t; \boldsymbol{\eta}) + u_t, \\ \text{with} \quad \Phi(B)(1-B)(1-B^4)u_t &= \Theta(B)a_t. \end{aligned} \tag{4}$$

Although this does not take into account the cross-correlation structure of $\boldsymbol{u}_t$, it can be justified theoretically in that for the vector ARMA model (3), each component of $\boldsymbol{u}_t$ will individually follow an ARIMA model of the form (2). It will be demonstrated later, Section 3.6, that this procedure can lead to appreciable improvements in forecasting accuracy.

3.4. Time series estimation in the presence of outliers

Time series data are often subject to uncontrolled or unexpected interventions from which various types of outlying observations are produced. Outliers in time series, depending upon their nature, may have a moderate to substantial impact on the effectiveness of model specification, estimation and forecasting. In this work, the approach of Chang, Tiao and Chen (1988), Tsay (1988) and Chen and Liu (1993) is applied to each of the behavioral equations to identify potential outliers and re-estimate the model parameters accordingly. The types of outliers considered are innovational outlier (IO), additive outlier (AO), temporary change (TC) and level shift (LS).

Specifically, each behavioral equation in (1) is first estimated by OLS to obtain the residuals. Next an ARIMA model is specified for the residuals and the behavioral equation is modified accordingly to account for the dynamic structure in the residuals. Then an outlier detection and joint maximum likelihood estimation procedure is applied to each of the modified behavioral equations of the form (4). Finally, putting all the behavioral equations together and combining with identities, the model forecasts are solved using again the Gauss-Seidel algorithm. The resulting fitted model using quarterly data from 1966:1 to 1995:2 will be denoted as Macro-econometric time series model METSM. The complete specification of the behavioral equations of METSM is given in Table 2(a).

For both the MEM and the METSM, simultaneity does not enter until the stage where forecasts are obtained. In theory the two-stage least squares (2SLS), full information maximum likelihood (FIML), and other methods which take into account simultaneity at the estimation stage in the MEM can be used to sharpen the estimates. However our experience shows that 2SLS estimates do not differ much from OLS estimates, a typical phenomenon observed when the number of parameters is large relative to the number of observations. In addition, the out-of-sample forecasting performance is worse when using 2SLS than using OLS in our MEM. The method of FIML is extremely computationally burdensome and is not attempted here.

Similarly, in theory, the dynamic structure of the error terms should be taken into account to obtain consistent estimates of the parameters and hence consistent identification of the dynamics of error terms. Thus, the instrumental variable (IV) estimate derived from the proper reduced form is preferred to the OLS one. However, as the number of exogenous variables is typically large relative to the sample size, OLS and IV estimates are very close whereas the former are much easier to compute.

3.5. The main differences between MEM and METSM

While the model METSM is obtained from the model MEM by taking into account the autocorrelation structure of the residuals, it is worth noting the main differences between these two models.

1. A constant term for each equation and seasonal dummy variables Q1,Q2 and Q3 for most equations are included in the MEM system. For behavioral equations in the METSM system, the constant terms are dropped if the estimates are not significantly different from zero at the 5% level. Similarly, since the ARIMA model (4) for the error term can accommodate some seasonal features, seasonal dummies Q1,Q2 and Q3 are eliminated in a number of cases.

2. There is a heavy use of lagged dependent variables in the MEM model. According to Fair (1984), they can be regarded as accounting in part for expectational effects and in part for lagged adjustment effects. However, it seems redundant to have lagged dependent variables and AR parameters in the error term at the same time. We have in many cases moved lagged dependent variables to the ARIMA part of the error term. The efficacy of such consolidation is illustrated in the next section. Further studies are, however, required to develop a more systematic approach in the specification of lagged variables.

3. We have used dummy variables D1-D4 to account for some structural changes in MEM. In METSM, since we apply an iterative outlier detection and estimation procedure, many structural changes can be identified and then adjusted. Thus it is unnecessary to manually add dummy variables for potential

structural changes. However, the number of identified outliers depends on the nature of changes and the critical values chosen. The procedure might not be able to detect all possible structural changes. The difficult situations arise when outliers occur at (or near) the end of the series. Then, there exists little information to identify the types of outliers involved, which makes it difficult to estimate the impact of the detected outliers on the forecasts. Judgmental decisions are, therefore, required to produce forecasts when outliers occur near the forecast origin.

3.6. Forecasting with autocorrelated errors

We use a simple example to illustrate the impact of autocorrelated errors on forecast performance, assuming the parameters are known *a priori*. Let y_t be generated by the following regression model with autocorrelated errors:

$$y_t = \gamma x_{t-1} + u_t, \tag{5}$$

where $u_t = \phi u_{t-1} + a_t$, $|\phi| < 1$, $a_{t's}$ are i.i.d. $N(0, \sigma_a^2)$, and the $\{u_t\}$ and the $\{x_t\}$ processes are assumed independent.

It is well known that, under squared error loss, the optimal forecast of y_{t+1} given information up to time t, denoted as $E(y_{t+1}|I_t)$ where $I_t = \{y_t, y_{t-1}, \ldots; x_t, x_{t-1}, \ldots\}$, is

$$E(y_{t+1}|I_t) = \phi y_t + \gamma(x_t - \phi x_{t-1}),$$

and the variance of the forecast error is $E[y_{t+1} - E(y_{t+1}|I_t)]^2 = E(a_{t+1}^2) = \sigma_a^2$.

Now, if the dynamic property of the error term is ignored, the resulting forecast $\hat{y}_{t+1}$ and the associated variance are, respectively,

$$\hat{y}_{t+1} = \gamma x_t$$
$$E(y_{t+1} - \hat{y}_{t+1})^2 = E(u_{t+1}^2) = \frac{\sigma_a^2}{1-\phi^2}.$$

The inefficiency of $\hat{y}_{t+1}$ can be measured as

$$\frac{\sigma_a^2}{1-\phi^2} - \sigma_a^2 = \frac{\phi^2\sigma_a^2}{1-\phi^2}.$$

This can be substantial when $|\phi|$ is close to one. It is a common practice, especially in the econometric literature, to add lagged values of the *dependent* variable y_t to the regression to account for potential autocorrelations in the errors. In particular, the lagged-one value is often used, and this is, in fact, the case for the MEM. See Table 2(a). For the regression structure (5), this would lead to fitting a model of the form

$$y_t = \beta y_{t-1} + \eta x_{t-1} + c_t, \tag{6}$$

where c_t is the error term. It is interesting to investigate the forecasting efficiency of (6) with respect to the underlying model (5). For simplicity, we assume that x_t follows the autoregressive model $x_t = \alpha x_{t-1} + b_t$, $|\alpha| < 1$, and the $b_{t's}$ are i.i.d. $N(0, \sigma_b^2)$.

From (5), we see that

$$y_t = \phi y_{t-1} + \gamma x_{t-1} - \gamma\phi x_{t-2} + a_t,$$

and (6) is equivalent to absorbing $-\gamma\phi x_{t-2}$ into the error term c_t. The corresponding forecast of y_{t+1} will then be basd on (y_t, x_t), i.e.,

$$\tilde{y}_{t+1} = E(y_{t+1}|y_t, x_t) = \phi y_t + \gamma x_t - \gamma\phi E(x_{t-1}|y_t, x_t).$$

Under the assumptions made, it is straightforward to verify that

$$E(x_{t-1}|y_t, x_t) = [\gamma(1-\phi^2)y_t + \alpha\omega x_t]/[\omega + \gamma^2(1-\phi^2)],$$

with $\omega = \sigma_a^2/\sigma_b^2$, and that the mean squared error of $(y_{t+1} - \tilde{y}_{t+1})$ is

$$E(y_{t+1} - \tilde{y}_{t+1})^2 = \sigma_a^2\,[1 + \frac{\phi^2\gamma^2}{\omega + \gamma^2(1-\phi^2)}].$$

The inefficiency of $\tilde{y}_{t+1}$ can similarly be measured by

$$E(y_{t+1} - \tilde{y}_{t+1})^2 - \sigma_a^2 = \frac{\phi^2\gamma^2}{\omega + \gamma^2(1-\phi^2)}\,\sigma_a^2.$$

Contrary to what might be expected, the efficiency loss of $\tilde{y}_{t+1}$ can in fact be appreciable when ω is small, $\sigma_b^2 >> \sigma_a^2$, and $|\phi|$ is close to one. Of course, this inefficiency would disappear if the lagged independent variable x_{t-2} were included, but that would depend on the nature of the autocorrelations of u_t. This example demonstrates that care must be exercised in the specification of the dynamic structure of the model in a time series regression.

The above results can be readily extended to the case of a simultaneous equation model obtained using (1) and (3) for, in the corresponding reduced form, each behavioral variable is linearly related to its own past values and exogenous variables, plus an autocorrelated error term.

4. Forecast Performance Comparison

4.1. Comparison of UTS, MEM and METSM

The quarterly data considered in this paper are from 1966:1 to 1995:2 and consist of 118 time series observations for each variable. We consider out-of-sample forecasting comparisons. For this purpose, the 102 observations from 1966:1 to 1991:2 are used to start the estimation, and the remaining data are reserved for forecasting evaluation. Specifically, we first use data from 1966:1 to 1991:2 to estimate the specified UTS, MEM and METSM models and to compute 1 to 4-quarter ahead forecasts and the corresponding forecast errors, using the procedures discussed in Section 3. Next, we advance the forecasting origin by 1 quarter, re-estimate the models using all the data through 1991:3, and use the newly estimated models to compute 1 to 4-quarter ahead forecasts and their forecast errors. This rolling estimation-forecasting procedure is repeated until the forecasting origin reaches 1995:1, where only 1-quarter ahead forecasts are computed. Thus, for the 1-quarter ahead prediction there are 16 forecast errors, for the 2-quarter ahead prediction there are 15 forecast errors, and so on. We use the root mean squared error (RMSE) and the root mean squared proportional error (RMSE in %) as the forecasting comparison criteria. Let $\hat{y}_{it}$ be the forecast of variable i for period t, and let y_{it} be the actual value. Here $\hat{y}_{it}$ can be a prediction for more than one period ahead. Assuming that observations on $\hat{y}_{it}$ and y_{it} are available for $t = 1, \ldots, n$, the two measures are

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_{it} - \hat{y}_{it})^2} \quad \text{and} \quad \text{RMSE in } \% = 100 \times \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\frac{y_{it} - \hat{y}_{it}}{y_{it}})^2}\,.$$

In our study, $n = 16$ for 1-quarter ahead prediction, $n = 15$ for 2-quarter ahead prediction, and so on. Since the RMSE in % is invariant to the scaling of the variable considered, we apply it to most of the variables except those measured in percent, such as the unemployment rate and the interest rate, for which the RMSE is used.

The use of out-of-sample forecasts to compare macro-econometric models is common in the literature; see, for example, Fair (1984), Ch. 8. In computing forecasts of macro-econometric models, forecasts of exogenous variables are needed. For the first 18 nondeterministic exogenous variables in Table 1(c), the values used are out-of-sample predictions of univariate ARIMA models specified for these exogenous variables. The forms of the univariate models used are given in Table 3(b).

Table 4 gives the RMSE in % of forecasts of the three models UTS, MEM and METSM for the period from 1991:3 to 1995:2. We have also included the corresponding results using the original DGBAS model in Ho (1992) in the last panel of the table, denoted as DGBAS_M, for further comparison. From the table, we make the following observations. First, as might be expected, for the three models UTS, MEM and METSM, the accuracy of forecasts deteriorates as the forecasting horizon increases. Second, compared with the other two models, the performance of the METSM seems more stable over time. Third, the macro-econometric model with time series residuals METSM appreciably improves the forecast accuracy over the standard MEM model. Fourth, UTS models also fare

Table 4. Comparison of forecasting performance for **UTS**, **MEM**, **METSM** and **DGBAS_M** : 1- to 4-quarter ahead (RMSE in %)

No.	Variable Name	UTS 1	UTS 2	UTS 3	UTS 4	MEM 1	MEM 2	MEM 3	MEM 4
Private Consumption									
C1	Private Food Consumption	0.6	0.8	0.7	0.7	3.6	4.9	5.7	6.5
C2	Private Nonfood Consumption	1.5	1.7	1.6	1.9	4.0	6.0	7.3	8.6
Private Capital Formation									
I1	Private Fixed Investment	6.1	6.7	5.9	5.8	6.6	6.9	7.3	7.2
I2	Change in Inventory	74.8	73.7	76.1	70.6	117.7	176.3	206.0	224.2
I3	Depreciation	4.9	6.3	6.4	5.2	4.5	4.2	4.1	3.9
International Trade									
T1	Imports of Goods	5.1	4.2	5.6	6.1	5.4	4.9	6.9	7.6
T2	Imports of Services	5.2	7.1	7.6	7.5	6.1	7.7	7.1	6.0
T3	Exports of Goods	2.9	4.2	4.7	4.8	2.6	3.1	3.4	3.4
T4	Exports of Services	8.3	12.2	15.5	18.2	9.4	14.5	18.2	20.5
T5	Imports of Goods from U.S.A.	9.1	8.4	8.5	7.9	8.3	6.9	6.8	6.9
T6	Imports of Goods from Japan	4.7	4.7	5.4	5.2	5.7	6.1	8.4	10.3
T7	Imports of Goods from Hong Kong	11.6	13.1	17.7	15.9	14.8	19.6	24.7	27.7
T8	Imports of Goods from Other Areas	5.2	5.9	7.4	8.6	5.9	7.6	10.3	12.1
T9	Exports of Goods to U.S.A.	4.4	5.9	5.5	3.9	4.6	5.6	5.8	6.0
T10	Exports of Goods to Japan	5.8	8.2	9.9	10.9	5.4	7.4	8.6	9.0
T11	Exports of Goods to Hong Kong	3.5	3.3	3.9	3.9	7.2	7.6	8.7	10.3
T12	Exports of Goods to Other Areas	3.4	4.4	5.3	6.1	4.5	6.1	5.5	5.2
Government									
G1	Nominal Government Total Tax Revenue	8.8	8.9	9.8	10.2	11.4	13.2	14.7	15.1
Financial Market									
F1	Market Interest Rate*	0.2	0.3	0.3	0.3	1.7	1.7	1.7	1.8
F2	One-year Time Deposit Rate*	0.2	0.5	0.6	0.6	0.3	0.6	0.7	0.8
F3	Quasi Money	2.3	3.3	3.6	3.4	16.9	18.6	19.1	20.2
F4	Exchange Rate	1.5	2.7	3.7	4.7	1.6	3.1	5.1	7.3
Demand									
D1	GDP of Agriculture Sector	3.9	3.9	4.1	4.3	4.2	4.2	4.2	4.0
D2	GDP of Industry Sector	1.3	1.5	1.6	1.8	9.2	9.1	9.2	8.3
Labor									
L1	Unemployment Rate *	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3
L2	Labor Force	0.4	0.5	0.5	0.6	1.0	1.0	1.1	1.1
L3	Manufacture Wage Income Index	1.4	1.7	1.7	1.9	4.3	4.0	3.8	3.8
Supply									
S1	Potential GDP per Capital Stock	0.4	0.6	0.5	0.4	2.3	1.8	2.0	1.8
Price									
P1	Import Price Deflator	1.9	3.1	3.9	4.5	3.7	4.2	4.2	5.7
P2	Wholesale Price Index	1.2	2.3	2.8	3.1	4.6	6.9	7.8	8.1
P3	Consumer Price Index	1.0	1.4	1.4	1.4	1.4	2.1	3.0	3.9
P4	Private Food Consumption Price Deflator	2.1	2.6	3.3	3.6	2.6	3.4	4.4	5.3
P5	Private Nonfood Consumption Price Deflator	0.6	0.7	0.6	0.7	3.0	3.7	4.4	5.3
P6	Government Consumption Price Deflator	0.9	0.8	0.8	0.8	7.3	8.3	9.0	9.1
P7	Factor Income from Abroad Price Deflator	1.0	1.2	1.3	1.5	4.1	5.0	5.8	6.6
P8	Private Fixed Investment Price Deflator	2.1	3.2	3.2	2.1	7.0	6.9	6.8	5.6
P9	Government Fixed Investment Price Deflator	2.3	2.9	3.3	3.2	8.9	9.3	9.1	7.7
P10	Public Enterprise Fixed Investment Price Deflator	1.9	2.9	2.6	1.7	5.6	5.3	5.2	4.9
P11	Change in Inventory Price Deflator	2.6	3.1	3.4	3.8	8.2	10.0	10.7	11.0
P12	Depreciation Price Deflator	3.9	4.6	5.5	5.1	7.3	7.5	7.7	6.6
P13	Export Price Deflator	2.0	2.9	3.8	3.7	5.9	8.3	9.2	9.0

* RMSE, not in %

** Equation is not included in the model

Table 4. (continued)

No.	Variable Name	METSM 1	METSM 2	METSM 3	METSM 4	DGBAS_M 1	DGBAS_M 2	DGBAS_M 3	DGBAS_M 4
Private Consumption									
C1	Private Food Consumption	0.7	0.9	0.9	0.9	1.1	1.5	1.3	0.9
C2	Private Nonfood Consumption	1.7	2.1	2.0	2.2	11.0	11.2	11.7	11.9
Private Capital Formation									
I1	Private Fixed Investment	6.2	7.3	6.2	5.9	24.8	21.8	19.7	19.5
I2	Change in Inventory	426.2	448.0	497.2	512.6	89.4	114.3	100.4	102.8
I3	Depreciation	5.0	5.8	5.1	4.0	4.5	4.3	4.0	3.9
International Trade									
T1	Imports of Goods	4.7	4.6	5.4	6.4	4.7	3.6	5.4	5.8
T2	Imports of Services	6.4	7.6	7.4	7.1	6.2	7.8	7.9	7.9
T3	Exports of Goods	2.6	3.1	3.8	4.2	2.8	3.0	3.6	3.5
T4	Exports of Services	10.8	14.6	17.4	20.1	9.2	14.4	18.3	21.1
T5	Imports of Goods from U.S.A.	8.3	8.5	8.4	7.9	7.7	6.0	5.9	6.2
T6	Imports of Goods from Japan	5.4	4.5	5.7	5.5	4.9	3.8	4.9	4.9
T7	Imports of Goods from Hong Kong	12.3	13.0	15.5	17.9	33.7	37.0	41.0	44.7
T8	Imports of Goods from Other Areas	6.2	7.2	8.3	9.6	5.1	6.0	8.0	8.9
T9	Exports of Goods to U.S.A.	3.9	5.0	4.4	3.9	5.2	8.3	9.7	11.6
T10	Exports of Goods to Japan	5.4	7.4	9.0	10.0	5.2	7.1	7.6	6.0
T11	Exports of Goods to Hong Kong	4.9	4.8	5.6	7.1	6.9	6.7	7.6	9.5
T12	Exports of Goods to Other Areas	3.3	3.6	4.2	4.4	4.0	5.4	5.9	5.7
Government									
G1	Nominal Government Total Tax Revenue	7.8	8.1	8.3	7.0	18.8	20.4	21.0	20.9
Financial Market									
F1	Market Interest Rate*	0.2	0.4	0.5	0.5	NA**	NA	NA	NA
F2	One-year Time Deposit Rate*	0.2	0.4	0.5	0.5	NA	NA	NA	NA
F3	Quasi Money	2.0	3.2	3.9	4.5	19.0	20.0	20.8	22.0
F4	Exchange Rate	1.6	2.7	3.9	5.2	1.7	3.1	4.3	5.3
Demand									
D1	GDP of Agriculture Sector	4.2	4.4	4.6	4.7	9.7	9.4	10.4	10.6
D2	GDP of Industry Sector	1.3	1.3	1.5	1.7	8.6	8.9	9.0	8.9
Labor									
L1	Unemployment Rate *	0.1	0.1	0.1	0.1	0.2	0.3	0.3	0.3
L2	Labor Force	0.5	0.6	0.6	0.7	0.7	0.6	0.6	0.6
L3	Manufacture Wage Income Index	1.3	1.2	1.4	1.6	10.5	10.5	10.7	9.2
Supply									
S1	Potential GDP per Capital Stock	0.5	0.8	1.0	1.3	1.9	1.9	1.9	1.7
Price									
P1	Import Price Deflator	2.4	3.6	4.1	4.8	4.5	5.1	4.5	5.2
P2	Wholesale Price Index	1.5	2.7	3.4	3.8	5.0	5.8	6.1	6.4
P3	Consumer Price Index	1.2	1.6	2.0	2.5	11.0	11.8	12.3	12.9
P4	Private Food Consumption Price Deflator	2.5	3.3	3.9	4.5	11.8	12.6	13.2	13.9
P5	Private Nonfood Consumption Price Deflator	0.9	1.1	0.9	0.9	12.4	13.1	13.6	14.1
P6	Government Consumption Price Deflator	1.0	1.0	1.0	1.1	16.4	17.3	17.9	17.8
P7	Factor Income from Abroad Price Deflator	1.6	2.2	2.7	3.4	12.4	13.1	13.6	14.2
P8	Private Fixed Investment Price Deflator	2.0	3.0	2.6	1.7	20.3	21.0	21.4	21.7
P9	Government Fixed Investment Price Deflator	2.3	3.6	4.2	4.6	24.9	25.7	26.1	26.3
P10	Public Enterprise Fixed Investment Price Deflator	2.3	3.1	3.0	3.0	15.8	16.5	16.9	17.3
P11	Change in Inventory Price Deflator	3.7	4.9	5.4	5.5	9.3	10.1	10.4	10.8
P12	Depreciation Price Deflator	4.2	4.4	4.1	4.2	NA	NA	NA	NA
P13	Export Price Deflator	2.8	4.0	4.8	4.7	6.5	7.2	7.6	7.6

* RMSE, not in %

** Equation is not included in the model well compared with the MEM, and are slightly better in performance than the METSM. Fifth, the forecasting performance of the DGBAS_M is much worse compared with the MEM and METSM. This is especially noticeable in the price sector, where the improvement is substantial from the DGBAS_M model to the MEM and then to the METSM. The result here provides justifications for our modification of the original DGBAS model in Ho (1992) and for incorporating the time series techniques.

Table 5. Comparison of forecasting performance for **MEM**, **METSM**, and **DGBAS** published forecasts 1- to 4-quarter ahead (RMSE in %)

	MEM				**METSM**				**DGBAS(published)**			
Variable Name	1	2	3	4	1	2	3	4	1	2	3	4
Gross National Product	3.4	3.8	2.7	3.5	1.6	2.3	2.3	2.8	0.7	1.2	1.3	1.6
Private Food Consumption	3.4	4.5	4.9	5.6	0.8	0.9	0.8	0.8	0.9	1.1	1.3	1.3
Private Nonfood Consumption	4.3	5.5	6.6	8.5	2.1	3.0	3.7	4.5	2.1	2.4	2.8	2.9
Private Fixed Investment	15.5	14.0	15.9	14.8	11.1	15.5	15.1	14.5	9.4	11.3	13.4	13.8
Exports of Goods & Services	3.3	4.7	5.6	6.6	3.7	5.4	5.9	5.8	3.2	4.6	4.9	5.0
Imports of Goods & Services	4.3	5.8	7.0	8.7	4.1	5.3	5.6	6.5	3.6	5.8	5.4	5.5
Wholesale Price Index	4.2	5.4	6.2	8.0	1.7	2.8	3.5	3.6	1.1	1.7	2.5	3.1
Consumer Price Index	1.4	2.0	2.7	3.5	1.0	1.2	1.4	1.8	0.8	1.1	1.1	1.2
Gross National Product Price Deflator	3.0	4.2	5.4	6.6	0.8	1.3	1.6	1.6	0.5	0.7	0.9	1.1
Private Food Consumption Price Deflator	2.2	2.2	2.4	2.7	2.2	2.6	2.6	2.6	1.8	2.7	2.9	3.0
Private Nonfood Consumption Price Deflator	2.4	3.2	4.0	4.8	1.2	1.6	1.5	1.6	0.7	0.6	0.7	0.7
Private Fixed Investment Price Deflator	4.9	4.9	4.5	4.6	1.2	1.4	1.8	1.8	1.0	1.4	1.7	2.1
Export Price Deflator	5.2	6.1	6.9	8.7	2.1	3.4	4.1	4.4	0.9	1.9	3.2	4.0
Import Price Deflator	5.5	7.0	9.3	12.2	2.4	3.9	5.2	6.6	1.4	2.1	3.6	4.8
Change in Inventory Price Deflator	7.4	8.4	9.2	10.9	2.6	3.5	3.8	3.8	3.3	3.1	2.9	3.0
Factor Income from Abroad Price Deflator	3.7	4.5	5.6	5.9	1.2	1.7	2.1	2.7	0.7	1.0	1.0	1.3

Data span : 66:1 – 94:1

The forecasting performance is based on : 1-step forecast : 89:3 – 94:1 (19 quarters)
2-step forecast : 89:4 – 94:1 (18 quarters)
3-step forecast : 90:1 – 94:1 (17 quarters)
4-step forecast : 90:2 – 94:1 (16 quarters)

4.2. Comparison with the published forecasts of the DGBAS

To further assess the efficacy of the models considered, we have obtained the published 1- to 4-quarter ahead forecasts for the period from 1989:3 to 1994:1 made by the DGBAS on a number of key endogenous variables. These published forecasts were partially based on the DGBAS_M, but adjusted, in some cases substantially, using other information available at the time of publication and subjective judgment. In addition, forecasts of some of the variables were made in the middle of the quarter rather than at the beginning when model forecasts were made. In 1995 the DGBAS changed the deflators' base year from 1986 to 1991 and revised the database according to the 1991 census of industry and business, so their old forecasts are not comparable with the revised data which we have used to obtain the results in Table 4. Therefore, we have calculated the RMSE in % for the DGBAS's published forecasts based on data before the revision, and applied the same database to the MEM and METSM for comparison as well. Table 5 provides the results of a forecast performance comparison for the MEM, the METSM and the published forecasts. From the table, it is seen that the published forecasts by the DGBAS markedly outperform those of the MEM and are also marginally better than those of the METSM. A key endogenous variable of interest is the GNP, for which the published forecasts performed substantially better than the METSM.

While we do not know the adjustment methods and any additional information used by the DGBAS to obtain the published forecasts of the GNP, one of the possible reasons for their superior performance may be the impact of aggregation. Note first from Table 2(b) that the GNP is a linear aggregate of components which are either behavioral variables themselves or functions of behavioral variables, and forecasts from the models (MEM or METSM) are the corresponding linear aggregates of forecasts for the individual components. To investigate the possible impacts of aggregation on forecasting, we have employed the same database and calculated forecasts of the GNP by two alternative time series methods. The first one is to fit and forecast GNP directly using a UTS model which is of the form $(1-\phi B^4)(1-B)(1-B^4)y_t = a_t$. The second one is to fit UTS models to the GNP's components and then aggregate their corresponding forecasts to obtain the forecasts for the GNP. Since the second method uses more information, one might expect that it would outperform the first one in forecasting. However, empirical analysis indicates opposite results.

For forecasts of the same period from 1989:3 to 1994:1 as in Table 5, the RMSE in % for 1- to 4-quarter ahead forecasts for these two methods are given below:

Quarter	1	2	3	4
The 1st Method : UTS on GNP	0.8	1.2	1.4	1.5
The 2nd Method : UTS on Components	1.8	2.6	2.4	1.9

By comparing the above results with the corresponding ones in Table 5 for the GNP, we can make the following observations. First, the performance of the first method based on a UTS model for the GNP is comparable with that of the published forecasts. Second, the first method substantially outperforms the second method based on UTS models for the components. Third, the performance of the second method is comparable with the METSM. It is indeed interesting to note that the forecast errors of the published forecasts are, in fact, highly correlated with those of the first method. The estimated correlation coefficient based on all 70 pairs of forecast errors is about 0.79, suggesting that the DGBAS's published forecasts for the GNP might have partially relied on some univariate time series forecasting model roughly comparable to the one used in the first method.

As to the "paradox" of the performance of the forecasts based on aggregate data vs. component series, it could be explained, at least partially, by the fact that the GNP series varies more smoothly than its components since the process of aggregation often cancels out the variation within each component. The UTS method can more easily capture the regularity embedded in the aggregate GNP series and hence forecast well. However, when modeling the components series, model mis-specification is more likely to arise and summing over the component forecasts can compound the mistakes. Consequently, the resulting forecast might not perform well. This topic is currently being investigated.

In practice, models built from past data are usually far from perfect for prediction, and other available information and subjective judgment are often incorporated to produce the final forecasts. The results in Table 4 and 5 indicate that proper use of time series models to take into account the autocorrelations in the residuals of macro-econometric models can help maintain the substantive relations between variables and at the same time substantially improve the accuracy of forecasts. While such an approach will never completely replace subjective judgment, it will tend to provide a better basis upon which further judgments need to be made.

5. Two-way Tables for the METSM System

In this section, we present three two-way tables summarizing information from the METSM. While the post-sample forecasting performance of the UTS models and the METSM are comparable, a distinctive advantage of the METSM approach is that it incorporates substantive economic reasoning into the model, and in suitable circumstances can be used for policy evaluation. A practical difficulty in working with the METSM approach is its complexity. Even with a medium-size model such as the one considered here, the METSM model typically involves a fairly large number of behavioral variables, exogenous variables, their lagged values, and identities, making it difficult to comprehend the interrelationships among the variables. Of course, one simplifying approach is to work with the "reduced-form" of the model which directly links the endogenous behavioral variables to the exogenous variables. This, however, would lose all the information on the simultaneous relations among the behavioral variable which may be of considerable interest to the investigator.

Another potentially useful approach is to construct a two-way table showing the direct relations between behavioral variables as outputs and behavioral (including lagged values) and exogenous variables as inputs. It is an extension of the input-output analysis. The original input-output table can be traced to Leontief (1936) and (1941). The idea of input-output models took off and was rapidly developed in a number of economic areas which include regional studies, national account, price simulation, control and optimization, international trade and the Project LINK world model. Here we find it also useful to apply the input-output table to summarize all the information on the simultaneous relationships among the behavioral and exogenous variables.

The relations of the METSM in a two-way table is shown in Table 6. The behavioral equations are represented by the rows so that each row represents a behavioral equation of the model. The columns represent input variables. Here we have decomposed the identities into their component-wise input endogenous variables and exogenous variables. In the table, a 'X' indicates that the corresponding input variable (including lagged values) enters the behavioral equation represented by the row. For example, the table shows that import of goods MG depends on TVMUSA, TVMJAP, TVMHK, and TVMOTH. This information can be readily obtained by inspection of the structure of the behavioral equations in Table 2(a) and the identities in Table 2(b). For simplicity we have ignored the time series structures in the error terms of the model and the seasonal and other deterministic dummy variables. The diagonal entries of the table are left blank because we can move the lagged dependent variables to the error terms. This table makes it easier to ascertain the structural relations and identify a subset of recursive system. The entries in the table show, in a succinct way, which input variables are affecting a particular output behavioral variable, and which output behavioral variables are affected by a particular input. For examples, CF and CO as outputs are affected by a large number of inputs, but GDPAGR, GDPIND and PD as inputs have no effect on any output behavioral equations. MQM is affected by many inputs but itself has direct influence only on CO. MKRM has effect on IBF and TDR1Y but not on MQM. Such a table certainly contains more information than the reduced form, and can, in fact, be used as a partial check of the theoretical validity of the relations in the model considered.

In Table 7 we show qualitatively the estimating results of the METSM by presenting the signs of the estimated coefficients. Most of the signs are correct as expected from economic theory. For example, an increase in YDD will increase CF and CO, a standard consumption theory. There are only three estimates with incorrect signs and are statistically significant at the 5% level. They are indicated by circles in the table. In contrast, seven estimates in the original DGBAS model have incorrect signs. All estimation results are based on data over the period 1966:1 - 1995:2.

Table 8 shows the information on outliers identified in the METSM. A large number of outliers are identified in late 1973 and 1974, the time of the first oil crisis. There has also been a cluster of outliers for the trade variables after 1986. These variables have undergone a great deal of fluctuation since 1986, partly the result of the change of the exchange rate system from a fixed model under government control to a floating model determined by the market. Also, the innovational outliers in 1988 - 90 associated with the export and import from Hong Kong might be due to policy changes on investment in mainland China.

Table 6. Two-way table for the METSM

SECTOR	EQUATION NO.	VAR. TYPES	ENDOGENOUS (Including lags)																																							
		EQUATION NO.	C1	C2	I1	I2	I3	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	G1	F1	F2	F3	F4	D1	D2	L1	L2	L3	S1	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
		INPUT / OUTPUT	CF	CO	IBF	J	D	MG	MS	XG	XS	TVMUSA	TVMJAP	TVMHK	TVMOTH	TVXUSA	TVXJAP	TVXHK	TVXOTH	TAXTTN	MKRM	TDRIY	MQM	E	GDPAGR	GDPIND	U	NF	PWM	QFKSS	PM	WPI	CPI	PCF	PCO	PCG	PFIA	PIBF	PIG	PIPC	PJ	PD	PX
1	C1	ln(CF)		X	X	X	X	X	X	X	X									X											X			X	X	X	X	X	X	X	X		X
	C2	ln(CO)	X		X	X	X	X	X	X	X									X			X								X			X	X	X	X	X	X	X	X		X
2	I1	ln(IBF)	X	X		X	X	X	X	X	X										X													X	X	X		X	X	X	X		X
	I2	J	X	X	X			X	X	X	X																							X	X	X		X	X	X	X		X
	I3	D			X																																		X	X			
3	T1	MG										X	X	X	X																												
	T2	MS	X	X	X	X		X		X	X																									X	X		X	X			
	T3	XG														X	X	X	X																								
	T4	XS																																									
	T5	TVMUSA	X	X	X	X				X	X		X											X								X				X			X	X			
	T6	TVMJAP	X	X	X	X				X	X													X								X				X			X	X			
	T7	ln(TVMHK)	X	X	X	X				X	X		X																							X			X	X			
	T8	TVMOTH	X	X	X	X				X	X																				X	X				X			X	X			
	T9	TVXUSA																						X																			X
	T10	TVXJAP																						X																			X
	T11	TVXHK																						X																			X
	T12	sqrt(TVXOTH)																						X																			X
4	G1	ln(TAXTTN)	X	X	X	X		X	X	X	X																				X			X	X			X			X		X
5	F1	MKRM	X	X	X	X		X	X	X	X																				X					X	X		X	X			
	F2	TDRIY	X	X	X	X		X	X	X	X										X										X			X	X	X	X	X	X	X	X		X
	F3	ln(MQM)	X	X	X	X		X	X	X	X											X									X			X	X	X	X	X	X	X	X		X
	F4	E						X	X	X	X																				X												X
6	D1	GDPAGR	X																																								
	D2	ln(GDPIND)	X	X	X	X				X	X																									X			X	X			
7	L1	U			X		X																					X	X	X									X	X			
	L2	NF			X		X																				X		X	X									X	X			
	L3	ln(PWM)			X		X																				X	X		X									X	X			
8	S1	ln(QFKSS)			X		X																					X											X	X			
9	P1	PM																						X																			
	P2	WPI	X	X	X	X	X	X	X	X	X																X	X	X	X	X					X			X	X			
	P3	CPI			X		X																				X	X	X	X									X	X			
	P4	PCF																															X										
	P5	PCO																															X										
	P6	PCG																															X										
	P7	PFIA																															X										
	P8	PIBF																														X											
	P9	PIG																														X											
	P10	PIPC																														X											
	P11	PJ																														X											
	P12	PD																														X											
	P13	PX																														X											

Table 6. (continued)

SECTOR	EQUATION NO.	VAR. TYPES / EQUATION NO. / INPUT / OUTPUT	E1 MONN	E2 CGN	E3 IGN	E4 IPCN	E5 FIAN	E6 IR	E7 N	E8 PXUSA	E9 IGNPUSA	E10 WPIUSA	E11 PXJAP	E12 IGNPJAP	E13 WPIJAP	E14 EJAP	E15 GNPHK	E16 PHK	E17 EHK	E18 POILSAR	E19 TIME
			ENDOGENOUS (Including lags)																		
1	C1	ln(CF)		X	X	X	X														
	C2	ln(CO)	X	X	X	X	X														
2	I1	ln(IBF)		X	X	X															
	I2	J		X	X	X															
	I3	D			X	X															
3	T1	MG																			
	T2	MS		X	X	X	X														
	T3	XG																			
	T4	XS									X			X							
	T5	TVMUSA		X	X	X				X											
	T6	TVMJAP		X	X	X							X			X					
	T7	ln(TVMHK)		X	X	X															
	T8	TVMOTH		X	X	X															
	T9	TVXUSA									X	X									
	T10	TVXJAP												X	X	X					
	T11	TVXHK															X	X	X		
	T12	sqrt(TVXOTH)									X			X							
4	G1	ln(TAXTTN)		X	X	X	X														
5	F1	MKRM	X	X	X	X	X														
	F2	TDRIY		X	X	X	X	X													
	F3	ln(MQM)		X	X	X	X														
	F4	E																			
6	D1	GDPAGR																			
	D2	ln(GDPIND)		X	X	X															
7	L1	U			X	X															
	L2	NF			X	X			X												
	L3	ln(PWM)			X	X															
8	S1	ln(QFKSS)			X	X										X				X	X
9	P1	PM								X			X			X				X	
	P2	WPI		X	X	X															
	P3	CPI			X	X															
	P4	PCF																			
	P5	PCO																			
	P6	PCG																			
	P7	PFIA																			
	P8	PIBF																			
	P9	PIG																			
	P10	PIPC																			
	P11	PJ																			
	P12	PD																			
	P13	PX																			

Table 7. Qualtative estimating results for the METSM

SECTOR	EQUATION NO.	VAR. TYPES	BEHAVIORAL							LAGGED					IDENTITY												EXOGENOUS								
		EQUATION NO.	C1	G1	F1	F2	P1	P2	P3	C2	T6	L1	P2	P3	IT1	IT2	IT4	IF1	IF3	ID4	ID9	ID10	ID12	ID14	IS1	IP5	E3	E6	E7	E9	E12	E14	E15	E18	E19
		INPUT / OUTPUT	CF	TAXTTN	MKRM	TDRIY	PM	WPI	CPI	CO-1	TVMJAP-4	U-1	WPI-1	CPI-1	TVM	TVX	X	MKRMR	MON	KSS-1	GNP	GNPN	TD	YDD	PDT	CPGDP	IGN	IR	N	IGNPUSA	IGNPJAP	EJAP	GNPHK	POILSAR	TIME
1	C1	ln(CF)																				+											
	C2	ln(CO)								+												+											
	I1	ln(IBF)																−		⊕															
2	I2	J																							+									
	I3	D																		+															
	T1	MG													+																				
	T2	MS																			+														
	T3	XG														+																			
	T4	XS																												+	+				
3	T5	TVMUSA									+												+												
	T6	TVMJAP																					+												
	T7	ln(TVMHK)									+												+												
	T8	TVMOTH																					+												
	T9	TVXUSA																												+					
	T10	TVXJAP																													+				
	T11	TVXHK																														+			
	T12	sqrt(TVXOTH)																												+	+				
4	G1	ln(TAXTTN)																				+													
	F1	MKRMR																	−		+														
5	F2	TDRIY			+																							+							
	F3	ln(MQM)				−															+														
	F4	E																																	
	F5	GBN		−																							+								
6	D1	GDPAGR	+																																
	D2	ln(GDPIND)															+																		
	L1	U										+																							
7	L2	NF																											+						
	L3	ln(PWM)																							+										
8	S1	ln(QFKSS)																														⊖		−	+
	P1	PM																																+	
	P2	WPI					+						+																						
	P3	CPI												+																					
	P4	PCF							+																										
	P5	PCO							+																										
9	P6	PCG							+																										
	P7	PFIA							+																										
	P8	PIBF						+																											
	P9	PIG						+																											
	P10	PIPC						+																											
	P11	PJ						+																											
	P12	PD						+																											
	P13	PX						+																											

Table 7. (continued)

SECTOR	EQUATION NO.	VAR. TYPES: INPUT / OUTPUT	M2	DGDP	RPMUSA	RPMJAP	PMWPI	RPXUSA	RPXJAP	RPXHK	PXE	XMND12	TDX	PWMPDT	NFK88	PXUSAE	PXJAPE	GDPQF
1	C1	ln(CF)																
	C2	ln(CO)	+															
2	I1	ln(IBF)		+														
	I2	J		+														
	I3	D																
3	T1	MG																
	T2	MS																
	T3	XG																
	T4	XS																
	T5	TVMUSA			−													
	T6	TVMJAP				+												
	T7	ln(TVMHK)																
	T8	TVMOTH					−											
	T9	TVXUSA						−										
	T10	TVXJAP							−									
	T11	TVXHK								−								
	T12	sqrt(TVXOTH)									+							
4	G1	ln(TAXTTN)																
5	F1	MKRMR																
	F2	TDRIY																
	F3	ln(MQM)																
	F4	E										+						
	F5	GBN																
6	D1	GDPAGR																
	D2	ln(GDPIND)											+					
7	L1	U												⊖				
	L2	NF												+				
	L3	ln(PWM)																
8	S1	ln(QFKSS)													+			
9	P1	PM														+	+	
	P2	WPI												+				+
	P3	CPI												+				
	P4	PCF																
	P5	PCO																
	P6	PCG																
	P7	PFIA																
	P8	PIBF																
	P9	PIG																
	P10	PIPC																
	P11	PJ																
	P12	PD																
	P13	PX																

FUNCTIONS OF ENDOGENOUS & EXOGENOUS

M2=MON+MQM
DGDP=GDP-GDP(-1)
RPMUSA=PXUSA*E/WPPI
PRMJAP=PXJAP*E/EJAP/WPI
PMWPI=PM/WPI
RPXUSA=PX/WPIUSA*E
RPXJAP=PX/WPIJAP*E/JAP
RPXHK=PX/PHK*E/EHK
PXE=PX/E
XMND12=XMND+XMND(−1)+XMND(−2)
TDX=TD-X
PWMPDT=PWM/PDT
NFK88=NF/K88
PXUSAE=PXUSA*E
PXJAPE=PXJAP*E/EJAP
GDPQF=GDP/QF

Table 8. Outliers in the METSM

SECTOR	EQ. NO.	YEAR	1966				1967				1968				1969				1970				1971				1972				1973				1974				1975			
		QUARTER	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
		NO.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
		Var. Name																																								
1	C1	ln(CF)																														L			I							
	C2	ln(CO)																																								
2	I1	ln(IBF)															A		A										A			A		A								
	I2	J																																								
	I3	D																																								
3	T1	MG																																	A		A					
	T2	MS																																								
	T3	XG																										T		A												
	T4	XS																																								
	T5	TVMUSA																																								
	T6	TVMJAP																																								
	T7	ln(TVMHK)																																								
	T8	TVMOTH																																								
	T9	TVXUSA																																								
	T10	TVXJAP																																								
	T11	TVXHK																																								
	T12	sqrt(TVXOTH)																																								
4	G1	ln(TAXTTN)																																								
5	F1	MKRMR																	A																I							
	F2	TDRIY													I																			I	T	A		I	A			
	F3	ln(MQM)																																I								
	F4	E																																								
6	D1	GDPAGR																																								
	D2	ln(GDPIND)													A																											
7	L1	U								I																												A				
	L2	NF																															I									
	L3	ln(PWM)																													T			L								
8	S1	ln(QFK88)																		I																L					L	
9	P1	PM																																	L				L			
	P2	WPI																													T				A			A				
	P3	CPI																																	A							
	P4	PCF																																								
	P5	PCO																																								
	P6	PCG																																								
	P7	PFIA																																								
	P8	PIBF																																L								
	P9	PIG																																								
	P10	PIPC																																								
	P11	PJ																																								
	P12	PD																																								
	P13	PX																																	I					I		

NOTE: A=AO; I=IO; T=TC; L=LS;

Table 8. (continued)

SECTOR	SEQ. NO.	YEAR	1976				1977				1978				1979				1980				1981				1982				1983				1984				1985			
		QUARTER	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
		NO.	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80
		Var. Name																																								
1	C1	ln(CF)																																								
	C2	ln(CO)													A																											
2	I1	ln(IBF)																																								
	I2	J																																								
	I3	D																																								
3	T1	MG														T																										
	T2	MS																																								
	T3	XG				A	A									T																										
	T4	XS																																								
	T5	TVMUSA																																								
	T6	TVMJAP																																								
	T7	ln(TVMHK)					T																																			
	T8	TVMOTH					T																																			
	T9	TVXUSA																																								
	T10	TVXJAP																																								
	T11	TVXHK																																								
	T12	sqrt(TVXOTH)																																								
4	G1	ln(TAXTTN)																																								
5	F1	MKRMR																																								
	F2	TDRIY																																								
	F3	ln(MQM)																																								
	F4	E											L																													
6	D1	GDPAGR																																								
	D2	ln(GDPIND)																																								
7	L1	U																																							I	
	L2	NF																																								
	L3	ln(PWM)									T																															
8	S1	ln(QFK88)							A																																	
9	P1	PM																									I															
	P2	WPI																A	T																							
	P3	CPI																			T																					
	P4	PCF							A																																	
	P5	PCO																	I																							
	P6	PCG																																								
	P7	PFIA													T				T			A									L											
	P8	PIBF																																								
	P9	PIG																																								
	P10	PIPC											I																													
	P11	PJ																							A				A							A						
	P12	PD																																								
	P13	PX																																								

NOTE: A=AO; I=IO; T=TC; L=LS;

Table 8. (continued)

SECTOR	EQ. NO.	YEAR	1986				1987				1988				1989				1990				1991				1992				1993				1994				95	
		QUARTER	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2
		NO.	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118
		Var. Name																																						
1	C1	ln(CF)																																						
	C2	ln(CO)																		A																				
2	I1	ln(IBF)																																						
	I2	J						L													T																			A
	I3	D																									I							I						
3	T1	MG									T	I													A										T					
	T2	MS			T																																			
	T3	XG																																						
	T4	XS																												L					A					
	T5	TVMUSA									T		T																	I					I					
	T6	TVMJAP																																						
	T7	ln(TVMHK)									I		I		A																									
	T8	TVMOTH									A																													
	T9	TVXUSA																																						
	T10	TVXJAP																		A																				
	T11	TVXHK											I																		L		I		I		A			
	T12	sqrt(TVXOTH)																																						
4	G1	ln(TAXTTN)				I																																		
5	F1	MKRMR														L																								
	F2	TDRIY														I																								
	F3	ln(MQM)														L																								
	F4	E						I																																
6	D1	GDPAGR																																A						
	D2	ln(GDPIND)																																A						
7	L1	U																																						
	L2	NF																																						
	L3	ln(PWM)																																						
8	S1	ln(QFK88)																																						
9	P1	PM	L																																					
	P2	WPI																																						
	P3	CPI																																			A			
	P4	PCF																				L															T			
	P5	PCO																																						
	P6	PCG	I		T																																			
	P7	PFIA																																						
	P8	PIBF																																						
	P9	PIG																									I													
	P10	PIPC																																						
	P11	PJ																																						
	P12	PD																						I			I		A								A			
	P13	PX																																						

NOTE: A=AO; I=IO; T=TC; L=LS;

6. Conclusion

In this paper, we have extended the quarterly DGBAS model by adjusting its residuals via ARIMA models and modifying a number of the behavioral equations. We have demonstrated that such an approach can lead to improvement in forecasting. Specifically, we have compared the forecasting accuracy of the univariate time series models UTS, the standard macro-econometric model MEM, and the adjusted model METSM, and found that time-series adjustment of macro-econometric model can help maintain substantive relations and, at the same time, produce substantially more accurate and stable forecasts.

For the METSM, we have proposed a two-way table to display the direction of relations between the input and output variables. We have also presented a table of outliers detected in the METSM. These outliers can provide useful information on possible structural shifts in the model. For example, we have detected a number of outliers in trade variables after 1988, when the change of exchange rate determination occurred. This major intervention may have led to changes in relations affected by exchange rates. In future work, it will be interesting to develop a more systematic approach to study the regime shifts. For example, we can apply backfitting techniques to identify regime shift functions and use the methods of best subset regression and variable selection in regression analysis to determine the final model, as in Chen and Tsay (1993).

While in this paper our main focus has been on forecasting, we plan to conduct a careful investigation of statistical issues involving policy evaluation. Another important issue in macro-econometric modeling is the use of data with different frequencies such as monthly and quarterly observations. For forecasting future observations, the conventional way is based on the correlation structure of the one-period-ahead forecasts made from data with different frequencies to derive a combined forecast. This approach, however, ignores the possible dynamic structure of data from different sources and we intend to develop appropriate methods to obtain more accurate combined forecasts.

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COMMENT

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I am a strong believer in the use of post-sample forecast evaluations to compare the quality of models. It allows a fairly uncontroversial comparison without the obvious insample problems of data-mining and the multiple use of data for specification searching, estimation and evaluation. If one can fully design an experiment it is preferable to add elements to models one at a time. Thus, for example, if model 1 uses a simple form and information set then model 2 should not **both** use a wider information **and** introduce a non-linear specification, because if model 2 performs better than model 1, then one does not know what is the reason. If model 1 is the better of the two, one cannot conclude, perhaps, that either non-linearity or the wider information set used by itself would not have produced a better result.

In this paper post-sample forecasts are compared for four models; (i) univariate time series (UTM); (ii) a specified macro model with no analysis of the time series properties of the residuals (MEM), although under an assumption of normality. This model is a modified form of the original DGBAS model of the Taiwan economy; (iii) The MEM model but with multivariate time series analysis of the residuals, in the form of a vector-ARMA model-fitting, giving METSM; and (iv) the DGBAS model. Any large scale macro model is likely to be complicated. Those in (ii) and (iii) have 90 variables classified as exogenous and a further 26 as exogenous, leading to a system of 41 behavioral equations and 49 identities. Thus, essentially, there are 41 variables to be used as dependent variables and to be forecast, but the whole system is too lengthy to present fully in a journal article. A macro-model usually contains non-linear elements, although this appears not to be discussed and the specification represents the viewpoint of a Bayesian with strong views-many coefficients are put to zero, for example, as when certain variables are declared "exogenous". There is nothing wrong with that provided these viewpoints are correct, or nearly so. Otherwise, the model is being constrained away from the truth. One solution for this difficulty is to test for "exogeneity". For example, it is here assumed that money is exogenous, whereas in most economies there is evidence for a reaction function, in which the supply of money depends on the state of the economy and then the residual to this equation becomes the exogenous component of money.

In terms of the experiment, the models in (i), (iii), and (iv) make useful comparisons. MEM differs from DGBAS by a set of improved specifications, and METSM differs from MEM by the improved modeling of residuals. Only UTS and the others are difficult to compare as they differ in more than one element. For example, METSM uses both economic knowledge in its specification and multivariate time series analysis in forming the model, whereas UTS uses only univariate methods. What is clearly missing is an intermediate class of models in which the 41 variables are analyzed directly using multivariate or vector ARIMA techniques, without imposing the economic constraints. This is now done frequently at other Central Banks using error-correction models and cointegration, at least for sub-sets of variables.

Turning to the results, I have just considered one-step forecasts and ranked the techniques, giving a score of 1 if the method is best, $1\frac{1}{2}$ if equal best with one other method and so forth, ignoring rows in which there was an NA. On such a scaling the forecasts from DGBAS were worse and from MEM next worse; those from METSM had an average score of 2.17 (17% having a rank of 1, 30% having a rank of 1 or $1\frac{1}{2}$) and those from UTS had an average score of 1.58 (59% had rank 1, 67% had rank 1 or $1\frac{1}{2}$). It is remarkable how well the UTS forecasts performed relative to the others given that the method used, due to Box and Jenkins (1970), are now over a quarter of a century old, are based on a very limited information set, and do not have the benefits of the economic knowledge and theory embedded in the other three models. I have to believe that the forecasts from the missing part of the experiment, using VARIMA models directly on the variables, would prove superior to all of the forecasts shown here. In head to head competition the UTS forecasts have lower RMSE compared to those from METSM on 73% occasions for one-step and 68% of occasions for fourstep forecasts (ignoring ties). Of course, these figures are just indications, one really should be presenting tests of significance of the null that pairs of RMSE's are equal, as proposed in Chapter 9 of Granger and Newbold (1986), for example.

This paper has an old-fashioned feel to it. UTS comparisons with econometric models were in vogue twenty years ago. What is new is the application of VARIMA models to residuals from econometric models, although this is not a new technology. Rather newer would be the use of VARIMA modeling, including error-correction models, perhaps applied to the variables designated endogenous but certainly to the exogenous variables. One way of improving the MEM and METSM model forecasts would be to improve the forecasts of the exogenous variables, which can be achieved by using multivariate time series models for them. In so doing, some reclassification of variables will be required. However, this is still a decade-old technology. To be more up-to-date, specification tests to search for missing non-linearity say, or for the effects of structural breaks will need to be considered, at least for the key variables.

An econometric model is never a final product but is always an on-going process and my comments should be taken as constructive criticism to suggest directions in this process.

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COMMENT : A DYNAMIC APPROACH TO STRUCTURAL MODELLING

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1. Introduction

Tiao et al. (1998) make the very general and important point that a good forecasting model must be an adequate representation of the data. They do this by taking a well-respected macroeconomic model and testing the residuals from the models equations for broad conformity with the assumption that they are white noise. The model fails this test and so they correct this by building ARIMA time series models of the residuals. They then demonstrate that this augmented model outperforms the original model significantly in a range of forecasting situations.

I have no doubt that these broad conclusions are correct, indeed it is a central tenet of the dynamic modelling tradition, which I come from, that a good estimated equation should pass a very broad range of diagnostic procedures which would certainly include tests for serial correlation and residual misspecification. However simply passing these tests and forecasting well would not, in my view, be sufficient to ensure that a model is an adequate representation of the data. In this comment I would like to briefly outline the dynamic modelling tradition which has grown from the work of Dennis Sargan and his many students and to discuss where this would have led to differences in modelling techniques to that used in Tiao et al. I will argue that this general approach to modelling would have led to at least two significant differences; first the structural form of many of the equations may have been rejected. Second the approach of modelling the error processes may impose an invalid set of restrictions on the parameters of the general dynamic model which should be relaxed.

2. The Principle of Model Reduction

The framework used in dynamic modelling is that associated with Sargan and Hendry in many papers and which is summarised in Hendry, Pagan and Sargan (1984), a simple account may be found in Hall Cuthbertson and Taylor (1992), Chapter 4. The framework begins by setting out a completely general statement of the world, the data generation process (DGP) and thereby clearly specifying the steps which are necessary to go from this general statement to a model which may be estimated and used for policy analysis. If all the steps are valid then the result is a valid model. The use of this framework is however mainly that by clearly specifying the steps we are implicitly taking when we formulate a model we can categorise all the possible mistakes which we might make in practical estimation. So, let x_t be a vector of observations on all variables in period t, and let $X_{t-1} = (x_{t-1}, \ldots, x_0)$, then the joint probability of the sample x_t, the DGP, may be stated as,

$$\prod_{t=1}^{t} D(x_t | X_{t-1}; \alpha), \tag{1}$$

where α is a vector of unknown parameters. The process of econometric model building consists of simplifying this very general statement of the world to the point at which it becomes feasible to use the model in practical analysis. This process of simplification is termed model reduction and consists principally of the following four steps.

1. Marginalise the DGP. The full DGP contains far more variables than we are normally interested in, or can possibly deal with. We therefore reduce this set by selecting a set of 'variables of interest' and relegate all the rest of the variables to the set which are of no interest to the issue at hand.
2. Conditioning assumptions. Given the choice of variables of interest we must now select a subset of these variables to be treated as endogenous (Y_t), these variables are then conditioned on the remaining exogenous variables (Z_t). For valid estimation the Z_t variables should be at least weakly exogenous.
3. Selection of functional form. The DGP is a completely general functional specification and before any estimation can be undertaken a specific functional form must be assumed. In many cases this is either a linear or log-linear specification.
4. Estimation. The final stage involves assigning values to the unknown parameters of the system, this is the process of econometric estimation.

Given the general DGP in (1) it is possible to represent the first two stages in the model reduction process by the following factorisation, where the function 'B' represents what one might usually refer to as the structural equations of interest.

$$D_t(x_t|X_{t-1};\alpha_t) = A_t(W_t|X_t;\alpha_t)B_t(Y_t|Y_{t-1},Z_t;\alpha_t)C_t(Z_t|Y_{t-1},Z_{t-1};\alpha_t). \qquad (2)$$

The first component, A, specifies the determination of W, the variables of no interest as a function of all the variables. The second term, B, gives the determination of the endogenous variables of interest as a function of lagged endogenous variables and all exogenous variables of interest. The final term C gives the determination of the exogenous variables as a function of largged exogenous and endogenous variables.

These steps are all crucial in the formulation of an adequate model. If the marginalisation is incorrect then this implies that some important variable has been relegated to the set of variables of no interest. This is then the classic error which gives rise to omitted variable bias. If the conditioning assumptions are incorrect then we have falsely assumed that an endogenous variable is exogenous and so we generate the problem of simultaneous equation bias at the estimation stage and we may also be seriously misled about the nature of causality within the system. If the functional form is wrong either because of an inadequate dynamic specification or an incorrect assumption of linearity then the axiom of correct specification is violated and the estimation stage can not be carried out in a satisfactory way. Finally estimating the unknown parameters has all the usual econometric problems attached to it which we are aware of.

The point which is emphasised by this decomposition is that all the most important mistakes are generally made in the first three steps before estimation actually begins. The process of dynamic modelling then becomes a pragmatic one of iterating between these stages while continually testing the model in as comprehensive way as possible. As soon as the model fails a test we do not simply find a way of correcting the problem (e.g. if we fail a test for serial correlation in the residuals we do not simply estimate a model with first order serial correlation) instead we go back to the earlier stages to find out where the problem is coming from. Is it in the marginalisation, the conditioning or the functional form? And then we correct the problem at its root.

I would also interpret the term test very broadly to mean not only conventional tests of the properties of the residual but also parameter constancy, model stability and, even more broadly, to consistency of the model with economic theory and encompassing of other competing models.

This view model reduction also establishes a very general principal of model testing which we refer to as the general to specific methodology. The idea here is very simple. Once we have made a mistake in model specification this biases all conventional statistical tests. So if we start from a misspecified model and test it the tests will be a very poor indication of the direction of the misspecification. For example, we may find serial correlation because of an omitted variable, clearly we would be wrong to adjust the model for serial correlation rather than include the missing variable. The only way to perform valid tests in then to start from a very general dynamic model which passes our broad range of diagnostic tests and then to test down to a specific model which is an adequate representation of the data.

3. The Implications for the Tiao et al. Procedure

So how would this approach have altered the analysis of Tiao et al? It would certainly have confirmed the inadequacy of the MEM model. By finding significant serial correlation in the residuals of most of the structural equations we know that the MEM model was not an adequate representation of the data. But this approach would have suggested going back to the equations themselves and searching for the source of the misspecification rather than simply fixing this one diagnostic which is essentially what is being done here by building residual models.

This misspecification may have been in terms of any of the categories outlined above, the marginalisation or conditioning may be wrong for example, and this may be causing the serial correlation.

The first basic are I would consider is that it is clear from Section 2.5 (the data transformation section) that many of the original equations adopted a functional form which is not compatible with economic theory. The linear regression equation often violates the most basic requirements of homogeneity of degree one between inputs and outputs which theory gives rise to. This has been corrected in some sectors but not others. As I read Table 2a, all the price equations are still specified in level (not logarithmic) form; this means that if there is any non price variable in the equation (which includes even a constant or seasonal dummies) then if we double the input prices, the output price cannot double. That is to say a functional form has been chosen which makes it impossible for the model to obey this basic principal of demand theory.

The second area of divergence is in the way the apparent dynamic misspecification in MEM has been dealt with. Building ARIMA models of the residuals will certainly increase the model's forecasting ability considerably. But it does not help us to get closer to a good model. I would view this approach as essentially compensating for a bad model rather than trying to correct it at a fundamental level. There are two illustrations of this.

First, we are not given details of individual residual models but Tiao et al's equation (4) makes it clear that in general a full ARIMA model in being used which includes the integrated term. This means that some of the equation residuals are non-stationary, which in turn implies that the equations do not contain a cointegrating vector in the sense of Engle and Granger (1987) or Hall (1986). The dynamic modelling approach would strongly recommend that this should be dealt with by returning to the marginalisation stage of the modelling process and finding the missing variables. This would allow cointegration and remove the unit root in the error term. What we are saying here is that the equations are so badly specified that they do not cointegrate. I would argue that correcting this misspecification at its root is much more useful, in terms of improving the model, than simply masking the effect by modelling the error process.

Second, the process of putting all the dynamics into the residuals actually implies a restriction on the general model which may, or may not, be valid, but which can be tested. This point was first made by Hendry and Mizon (1978) and is easily illustrated by a simple example. Suppose we have the following model which has incorrectly over-simplified the dynamic structure so that the residuals exhibit an AR(1) process.

$$\begin{aligned} Y_t &= \beta X_t + u_t \\ u_t &= \alpha u_{t-1} + \nu_t. \end{aligned} \tag{3}$$

Now this can be represented as

$$Y_t = \alpha Y_{t-1} + \beta X_t - \alpha\beta X_{t-1} + \nu_t. \tag{4}$$

There is a common factor linking the coefficients of the lagged variables in this equation. We could, based on the general to specific principle, state an unrestricted general model

$$Y_t = \delta_1 Y_{t-1} + \delta_2 X_t + \delta_3 X_{t-1} + \nu_t \tag{5}$$

and we could test to see if the unrestricted coefficients δ_i can be restricted to have a suitable common factor. If this restriction is acceptable then the serially correlated residual model is a more parsimonious representation and is a useful simplification. if the restriction is not acceptable then the residual model is rejected. In the general notation of Tiao et al's equation (4), the test becomes one of testing the general common factor imposed by

$$(\Phi(B)(1-B)(1-B^4))^{-1}(y_t - f(y_t, y_{t-}, X_t; \eta)) = u_t. \tag{6}$$

In economic terms this means that the dependent variable will be forced to adjust at the same speed to all the right hand side variables, which may be highly unrealistic. This common factor analysis is the more systematic approach called for in point 2 of section 3.5.

Conclusion

I applaud this attempt to improve the dynamic structure of a macroeconomic model. It is certainly true that many models are seriously misspecified, especially with respect to their dynamic structure. Models are used for many purposes other than forecasting, policy analysis is one important use, another is to aid and articulate our understanding of how the economy works. By modelling the dynamics of the misspecified model we will certainly improve the forecasting performance of a model. I have argued here however that the dynamic modelling tradition would suggest correcting the dynamic misspecification by respecifying the model and eliminating its fundamental problems. This would not only improve the forecasting ability of the model but also create a model which is a better representation of the economy and a better policy analysis tool.

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COMMENT

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The main purpose of the paper is "to develop a systematic procedure to improve the performance of econometric models by using statistical and econometric tools to incorporate important empirical characteristic into theoretically specified macroeconometric models". In this paper, the modified versions of Directorate-General Budget, Accounting and Statistics (DGBAS) model are adapted to demonstrate this procedure with the hope to obtain a "deeper understanding" of relations among economic variables, and substantial gains in forecasts of Taiwan's economy. Since the DGBAS model, like most macro-econometric models, is designed to forecast major economic variables and to conduct policy evaluations, the merits of the suggested procedure should be judged according to its success in accomplishing these goals.

Unfortunately, it is found that the model obtained by following the suggested procedure neither enhances better understanding of macro-economic relations and policy evaluations, nor does it provide a better forecast tool.

In order to give a systematic discussion, the comments will be arranged according to the sequence of the paper, and its sub-headings are used for easier reference. An overall remark, then, will be given at the end of this discussion.

I. Comments on "Block Structure and Main Feature of the Modified DGBAS Model"

The DGBAS model is originally designed to conduct policy evaluations and to forecast major economic variables, primarily real variables such as GNP, Consumption, Investment, Exports, Imports, etc., while the modified DGBAS model (MEM) still retains the static characteristics of Keynesian models that are known to suffer some serious shortcomings: ad hoc dynamic relations, fanciful identification constraints, etc.. However, in the process of modifying the DGBAS model, the authors make no fundamental and systematic changes in the theoretical structure, but rather arbitrarily change the specification of some behavioral equations to improve forecast performance. Although the changes in the specification slightly improve the model forecast performance (see Table 4 in the paper), they bring up many issues worthy of further discussion.

To save space, only changes in the specification of the money market equilibrium equation will be reviewed here. In a highly open economy like Taiwan's, it would not be considered reasonable to treat money stock (or money supply) as an exogenous policy variable, to limit the determinants of nominal interest rate only to GNP and money stock, and to ignore the interactions among four financial assets markets.

II. Comments on "Estimation, Time Series Modeling and Forecasting Procedures"

1. In the univariate time series (UTS) model, each behavioral variable is constructed using the standard interactive model building procedure suggested by Box and Jenkins (1976). In the literature, the model is always used as a benchmark to set the minimum forecast performance for any decent macroeconometric model. Surprisingly, this model outperforms the three other models in the paper (see Table 4). And note that the authors make no attempt

to improve the forecast ability of UTS by further dealing with deterministic trends, outliers and structure breaks.

2. Methodologically, a system of simultaneous equations can be unbiasedly and efficiently estimated by applying OLS to each equation only if the system satisfies the extremely strict Wold recursive conditions; otherwise, there will be simultaneous bias and inefficiency. In this paper, the structure of the MEM model does not satisfy the block-recursive conditions, not to mention the Wold recursive conditions. Thus, a biased and inefficient result is inevitable. Although the authors mention that two-stage least squares (2SLS), full information maximum likelihood (FIML) and other methods can be used to sharpen the estimates, it is necessary to point out that the application of instrumental variable (IV) or 2SLS can only decrease bias, while three-stage least squares (3SLS) and FIML can be used to improve the efficiency. Personally, I would seriously consider adapting optimal IV or 2SLS methods even though they might worsen the efficiency in small samples.
3. Indeed, theoretically incorporating auto- and cross-correlations of the error terms will improve the efficiency of the estimation of macro-econometric models. However, modeling the error term as a vector ARMA model is not operational even in small models, and alternatively specifying each error term as a univariate ARMA model is impossible or at least difficult to justify. More importantly, although there is no prior restriction as to specifying the dynamic structure of behavioral equations or their error terms, moving stochastic deseasonality and intertemporary correlation to the error term in constructing the MEMTS model does have several drawbacks. This king of modification of econometric model usually causes difficulties in evaluating policy, interpreting empirical results, and estimating the model. Therefore, it is preferable to specify sufficient lagged dependent and independent variables in the behavior equations.

   The authors, using the example in Section 3.6, try to establish that the specification of a regression model with auto-correlated error term is a better choice than that of a regression model with lagged dependent variables. However the example essentially shows that the latter model is mispecified only if the former specification is correct, and vice versa.

III. Comments on "Forecast Performance Comparison"

By closely examining the summary of forecasting performance of the UTS, MEM, MEMTS, and DGBAS-M models provided in Table 4, one can definitely conclude that the UTS model forecasts fairly well compared to the MEMTS. And the MEM model is slightly better in forecast performance than DGBAS-M model. More specifically, among 41 behavioral equations, the averaged forecast performance of four horizons of the UTS are ranked first or second in 24 and 11 equations, while MEMTS is so ranked in 9 and 22 equations. Alternatively, as to the performance of one to four forecast horizons, the UTS model has equal or less RMS than the MEMTS model in 30, 27, 26, and 29 equations respectively. On the other hand, the MEM (the modified version of DGBAS model) gives only a marginal improvement in forecasting over the DGBAS-M model.

In sum, based only on forecast performance, the modification of theoretical specifications resulting in the MEM model yields only slight improvement. And incorporating dynamic structure into the MEMTS model gives better performance than the MEM model, though the performance is much worse than for the UTS.

IV. Summary of the Comments

Forecast performance is not the only criterion for empirical model comparison; however, it is important for preliminary evaluation of any dynamic macro-econometric model. For real world applications, one also expects macro-econometric models to provide better understanding of interactions among major economic variables as well as more reliable policy evaluations. However, according to the forecast comparison above, the proposed MEMTS model is significantly outperformed by the UTS model. There is a serious question about what we have gained from following the authors' procedure. Does it actually enhance the understanding of the dynamics of Taiwan economy? Does it provide more reliable policy evaluations? And, importantly, does it reduce the cost of constructing and estimating the econometric models?

There is no doubt that using time series techniques to detect the intertemporary relations of variables and residuals, and using them to modify the specification of model will improve the performance of models. It is equally obvious that the model specification and estimation should be chosen to serve the purpose of the model. Therefore, in macro-econometric model building, the model with rich dynamic behavioral equations is preferred to one with static behavioral equations and rich dynamic error terms, because the latter is unobservable and has no policy implication. Finally, in modifying the theoretically-specified model, proper care should go into the exogeneity of variables and the interactions among markets and sectors.

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COMMENT

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This paper extends the quarterly DGBAS model by adjusting its residuals via ARIMA models and by modifying a number of behavioral equations. It demonstrates that such an approach can produce more accurate and stable forecasts. It is indeed a very interesting and stimulative paper. I agree with the authors about the usefulness of ARIMA modeling approach in improving the forecast accuracy. However, I do believe that respecting the specification and dynamic structure of the model is more important. I shall illustrate my point by an example. In addition, I will raise the issue of how much more efficiency comes from using the complicated ARIMA error-correcting procedure over the conventional AR procedure, especially when the sample size is small.

For simplicity, I will focus my discussion on private consumption to illustrate the importance of model specifications. In the paper, private consumption is divided into food consumption and nonfood consumption, and their specifications can be stated as follows:

$$\begin{aligned} l_n(\mathrm{CF}) &= a_0 + a_1 l_n(\mathrm{YDD}) + a_2 l_n(\mathrm{CF}(-1)) + a_3 Q_1 + a_4 Q_2 + a_5 Q_3 + u_{1t}, \\ l_n(\mathrm{CO}) &= b_0 + b_1 l_n(\mathrm{YDD}) + b_2 l_n(\mathrm{MON} + \mathrm{MQM}) + b_3 l_n(\mathrm{CO}(-1)) \\ &\quad + b_4 Q_1 + b_5 Q_2 + b_6 Q_3 + u_{2t}. \end{aligned}$$

Here CF is real private food consumption, CO is real private nonfood consumption, YDD is real disposable income, MON and MQM are narrowly defined money supply MIB and Quasi-money respectively, Q_1, Q_2, Q_3 are seasonal dummies, u_{1t} is specified as an AR(1,4) MA(1) series and u_{2t} is an AR(4) MA(1) series with numbers in parentheses representing lags.

There is no doubt that disposable income is the most important factor for explaining the behavior of private consumption. However, stock market is another key variable. For example see Lin, Wu and Chen (1997). This is particularly true for Taiwan, where stock constitutes an important part of wealth. More specifically, the ratio of market value of stock to nominal GDP is about 1.1. Furthermore, stock transaction service fees are imputed as one component of private consumption. By definition, high stock transaction volume generates high private consumption. Moreover, since private food consumption has a significant inertial effect, which is also influenced by the fluctuation of food prices, we include time trend and change of food prices in our private food consumption model. Therefore, our private food consumption and nonfood consumption functions can be expressed as follows:

$$\begin{aligned} l_n(\mathrm{CF}) &= a_0 + a_2 l_n(\mathrm{YDD}) + a_2 l_n(\mathrm{VSTOCK}) + a_3[l_n(\mathrm{PF}) - l_n(\mathrm{PF}(-1))] \\ &\quad + a_4 \mathrm{Trend} + a_5 l_n(\mathrm{CF}(-1)) + a_6 Q_1 + a_7 Q_2 + a_8 Q_3 + \varepsilon_{1,t}, \\ l_n(\mathrm{CO}) &= b_0 + b_1 l_n(\mathrm{YDD}) + b_2 l_n(\mathrm{VSTOCK}) + b_3 l_n(\mathrm{CO}(-1)) + b_4 l_n(\mathrm{CO}(-4)) \\ &\quad + b_5 l_n(\mathrm{CO}(-5)) + b_6 Q_1 + b_7 Q_2 + b_8 Q_3 + \varepsilon_{2,t}, \end{aligned}$$

where VSTOCK is real market value of stock, PF is price indexes of food, $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are residuals, both specified as AR(1,4) series.

We update the data to 1996:4 and do the model forecasting performance comparison by using the same procedure and criteria as in Tiao et al. Table 1 and Table 2 give the RMSE in % of forecast of our modification (Model 1), Tiao et al's model with error correction AR(1,4)(Model 2A), with error correction AR(1,4) and MA(1)(Model 2B), and the DGBAS_M model of Ho (1992)(Model 3) for the period from 1993:1 to 1996:4. This is for the case of private food consumption and nonfood consumption, respectively. From these tables it can be seen that our model has a better out of sample forecast performance than do the Tiao et al. models.

Table 1. Comparison of forecasting performance for different models: 1-to-4-quartes ahead: the case of private food consumption (RMSE in %)

CF	1^{st} period forecast	2^{nd} period forecast	3^{rd} period forecast	4^{th} period forecast
MODEL 1	0.5499	0.7318	0.7706	0.7662
MODEL 2A	0.6122	0.9338	1.0481	1.0786
MODEL 2B	0.8184	1.1153	1.0050	0.8349
MODEL 3	1.0923	1.3459	1.3222	0.6964

MODEL 1 : our modified model: equation (1') with error correction AR(1,4)
MODEL 2A : Tiao et al. model: equation (1) with error correction AR(1,4)
MODEL 2B : Tiao et al. model: equation (1) with error correction AR(1,4) & MA(1)
MODEL 3 : DGBAS_M model

Table 2. Comparison of forecasting performance for different models: 1-to-4-quarters ahead: the case of private nonfood consumption (RMSE in %)

CO	1^{st} period forecast	2^{nd} period forecast	3^{rd} period forecast	4^{th} period forecast
MODEL 1	1.2118	1.4030	1.5884	1.7124
MODEL 2A	1.3661	1.4256	1.7116	2.0135
MODEL 2B	1.4061	1.4842	1.7362	2.0187
MODEL 3	5.4290	5.5378	6.0251	6.1918

MODEL 1 : our modified model: equation (2') with error correction AR(1,4)
MODEL 2A : Tiao et al. model: equation (2) with error correction AR(1,4)
MODEL 2B : Tiao et al. model: equation (2) with error correction AR(1,4) & MA(1)
MODEL 3 : DGBAS_M model

To evaluate how much we can gain by adopting the ARMA error correcting procedure, we reestimate the Tiao et al. consumption function, but with only an AR residual correction, and we put the resulting forecast evaluation in model 2A. By comparing the model forecasting performance between Model 2A and 2B we note that, except for the 3rd and 4th quarter out-of-sample forecasts of private food consumption, model 2A performs better than 2B. In other words, including the MA term in the error-adjusting process does not necessarily improve the accuracy of model forecasting. This result casts doubt about the usefulness of MA terms in residual correction. From the historical pattern of private food and nonfood consumption of Taiwan, it can be noted that private food consumption is a stable trended series and nonfood consumption is a volatile series. As was mentioned above, the stock market accounts for a good deal of the behavior of Taiwan private consumption, and especially for nonfood consumption in recent decades. Omitting it might lower the accuracy of model forecasts. Moreover in the case of a volatile series, omitting an important explanatory variable might create a pseudo structural change in the series. Without properly taking into account a possible structural change, one might incorrectly find an MA term in the errors. This might explain my findings.

Though we have shown that model specification is very important for empirical research, it certainly will not lessen the importance of the constructive method advocated by Tiao et al. However, the amount of efficiency gained by adopting an ARMA error correcting procedure over a simple AR correcting procedure when the sample size is small, and when there exist possible structural changes, is an interesting topic for future research.

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REJOINDER

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C. M. Hsu, C. F. Lin, C. S. Mao and C. S. Ho, R. W. Liou, Y. F. Yang

We thank all the discussants for their comments and suggestions. Forecasting macroeconomic variables is not a simple task; it requires team effort and collaboration between economists and statisticians and between academic researchers and practitioners. If forecasting were easy, the paper would not have been written. Therefore our goal is not to resolve all the issues involved in macroeconomic forecasting, even though we would prefer that. As such, there is plenty of room for improvements and we appreciate the constructive comments of the discussants. Our reply is based on the same idea, namely to improve macro-economic forecasting in an imperfect situation.

1. Forecasting and Policy Simulation

We agree totally with Professor Hall that an ideal model serves many purposes. Dynamic macroeconomic models should be able to produce accurate forecasts, to provide informative policy implications, and to enhance our understanding of how the economy works. Unfortunately all existing models, including ours, are misspecified. They may not be able to achieve these three goals simultaneously. We took an easy approach by emphasizing forecasts while keeping the discussion of policy simulation to a minimum. Our reason is simple. As a trade-oriented economy, and given the unique political environment, Taiwan's economy depends heavily on economies of its neighboring countries and the United States, and on political relationship with China. Consequently, a policy simulation using the entertained model that relies totally on Taiwanese variables may not be sufficient. A carefully extended model that focuses on the key variables of interest and makes use of domestic and foreign variables may fare better in policy simulation.

When policy simulation is the main focus of a macroeconomic model, long-run properties such as stability and equilibrium become very important. The model should be forward looking, rather than pure data fitting. It is here we believe that the principle of model reduction discussed by Hall is most relevant.

2. Model Improvements

We are delighted to see that simple modifications by Dr. Wu can substantially improve the forecasting accuracy of food and non-food consumptions. It goes a long way to show that experience and substantive knowledge are helpful in model refinements. Macroeconomic models are summary statistics that attempt to draw a balance between the knowledge of model builders and the information contained in the historical data. We used the DGBAS model as the initial model because it accumulated economists' view of the Taiwan economy over more than three decades. The model is imperfect, but it is one of the few models used by the government. We used time-series techniques to supplement the model so that our modifications would not dramatically alter the basis on which the government uses the data. The use of AR or ARMA model for the residuals does not alter the basic structure of the model. Lagged observations (the AR model) and lagged innovations (the MA model) serve as proxies for the missing variables (or information in general) that we would like to have. In this sense, we see no major difference between using AR and MA models for the residuals. The important things to consider are parsimony in parameters, easy in estimation, and finite-sample improvement in forecasting. If simple AR models can achieve the goals of macroeconomic models, then there is no reason to entertain other models. However, there exist no theoretical or empirical reasons to show that using AR models for residuals is sufficient. As such, one should not dismiss *a priori* the contributions of MA models. In fact, MA models are a natural consequence of linear aggregations. For example, gross national product (GNP) is a linear combination of several economic variables. If one assumes linear AR models for each components of the GNP series, then the model for GNP will have an MA component.

3. Model Comparisons

As pointed out clearly by Professor Granger, model comparison involves many factors and is not necessarily informative in pinpointing the source of model deficiency. We used univariate time series (UTS) model as a benchmark to calibrate the forecasting ability of the other models. The fact that UTS models outperform other models in short-term forecasts is well-known in the literature. For Taiwan's economic data, this result also appears in Lin et al. (1997). It shows that lagged observations and lagged innovations can serve as a good proxy for the information we would like to have, and that macroeconomic models have plenty of room for improvement.

Part of the superior forecasting ability of UTS models can be explained by aggregation. The MEM model predicts gross domestic product (GDP) by adding together the forecasts of individual GDP components, whereas the UTS model uses the aggregated GDP series to produce forecasts. Because the aggregated GDP series is much smoother than the individual components, it is easier to find an adequate model for the GDP series. More accurate forecasts then follow. In fact one can study this phenomenon theoretically in the spirit of the Central Limit Theorem.

It should also be noted that for longer term forecasts, under very general conditions, forecasts from multivariate structural time series models and their corresponding UTS models should yield the same results.

We were happy to see that the marriage between macroeconomic models and time series techniques produces marked improvements over the pure macroeconomic model in out-of-sample forecasts. However, we were not satisfied with the improvements. Much remains to be done to further improve the models. Using vector models with co-integration constraints is a possibility. However, because there exists no true model, it is not clear that imposing co-integration can substantially improve the out-of-sample forecasts; see Lin and Tsay (1996).

4. Methodology: Theory Versus Practice

Methodologies differ in efficiency, with good ones achieving the maximum efficiency faster. In applications, methodologies encounter two difficulties. The first difficulty is that the real world never follows the assumptions we put forward in developing the methodology. The second difficulty is that practitioners are faced with various constraints and limitations. They cannot exploit fully the power of the methodology. In our paper, we do not claim that the methodology we use is the best methodology one could have, rather that it is a widely applicable methodology that uses iterative procedures to continually refine a macroeconomic model. It allows for interaction between theory and practice in an iterative fashion. The existing imperfect theory leads to a misspecified model. The forecasting comparisons point toward improvements that may in turn lead to a better understanding of the macroeconomic theory. Iterations then take place. The fact that the METSM model outperforms the original MEM model reaffirms the common belief that the MEM model is misspecified. The fact that time series outlier detection identifies many outliers shows that there maybe structural changes in the Taiwan economy. Results like those shown in the paper should provide direction for refining the model. Thus, contrary to Professor Waung's summary, we believe that the adopted methodology is fruitful.

5. Rationale for Modeling Residuals

We disagree with Professor Waung about the value of using ARMA models to improve econometric models. The existence of serial correlations in the residuals shows that the econometric model used is misspecified and that the residuals of the econometric model are predictable. Thus, the prediction of the original variables can be improved. Using ARMA models to describe the serial correlations in the residuals represents an approach for improving forecasts. An alternative approach is to search for the missing variables of the system, leading to an even larger system of equations. It should be noted that the ARMA model of residuals changes the dynamic structure of the macroeconomic model. Therefore, the ARMA structure cannot be ignored in forecasting or in policy simulation.

We agree with Professor Hall that the ARMA model of residuals imposes constraints on the model parameters. This is different from the common practice of adding lagged dependent variables. As illustrated by a simple model in the paper, the latter approach may encounter some adverse effects on forecasting. On the other hand, the ARMA specification can avoid the adverse effects.

6. Specific Reply

Professor Hall raised the issue of using log transformation in the Price equation. We chose the linear form instead of a nonlinear one because the linear form produces more accurate out-of-sample forecasts. We agree with Dr. Wu and Professor Waung that the financial sector plays an increasingly important role in the Taiwan economy. With increased sample size, a careful study of the sector should be feasible. However, given the volatility and the gradual internationalization of the Taiwan financial market, there is little economic theory to aid in modeling the sector. Treating the money supply as an endogenous variable has some appeal from a theoretical viewpoint, but any misspecification of the money supply function may result in inferior forecasts. For example, a model with built-in rational expectation in the financial sector generally produces inferior forecasts than the one that does not use rational expectation.

Our limited experience in forecasting Taiwan's economy showed that 2SLS and OLS methods produce similar results both in estimation and in forecasting, a conclusion in agreement with that found in the literature. Thus, we decided not to use the 2SLS method.

Finally, we would like to point out that the seasonal ARMA models employed for the residuals encompass several models commonly used in the economic literature. For example, a deterministic trend model is included by allowing for the MA polynomial to have roots on the unit circle. Similarly, our time series outlier detection procedure includes level shifts, temporary level changes, additive outliers, and innovational outliers so that certain structural changes are considered in the paper. An alternative approach for handling structural breaks is to use methods discussed in Allen and Hall (1997).

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