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Tracking the Emission of Carbon Dioxide by Nation, Sector, and Fuel Type: A Trace Gas Accounting System (TGAS)

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Abstract *This paper describes a new methodology that can be used to estimate an efficient econometric model of global emissions of carbon dioxide (CO_2) by nation, sector, and fuel type. Equations for fuel intensity are estimated for coal, oil, natural gas, electricity, and heat for each of six sectors: agricultural, industrial, commercial, transportation, residential, and other. Up to five equations are estimated for each sector simultaneously (seemingly unrelated regressors) using generalized least*

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squares. The methodology is validated by choosing four very different economic systems, France, the Republic of Korea, India, and Poland, estimating demand equations, generating an ex ante out of sample forecast, and comparing the results with the historical record, as represented by data compiled by R. M. Rotty and G. Marland. The accuracy of the backcast relative to the historical record varies by nation. The backcasts for France, Poland, and the Republic of Korea are consistent with the historical record; the results for India suggest that errors may lurk in the record used as a benchmark to track the emission of CO_2 from fossil fuels.

Keywords energy demand, global warming, carbon taxes.

Introduction

In 1938 Callendar (1938) posed two questions: When will the atmospheric concentration of carbon dioxide (CO_2) double and how will this doubling affect climate? Using a sample model, Callendar concluded that the atmospheric concentration of CO_2 would double (reach 360 ppm) by the end of the 22nd century and that this doubling would increase the Earth's mean temperature 3 degrees centigrade. His estimate of a 3-degree warming is consistent with current hypotheses, but his projection for the period of this build-up differs greatly from historical movements. By 1988, the atmospheric concentration of CO_2 at Mauna Loa was 351 ppm (Boden et al., 1990).

It is easy to find error in a projection made 50 years ago, but much can be learned from the cause(s) of Callendar's inaccuracy. Callendar forecast the build-up of CO_2 by extrapolating the rate at which its concentration in the atmosphere increased between 1900 and 1936, but the increase in the atmospheric concentration of CO_2 is not related directly to the passage of time. Rather, the accumulation of CO_2 in the atmosphere is related to the reduction of biomass in the planet's ecosystems and the combustion of fossil fuels by human economic activity. Increased emission by economic activity probably is responsible for much of the Callendar's inaccuracy. Since 1940, the emission of CO_2 by economic activity has increased nearly sixfold, while the emission of CO_2 from biota and soils has increased about twofold (Houghton et al., 1983). Two factors affect the emission of CO_2 from economic activity, the level of economic activity and changes in the quantity of fossil fuel used to produce a unit of economic output (fuel intensity). Because Callendar did not model economic activity and fuel intensity explicitly, he did not foresee how changes in these two variables would increase the release of CO_2 from economic activity relative to the period between 1900 and 1938 and push forward, by two centuries, the date at which the concentration of CO_2 in the atmosphere would reach 360 ppm.

The magnitude and rate of increase at which economic activity emits CO_2 make the relation between fuel use and economic activity an important topic in the research agenda regarding the "greenhouse effect." Policymakers need a thorough understanding of the relation between energy use and economic activity to develop strategies for mitigating the emission of CO_2 and other "greenhouse gases" because the cost/benefit ratio will be an important criterion by which mitigation strategies will be evaluated (Gaskins and Stram, 1990). Reliance on the cost/benefit ratio implies that policymakers need to know the point(s) in the production or consumption process at which the use of fuel can be reduced or shifted to fuels that emit less CO_2 per heat unit with relatively little effect on economic activity. Because each nation has a unique economic, political, and demographic structure, technological base and infrastructure, product mix, and resource base, the point where mitigation strategies are most cost effective varies among nations. These differences among nations must be represented explicitly by the tools used to develop and evaluate mitigation strategies. Existing models do not represent the point(s) in the production process at which the emission of CO_2 can be reduced at least cost.

This paper describes a methodology for building a global model that can assess least cost strategies for reducing emissions of CO_2 over the short run: a Trace Gas Accounting System (TGAS). TGAS is a world energy model that is designed to forecast the emission of CO_2 by nation, sector, and fuel (Fig. 1). This allows TGAS to represent explicitly the opportunities to reduce fuel use or substitute fuels that emit less CO_2. The description of TGAS is divided in four parts, the limits on existing models that motivate the construction of a new model; the analytical techniques used to quantify fuel intensity by nation, sector, and type; the empirical results for four nations, France, India, the Republic of Korea, and Poland, that are used to test the methodology; and the validation of the new methodology by translating final energy demand into primary energy demand, converting primary energy demand to emissions of CO_2, and comparing an out of sample ex post forecast of CO_2 emissions generated by TGAS with the historical record compiled by Rotty and Marland (1984).

Existing Models

Many models can and are used to forecast the emission of CO_2 and other greenhouse gases (Hoeller et al., 1990). An accurate forecast for the emission of CO_2 and identification of the points at which these emissions can be reduced at least cost depend on the forecast of energy demand because the release of CO_2 is related directly to fuel consumption via fuel specific emission factors. Consequently, the accuracy of the forecast for the emission of CO_2 and the accuracy of cost estimates for emission reduction depend on the accuracy with which the model can translate information on economic activity, energy prices, technical change, and political events into energy demand. The relation between economic activity and fuel use can be simulated at several levels using several techniques. This section reviews how existing models of CO_2 emissions forecast energy demand.

Models to forecast the emission of CO_2 and assess the cost of abatement can be described by two classifications: global models and national models. The discussion of existing models is organized along these categories because the scope of coverage and the forecast horizon influence the technique that is used by the model to forecast energy demand. Global models often use simple techniques to forecast energy demand because of their extensive scope and long forecast horizon. On the other hand, national models often use sophisticated techniques to forecast energy demand because their forecast horizon is relatively short and their scope is relatively narrow. Neither set of models can be used to assess the short-run economic costs of international efforts to reduce emissions of CO_2 because of limits on their scope or the techniques used to simulate energy demand.

Global models forecast the emission of CO_2 by the entire world. Furthermore, most of the global models have a long forecast horizon, such as the year 2100. To maintain their extensive coverage and their long forecast horizon, most global models use relatively simple technique to model energy demand. These simple techniques limit the amount of useful information that they can convey. The most important limits on the information they generate are associated with the level of aggregation and the failure to

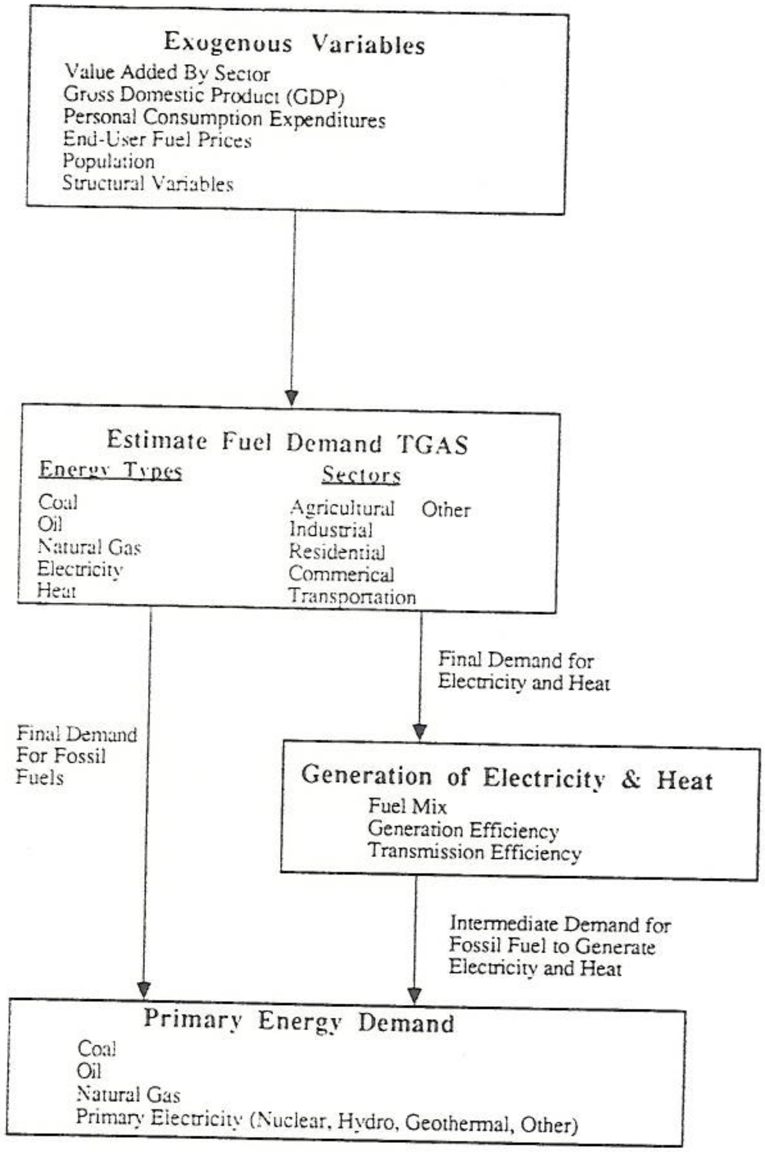

Figure 1. Overview of the TGAS model.

estimate behavioral equations from historical data. As a result, these models cannot be used to assess accurately least cost policies to slow emissions over a relatively short horizon, such as the next two decades. These limits have not been important in debate up until now because estimating the cost of reducing emissions has not been the major purpose of these global models. Rather, most are used to evaluate the magnitude of changes in prices and energy efficiency that are needed to keep emissions at a specified level.

Most of the global models now used to forecast the emission of CO_2 aggregate energy use by regions (Hoeller et al., 1990). At one extreme, the model of Nordhaus (1990) has no regional detail. Other models disaggregate energy use; nevertheless, the level of aggregation is much greater than the national level. For example, Manne and Richels (1990) break world energy use into five regions, Whalley and Wigle (1990) break world energy use into six regions, Edmunds and Reilly (1983) break world energy use into nine regions, and the IEA model (1990) breaks world energy use into ten regions. Within these regions, few of the global models disaggregate fuel use by sector, such as the industrial, transportation, or residential sector.

The high degree of aggregation used by the global models limits their ability to assess accurately the costs of reducing emissions of CO_2. A high degree of aggregation reduces the accuracy of cost estimates for reduction because the opportunity to conserve and substitute for fuel varies greatly among nations, sectors, and fuels. The cost estimates for reducing fuel use generated by highly aggregated global models are likely to be biased so that they over- or underestimate the cost of reducing CO_2 emissions. For example, a single estimate of an entire region's or economy's ability to conserve or substitute for oil aggregates the potential for such changes in the agricultural, industrial, residential, commercial, transportation, and other sectors. As such, regional or economywide analyses measure an average cost of reducing emissions, which represents the cost in each of six sectors weighted by the sector's share of total oil use. Consequently, highly aggregated models cannot identify the nations, sectors, or fuels that have the lowest cost of reducing emissions. This average cost becomes increasingly biased as the fraction of total oil use consumed by sectors or nations within regions changes over time. The direction of this bias depends on the change in the sectoral or national share of total oil use. For example, if the share of oil use by the transportation sector grows relative to the share of oil use by the industrial sector, models that aggregate all uses of oil may underestimate the cost of reducing CO_2 emissions because the potential for conservation and substitution in the transportation sector probably is smaller than in the manufacturing sector.

The bias in the price elasticities that is caused by the regional level of aggregation is exacerbated by the use of regional prices as independent variables in the equations for energy demand. Energy prices to end-users vary greatly among nations within regions and among sectors within nations. These variations affect the ability of pricing policies, such as a carbon tax, to reduce emissions of CO_2. This variation affects both the size of the carbon tax needed to achieve a given increase in energy prices and the size of the price increase among fuels. For example, Kaufmann (1991) finds that in at least seven OECD nations the price of natural gas relative to oil for industrial end-users is such that a carbon tax increases the price of natural gas relative to oil. These nation and sector specific differences affect both the size and the direction of substitution and are not captured accurately by models that aggregate energy prices and consumption to the regional level.

The specification that is used by global models to simulate the emission of CO_2 also limits the amount and quality of information regarding the costs of abatement. Many global models forecast the emission of CO_2 in three steps:

$$\text{Fuel Intensity} = f\,(\text{Prices, Technical Change}) \tag{1}$$

$$\text{Total Fuel Use} = \text{Fuel Intensity} \times \text{Economic Activity} \tag{2}$$

$$\text{Emission of } CO_2 = \text{Total Fuel Use} \times \text{Emission Rate} \tag{3}$$

In the first step, the model calculates the intensity of fuel use based on prices and technical change (Eq. 1). The remaining equations are identities, which convert energy intensity to total fuel use (Eq. 2) and total fuel use to emission of CO_2 (Eq. 3).

The heart of the model, which is the behavioral equation for fuel intensity, uses a simple specification. The forecast for fuel intensity is based on two variables: energy prices, which is represented by the own-price elasticity of demand, and technical change, which is represented by the autonomous increase in energy efficiency (AIEE). The definition of own-price elasticity of demand is similar to that used in standard economic analyses. It represents the percent change in fuel use that is associated with a 1 percent increase in the real price of the fuel. AIEE captures all other effects on fuel intensity.

The amount of information available from the simple specification is limited further by the process by which many global models are parameterized. The values used for the own-price elasticity of demand and AIEE often are not estimated from historical data. Instead the modelers use their judgment to choose values for these parameters for each region and fuel. For example, only three (including TGAS) of the eleven models exercised by the Stanford Energy Modeling Forum to investigate global warming estimate their equations for energy demand (Beaver and Huntington, 1991). In general, the models use values for the own-price elasticity of about 0.4 and assume that AIEE decreases fuel intensity between 0 and 2.0 percent per year (Hoeller et al., 1990). The lack of values derived from statistically based analyses limits the reliability of cost estimates for reducing CO_2. The cost estimates for achieving a level of reduction can be raised or lowered arbitrarily by changing the value for the price effect or the AIEE.

The other category of models—national models—forecasts the emission of CO_2 by individual nations. To assess the effects of least cost policies accurately, national forecasts of CO_2 emissions must be based on a coherent view of world economic activity. Without this information, national models may give a biased estimate of the effect of reducing CO_2 emissions. For example, it may be possible for a nation to reduce CO_2 emissions at a relatively low cost by reducing the production of goods that have a high fuel intensity, especially raw materials such as chemicals and steel. For example, the U.S. reduced its energy use over the last 15 years by importing energy-intensive raw materials (OTA, 1990). This strategy may not be feasible at a global scale because many of the raw materials that have high fuel intensities are critical inputs to downstream industries.

Despite the limits imposed by the scope of national models, the methods used to forecast energy demand by national models, such as econometric techniques, input-output analyses, and models of energy end-use, can assess the costs of reducing the emission of CO_2 more accurately than the techniques used by global models. Nevertheless, the use of many of these more sophisticated techniques to forecast emissions of CO_2 at the global level is limited by the availability of data and the forecasts generated by macroeconomic models. For example, Hogan (1989) and Ingham and Ulph (1990) use sophisticated econometric techniques to estimate dynamic putty-clay models of energy demand. These models capture the dynamic adjustments to changes in energy prices within a multifactor environment. The information contained in such models is critical to the formulation of least cost strategies for reducing emissions of CO_2. The estimation of these models depends heavily on data regarding factor inputs. Unfortunately, the availability of data regarding capital use limits the nations and sectors for which these models can be estimated. Data for capital stock rarely are available at a sectoral level other than industry in developed nations and are virtually unavailable at any level for developing nations. These limits on data are reinforced by the forecasts generated by macroeconomic models. Very few macroeconomic models forecast capital stock; therefore, it is difficult to generate consistent forecasts of the world macroeconomy that can be used to drive the models.

Input-output (I-O) techniques often are used to forecast energy use given a vector of final demand (Bullard et al., 1978; Hannon, 1982). Although I-O models give detailed information regarding fuel use to produce particular goods or services, the use of I-O models to evaluate the costs of reducing CO_2 emissions is limited. One limit is the availability of I-O tables. National I-O tables are available for many developed nations but relatively few developing nations. The United Nations Global Input-Output Model (UNGIOM) and the OECD/GREEN model have I-O tables for the entire world, but these tables represent regions and so suffer from the same aggregation bias described previously.

Another type of national model attempts to forecast energy use by examining end-use technologies. These models attempt to describe the type, efficiency, and prevalence of energy-using capital equipment. For example, end-use models forecast the demand for motor gasoline from information regarding the size of the automobile fleet, its fuel efficiency, and the number of miles traveled. The end-use approach is appealing because it represents explicitly the tasks and technologies that use energy, but shortcomings associated with the data and structure prevent these models from evaluating the costs of abating emissions of CO_2. Rarely do these models represent explicitly the market mechanisms that influence the choice of technologies. This forces the user to assume exogenously the types of technologies that are available now and in the future, and the degree to which various energy efficient technologies are adopted. For example, the user must assume that somehow the average fuel efficiency of the automobile fleet doubles or triples or that consumers purchase the most efficient air conditioners. Without information regarding the rate and cost at which technologies penetrate the market, end-use models cannot evaluate least cost strategies but rather can evaluate only command and control strategies. Models of energy end-use also ignore the energy used to produce higher cost capital. The capital requirements of energy efficient technologies are higher than less efficient models. Even if an energy efficient technology is economically viable, some portion of the energy conserved by the fuel efficient technology is offset by an increase in energy use by the capital-producing sector of the economy. Finally, the applicability of the end-use models is limited by data. Many uses of fuel do not produce output that can be quantified as easily as can passenger miles per gallon. It is difficult to measure the efficiency of the service sector. Furthermore, very few nations have a complete inventory of energy-using capital equipment. It is possible to assemble such data, but the surveys needed to do so are time-consuming and expensive.

TGAS: A Compromise Between Global and National Models

In order to evaluate the cost of reducing emissions of CO_2 accurately, the technique used by TGAS strikes a compromise between the very simple techniques used by the existing global models to forecast energy demand and the very sophisticated techniques used by national models. Because the emission of CO_2 depends on the structure of the world economy, TGAS is a global model. Because the cost of reducing emissions varies, TGAS is estimated from historical data by nation, sector, and fuel. Because the rate of emission depends on economic activity and because policies to reduce emissions will affect economic activity, the degree of disaggregation used by TGAS is consistent with the level of disaggregation used by global macroeconomic models. Taken together, this approach alleviates the bias that is built into equations estimated at a more aggregated level, represents explicitly the economic behaviors that influence the choice of technology, and allows the model to evaluate least cost strategies for reducing emissions.

Econometric Specification

To measure the effect of technical change and substitution accurately, equations for final energy demand must be specified correctly, the data needed to estimate the equations must be available, and the proper econometric techniques must be employed. This section describes how the econometric specification used by TGAS to simulate energy demand strikes a viable methodological compromise between the simple techniques used by global models and the sophisticated techniques used by national models. The general econometric specification used to quantify the effect of conservation, substitution, and product mix on fuel intensity is given by

$$\text{Fuel Use/Activity} = f(\text{fuel price, product mix, economic development, time}) \quad (4)$$

Specifying the level of aggregation to measure the numerator and denominator of the dependent variable, fuel use and economic activity, and the relevant independent variables is critical if the cause(s) of change is (are) to be measured accurately. Final demand for fuel is disaggregated into six sectors: agricultural, industrial, commercial, residential, transportation, and other.[1] These six sectors are chosen because the technical opportunities for substitution and the behavioral response to changing prices are similar within sectors relative to the differences that exist among sectors (Bohi and Zimmerman, 1984). For example, the opportunities to replace oil use in the industrial sector are similar among many manufacturing processes, but as a group these opportunities are different from the opportunities to replace oil use in the transportation sector. These differences imply that the technical, economic, and political aspects of mitigating CO_2 emissions differ greatly among these sectors; therefore, the six sector level of disaggregation enables TGAS to identify the nations, sectors, and fuels where policy to reduce emissions is most cost effective.

The level of disaggregation that is used to estimate Equation 4 also is consistent with the data that are available to measure fuel intensity. Historical data for fuel use by the agricultural, industrial, transportation, residential, commercial, and other sectors are available from the International Energy Agency (IEA) for a period sufficient to estimate statistically meaningful econometric equations. Historical data that reflect the level of economic activity by these six sectors also are available. Finally, the six sector level of disaggregation is consistent with the level of disaggregation at which many large econometric models such as project LINK forecast economic activity (Waelbroeck, 1976).

We calculate the independent variable in Equation 4, fuel intensity, by matching data for fuel use with data for economic activity (Table 1). The six sectors of fuel use represent activities associated with economic production and consumption, and it is possible to match data for fuel use by sector with a measure of that sector's economic activity. On the production side of the economy, agricultural, industrial, and commercial fuel intensities are calculated by dividing fuel use by real value added. On the consump-

[1]See EIA. *Energy Balances of OECD Nations* for a definition of sectors.

Table 1
Calculation of Fuel Intensities

Sector	Numerator	Denominator[a]
Agricultural	Fuel use by agriculture	Value added agriculture (ISIC 1)
Industrial	Fuel use by industry	Value added industry (ISIC 2 & 3)
Commercial	Fuel use by the commercial sector	Value added commercial (ISIC 6 & 8)
Transportation	Fuel use by the transportation sector	GDP
Residential	Fuel use by the residential sector	Personal consumption expenditures
Other	Fuel use by the other sector	GDP

[a]In centrally planned economies, net material product is used in place of GDP, consumption of the population is used in place of personal consumption expenditures, and net material product by kind of activity in the material sphere is used in place of value added by sector.

tion side of the economy, residential fuel intensities are calculated by dividing fuel use by real personal consumption expenditures. Fuel use by the transportation sector powers both economic production (fuel used to move goods and services) and economic consumption (fuel used by private individuals to move themselves). As a result, transportation fuel intensities are calculated by dividing fuel use by real gross domestic product (GDP). Finally, fuel use by the other sector is an amalgam of unclassified uses of energy as a fuel.[2] Fuel intensities for the other sector are calculated by dividing fuel use by real GDP, because real GDP is the most inclusive measure of activity by the general economy.

For each of the six sectors, we calculate intensities for five forms of energy: coal, oil, natural gas, electricity, and heat. In the transportation sector, this level of disaggregation is taken one step further. The consumption of motor gasoline is separated from the consumption of other refined petroleum products used in the transportation sector. Disaggregating energy use by five fuels is consistent with opportunities for technical change and the goal of forecasting the emission of CO_2 by fuel and sector. The most significant aspects of substitution allow firms and/or households to choose among fuel types rather than grades of the same fuel. Similarly, there is little variation in the amount of CO_2 released per heat unit within a fuel type (residual fuel oil versus distillate fuel oil) relative to the large variations that exist among fuel types (natural gas versus coal).

The dependent variable in Equation 4, fuel intensity, is regressed against a set of independent variables that are chosen based on micro- and macroeconomic theory. Microeconomic theory states that the price of fuel is one of the most important determinants of fuel use per unit output. Furthermore, least cost strategies for reducing the emission of CO_2 will be implemented through policies that change the absolute and relative prices of fuel, such as a carbon tax. The current emphasis on least cost policies makes it critical that the econometric analysis quantify the effect of absolute and relative changes in fuel price on fuel intensity.

Another set of independent variables, product mix, is determined by the level of aggregation used to estimate equations. The six sector level of disaggregation implies that economic activity by each sector is homogeneous (e.g., real value added by the industrial sector, real personal consumption expenditures). These assumptions are simplifications, and changes in mix do occur within each of these sectors. Changes in mix

[2]Fuel use by the other sector does not include nonenergy uses of fuel.

within a sector affect fuel use per unit output by a sector if the fuel intensity of activities within the sector varies. For example, if the fraction of output by the industrial sector that consists of goods with a high fuel intensity increases, the fuel intensity of the entire sector will increase. The econometric specification attempts to quantify the effects of changes in product mix by using the fraction of GDP accounted for by a category as an independent variable. If the fraction of GDP that originates in the industrial sector rises over time, this increase can be interpreted as a change in the type of goods produced. The effect of such changes varies by sector. If the fraction of GDP that originates in the industrial sector rises, this increase may be interpreted as industrialization. Industrialization in developing nations often is associated with the production of goods that have a fuel intensity larger than the average fuel intensity of goods already in production. In the Republic of Korea, steel production grew faster than value added in the industrial sector and real GDP.[3] As a result, the fraction of GDP that originated in the industrial sector grew. The fuel intensity of steel production is large relative to most other industrial goods, and the increase in steel production may raise the fuel intensity of the industrial sector in these nations (Williams et al., 1987). In developed economies, a decline in the fraction of GDP that originates in the industrial sector is associated with a shift away from heavy smokestack industries and a decrease in the fuel intensity of output. Such is the case for the U.S. (Marley, 1984). Based on this interpretation, the regression coefficient associated with the fraction of GDP that is accounted for by value added in the industrial sector should have a positive sign.

On the other hand, a rise in the fraction of GDP that originates in the commercial sector may represent a shift toward services that have a small fuel intensity. The first services provided by the commercial sector often are relatively energy intensive. As an economy matures, services that rely on information proliferate, and providing such services usually require less energy. This type of change lowers the average fuel intensity of the commercial sector. Based on this interpretation, the regression coefficient associated with the fraction of GDP that originates in the commercial sector should have a negative sign.

Fuel intensity also may be affected by a nation's stage of economic development. These changes can be proxied by per capita GDP or per capita consumption. Again, the effect of economic development on fuel intensity varies among nations. Early in economic development, an increase in per capita GDP may increase the quantity of fuel used to provide an average dollar's worth of personal consumption. During this period, people often switch from noncommercial to commercial fuels, electrify their homes, and buy fuel using appliances (Dunkerley et al., 1981). During later stages of economic development, the basic need for fuel is satisfied, and consumption turns toward nonfuel goods and services. This change may reduce residential fuel intensity.

Fuel intensity also is affected by events that extend beyond traditional economic variables. These events are associated with qualitative rather than quantitative change. The econometric equations must be able to measure the effect of qualitative change when these events affect fuel intensity. For example, strikes by Solidarity in Poland and the first and second oil shocks may have an important effect on fuel intensity in some sectors in some nations. The effects of these qualitative changes are represented by dummy

[3]In the Republic of Korea, steel production grew 69-fold between 1972 and 1987, industrial production grew 10.1-fold, and GDP grew 3.4-fold. Data are from the *Industrial Statistics Yearbook* and the *United Nations Yearbook of National Accounts*.

variables. Such representations allow the econometric analysis to quantify the effects of qualitative changes in the economic and political environment.

Finally, there may be some changes in fuel intensity that cannot be measured by quantitative or dummy variables for qualitative change. Technical change is a factor that may affect fuel intensity but cannot be measured easily by quantitative or qualitative variables. For these factors, a time trend may be used to account for the variation in fuel intensity. In general, the use of a time trend represents a failure, the inability to link changes in fuel intensity with specific economic or political conditions. In this spirit, the econometric equations specify a time trend only when the use of other variables fails. When used, the time trend usually is specified as a logarithmic value. A linear increase or decrease in a time trend may produce nonsensical results if the model is used to forecast over a long horizon.

Estimation Technique

The econometric equations can be estimated at the level of aggregation described above because the requisite data are available.[4] These data can be used to estimate equations for fuel intensity by nation, sector, and fuel type of the form given by Equation 4. The five equations for fuel intensity in a sector may be written as:

$$\mathrm{EI}_{\mathrm{coal}} = \beta_i X_i + \mu_{\mathrm{coal}} \tag{5}$$

$$\mathrm{EI}_{\mathrm{oil}} = \beta_i X_i + \mu_{\mathrm{oil}} \tag{6}$$

$$\mathrm{EI}_{\mathrm{gas}} = \beta_i X_i + \mu_{\mathrm{gas}} \tag{7}$$

$$\mathrm{EI}_{\mathrm{elec}} = \beta_i X_i + \mu_{\mathrm{elec}} \tag{8}$$

[4]Whenever possible, we obtain data from one source to ensure consistency. All data for economic activity, such as value added, personal consumption expenditures, and GDP, are obtained from the United Nations and are published in the *United Nations Yearbook of National Accounts*. All data are reported in real units of the national currency. Data for fuel use by sector are obtained from the International Energy Agency and are published in the IEA's *Energy Balances of OECD Nations* and *Energy Balances of Developing Nations*. Data from the OECD yearbooks are reported in million metric tons of oil equivalent and data for developing nations are reported in thousand tons of oil equivalent. Data for electricity are reported in tons of oil equivalent based on the heat equivalent of electricity rather than the quantity of fossil fuel used to generate electricity.

Unfortunately, there is no single source for the price of fuel. Instead, these data are obtained from yearbooks published by national agencies. Data for the price for coal mining, mineral oils, and electricity and fuels, power, light, and lubricants in India are obtained from *Statistical Abstract*, published by the Central Statistical Organisation, Department of Statistics, Ministry of Planning, Government of India. Prices for gasoline, diesel, briquette anthracite, and electricity in the Republic of Korea are obtained from the *Korean Statistical Yearbook* and backcast with deflators for the petroleum products, coal products, and electricity from the *Economics Statistical Yearbook*, published by the Bank of Korea. Prices for gasoline, diesel fuel, fuel oil, natural gas, and electricity are obtained from *Energy Prices and Taxes*, published by the International Energy Agency, and backcast with deflators for coal, petroleum products, natural gas, and electricity obtained from *Tableaux de L'energie Francaise 1949–1979*, published by the Institut National de la Statistique et des Etudes Economiques. Prices for coal, gasoline, fuel oil, natural gas, and electricity in Poland are obtained from *Rocznik Statystyczny*, published by Ministerstwo Oswiaty i Wychowania.

$$\mathrm{EI}_{\mathrm{heat}} = \beta_i X_i + \mu_{\mathrm{heat}} \tag{9}$$

in which EI is the intensity of fuel use in the industrial sector, β_i is a vector of regression coefficients, X_i is a vector of independent variables, and μ_i are the error terms.

The equations for each sector are estimated using generalized least square (GLS) techniques because estimating Equations 5–9 individually or stacked using ordinary least squares (OLS) techniques is inefficient. Regression coefficients for Equations 5–9 that are estimated using OLS techniques will be efficient only if the error terms (μ_i) have zero covariance, that is, if there is no relation between any of the error terms. If there is some relation between the error terms and the potential for interfuel substitution gives good reason to believe that the error terms covary, the regression coefficients estimated by OLS techniques will be inefficient. The degree of inefficiency increases in proportion to the degree of covariance between the error terms.

The process by which a firm chooses the mix of fuels used to produce output implies that the error term will vary systematically among Equations 5–9 and, therefore, OLS estimates will be inefficient. When a firm chooses a method to produce output, it chooses a combination of inputs that minimizes total costs. This combination includes the type and quantity of up to five fuels. The quantity of coal, oil, natural gas, electricity, and heat that is used to support a level of economic activity represents the outcome of a simultaneous decision.[5] Because substitution among fuels plays an important role in determining the cost-minimizing combination of inputs, changes in the use of one fuel may affect the use of the other fuels. The simultaneity of the decision and the possibility for substitution among fuels imply that the error terms for each of the equations for fuel intensity in each sector may be correlated. For example, interfuel substitution between coal and oil may imply that a negative error term associated with the equation for coal intensity may be associated with a positive error term associated with the equation for oil intensity.

The inefficiency that is introduced by the cross correlation of the error terms can be avoided by creating a system of equations for fuel intensity for each sector (seemingly unrelated regressions, SUR) and estimating them simultaneously with GLS techniques.[6] In summary, GLS techniques relax the assumption concerning the independence of the error terms. Estimating a SUR system with the GLS technique does not carry any hidden bias relative to the more traditional OLS technique. If the error terms in the equations for fuel intensity of a sector are completely uncorrelated, the results obtained using GLS techniques will match the results obtained using OLS techniques.

[5]Berndt and Wood (1979) show that the production function is weakly separable. Even in their model, decisions regarding the mix of fuel are made simultaneously.

[6]The inefficiency introduced by OLS techniques can be illustrated as follows. The equation for oil intensity in the French industrial sector that is estimated using GLS from the SUR system is given by

$$\underset{(2.86)}{\mathrm{Oil} = 0.796\mathrm{E}\text{-}04} - [\underset{(5.48)}{0.790\mathrm{E}\text{-}06 * \mathrm{OLPR}(1\text{-}2)}] + (\underset{(3.61)}{0.575\mathrm{E}\text{-}04 * \mathrm{NGPR/OLPR}})$$
$$\text{Adjusted } R^2 = 0.893 \quad \text{Breusch - Pagan} = 0.059 \quad \mathrm{DF} = 12$$

If the oil equation is estimated individually using OLS techniques, the following result is obtained:

$$\underset{(4.78)}{\mathrm{Oil} = 0.131\mathrm{E}\text{-}03} - [\underset{(7.43)}{0.916\mathrm{E}\text{-}06 * \mathrm{OLPR}(1\text{-}2)}] + (\underset{(0.96)}{0.190\mathrm{E}\text{-}04 * \mathrm{NGPR/OLPR}})$$
$$\text{Adjusted } R^2 = 0.932 \quad \text{Durbin Watson} = 2.14 \quad \rho = 0.367 \quad \mathrm{DF} = 12$$

The coefficient for the price of gas relative to oil is statistically insignificant when OLS techniques are used to estimate equations individually.

Many independent variables can be used to explain the historical variation in fuel intensity. Because there is no a priori theoretical basis for choosing one specification, many specifications for Equations 5–9 are estimated for each sector. From these many specifications, the "best" is used in TGAS. Many criteria are used to choose the "best" set of equations for a sector. The sign on the regression coefficients is used as the primary criterion to evaluate equations. Specifications that generate regression coefficients with signs opposite to those predicted by economic theory are eliminated immediately. For example, to be eligible for further consideration, the regression coefficient for the own-price effect on fuel intensity must be negative and the regression coefficients for cross price effects must be positive. The statistical significance of regression coefficients also is an important criterion to choose among equations. The statistical significance of the regression coefficients is evaluated by their t statistics. The usual econometric threshold for statistical significance ($p < 0.05$) is used. Finally, a general Lagrangian multiplier test is used to analyze the error term for serial correlation because the Durbin Watson test is not applicable for equations estimated using GLS techniques (Breusch and Pagan, 1979).

Relatively little emphasis is placed on the R^2 of individual equations as a criterion to choose among equations. Clearly, a high R^2 is desirable, because it indicates that the independent variables account for a relatively large fraction of the historical variation in fuel intensity. Nevertheless, there are several reasons to believe that the R^2 of the equations estimated for TGAS will be lower than those associated with previous models. This reduction is caused by the econometric specification and the estimation technique. As described below, the reduction in R^2 does not reflect a methodological weakness.

Many models of energy demand estimate their equations by regressing fuel demand against economic activity, prices, product mix, etc.; for example,

$$\text{Fuel Use} = f\,(\text{Output, fuel price, product mix, economic development, time}) \tag{10}$$

Moving economic output to the right-hand side of Equation 10 makes fuel demand the dependent variable, whereas fuel intensity is the dependent variable in Equation 4. As such, the R^2 of the two specifications cannot be compared. Furthermore, there is good reason to believe that the specification given by Equation 10 has a large R^2 built in. Although no direction of causality can be assigned to fuel use and economic activity (Yu and Hwang, 1984; Akarca and Long, 1980), they tend to grow together in many nations (Hall et al., 1986). The trend in the two variables allows economic activity to account for a large fraction of the total variation in fuel use. Dividing fuel use by economic activity removes this trend and reduces the high R^2.

The iterative GLS estimation of simultaneous equations also tends to reduce the R^2 relative to single equation OLS estimations. Iterative GLS estimation minimizes the residual sum of squares (maximizes R^2) for the system of equations, while OLS estimation minimizes the residual sum of squares (maximizes R^2) for an individual equation. Thus, not only may the coefficients obtained by OLS methods be inefficient due to the correlation of error terms among equations, but this inefficiency may allow single equation estimates to increase the R^2 by ignoring the cross correlation of error terms.

Results

The method described in the previous section is used to estimate equations for fuel intensity in four nations: France, the Republic of Korea, India, and Poland. These four nations are chosen because they represent a wide range of economic systems: a developed economy, France; an economy that undergoes rapid development, the Republic of Korea; a developing economy, India; and a centrally planned economy (at least during the period of analysis), Poland. The regression results satisfy most of the standard criteria for statistical significance and seem to account for most of the historical variation in fuel intensity. All but three of the regression coefficients, other than the intercept, are statistically significant ($p < 0.05$). The regression coefficient for the price of coal relative to electricity in the equation for the intensity of electricity use by the transportation sector in India, the regression coefficient for the price of natural gas relative to coal in the equation for the intensity of heat use by the industrial sector in Poland, and the regression coefficient for the price of oil relative to electricity in the equation for the intensity of electricity use by the residential sector in Poland are significant at the ($p < 0.1$) level. These variables are included, despite their lower level of statistical significance, to quantify a price effect.

Despite expectations of a low R^2 for individual equations, the R^2 for most of the equations are high and indicate that the independent variables can account for most of the historical variation in fuel intensity. Nevertheless, there are five notable exceptions: the intensity of motor gasoline use by the French transportation sector ($R^2 = 0.285$), the intensity of coal ($R^2 = 0.23$) and oil ($R^2 = 0.195$) use by the Indian industrial sector, the intensity of electricity use by the Indian transportation sector ($R^2 = 0.116$), and the intensity of heat use by the Polish industrial sector ($R^2 = -0.04$). The low R^2 for these equations may be caused by the relative stability of these fuel intensities. The electricity intensity of the French transportation sector moves over a range of 10 percent, the Indian fuel intensities move over a range of 12 to 25 percent, and the heat intensity of Polish industry moves over a range of 28 percent. The lack of data for the price of heat also contributes to the low R^2 for the Polish heat equation. Regardless of the cause, the low R^2 should not cause too great a problem for estimating the emission of CO_2. The narrow range of change for the fuel intensities indicates that the unexplained portion of the variation is small relative to the fuel intensity.

The error term is serially correlated in eleven of the sixty-six equations estimated ($p < 0.05$). Problems of serial correlation in most of these eleven equations may be attributed to difficulties that are associated with quantifying technical change. Serial correlation of the error term is expected in processes driven by technical change, because it is difficult to measure technical change. Technical change probably has its greatest effect on fuel intensities for coal and heat use in all sectors and electricity use by the transportation sector. Regardless of price, technical change makes the use of coal and heat relatively undesirable and drives the substitution of electric locomotives for coal locomotives. Consistent with the effect of technical change, the error terms in equations for coal and electricity intensity by the transportation sector in France have statistically significant levels of serial correlation. Several of the remaining equations with statistically significant levels of serial correlation are for Poland and India. Poland is a centrally planned economy, and India is a mixed economy. As such, government plans play an important role in the allocation of energy. Without specific information regarding these plans, the omitted variable bias associated with the absence of quantifiable information regarding centrally planned decisions is good reason to expect serial correlation of the error term.

Most (fifty-six) of the sixty-six equations include fuel prices as an independent variable. The presence of a price effect is expected given the role that prices play in determining the cost minimizing combination of factor inputs. Seven of the ten equations that have no price effect are for Poland and India. The central planning process in both these countries deemphasizes price as a decision variable. Indeed, it is surprising that thirteen of the eighteen equations for Poland include a price effect. The equations that do not have price effects in the market economies, France and the Republic of Korea, are for the intensity of coal and electricity use by the transportation sector. As described above, coal and electricity intensities for the transportation sector probably are driven by technical change; therefore, prices have little effect on fuel intensity.

When price variables are present, they appear in two forms: own-price and cross price effects. The own-price effect is measured by the real price of the fuel, and the cross price effect is measured by the price of fuel relative to another fuel. The form in which the price effect appears is determined, in part, by the ease of interfuel substitution. Own-price effects predominate in sectors where interfuel substitution is difficult. Cross price effects predominate in sectors where interfuel substitution is relatively easy. For example, the industrial sector uses fossil fuels to generate heat and many industrial boilers can use coal, oil, or natural gas. Consistent with this potential for interfuel substitution, the equations for fossil fuel intensities in the French industrial sector all have cross price effects. On the other hand, there is less potential for interfuel substitution in the transportation sector. Consistent with this difficulty, few of the equations for the intensity of fuel use by the transportation sector have cross price effects.

Income, as measured by per capita GDP or per capita consumption, has an important effect in many of the equations for fuel intensity. The income effect varies by level of development. Fuel intensity is related to income in developing nations such as India, the Republic of Korea, and Poland. A positive income effect predominates in the Indian and Korean residential sector, where increasing income allows households to substitute commercial fuels, such as oil and electricity, for noncommercial fuels, such as fuelwood, charcoal, and biomass. On the other hand, the regression coefficient for per capita GDP in Poland is negative. The government in Poland subsidized fuel prices for the period analyzed, allowing even the poorest households to buy commercial fuels. As a result, Polish households spend their marginal income on nonfuel goods and services, and this reduces residential fuel intensities. Per capita GDP has little effect on fuel intensity in France. France is a developed nation, and changes in income have little effect on fuel intensity.

Finally, structural changes, as represented by dummy variables, have an important effect on fuel intensity in some nations and sectors. The oil shocks of the 1970s and early 1980s have the greatest effect on market economies, France and the Republic of Korea, and a lesser effect on the mixed economy of India. As expected, the oil shocks increase the intensity of nonoil fuels and decrease the intensity of oil use. The oil shocks have no effect on fuel intensities in Poland because local fuel prices do not reflect world prices. Local conditions also have an important effect on fuel intensity. In Poland, labor disruptions led by Solidarity increase the intensity of fuel use in all sectors except the residential sector. This result is consistent with the hypothesis that the labor disruptions decrease the efficiency of production. In the residential sector, the regression coefficient for the Solidarity dummy variable is negative. This may indicate that the disruptions lead to a shortage of electricity, which the government rationed away from the residential sector. In India, student protests in Assam shut down the transport of oil and natural gas, and this disruption reduced the intensity of natural gas use by the industrial sector.

Validating the New Methodology

The ability of TGAS to quantify the link between energy use and economic activity and its ability to generate a reliable forecast of CO_2 emissions are validated by comparing an ex post out of sample forecast (backcast) of CO_2 emissions generated by TGAS with the historical record. The integrity of this validation is maintained several ways. To test the general applicability of the new methodology, the four nations used in this validation represent a wide range of economic systems: a developed economy, France; an economy that is undergoing rapid development, the Republic of Korea; a developing economy, India; and a centrally planned economy (at least during the period of analysis), Poland. The period of the backcast is chosen to prevent the validation from degenerating into an exercise in curve fitting. The equations for fuel intensity are estimated with data that start in 1971, but the backcast extends to the late 1950s and early 1960s, depending on the availability of data. The timing of the break between the period of estimation and the period of the backcast provides an additional test of the methodology. Energy prices changed dramatically in the early 1970s. Some argue that this change alters the relation between energy use and economic activity (Uri and Hassanein, 1985). Such a change would cause the backcast to deviate significantly from the historical record. If the backcast reproduces the historical record well, such accuracy may indicate that the dramatic price changes in the 1970s and 1980s did not alter the behavioral relation between energy use and economic activity and would give us good reason to believe that the behavioral relations that prevailed in the 1970s and 1980s can be used to forecast the emission of CO_2 in the 1990s and the beginning of the next century. Finally, the integrity of the validation is maintained by comparing the backcast to an independent estimate for the release of CO_2 (Rotty and Marland, 1984). The use of an independent estimate is necessary because the IEA does not publish data on energy use for developing nations before 1971.

Calculating Total Energy Demand and CO_2 Emissions

Before proceeding with a description of the validation, we describe the steps by which the fuel intensities estimated by TGAS are translated into primary energy demand and how primary energy demand is translated into CO_2 emissions. The equations for fuel intensity cover final energy demand, but they do not include intermediate uses of fuel. The intermediate use of fuel to produce fuel, generate electricity, and produce heat may emit large amounts of CO_2. The quantity of CO_2 emitted by intermediate uses of fuel depends on the quantity of fuel produced domestically, the quantity of fossil fuel used to produce fuel, the mix of fuel used to produce electricity and heat, generation efficiencies, and line losses (Fig. 2). To backcast the fuel used to produce fuel, which is termed own use (e.g., fuel used to pump and refine petroleum, dig coal, etc.), we assume that the fraction of total fuel consumption that is used for "own use" remains constant. For example, Poland used 1.0–2.3 percent of its coal to produce coal between 1971 and 1987. For years prior to 1971, we increased total coal use by 1.0 percent to account for "own use" of coal. The quantity of CO_2 that is released by the intermediate use of coal, oil, and natural gas to generate electricity and heat is calculated from the final demand

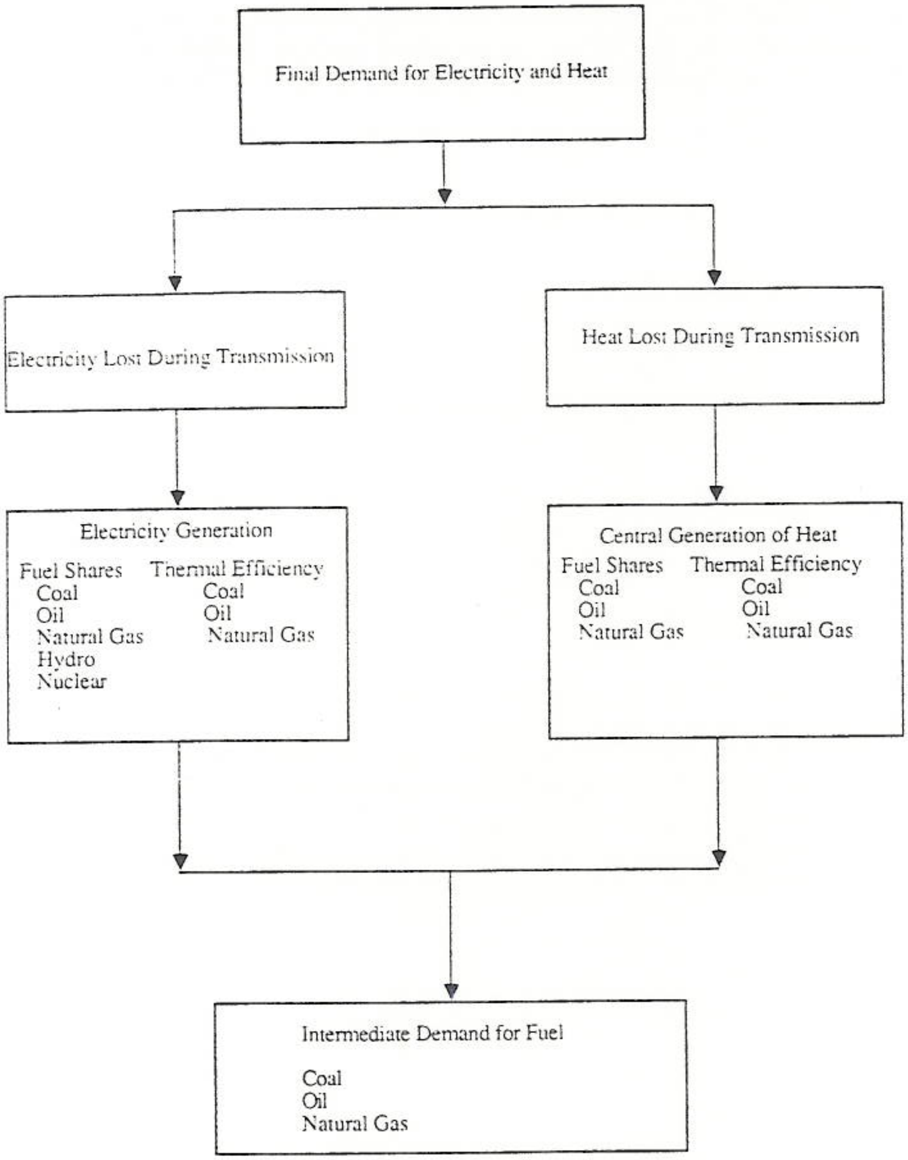

Figure 2. Intermediate demand for energy.

for electricity and heat (Fig. 2). Final demand for electricity and heat is summed across the five sectors, adjusted for line losses, and translated into the primary fuels from which it is generated. This translation is accomplished using historical data for line losses, generation mix, and power plant efficiencies. The mix and thermal efficiency of electricity and heat generation allow TGAS to calculate the coal, oil, and natural gas that is burned by the utility sector.

Calculations regarding the intermediate use of fuel are summed with the forecast for final demand for oil, coal, and natural gas to calculate the release of CO_2 by fuel and sector. The emission of CO_2 is calculated by multiplying sector specific fuel use by a fuel specific emission factor.[7] The quantity of CO_2 that is released per unit of oil or natural gas combusted varies only slightly among refined products or the heat content of gas; therefore, the same emission factor is applied to all nations. The quantity of CO_2 released per unit of coal combusted varies greatly among ranks of coal. To account for these differences, nation specific CO_2 emission factors for coal are used (Rotty and Marland, 1984).

Comparison of Backcast with the Historical Record

The accuracy of the backcast relative to the historical record varies by nation. The backcasts for France, the Republic of Korea, and Poland are close to the historical record. The ability to backcast the release of CO_2 by France is not surprising (Fig. 3). France is a developed nation. The data for economic activity, fuel consumption, and fuel prices are expected to be accurate. A well-established market and the availability of capital for investment should allow France to change fuel intensities as predicted by economic theory. The close match between the backcast and historical record for the Republic of Korea indicates that the methodology may be able to forecast the release of CO_2 by economies that undergo large quantitative and qualitative changes (Fig. 4). Over the previous 30 years, the Korean economy has developed a strong central market, has increased economic output dramatically, and has changed its output mix from agricultural to industrial goods. Finally, the close match between the backcast and historical record for Poland indicates that the methodology may be used to analyze the emission of CO_2 in centrally planned economies (Fig. 5).

The results are less encouraging for India (Fig. 6). As with Callendar, however, much can be learned from the cause of our inaccuracy. The backcast for India follows the record compiled by Rotty and Marland closely prior to 1971, which is the period for the true backcast. The backcast diverges from the historical record in 1977 and is roughly parallel thereafter. Nearly all the difference between the backcast generated by TGAS and the record compiled by Rotty and Marland (1984) is associated with coal use. According to Rotty and Marland, coal consumption increased 24.7 percent in 1977. This increase is not consistent with data for energy consumption compiled by the EIA and the United Nations. Rotty and Marland compile their record of CO_2 emission from data for energy supply. The lack of corroborating evidence from data for energy consumption may imply that the large increase in emissions from coal that is reported by Rotty and Marland (1984) is a statistical discrepancy.

Conclusion

This paper describes a new model for estimating the release of CO_2 by nation, sector, and fuel. This level of disaggregation eases many of the limits on existing models, such as the very simple econometric specification, the lack of disaggregated information regarding fuel use by nation, sector, and type, the lack of behavioral parameters esti-

[7]The same emission factor is used for each nation to calculate metric tons of carbon released per metric ton oil equivalent of liquid fuel and natural gas consumed: liquid fuels (783 MT carbon/MTOE); natural gas (579 MT carbon/MTOE). Nation specific factors are used for coal: France (1030 MT carbon/MTOE); India (1031 MT carbon/MTOE); Poland (1109 MT carbon/MTOE); and the Republic of Korea (1204 MT carbon/MTOE). Emission factors are from Rotty and Marland (1984).

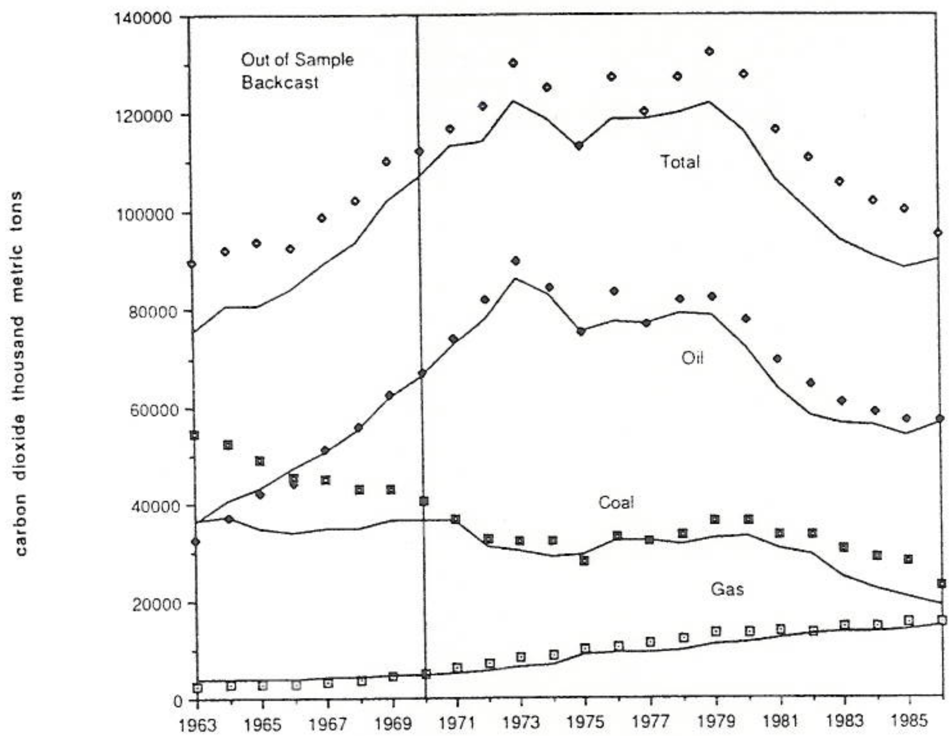

Figure 3. Emissions of carbon dioxide in France from coal (closed squares), oil (closed diamonds), natural gas (open squares), and total (open diamonds) reported by Rotty and Marland and values generated by TGAS (solid line).

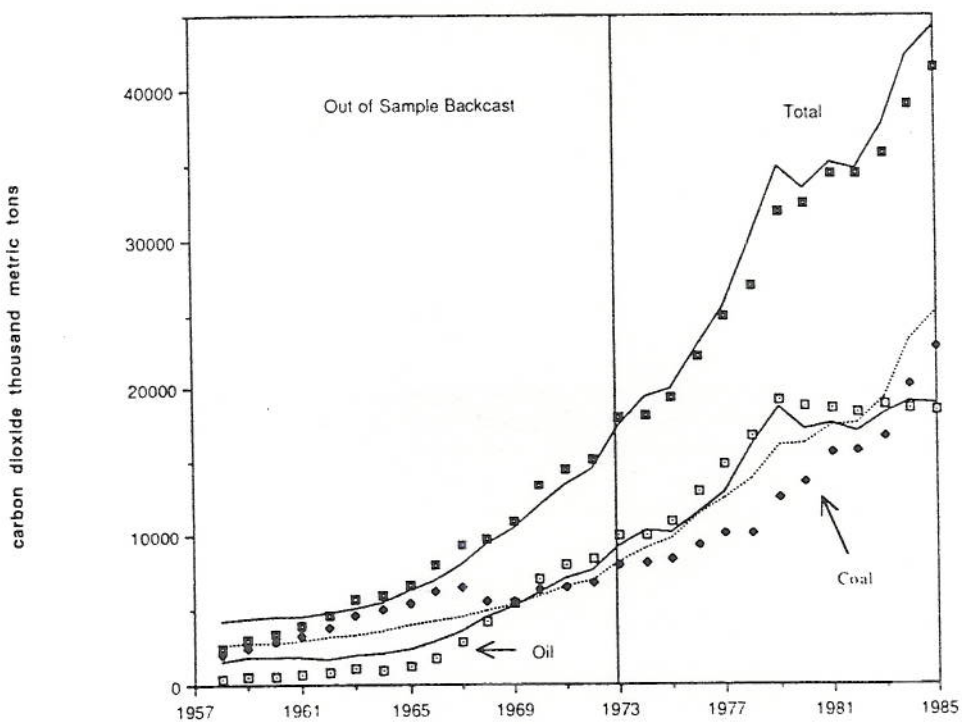

Figure 4. Emissions of carbon dioxide in the Republic of Korea from coal (closed circles), oil (open squares), and total (closed squares) reported by Rotty and Marland and values generated by TGAS (solid line).

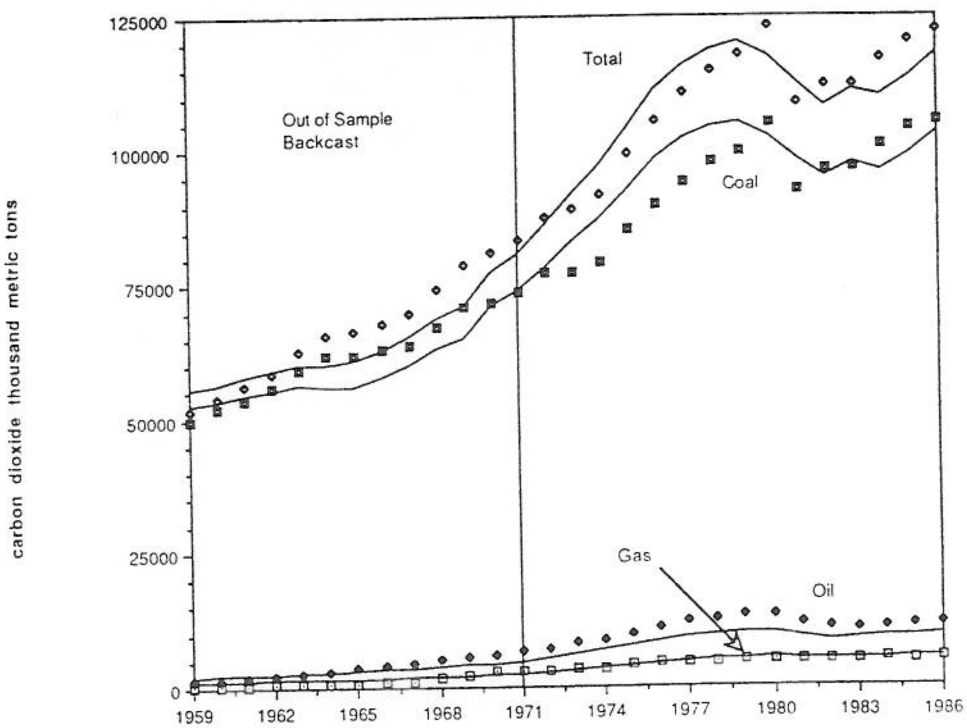

Figure 5. Emissions of carbon dioxide in Poland from coal (closed squares), oil (closed circles), natural gas (open squares), and total (open circles) reported by Rotty and Marland and values generated by TGAS (solid line).

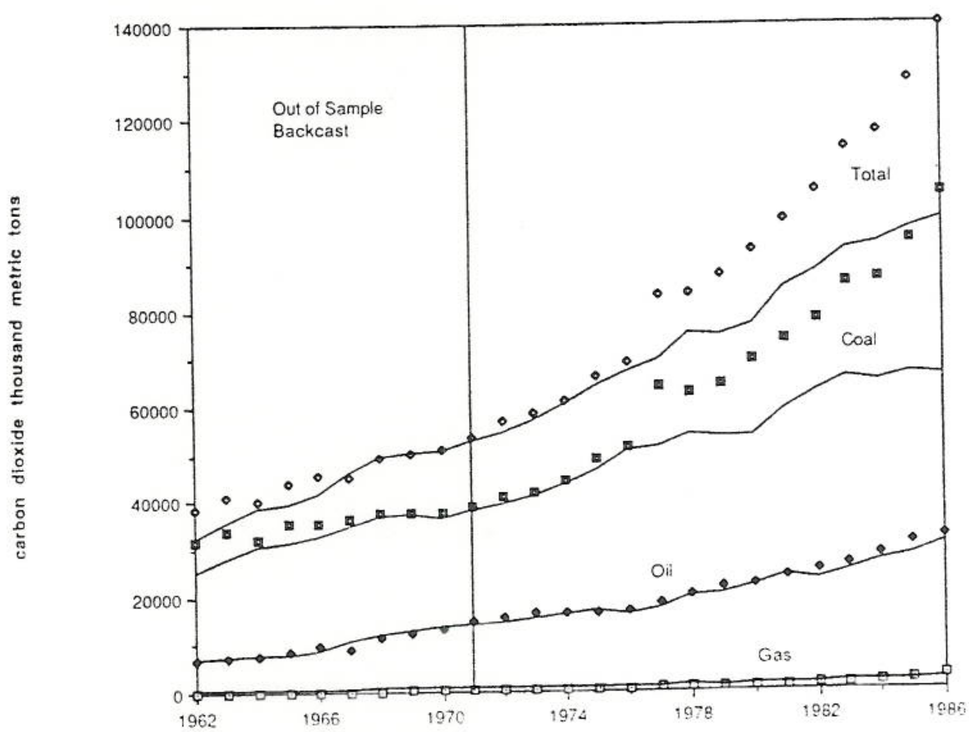

Figure 6. Emissions of carbon dioxide in India from coal (closed squares), oil (closed circles), natural gas (open squares), and total (open circles) reported by Rotty and Marland and values generated by TGAS (solid line).

mated from historical data, and the inefficiency introduced by OLS estimation techniques. The results of the estimation techniques indicate that it is possible to estimate statistically meaningful equations for fuel intensity by nation, sector, and fuel for a variety of economies. The validation indicates that these equations can be used to backcast the release of CO_2 accurately. Based on these results, we have estimated equations for twelve other nations (Piccot et al., 1991). Currently, these equations are being used in conjunction with Project LINK to evaluate the effects of a carbon tax on economic activity and the emission of CO_2 (Kaufmann et al. 1991). Ultimately, we hope to estimate equations for seventy-eight nations. When complete, TGAS will be able to forecast global emission of CO_2 from a consistent set of macroeconomic drivers and deliver information regarding the source and cost of abatement for emissions by nation, sector, and fuel.

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