Energy Demand and CO_2 Emission Forecasting Using State Space and Dynamic CGE Models

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Abstract: The purpose of this paper is to forecast energy demand and CO_2 emissions for Taiwan over the period 1999-2015. Two models are constructed for this purpose: one is a state space model and the other is a dynamic computable general equilibrium (CGE) model. The state space model is built based on detailed time series data on energy consumption spanning from 1961 to 1998, and the estimation is based on Kalman filter techniques. The dynamic CGE model used is the TAIGEM-D model, a multisectoral model of the Taiwan economy developed specifically to analyze climate change response issues. Total CO_2 emission forecasts are computed using all the energy demand forecasts, with some adjustments and transformation. Results show that both models generate quite similar trends in total CO_2 emissions. Discrepancies, however, are found to exist in the structure of energy demand between the two models.

I. Introduction

The growing concerns over the potential effects of global warming on our living planet have, again, drawn a lot of attention on energy use. It was only a decade ago that the collapse of world energy prices has loosened the threat of energy crisis to the policy makers and the general public. Now, the scientific evidence of a close relationship between energy consumption and carbon dioxide (CO_2) emissions, which are believed to contribute to global warming, has revived the energy use a central issue in environmental and economic policy arena.

The 1997 Kyoto Protocol to the United Nations Framework Convention on Climate Change (UNFCCC), if ratified, requires the participating countries to implement substantial cuts in greenhouse gas (GHG) emissions. Although an “inverse-U” relationship between per-capita income and CO_2 emissions has been found in various studies,[5] the economic costs of compliance might still be considerably high. To measure the economic costs of a country in mitigating global warming, a basic task that needs to be done is the projection of the level of future CO_2

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[5] For example, Schmalensee, Stoker, and Judson (1998) estimated the reduced-form Engel curves for per-capita CO_2 emissions and commercial energy consumption, and found that there exists a significant "inverse-U" relationship between per-capita income and CO_2 emissions and a weaker relationship between per-capita income and energy consumption. In a latter paper, Judson, Schmalensee, and Stoker (1999) extended the analysis to disaggregated economic sectors, and found that the share household sector's aggregate energy consumption tends to fall with income, the share of transportation tends to rise, and the share of industry follows an "inverse-U" pattern.

emissions. This projection serves as a benchmark with which targeted emission levels can be compared. It is also this projection that we are able to estimate how much effort needs to be devoted to in the years to come to meet the reduction targets.

However, forecasts of future CO_2 emissions depend mainly on forecasts of the demands for energy. Therefore, reliable energy demand forecasts are considered crucial both for the measurement of abatement costs and for the design and implementation of national global warming policy. Previous studies on energy demand forecasting have been focusing on the demands for specific energies for some sectors. For instance, Banaszak, Chakravorty and Leung (1999) forecasted the demand for gasoline and diesel in the ground transportation sectors of South Korea and Taiwan. Chan and Lee (1997) focused on the forecasts of the demand for coal in China. McMenamin and Monforte (1998) forecasted the short-term demand for electricity in the Southwest U.S., etc. The methodologies used in the previous energy demand studies, in addition to the standard tools of econometric and time series models, have been extended to other approaches such as neural network (see e.g., McMenamin and Monforte, 1998) and computable general equilibrium (CGE) models (see e.g., Adams and Dixon, 1997).[6]

Forecasting CO_2 emissions for the purpose stated earlier, an exhausted estimation covering all or near all sources of emissions is required. As such, forecasting the demand of simply some of the energy used in the economy or some of the end-use sectors will not be sufficient to meet the requirements. In view of this, we should either use individual forecasting model for every energy commodity or apply a systematic model that covers all energy commodities in the economy in order to forecast the total demand for energy.

The objective of this paper is to forecast energy demand and CO_2 emissions for Taiwan over the period 1999-2015. Two models are constructed for this purpose: one is the state space model and the other is a dynamic CGE model. The state space model is built based on detailed time series data on energy consumption spanning from 1961 to 1998, and the computation is based on Kalman filter techniques. For individual energy, a separate model is constructed to forecast its future demand. Total CO_2 emission forecasts are then computed using all the energy demand forecasts, with some adjustments and transformation. The dynamic CGE model used is TAIGEM©-D model, a dynamic, multisectoral CGE model of the Taiwan economy, developed specifically to analyze climate change response issues. TAIGEM©-D is derived from the ORANI model and the MONASH model. The most significant features that distinguish TAIGEM©-D from MONASH are the coverage of GHG emissions and the inclusion of interfuel substitution and technology bundles. The forecasting results generated from the two models are compared and analyzed, which should provide a useful basis of double-checking the important benchmark emission levels.

The structure of the paper is as follows. Section II outlines the state space and CGE models used for forecasting as well as the data complied for estimation. Section III presents the forecasting results. Comparison of the results generated from the two models is also included in this section. Section IV provides summary and some

[6] Adams and Dixon's analysis, however, is not restricted to energy sectors. The CGE model they used can forecast the demand for over 100 commodities and services.

concluding remarks.

II. Data and Methodologies

1. Models

The forecasting methods used in this study are a set of state space models and a dynamic CGE model - the TAIGEM©-D model. The state space model is an extension of the classical linear model to allow parameter variation (Harvey and Phillips, 1982). The conventional state space formulation is as follows:

$$y_t = x_t \beta_t + u_t ; t = 1, \ldots, n, \qquad (1)$$

$$\beta_t = \varphi_t \beta_{t-1} + z_t \alpha_t + \varepsilon_t \qquad (2)$$

where in equation (1), *y* is dependent variable, *x* is a 1xk vector of predetermined variables, • is a kx1 vector of unknown regression coefficients, and *u* is a white noise with variance • ^{2}. The parameter vector• is assumed to be generated by a process represented in equation (2), in which • is a kxk matrix, z is a kxm matrix of observations on m non-stochastic variables, • is a mx1 vector, and • is a kx1 vector of serially uncorrelated process noise with mean zero and covariance matrix • . The error vectors *u* and • are serially and contemporaneously uncorrelated, and uncorrelated with • .

The Kalman filter technique is a tool for estimating equation (2) in an optimal way and for updating the estimates when new observations become available. If an initial estimate of • in equation (1) is available or assumed, the Kalman filter provides an optimal predictor for • . Once a new observation is available, Kalman filter also provides an updating equation for • .[7]

TAIGEM©-D is developed specifically to analyze climate change issues, such as baseline forecasting, climate change response policies, and is derived from ORANI (Dixon, Parmenter, Sutton and Vincent, 1982). TAIGEM©-D distinguishes 160 sectors, 6 types of labor, 8 types of margins and 170 commodities. The most significant features of TAIGEM©-D are the inclusion of interfuel substitution, technology bundles and dynamic mechanism capable of projecting the development of the economy through time. With TAIGEM©-D we are able to make annual projections of CO_2 emissions, GDP growth rates, and other economic variables. When using TAIGEM©-D to forecast energy demand, we solve the large (160 industries) recursive model with externally supplied, realistic macroforecasts.

For the production structure of non-electricity sectors, TAIGEM©-D allows each industry to produce several commodities. Commodities destined for export are distinguished from those for local use. The multi-input, multi-output production specification is kept manageable by a series of separability assumptions. The input demand of industry production is formulated by a five-level nested structure, and the

[7] The software used for estimation is Stamp 5.0. See Harvey (1989) for details on the Kalman filter technique and the estimation procedure.

production decision-making of each level is independent. Assuming cost minimization and technology constraint at each level of production, producers will make optimal input demand decisions. At the top level, commodity composites and a primary-factor composite are combined according to a Leontief production function. Consequently, inputs are demanded in direct proportion to the industry activity. At the second level, each commodity composite is a CES (constant elasticity of substitution) function of domestic goods and the imported equivalents (the Armington assumption). Energy and primary-factor composites are also specified as a CES aggregate of energy composites and primary-factor composites.

At the third level, the primary-factor composite is a CES aggregation of labor, land, and capital, and the energy composite is a CES aggregate of coal products composites, oil products composites, natural gas products composites, and electricity. At the fourth level, the labor composite is a CES aggregate of managers, professional specialists, white collars, technical, workers, and unskilled workers. Also, the coal products composite is a CES aggregate of coal and coal products; the oil products composite is a CES aggregate of gasoline, diesel oil, fuel oil, and kerosene; the natural gas products composite is a CES aggregate of refinery gas, gas, and natural gas. At the bottom level the energy composite is a CES aggregate of domestic and imported goods.

Like ORANI model, the output structure of TAIGEM©-D allows for each industry to produce a mixture of all the commodities. Moreover, conversion of an undifferentiated commodity into goods destined for export and local use is governed by a CET (constant elasticity of transformation) transformation frontier.

The production structure of the electricity sector in TAIGEM©-D is modeled with the "technology bundle" approach derived from Australian ORANI-E and MEGABARE models. With this structure, electricity can be generated from coal, petroleum, gas, nuclear, hydo or renewable based technologies. The electricity industry substitutes between technologies in response to changes in their relative costs. In TAIGEM©-D, 10 known technologies are used to generate electricity, namely hydro, stream turbine-oil, stream turbine-coal, stream turbine-gas, combined cycle-oil, combined cycle-gas, gas turbine-oil, gas turbine-gas, diesel, and nuclear. All electricity generated from these technologies is transferred to the end-use electricity sector. The output of the electricity sector is a CRESH aggregate of each electricity technology, which requires fixed proportions of intermediate inputs, with the exception of energy inputs and primary factors.

2. Data

For the TAIGEM©-D model, the input-output database was compiled from the 150-sector Use Table of the 1994 Taiwan Input-Output tables. For the state space model, we compiled the energy consumption data from the Taiwan Energy Balances tables. The data for other endogenous and exogenous variables (such as energy prices, real GDP, population, index of industrial production, number of household, and average temperature, etc.) used in the state space model are compiled from either the AREMOS database or Monthly Statistics of the Republic of China.

The state space model is used to forecast the energy demand for 17 energy commodities that are considered to contribute to CO_2 emissions. Both mid-term (quarterly) and long-term (annual) forecasting are performed. A list of variables and their corresponding data periods for long-term forecasting are presented in Table 1 below. [8]

Table 1. Data and Variables for Long-term Forecasting (State Space Model)

Energy	Unit	Period	Remark
Coal-Power Plant	MT	1961• 1998	*
Coal-Cogeneration	MT	1988• 1998	*
Coal-End Use	MT	1961• 1998	*
Natural Gas	Km^3	1961• 1998	*
LNG-Power Plant	Km^3	1990• 1998	*
LNG-End Use	Km^3	1990• 1998	*
Gasoline-Motor	KL	1961• 1998	*
Diesel-Power Plant	KL	1961• 1998	*
Diesel-End Use	KL	1961• 1998	*
Fuel Oil-Aviation	KL	1961• 1998	*
Fuel Oil-Power Plant	KL	1961• 1998	*
Fuel Oil-Cogeneration	KL	1983• 1998	*
Fuel Oil-End Use	KL	1961• 1998	*
Coke	MT	1961• 1998	*
Kerosene	KL	1961• 1998	*
Refinery Gas	Km^3	1980• 1998	*
Coke Oven Gas-Cogeneration	Km^3	1983• 1998	*
Coke Oven Gas	Km^3	1961• 1998	*
LPG	KL	1961• 1998	*
Real GDP	Million NT$	1961• 1998	**
Industrial GDP	Million NT$	1961• 1997	**
Services GDP	Million NT$	1961• 1997	**
Index of Industrial Production	•	1961• 1998	**
Index of Manufacturing	•	1961• 1998	**
Population	Thousand	1961• 1998	**
Total Tons Transported	Thousand MT/Kilometer	1961• 1998	**
Number of Household	Number	1966• 1998	***

*• Energy Commission, 1999, Energy Balances in Taiwan, R.O.C.

**• AREMOS Database.

***• Monthly Statistics of the Republic if China.

III. Results and Analysis

1. State Space Model

For both the long-term and mid-term forecasting, we divided the data period into two sub-periods: historical simulation and *ex post* forecasting. The historical

[8] Due to the space constraint, we do not show the list of variables and their corresponding data periods for mid-term models here. Basically, the mid-term models have, in additional to the variables for long-term models, other variables on energy prices.

simulation covers the period 1961 to 1997 for long-term models and the period first quarter 1982 to fourth quarter 1997 for mid-term models. The *ex post* periods are used for testing the forecasting capability of the models. We use MAPE (mean absolute percentage error) to measure the performance of the forecasting models. The MAPEs of the long- and mid-term models are shown in Tables 2 and 3. Table 4 summarizes the distribution of the models according to their forecasting performance. From the tables, we can find that mid- and long-term forecasting together only 5 models have a MAPE value over 20%.[9] While the corresponding energies of those models have consumption patterns with wide variations, the results are not surprising. Since the shares of consumption of these energies are relatively low in Taiwan, the potential unreliable forecasts produced by the models will not be significant.

Table 2• Forecasting Periods and Performance of Long-term Models

Energy	Period		MAPE
	Historical Simulation	Ex Post simulation	
oal-Power Plant	1961• 1993	1994• 1998	4.82%
Coal-Cogeneration	1988• 1993	1994• 1998	8.78%
Coal-End Use	1961• 1993	1994• 1998	17.3%
Natural Gas	1961• 1993	1994• 1998	7.65%
LNG-Power Plant	1990• 1998		NA*
LNG-End Use	1990• 1998		NA*
Gasoline-Motor	1961• 1993	1994• 1998	4.87%
Diesel-Power Plant	1961• 1993	1994• 1998	65.83%
Diesel-End Use	1961• 1993	1994• 1998	9.31%
Fuel Oil-Aviation	1961• 1993	1994• 1998	19.58%
Fuel Oil-Power Plant	1961• 1993	1994• 1998	6.70%
Fuel Oil-Cogeneration	1983• 1993	1994• 1998	15.85%
Fuel Oil-End Use	1961• 1993	1994• 1998	5.18%
Coke	1961• 1993	1994• 1998	12.83%
Kerosene	1961• 1993	1994• 1998	52.57%
Refinery Gas	1961• 1993	1994• 1998	14.51%
Coke Oven Gas-Cogeneration	1983• 1993	1994• 1998	2.81%
Coke Oven Gas	1961• 1993	1994• 1998	19.64%
LPG	1961• 1993	1994• 1998	2.81%

*Not available due to insufficiency of data.

Table 3• Forecasting Periods and Performance of the Mid-term Model

Energy	Period		MAPE
	Historical Simulation	Endogenous	
oal-Power Plant	1982Q1• 1997Q4	1998Q1• Q4	6.69%
Coal-Cogeneration	1988Q2• 1997Q4	1998Q1• Q4	10.08%
Coal-End Use	1982Q1• 1997Q4	1998Q1• Q4	9.19%
Natural Gas	1982Q1• 1997Q4	1998Q1• Q4	2.98%
LNG-Power Plant	1990Q3• 1997Q4	1998Q1• Q4	9.15%
LNG-End Use	1990Q2• 1997Q4	1998Q1• Q4	7.16%

[9] They are diesel (power plant) and kerosene for long-term models and diesel (power plant), coke and kerosene for mid-term models.

Gasoline-Motor	1982Q1• 1997Q4	1998Q1• Q4	1.07%
Diesel-Power Plant	1982Q1• 1997Q4	1998Q1• Q4	58.24%
Diesel-End Use	1982Q1• 1997Q4	1998Q1• Q4	5.67%
Fuel Oil-Aviation	1982Q1• 1997Q4	1998Q1• Q4	1.65%
Fuel Oil-Power Plant	1982Q1• 1997Q4	1998Q1• Q4	14.13%
Fuel Oil-Cogeneration	1983Q3• 1997Q4	1998Q1• Q4	5.27%
Fuel Oil-End Use	1982Q1• 1997Q4	1998Q1• Q4	2.86%
Coke	1982Q1• 1997Q4	1998Q1• Q4	33.71%
Kerosene	1982Q1• 1997Q4	1998Q1• Q4	36.00%
Refinery Gas	1982Q1• 1997Q4	1998Q1• Q4	6.10%
Coke Oven Gas-Cogeneration	1983Q3• 1997Q4	1998Q1• Q4	3.85%
Coke Oven Gas	1982Q1• 1997Q4	1998Q1• Q4	9.41%
LPG	1982Q1• 1997Q4	1998Q1• Q4	3.32%

*Not available due to insufficiency of data.

Table 4• Summary of Long- and Mid-term MAPEs

MAPE Value / Mid- or long-term	0• 5•	5• 10•	10• 20•	20• • •	N.A.*
Long-term model	4	5	6	2	2
Mid-term model	6	8	2	3	0

* Not available due to insufficiency of data.

Table 5 presents a summary of test statistics of some major long-term estimation models. Basically, most of the models are considered as appropriate based on regular testing procedures.[10]

Table 5• Statistics of Major Long-term Energy Forecasting Models

Energy	Coal-Power Plant	Coal-Cogeneration	Coal-End use	LNG-End Use	Gasoline-Motor
Statistics	COAL_E	COAL_GE	COAL_F	GAS_F	M_OIL
Normality	1.418	0.48548	0.74194	3.181	12.97
H• 12•	26.82	3.176	2.362	1.466	13.13
DW	1.674	1.306	2.053	1.433	1.102

[10] In Table 5, Normality is a statistic for testing the normality of the model error terms. The critical value at 5% significance level is 5.99. H(12) is the statistic for testing the existence of heteroskedasticity in the error terms. DW is the usual Durbin-Watson statistics, and Q is the Box-Ljung statistic for testing autocorrelation in error terms. The critical value at 5% significance level for Q(8,6) is 12.59.

Q• 8, 6•	7.891	16.31	4.952	11.96	19.5
R^2	0.73536	0.5414	0.66658	0.57078	0.84732

Table 5• Statistics of Major Long-term Energy Forecasting Models• Continued•

Energy / Statistics	Diesel-Power Plant	Diesel-End Use	Fuel Oil-Aviation	Fuel Oil-Power Plant	LPG
	D_OIL_E	D_OIL_F	A_OIL	F_OIL_E	LPG
Normality	6.074	6.023	8.431	8.281	0.17862
H• 12•	49.52	3.831	21.3	13.07	1.66
DW	1.886	1.674	2.435	1.857	1.65
Q• 8, 6•	13.43	4.737	5.946	10.22	8.378
R^2	0.4028	0.58677	0.49118	0.62507	0.33736

Before conducting the *ex ante* forecasting, the models shown above are re-estimated using data for all periods. The *ex ante* forecasting results of the mid-term model are presented in Table 6,[11] and the forecasts of selected energy commodities are shown in Diagrams 1 to 4.

[11] Similarly, due to space constraint, we present here only the results for mid-term forecasting. The results for long-term forecasting are available upon request from the authors.

Table 6• Forecasts of Mid-term Energy Demand (State Space Model)

Energy	Unit	Forecasts							
		1999Q1	1999Q2	1999Q3	1999Q4	2000Q1	2000Q2	2000Q3	2000Q4
Coal-Power Plant	MT	4652100	5715100	6328200	5702200	4981900	6045000	6658100	6032100
Coal-Cogeneration	MT	764020	854760	962620	895760	795730	887440	994330	927470
Coal-End Use	MT	1589100	1663100	1688400	1770700	1684600	1758700	1784000	1866300
Natural Gas	Km^3	465020	417610	364410	440480	468620	422020	369140	444930
LNG-Power Plant	Km^3	786740	1121500	1355200	1048600	1074900	1409700	1643400	1336800
LNG-End Use	Km^3	230550	216110	209150	191020	171230	156790	149830	131700
Gasoline-Motor	KL	2239500	2348400	2448800	2365600	2329100	2438100	2538400	2455400
Diesel-Power Plant	KL	28392	107570	163650	64124	32811	111990	168070	68543
Diesel-End Use	KL	1195700	1295800	1317300	1305500	1195700	1295800	1317300	1305500
Fuel Oil-Aviation	KL	640140	662450	731760	714870	701530	723830	793150	776260
Fuel Oil-Power Plant	KL	1201700	1736900	1980700	1706900	1404400	1939600	2183400	1909700
Fuel Oil-Cogeneration	KL	234720	240520	245330	250240	252700	258500	263310	268220
Fuel Oil-End Use	KL	1685100	1778300	1747300	1785500	1710500	1803700	1772700	1810900
Coke	MT	1099200	1124800	1126300	1107900	1081800	1107400	1108900	1090500
Kerosene	KL	9703	18052	11423	7386	10057	18403	11775	7740
Refinery Gas	Km^3	332000	336710	345180	351360	341900	346610	355090	361270
Coke Oven Gas-Cogeneration	Km^3	82430	80291	85855	80653	86255	84116	89680	84478
Coke Oven Gas	Km^3	460430	472040	468160	470680	479360	490970	487080	489610
LPG	KL	748990	672000	619600	736190	757540	676480	628150	744660

Diagram 1. Long-term Forecasts of Gasoline-Motor

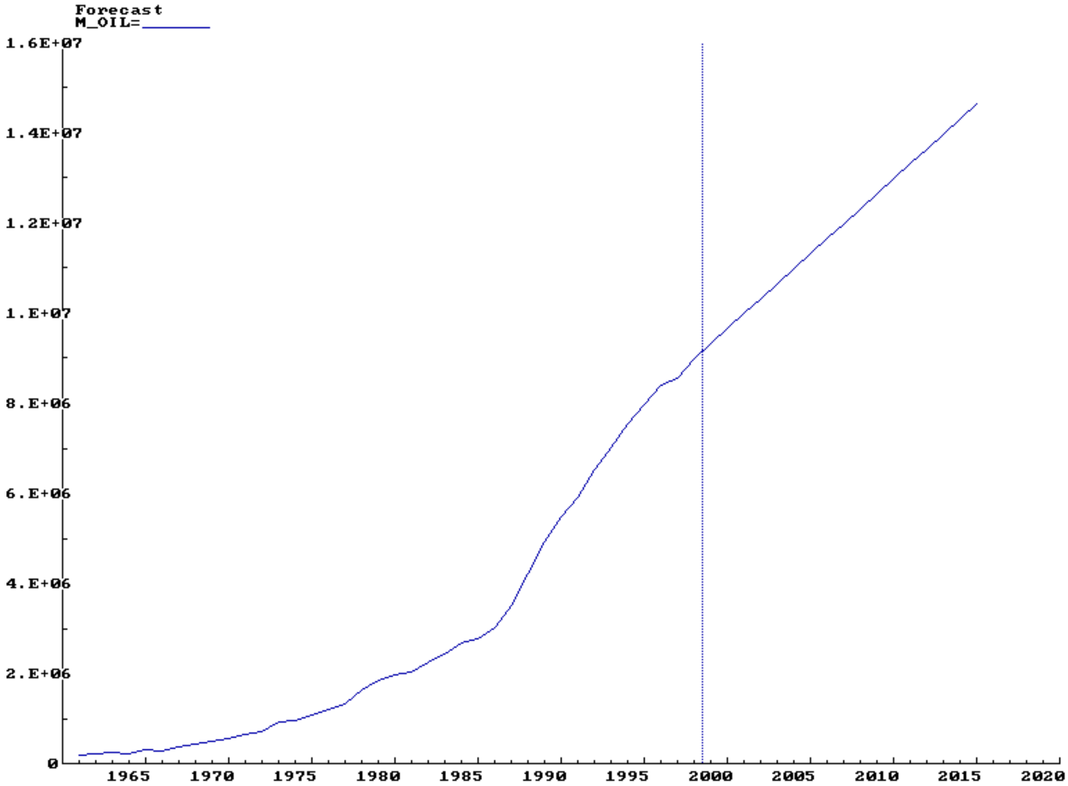


Diagram 2. Mid-term Forecasts of Gasoline-Motor

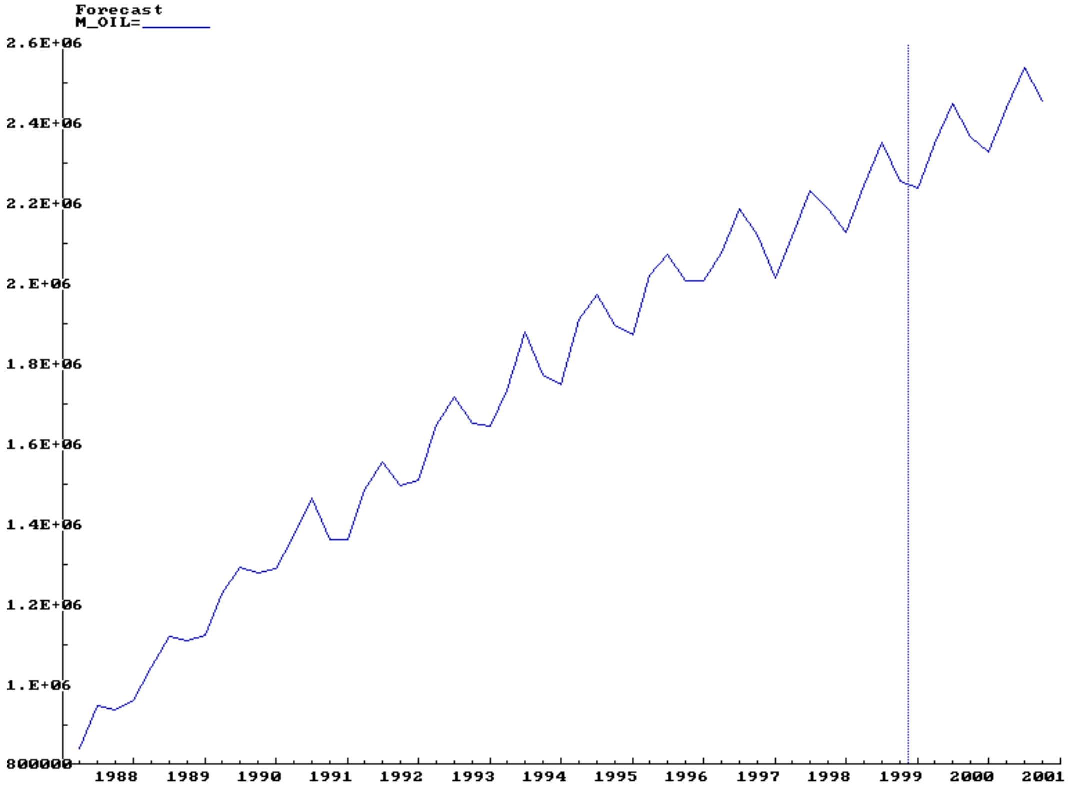


Diagram 3. Long-term forecasts of Fuel Oil – End Use

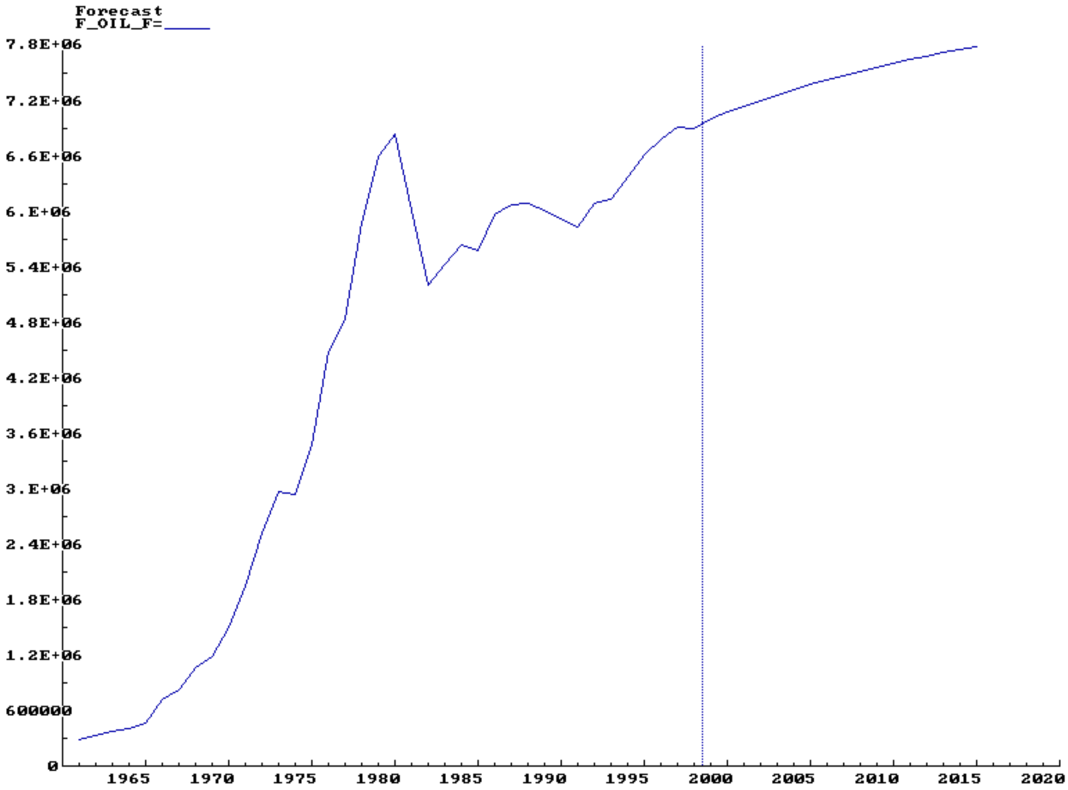
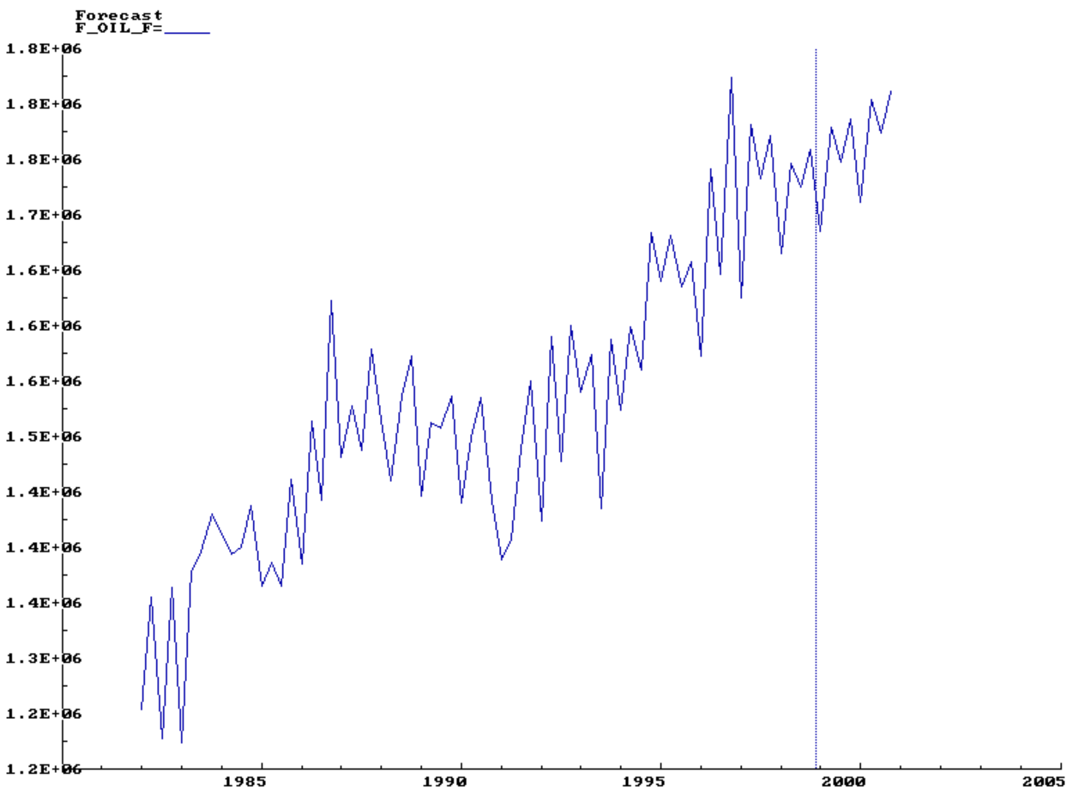


Diagram 4. Mid-term Forecasts of Fuel Oil – End Use



Using the forecasts generated from the mid- and long-term state space models, we computed the CO_2 emissions according to the IPCC formula. The results are shown in Tables 7 and 8, while Diagram 5 shows the structure of CO_2 emissions. Comparing Tables 7 and 8, we find that only slight differences exist between long- and short-term forecasts.

2. TAIGEM©-D Model

TAIGEM©-D model solves the demand for every commodity, including all the energy commodities, recursively for years 1995-2020. Using these estimates, together with base-year (1994) energy user prices, we then compute the CO_2 emission for every energy over the period 1995-2020. Since the forecasts of energy demand generated from the CGE model are in physical units, we have to convert them into thermal units first and then compute the level of CO_2 emissions according to the IPCC formula.

Table 9 presents the CO_2 emissions for some selected energy and Diagram 6 shows the structure of energy demand. Comparing Diagram 5 to Diagram 6, we find that some discrepancies exist between them. However, if we compare the total CO_2 emissions generated by the two models, we can find that their long-term trends of emissions are quite similar. This indicates that, if long-term trend of CO_2 emissions is the only target we need to get, then simpler time series forecasting models such as state space model, might not be a bad choice.

IV. Concluding Remarks

In this paper, we forecasted energy demand and CO_2 emissions for Taiwan over the period 1999-2015 using two models: one is a state space model and the other is a dynamic computable general equilibrium model. The state space model is built based on detailed time series data on energy consumption span from 1961 to 1998, and the estimation is based on Kalman filter techniques. The dynamic CGE model used is the TAIGEM-D model, a multisectoral model of the Taiwan economy developed specifically to analyze climate change response issues. Total CO_2 emission forecasts are computed using all the energy demand forecasts, with some adjustments and transformation. Results show that both models generate quite similar trends in total CO_2 emissions. Discrepancies, however, are found to exist in the structure of energy demand between the two models. Further analysis is needed to reconcile the differences.

Table 7. Long-term Forecasts of CO_2 Emissions (State Space Model)

Energy	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**
Coal	61.21	65.97	70.73	75.50	80.26	85.02	89.78	94.55	99.31
Natural Gas	12.14	13.77	15.40	17.03	18.65	20.28	21.91	23.53	25.16
Gasoline	17.93	18.57	19.21	19.85	20.49	21.13	21.77	22.41	23.05
Diesel	14.11	14.01	13.90	13.79	13.68	13.57	13.46	13.35	13.24
Fuel Oil	40.63	41.19	41.74	42.29	42.82	43.34	43.86	44.36	44.86
Other Prtl.	16.14	16.73	17.35	17.96	18.56	19.17	19.78	20.39	20.99
Coal Products	15.49	17.08	18.63	20.17	21.67	23.15	24.61	26.04	27.44
Total	177.66	187.32	196.97	206.57	216.13	225.66	235.16	244.63	254.05

Energy	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Coal	104.07	108.83	113.60	118.36	123.12	127.89	132.65	137.41
Natural Gas	26.79	28.42	30.04	31.67	33.29	34.92	36.55	38.18
Gasoline	23.69	24.32	24.96	25.60	26.24	26.88	27.52	28.16
Diesel	13.13	13.02	12.91	12.79	12.68	12.57	12.46	12.34
Fuel Oil	45.35	45.84	46.31	46.79	47.25	47.71	48.17	48.62
Other Prtl.	21.60	22.21	22.89	23.57	24.05	24.66	25.27	25.89
Coal Products	28.83	30.18	31.52	32.83	34.12	35.39	36.63	37.86
Total	263.45	272.83	282.23	291.62	300.76	310.02	319.25	328.45

Table 8. Mid-term Forecasts of CO_2 Emissions (State Space Model)

Energy	1999 Q1	1999 Q2	1999 Q3	1999 Q4	1999 Total	2000 Q1	2000 Q2	2000 Q3	2000 Q4	2000
Coal	12.89	15.15	16.52	15.40	59.96	13.73	15.99	17.36	16.24	63.33
Natural Gas	5.05	5.28	5.44	5.59	21.35	5.29	5.52	5.68	5.83	22.31
Gasoline	4.99	5.63	5.99	5.73	22.34	5.66	6.30	6.67	6.41	25.05
Diesel	2.46	2.94	3.24	2.80	11.44	2.86	3.34	3.64	3.20	13.04
Fuel Oil	4.94	5.64	6.17	5.50	22.25	5.46	6.16	6.69	6.02	24.33
Other Prtl.	3.64	3.93	4.18	3.83	15.58	3.68	3.97	4.21	3.86	15.72
Coal Products	5.64	6.16	6.45	6.11	24.37	5.78	6.29	6.59	6.25	24.91
Total	39.61	44.72	48.00	44.96	177.29	42.46	47.57	50.85	47.81	188.69

Diagram 5. Structure of CO_2 Emissions (State Space Model)

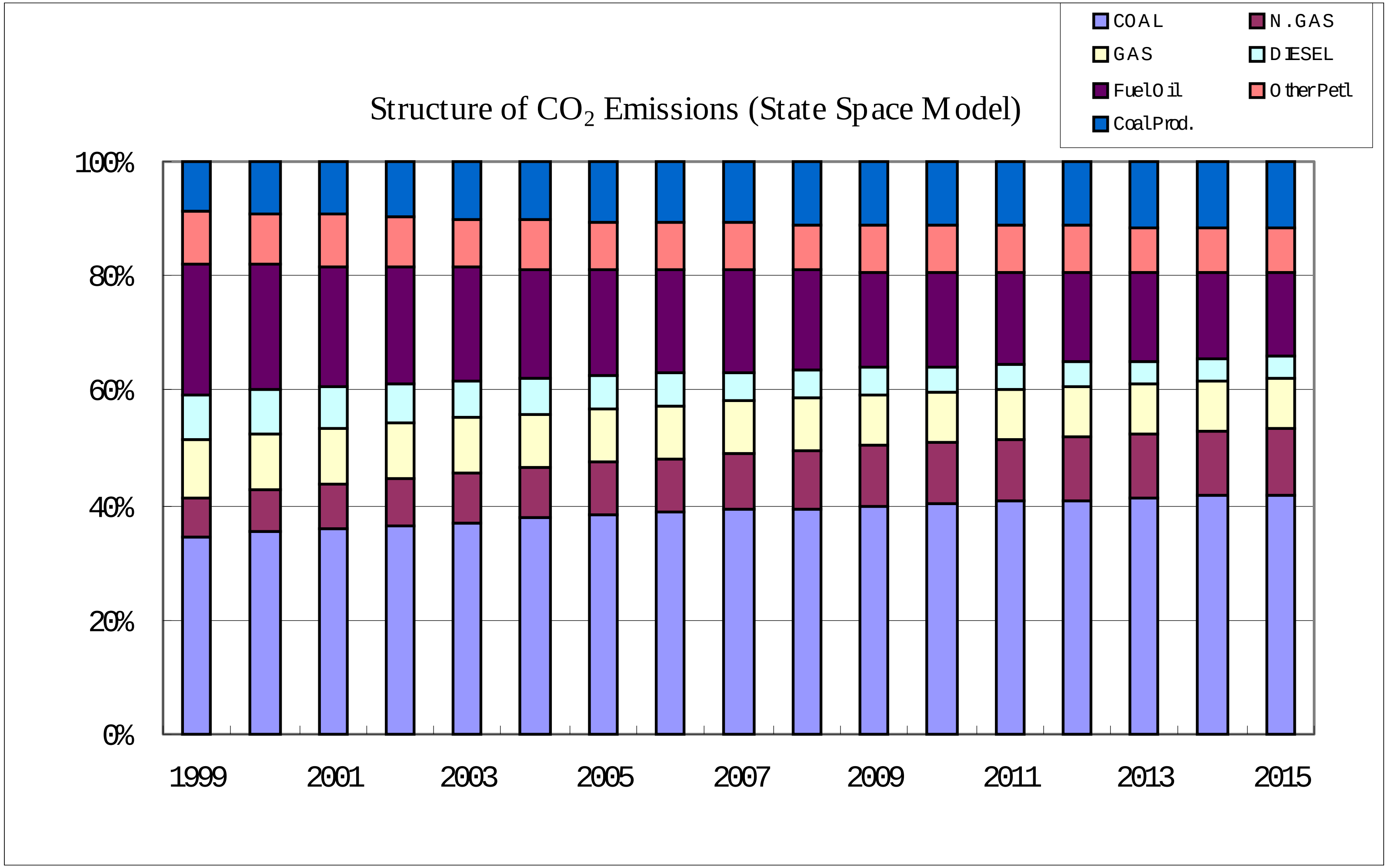


Table 9• CO_2 Emissions Forecasts (TAIGEM-D)

Energy	1995•	1996•	1997•	1998•	1999•	2000•	2001•	2002•	2003•	2004•	2005•	2006•	2007•
13 Coal	59.54	62.75	66.13	68.52	72.59	76.15	79.73	83.57	87.68	91.90	96.07	100.11	104.01
15 Natural gas	3.70	3.93	4.26	4.40	4.67	5.01	5.29	5.53	5.75	5.96	6.18	6.41	6.64
67 Gasoline	7.14	7.50	8.10	8.58	8.88	9.32	9.73	10.14	10.52	10.89	11.26	11.61	11.96
68 Diesel Oil	15.99	16.40	17.80	19.07	20.02	21.10	22.14	23.15	24.17	25.18	26.16	27.11	28.04
69 Fuel Oil-Aviation	4.17	4.41	4.68	4.83	5.09	5.39	5.66	5.92	6.17	6.42	6.66	6.90	7.13
70 Fuel Oil	31.96	33.07	35.63	37.27	39.69	42.35	44.66	46.78	48.88	50.92	52.87	54.72	56.50
71 Kerosene	0.46	0.49	0.51	0.53	0.56	0.59	0.62	0.64	0.67	0.69	0.71	0.73	0.76
72 Lubricator	1.01	1.10	1.14	1.16	1.25	1.32	1.39	1.45	1.51	1.57	1.63	1.70	1.76
73 Refinery Oil	7.72	8.07	8.66	9.32	9.78	10.31	10.79	11.23	11.64	12.02	12.38	12.72	13.06
74 Refinery Gas	2.19	2.31	2.38	2.40	2.53	2.63	2.72	2.81	2.89	2.97	3.04	3.11	3.18
75 Asphalt	18.74	19.95	20.68	21.42	23.55	25.13	26.57	27.95	29.33	30.70	32.05	33.38	34.68
Total	152.61	159.97	169.97	177.50	188.60	199.30	209.30	219.17	229.19	239.22	249.02	258.49	267.72

Energy	2008•	2009•	2010•	2011•	2012•	2013•	2014•	2015•	2016•	2017•	2018•	2019•	2020•
13 Coal	107.78	111.44	115.03	118.61	122.22	125.90	129.70	133.64	137.73	142.00	146.45	151.11	155.97
15 Natural gas	6.89	7.14	7.39	7.66	7.93	8.22	8.52	8.83	9.15	9.48	9.83	10.19	10.56
67 Gasoline	12.31	12.67	13.03	13.40	13.78	14.17	14.58	14.99	15.42	15.86	16.32	16.80	17.30
68 Diesel Oil	28.95	29.86	30.78	31.71	32.67	33.66	34.70	35.78	36.91	38.08	39.30	40.56	41.87
69 Fuel Oil-Aviation	7.37	7.61	7.85	8.09	8.33	8.58	8.84	9.10	9.37	9.65	9.94	10.24	10.55
70 Fuel Oil	58.25	59.98	61.72	63.48	65.30	67.20	69.20	71.29	73.48	75.77	78.15	80.63	83.20
71 Kerosene	0.78	0.80	0.83	0.85	0.88	0.90	0.93	0.96	0.98	1.01	1.04	1.08	1.11
72 Lubricator	1.83	1.90	1.97	2.04	2.11	2.19	2.27	2.35	2.43	2.52	2.61	2.70	2.80
73 Refinery Oil	13.39	13.74	14.10	14.47	14.85	15.26	15.68	16.11	16.56	17.03	17.52	18.02	18.54
74 Refinery Gas	3.25	3.33	3.40	3.47	3.54	3.62	3.69	3.77	3.85	3.93	4.02	4.10	4.19
75 Asphalt	35.96	37.23	38.49	39.76	41.06	42.39	43.77	45.20	46.71	48.28	49.93	51.66	53.48
Total	276.77	285.69	294.58	303.54	312.68	322.10	331.86	342.02	352.60	363.62	375.11	387.09	399.57

Diagram 6. Structure of CO_2 Emissions (TAIGEM-D)

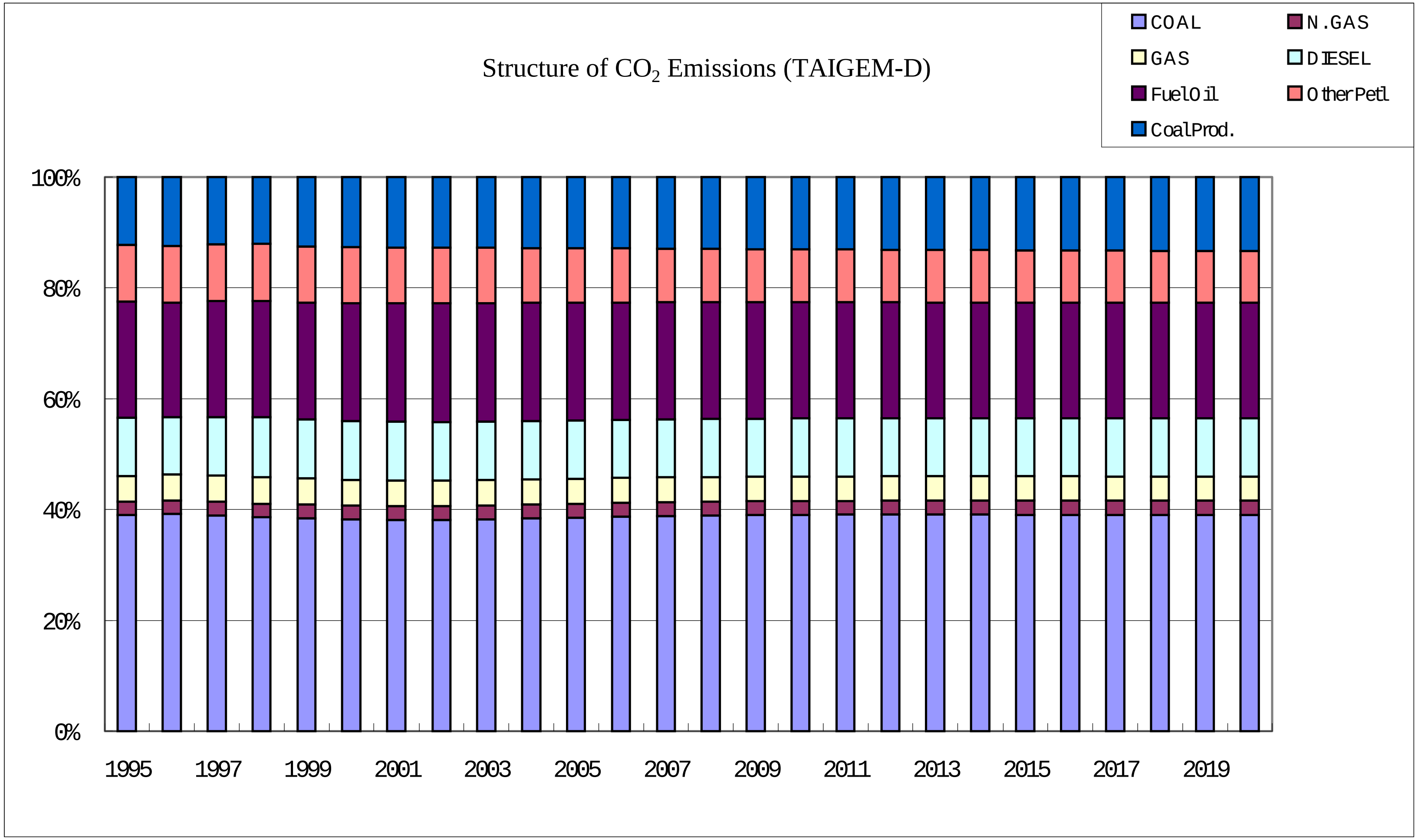
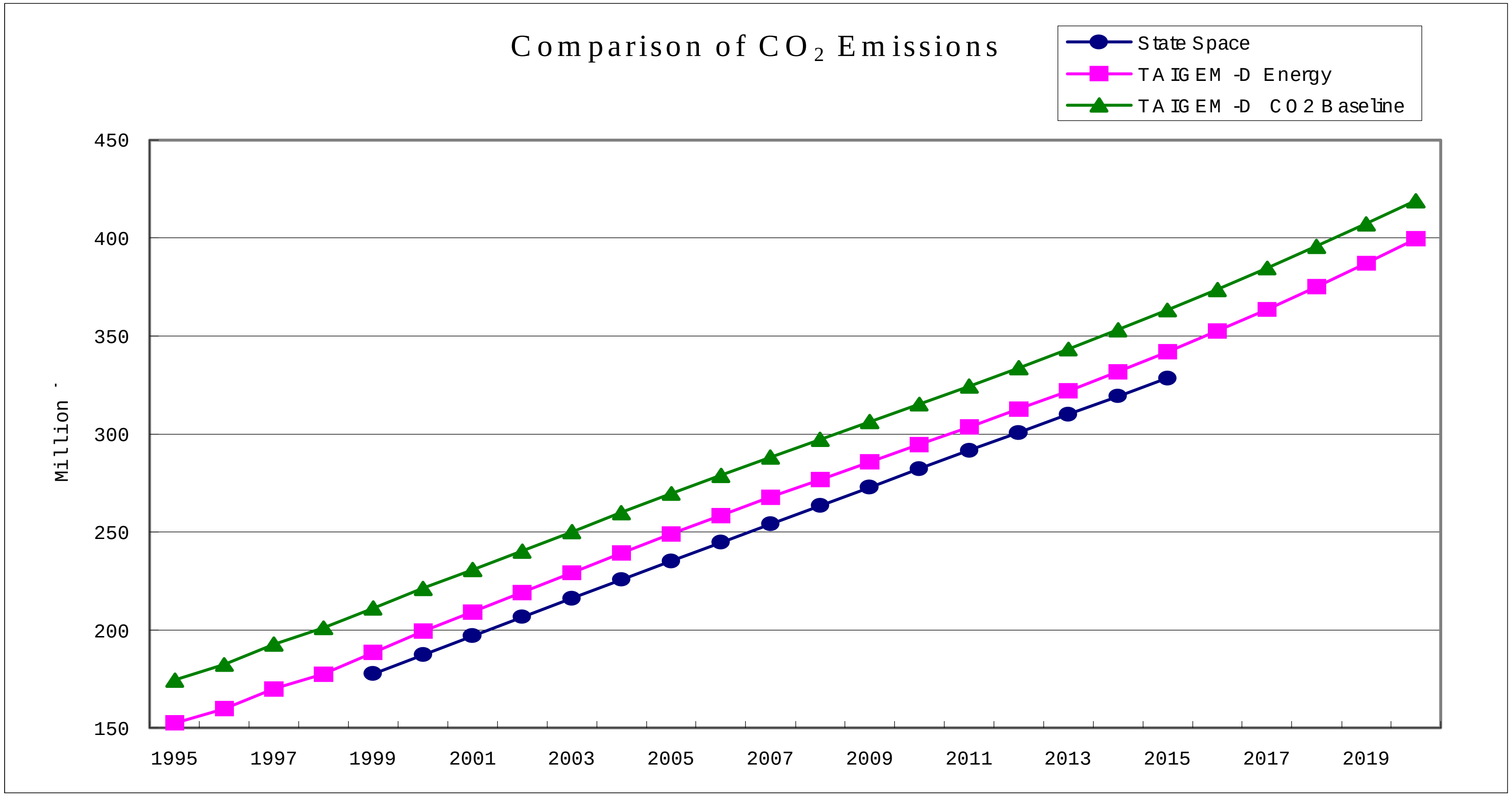


Diagram 7. Comparison of CO_2 Emissions



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