STRUCTURAL CHANGE IN THE CHICAGO REGION AND THE IMPACT ON EMISSION INVENTORIES IN A CONTINUOUS TIME MODELING APPROACH

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REAL 11-T-08 August, 2011

1. Introduction

Since at least the time of the industrial revolution, it has been observed that changes in economic activity can induce changes in the natural environment. Conversely, environmental changes can—and increasingly do—have economic consequences. For example, increased levels of by-production or trade will generally lead to increases in pollution and high regional pollution levels will affect households' location choices. As the interactions between economic and environmental systems are becoming stronger and more apparent, anticipating and understanding environmental changes induced by economic activity is becoming increasingly challenging for both environmental scientists and economists and for policy makers who must ultimately choose strategies to balance risks and costs. Therefore, many researchers have turned to what are termed 'integrated assessment' frameworks, comprising both economic and environmental models, for the purpose of conducting simulations that might inform us about what environmental changes lie ahead if economic activity should follow particular paths. The economic models employed in such frameworks are based on prevailing economic theories and include input-output models, national and regional macroeconomic models, and computable general equilibrium models. But these economic models, which tend to be formulated in discrete time, can present difficulties both in linking with natural science based models formulated in continuous time and in representing the ongoing development of environmental phenomena over time.

While the natural environment—especially the global climate—has been undergoing dramatically noticeable changes, even within the last decade (IPCC, 2007), there have also been important developments in the structure of regional economies. For example, Munroe *et al.* (2007) have found that interstate trade has been increasing but is dominated by intra-industry trade for the Midwest states. And empirical analyses by Hewings *et al.* (1998) have revealed the workings of a "hollowing out" process, which has resulted in a decrease in internal- and an increase in external-dependence in the economy of Chicago. Trade data suggest that the transportation intensity of production is greater than before and that non-polluting industrial sectors are likely to account for a larger share of economic activity than polluting sectors.

Motivated by both the need to model carefully these recent structural economic changes and the need to understand better the nature of environmental-economic interactions, we introduce in this paper a continuous-time Regional Econometric Input-output Model (REIM) for the Chicago economy that can be used to analyze at disaggregated sectoral and temporal levels the economic and environmental implications of changes exogenous to the economy. The model's solution yields estimates of emission inventories, which may be used to analyze environmental implications of various economic changes and policy restrictions. This model is the first integrated economic-environmental model of which we are aware that has been formulated and estimated in continuous time for the regional economy of a metropolitan area.[1] We believe that the model's formulation will enable it to enjoy greater compatibility with natural science-based models, which share such a formulation, and flexibility in projecting future emissions corresponding to alternative future economic scenarios and in evaluating emissions policies relevant to such scenarios.

In the next section, we discuss theoretical and empirical developments in integrated environmental-economic models and, in section 3, summarize the structure of the Chicago Regional Econometric Input-Output Model (CREIM), which has provided the basis for our model, and the methodologies used to reformulate it in continuous time. Section 4 is composed of two parts: a presentation of the integrated econometric-emission modeling system with two types of emission intensity (EMI) and a presentation of their simulation results to 2050. Changes in simulated emission inventories presented in section 4 are decomposed into two components, those due to technological changes and those due to the growth of production. This decomposition is performed in order to obtain an indication of which effect is likely to contribute more to future emission inventories. The implications of this decomposition are presented in section 5. The paper concludes with a summary of the simulation results and suggestions for further research.

2. Literature Review

Spatially referenced integrated environmental-economic models have shared some common frameworks. The economic component in integrated models usually consists of a regional or multiregional input-output model, a national or regional macroeconomic model, or a general equilibrium model describing the relationships among the economic sectors of the region(s);

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[1] Tao *et al.* (2010) employ such a model to examine effects of structural change on emissions over the entire Midwest United States at a higher level of sectoral aggregation.

whereas, the environmental component usually consists of models describing the generation and transport of pollutants and their subsequent interactions with the ecosystem of the region(s). In earlier studies attempting to assess quantitatively environmental impacts, two distinct models (Leontief, 1970, 1972; Isard, 1972) combined both the economic and environmental variables and their interactions in one operational form. Leontief (1970, 1972) enlarged the traditional input-output model to account for the generation of pollutants by the economic system and the operation of antipollution activities. Isard (1972) suggested a synthesis of the economic with the ecologic system using an input-output format. His model described the interactions within each system separately and then between the economic and the ecologic systems. In the 1980s, input-output models were widely used as an economic component to link an environmental model (Forsund, 1985; James, 1985; Ketkar, 1984, Lesuis *et al*., 1980; Pedersen, 1996; Rhee *et al*., 1984).

Since various input-output approaches such as a decomposition of the Leontief inverse matrix have been developed (Round, 1985; Oosterhaven et al., 1997; Sonis and Hewings, 1992, 1996), more recent studies have used structural analyses in an input-output model in order to examine the relationship between economic patterns and the development of emissions (Munksgaard *et al*., 2000; Fritz *et al*., 2002, Lenzen *et al*., 2004). The role of private consumption affecting CO_2 emissions in Denmark over 1966 to 1992 was analyzed by Munksgaard *et al.* (2005). Distinguishing between direct and indirect as well as domestic and imported CO_2 emissions, Munksgaard et al found that indirect emissions accounted for a major part of growth in total emissions from household consumption, although CO_2 emissions from direct consumption still exceeded the emissions from indirect consumption.

Fritz *et al*. (2002) adopted the field of influence approach of Sonis and Hewings (1992) to identify the changes in the direct coefficients table of an input-output model that created the largest impact on sectoral pollution multipliers. They pointed out that the service industries and some manufacturing sectors (for example, rubber and plastic) in the Chicago economy were increasing their output and employment and this growth is one of the *indirect* sources of air pollution by the non-polluting industries through their demands for inputs from polluting sectors. Hence, it is important to consider structural changes in formulating environmental regulations. In similar fashion, Lenzen *et al*. (2004) included a feedback-loop analysis with a detailed multi-regional input-output model to calculate CO_2 multipliers for trade between Denmark, Germany, Norway, Sweden and the rest of the world. They constructed an 1199 by 1199 matrix containing total, region-specific multipliers of intermediate demand, trade, energy consumption and CO_2 emissions and then captured direct, indirect and induced effects of trade.

In addition to those studies using input-output models to integrate the relationship between economic and environmental sectors, many simulation models for environmental impact analyses have also integrated environmental components. Some earlier studies, such as Hazilla and Kopp (1990), Jorgenson and Wilcoxon (1990a, b), and Conrad and Schroder (1993), used CGE models to estimate the costs of environmental regulations. Especially, after the Kyoto Protocol, which emerged from the United Nations Framework Convention on Climate Change (UNFCCC), called for a reduction in the emissions of carbon dioxide and five other greenhouse gases (GHG), a number of approaches based on general equilibrium modeling (CGE) have been used to quantify the greenhouse emission as a result of economic activity (Babiker *et al.*, 2001; Hertel and McDougall, 2003; Springer, 2002).

The MIT Emissions Prediction and Policy Analysis (EPPA) model has been used to analyze the processes that produce greenhouse-relevant emissions, and to assess the consequences of policy proposals intended to control these emissions with a CGE model of the world economy over a 100-year horizon (Babiker *et al.*, 2001). Their emission scenarios are used as inputs into an atmospheric chemistry-climate model along with scenarios of natural emissions of greenhouse gases (GHGs) from a Natural Emissions Model. Babiker *et al.* found that the inventory of climatically important substances highlighted the role of non-energy sources (e.g. agriculture, biomass burning) and developing countries as important current sources of many of these emissions.

Hertel and McDougall (2003) have developed a Global Trade Analysis Project (GTAP) model that is a static multi-region, multi-sector applied general equilibrium model. They have developed a land-use and greenhouse gas emission database to link model components together and assessed the costs of climate policies and their spillover effects via international trade and sectoral interaction. Springer (2002) has also assessed the allocational and distributional impacts of international climate policies, such as the Kyoto Protocol, on different regions of the world with the focus on the interaction of international trade in goods and international capital mobility. Springer's analysis used a dynamic, multiregional, multisectoral computable general equilibrium model. The empirical simulation analysis revealed that economic integration, as well as policies aimed at improving the diversification of the export structure of economics, may help to reduce the negative consequences connected with greenhouse gas abatement.

Specifications of the CGE models used in these studies are based on neoclassical theory with the central assumption being that all agents are acting with full information in perfectly competitive markets, so that all decisions are the result of optimization based on some assumption about the technology or the aggregate welfare function of the economy. There are other simulation models that follow macroeconomic theory and are based on assumptions that agents decide under conditions of bounded rationality in imperfect markets. The difference between these alternative models—e.g., COMPASS (COmprehensive Model of Policy ASSessment) (Uno, 2002) and GINFORS (Global INterindustry FORecasting System) (Meyer *et al.*, 2004)—and CGE models is that the former are macro-econometric input-output models. The core of both models is a multisector bilateral trade model and both systems characerize the interdependencies of economic and environmental development with respect to energy consumption. COMPASS and GINFORS are sectorally disaggregated and their behavioral parameters are estimated from time-series data by econometric methods. The estimated models are tested and equations are adapted until the models are able to reproduce history for a longer period. The models are then employed in simulations and forecasts of economic developments and their effects on markets and employment as well as global energy, resource and land consumption.

3. Continuous Time Modeling of CREIM (Chicago Regional Econometric Input-Output Model)

3.1 Chicago Regional Econometric Input-Output Model (CREIM) [2]

The Regional Economics Applications Laboratory (REAL) has constructed or overseen the construction of a number of impact and forecasting models for the Chicago metropolitan area, which encompasses Cook, Dupage, Kane, Lake, McHenry, and Will counties. One such model, the Chicago Regional Econometric Input-output Model (CREIM), is based on an initial formulation of Conway (1990, 1991), which was developed further by Israilevich *et al.* (1997). CREIM integrates econometric and input-output components, enabling impact analysis to be

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[2] This section is derived from Israilevich *et al.* (1996, 1997) and Israilevich (1998).

conducted as well as annual forecasts made for a 30-year horizon for up to 45 different NAICS-based industrial sectors (production, employment and income) and several major economic aggregates (such as gross regional product, wage rates, unemployment). CREIM is a computable regional general equilibrium model based on Marshallian equilibrium of outputs. The model combines traditional input/output analysis with time-series analysis. The input/output component in this model enables a detailed analysis of purchases and sales between industries, while the time-series component allows for the analysis of intertemporal change in the transaction flows of goods and services. Together, these two components yield a detailed analysis of structural change over time at the sectoral level. By taking into account transaction flows between industries, CREIM is able to yield estimates of the spillover or indirect effects within the economy that direct analysis cannot capture because it examines each sector irrespective of its effect on other sectors.

CREIM uses the input-output component as a deterministic linear predictor of output:

$$z_i^t = \sum_j a_{ij} x_j^t + \sum f_{ij} y_j^t + e_i n_i^t \qquad \forall_i = 1, \ldots, n \tag{1.1}$$

where f_{ij} is a normalized regional purchase coefficient in the final demand matrix,

$Y = \lfloor y_j \rfloor$ is the final demand vector consisting of personal consumption, investment, government expenditure, and net exports

$N = [n_i]$ is a vector of exogenous variables in regional economy such as GNP, national industrial production indices and other national data

$E = [e_i]$ is a vector of normalized regional gross export coefficients

$Z = [z_i]$ is the predicted output (x_i are observed output values)

t indicates the year at which output is predicted.

The difference between a traditional input-output approach and equation (1.1) is the weight assigned by (1.1) to each of the input coefficients. The weights are observed outputs, X, for each time period. In order to formalize the difference between the traditional input-output approach and equation (1.1), equation (1.1) can be rewritten in matrix form:

$$Z_{REIM} = AX + Y \tag{1.2}$$

where A is the input-output matrix and Y is a vector of aggregated final demand; the time index is omitted to simplify and all variables change in time. Denote the difference between the observed and estimated output as $\Delta = Z_{REIM} - X$.

Then equation (1.2) can be expressed as:

$$Z_{REIM} = \Delta + X = AX + Y \tag{1.3}$$

$$Z_{IM} = (I - A)^{-1} Y \tag{1.4}$$

$$\Delta + X - AX = \Delta + (I - A)X = Y \tag{1.5}$$

Equation (1.4) then can be rewritten with equation (1.5) as:

$$Z_{IM} = (I - A)^{-1} Y = (I - A)^{-1} \Delta + X \tag{1.6}$$

We can determine the difference between the input-output (IO) and REIM estimation of outputs as:

$$Z_{IM} - Z_{REIM} = \left[(I - A)^{-1} \Delta + X\right] - (\Delta + X) = \left[(I - A)^{-1} - I\right]\Delta \tag{1.7}$$

By using the power series decomposition of the Leontief inverse, we have:

$$Z_{IM} - Z_{REIM} = \left(A + A^2 + A^3 + \cdots + A^{\infty}\right)\Delta \tag{1.8}$$

It is clear that the difference between the traditional input-output estimates and those generated by equation (1.1) from CREIM will be amplified by the structure of the *A* matrix. Therefore, the differences between two estimates are related to the nature of the linkages between industries and can be measured by the indirect multiplier effects.

The dynamic equations of CREIM, in which adjustments in output, employment, and income are made, are specified as autoregressive schemes to turn this model into an econometric forecasting model as following equations.

$$\log\left(\frac{x_{it}}{z_{it}}\right) = \alpha_0 + \alpha_z \left(\frac{z_{i,t-1}}{x_{i,t-1}}\right) + \alpha_g g_{it} + \varepsilon_{it} \qquad \forall_i = 1, \ldots, N; \ \forall_t = 1, \ldots, T \tag{1.9}$$

Where $z_{i,t-1}$ is a lagged input-output-generated predicted output and g_{it} is the set of exogenous variables selected to explain the output variables.

Like equation (1.9) for output variables, the employment equation explains the relationship between an industry's total shipments and total employment. The equation is estimated with a dependent variable for the log of productivity. The equation is then normalized to isolate employment on the left-hand-side.

$$\log\left(\frac{n_{it}}{x_{it}}\right) = \alpha_0 + \alpha_z \left(\frac{x_{i,t-1}}{n_{i,t-1}}\right) + \alpha_g g_{it} + \varepsilon_{it} \qquad \forall_i = 1, \ldots, N; \ \forall_t = 1, \ldots, T \tag{1.10}$$

where n_{it} is employment of sector *i* at time *t*, x_{it} is output of sector *i* at time *t* and g_{it} is the set of exogenous variables selected to explain the employment variables.

The final equation in the industry block is the wage equation, also called the income equation. This equation describes the relationship between industrial employment and income. Again, the relationship is estimated with a dependent variable of the log of the ratio of income to employment which is equivalent to earnings per worker.

$$\log\left(\frac{y_{it}}{n_{it}}\right) = \alpha_0 + \alpha_z\left(\frac{n_{i,t-1}}{y_{i,t-1}}\right) + \alpha_g g_{it} + \varepsilon_{it} \qquad \forall_i = 1,\ldots,N;\ \forall_t = 1,\ldots,T \qquad (1.11)$$

where y_{it} is income of sector i at time t, n_{it} is employment of sector i at time t, and g_{it} is the set of exogenous variables selected to explain the income variables.

Each industry grouping has a variable lag structure shown in equations (1.9), (1.10) and (1.11), and when mixed with the econometric specifications of the final demand and demographic variables, the complete system of equations is then solved simultaneously and recursively (usually by a Gauss-Siedel method) to determine the forecasted values of the endogenous variable.

3.2 Continuous-time modeling[3]

The use of REIMs, such as CREIM, to study the impacts of structural changes in a regional economy and their impacts on emissions inventories is a reasonable choice, since interindustry impacts need to be traced and the temporal staging of effects needs to be broken out. Most REIMs employed in applied research to date have been specified in discrete–time for annually based time series. The dynamic equations of the models, in which adjustments in output, employment and income are made, tend to be specified as autoregressive schemes (see, for example, equation (11) above). For a judicious selection of regressors, whether endogenously or exogenously determined, much of the systematic variation in the difference between predicted and observed sectoral output can be accounted for, as can the variation in sectoral employment and income. Such models can be, and have been, used to convey a sense of what impacts are likely to have accumulated one year out, two years out, etc.

Where such models come up short is in indicating what the transition paths of sectoral adjustments would be at points in between the yearly intervals and, as noted above, what the

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[3] The first part of this section closely follows Donaghy *et al.* (2007).

short-term impacts of sub-interval events would be.[4] Of course, one can interpolate between solution points, but difference equations, by their nature, characterize what transpires at the *end* of one period and the *beginning* of the next, not what happens at points *in between*. So there is nothing in the specification of the model to suggest what shape an adjustment lag may assume. REIMs may also mislead us about the effects of unexpected events. Because the dynamic equations of REIMs are essentially autoregressive data-mining constructs, they may not represent causal relations. Hence some simulations can produce counterintuitive results, where feedback relationships or constraints dictated by theory are not present. As discussed above, these properties leave one ill-equipped to link a REIM with other models, which depict the continuous unfolding of events over periods of time that are shorter than the observation or solution interval of the REIM.

One response to this situation is to respecify the model in continuous time. Theoretical developments and software availability have permitted approximate and exact econometric estimation of linear continuous-time models (of both the structural-equation and frequency-domain varieties) from discrete-time observations since the early 1970s (Wymer, 1972; Bergstrom, 1976; Harvey, 1989), whereas approximate estimation of nonlinear differential equation systems has been possible since the mid 1970s and exact estimation since the early 1990s (Wymer, 1993, 1997). Recently continuous-time models have been extended to economic growth and convergence studies (Arbia and Paelinck, 2003) and various fields of spatial dynamic modeling (Donaghy, 2001; Donaghy and Plotnikova, 2004, Oud and Folmer, 2008).

The continuous-time approach to specification, estimation, and analysis has several features to recommend it for modeling structural changes in regional economies and their relationship with environmental systems. Continuous-time models provide a better characterization of ongoing aggregate economic activity than discrete-time models, and permit better handling of mixed samples (i.e. samples including data on stocks, flows, derivatives, point observations, and period averages). The estimates of continuous-time system parameters tend to be more efficient than

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[4] A good example of this problem is the modeling of the impact of floods; work by Mahidhara and Hewings (1996) revealed that over the course of a year, the negative impacts of the flood were often more than compensated by the growth impacts generated by federal and state disaster assistance programs. In this case, having a model that could chart the process on a weekly or monthly basis would have been incredibly valuable. In the case of the Katrina impact on New Orleans, the need for continuous time modeling in the recovery process was even more compelling, especially given the out-migration of one-third of the region's population and the significant loss of capital stock. Donaghy *et al.* (2007) for a demonstration of how a continuous-time REIM can be used to model the occurance and recovery from extreme events.

their discrete-time system counterparts (Phillips, 1991), and estimates of adjustment parameters, hence adjustment lags, are independent of the observation interval. Perhaps most importantly, once the parameters of a continuous-time system have been estimated, the model can (in theory) be solved for any time interval. On all these well-established points, see Gandolfo (1981). There are at least two other potential advantages to putting REIMs in continuous-time formulation: (1) it provides an opportunity to introduce explicitly functional forms suggested by theoretical explanations of events, or adjustment patterns, and to test explanations (i.e. to eliminate some of the 'black box' character of REIMs), and (2) it becomes possible to obtain point estimates of what interindustry sales coefficients are at a particular juncture, even between empirical observations.[5] There are some trade-offs in moving from a discrete-time to a continuous-time specification. One is that we forego some flexibility in capturing unsynchronized lags and leads for the effects of different regressors. Since Allen (1965), however, it has been well appreciated that continuous-time models with second-order (and higher-order) exponential lags can capture the shape of a broad spectrum of lag structures likely to be encountered among macroeconomic phenomena and, further, these lags can be implemented straightforwardly. For example, assume that at a given point in time, *t*, the underlying theoretical relationship between some endogenous variable, *Y*(*t*), and several predetermined variables, $X_1(t), X_2(t)$, and $X_3(t)$ is:

$$Y(t) = \alpha X_1(t) X_2(t) X_3(t)\,, \tag{12}$$

in which all variables are in levels and a possible additive stochastic error term is ignored for the sake of exposition. A first-order exponential lag relationship can be written as:

$$D \log Y(t) = \gamma \log(\alpha X_1(t)^{\beta_1} X_2(t)^{\beta_2} X_3(t)^{\beta_3} / Y(t)) \tag{13}$$

in which $1/\gamma$is the mean adjustment lag and $D = d/dt$ is the time differential operator. A second order lag can be written as:

$$Dy(t) = \gamma' \gamma \log(\alpha X_1(t)^{\beta_1} X_2(t)^{\beta_2} X_3(t)^{\beta_3} / Y(t)) - \gamma' y(t) \tag{14}$$

in which $y(t) = D \log Y(t)$. This equation can be used as a prototype for dynamic adjustment equations in a continuous-time specification of CREIM.

Information on the structure of the discrete-time CREIM was used to respecify the model in continuous time (i.e., in terms of differential equations). In the interest of developing a model

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[5] See Appendix B of Donaghy et al. (2005) for the derivation of formulas for updating estimates of interregional interindustry sales coefficients in a REIM at a given data point.

with a stable solution in simulations extending well beyond the sample period, we imposed a negative feedback disequilibrium adjustment relationship in each of the differential equations determining the value of an endogenous variable that was not an accounting identity. The continuous-time model was estimated with annual data for the period from 1969 to 2000. Because of the size of the overall model and the paucity of time-series observations, the model was estimated piecemeal by blocks of equations corresponding to actual output, employment, income, population and final demand using a nonlinear quasi-full-information maximum-likelihood (FIML) estimator in the program ESCONA of Wymer's (2004) WYSEA package. (Please see figure 1. Wymer (1993) and Donaghy *et al.* (2007) provide details of the estimation algorithm.)

<< *insert figure 1 here* >>

Since values of the exogenous variables are needed to conduct simulations beyond the period for which observations are available, a zero-order forcing function of time were also estimated for each of the exogenous variables. Assuming that the values of their coefficients should be determined independently of the model's parameters, the forcing functions to be used in generating future values of exogenous variables were estimated separately from the other equation blocks in the model.

In figures 2 to 4, the in-sample estimated output variables are aggregated by 6 sectors (Resources, Construction, Nondurable Manufacturing, Durable Manufacturing, TCU, Trade, FIRE, Services, and Government) and the growth trends of estimation results relative to base year (1970) are illustrated in comparison with the annual observed trend in CREIM. Output levels of all sectors fluctuated strongly in the 1980s and the estimated model captures these dynamics very well.

In figure 2, one can see that the aggregate output of the resource sectors increased by 8% from 1969 until the early 1980s, after which it decreased steadily until, in 2000, it was 5% lower than in the base year. The trend of construction and trade output was upwards except for a drop in the early 1980s. Estimated and observed output levels of durable and nondurable manufacturing and TCU are portrayed in figure 3. Output of durable manufacturing decreased in 1980s and was less than that of nondurable manufacturing from 1970 to 2000. But, both sectors recovered and by 2000 showed 2%-4% increases relative to the base year. By contrast, the output of TCU increased by 7% as of 1995 but then decreased through the rest of the sample period. Figure 4 indicates that, in comparison to other sectors, the output levels of FIRE, services, and government sectors achieved period increases of 9%, 10% and 12%, respectively.

<<insert figures 2,3 and 4 here>>

Figures 2 through 4 confirm that the estimated continuous-time CREIM fits the historical database well. Table 1 presents the means and standard deviations of the output variables and the normalized root-mean-square-errors (RMSE divided by the mean) of the in-sample dynamic forecasts for estimated output produced by the model. The imposition of the feedback structure (discussed above) may have resulted in RMSEs that were in some cases higher than could have been obtained with more widely used VAR specifications. But, table 1 and the figures 2 through 4, suggest the model solution with negative feedback adjustments imposed is consistent with the historical data that has been used to estimate REIMs for Chicago. To complete a qualitative analysis of the estimated model, formal analyses of local and global stability properties and sensitivity analyses would need to be conducted.

<<insert table 1 here>>

To examine the model's suitability for use in dynamic simulations out of sample we solved it forward for 50 years without any policy intervention. (While the model can be solved for any frequency desired, we highlight the solution at annual intervals.) The results of this out-of sample simulation suggests that the model, when linked with an appropriate emissions inventorying component, will support investigations of the relationships between structural changes in a regional economy and changes in emissions inventories.

<<insert fig5 here>>

The solution obtained for this baseline simulation, and portrayed in figure 6, suggests that, with the exception of durable manufacturing and TCU, output levels of the aggregated industrial sectors of the Chicago regional economy will increase steadily. The output of the resource sector is predicted to grow by 1.4% relative to its output level in 2000. The smallest increase, 0.2%, is shown in the construction sector. While in this solution the output of non-durable manufacturing and trade rises 4% and 1.2%, respectively, durable manufacturing and TCU decrease by 1.6% and 2% compared to their base values in 2000. Higher growth changes in FIRE, services, and government sectors are forecasted to increase by 15%, 9.8%, and 7.7% respectively.

In the next section, we discuss the integration of the continuous-time CREIM with a bloc of equations characterizing emissions of air pollutants for Chicago region. The integrated modeling system will then employed to examine potential effects on emissions of structural changes in the economy.

4. The Integrated Econometric-Emission Modeling System[6]

The strategy for predicting future emissions is to develop an integrated modeling system whose solution yields annual emission inventories based on detailed output from a continuous time CREIM (hereafter, CT-CREIM). The detailed output of CT-CREIM, for 45 sectors, makes it possible to construct emission inventories that match the 1999 National Emissions Inventory (NEI99). The basic emission identification of NEI99 is the source characterization code (SCC) in which each source category is divided into industry groups and further classified within the source category. The integrated econometric-emission modeling system uses the output of the CT-CREIM to identify SCCs in NEI99 for the point and area emission sources and calculates the associated emission factors and the activity level. As a first step in this study, we introduce emission intensity coefficients, which are based on historically observed emissions and levels of emission activities. These coefficients will be used to augment the CT-CREIM model to forecast emissions under different scenarios (see figure 5).

<<insert fig.6 here>>

4.1 Emission Intensity (EMI)

The development of the emission intensity coefficients, discussed in this section is derived from Tao *et al*. (2007).[7] In the present study we consider the seven so-called ‘criteria’ pollutants on which the U.S. E.P.A. keeps emissions inventories—carbon monoxide (CO), nitrogen oxide (NO_x), sulfur dioxide (SO_2), particular organic compound (PM10 and PM2.5 with diameter less than 10 and 2.5μm), volatile organic compound (VOC) and ammonia (NH_3). To analyze the production of emissions stocks, we will employ two different types of emission intensity coefficients: those which are assumed to be fixed through time and those which are time-varying. We develop future emission inventories in a manner similar to traditional approaches, in which emissions are a function of emission intensity (EMI) and levels of emission activities:

$$\text{Emission} = \text{EMI} \times \text{activity}, \qquad (16)$$

where EMI is defined by the emissions per unit of activity (ton/million $)

Emission intensities are usually calculated from data given in the 1999 National Emissions

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[6] Further details may be found in Tao *et al*. (2007).

[7] See Tao *et al*. (2007).

Inventory (NEI99). Calculating the coefficients from these data has the two advantages that the emission inventories will be available in a generally accepted format and the growth factors can be compared easily with other work in this area. To calculate the coefficients, the emissions from NEI99 inventories based on Source Classification Codes (SCCs) are first mapped into Standard Industrial Classification (SIC) codes. All point source SCCs and approximately 16% of area source SCCs can be associated with SIC codes. The remaining 80% area SCCs are assigned to a particular SIC following the EGAS mapping (Economic Growth Analysis System)[8] and an inferential analysis of SCC and SIC coding. Note that the remaining 4% of the area sources related to household activities and on-road mobile sources are excluded in this research. The point and area sources covered here are only 48% of total emission pollutants in the Chicago region. The resulting SCC-SIC mapping is then converted to the North American Industrial Classification System (NAICS) on which the economic sectors of the CT-CREIM are based (see table 2). In order to support particular thought experiments, to be discussed below, the fixed emission intensities, as calculated from NEI99, are assumed to remain constant into future. The implication of this assumption is that all emission changes result only from activity changes.

<<insert table 2 here>>

To accommodate changes in EMIs related to shifts of energy usage, technological change, and increasing demand of environmental protection, Tao *et al.* (2007) also developed time-varying sectoral emissions intensity coefficients from 1970 to 2002. Time varying EMIs were calculated using the NEI Air Pollutant Emission Trend data.[9] (http://www.epa.gov/ttn/chief/trends). Subsequently, the average annual percentage change rate (%) in EMI from each activity was calculated using equation (17).

$$EMI_t = EMI_0 \times \left(1 + \frac{rate}{100}\right)^n \qquad (17)$$

Where EMI_t is EMI for some future year t; EMI_0 is base year (1999) EMI; $rate$ is the average annual EMI change (%); and n is the number of years from 1999. This average annual EMI change reflects, collectively, the influence of historical technological, economic, and policy changes. For this study, it is assumed that there was no EMI change in the future—i.e., rate = 0—if the historical average annual EMI change was positive.) The EMI change rates listed in

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[8] http://www.epa.gov/ttn/chief/emch/projection/index.html

[9] http://www.epa.gov/ttn/chief/trends

table 3 were then assigned to each CREIM sector.

<<insert table 3 here>>

4.2 Simulation of the Model out-of Sample

Dynamic simulations of the integrated econometric-emission model were conducted by solving the model forward over the period from 2001 to 2050. Initial values of the endogenous variables were taken from year 2000 data and the time paths of the exogenous variables were extrapolated from the forcing functions of time, whose estimation was discussed above. The dynamic simulations were conducted using the Wymer's program APREDIC in his WYSEA package, which solves the set of nonlinear differential equations the model comprises with a variable-step variable-order Adams method.

To demonstrate the process of emission inventory development, we conducted a baseline simulation in which we projected emissions assuming no technological changes in the future. In this case, the current fixed emissions intensity coefficients based on the NEI99 inventory were used to calibrate a bloc of emissions equations in the econometric model. Since in this simulation any future emission changes are driven solely by future industrial activity levels, it is also necessary to conduct a second simulation in which time-varying EMIs are used to project future emissions that reflect the effect of technological advances in addition to changes in industrial activity levels.

<<insert fig. 7 here>>

In the case of fixed EMI (illustrated in figure 7), emissions of CO, NO_x, PM2.5, SO_2, and VOC increase by 78%, 30%, 1%, 4%, and 40%, respectively, by 2050. Only the emissions of PM10 are reduced by 10%. Compared to projected emissions under the fixed EMI, future EMI changes modeled by equation (17) using the historic change rates of EMI are shown in table 3. Under the time-varying EMI, the relative contribution to emissions from each industry changes at a different pace due to the different technology growth rate. This outcome implies that emissions change as a result of the combined effects of economic structural change as well as changes in technology and environment related-policy represented by time-varying EMI.

Projected emissions under the assumption of time-varying EMIs are significantly reduced, as shown in figure 8. Emissions of CO, NH_3, NO_x, PM10, PM2.5, SO_2 and VOC are reduced by 57%, 92%, 60%, 55%, 47%, 35% and 27%, respectively in comparison with the fixed EMI case in 2050. All pollutants except CO experience a steady decline from 1999 to 2050 under an overall decreasing trend in time-varying EMI. CO emissions are reduced by 74% in 2030 but grow again by 2% in 2050 compared with their 1999 level. This result implies that the future economic structure of Chicago area would contribute to an increase in CO emissions by 2050 in spite of the declining trend of time-varying EMI. These results will be discussed in more detail in the analysis of the sectoral percentage distribution of projected emissions.

<<insert fig. 8 here>>

Figures 9, 10 and 11 present profiles of pollutant emissions for the 9 different industry groups under the two different assumptions about emissions intensity. In 1999, the base year (see figure 9), resources, durable manufacturing and TCU accounted for the largest shares of overall pollution emissions. For example, resources contributed 25% of all CO emissions, 51% of NH_3 (51%), 25% of PM10, while TCU generated 43% of NH_3 (43%), 51% of NO_x , 30 % of PM10 and 21% of PM2.5. Durable manufacturing was a significant contributor to CO (29%), PM2.5 (33%) and VOC (38%) emissions while the service sector accounted for 16% of total CO and 14% of total VOC emissions. Assuming EMIs do not change from their 1999 values, it is projected that CO emissions produced by durable manufacturing and resources will drop significantly while TCU remains the leading producer of NH_3, NO_x, and SO_2 emissions (see figure 10). Note that, in the fixed coefficients scenario, overall emissions from the FIRE and service sectors increase significantly.

<<insert figs 9, 10, 11 here>>

In comparison with the fixed EMI, the relative contribution to emissions from each industry activity changes under the time varying EMI (see figure 11). PM10, PM2.5 and VOC emissions from resources almost double and, on the other hand, durable and nondurable manufacturing experience significant reductions in emissions, thus their contribution to total emissions decreases remarkably. Notwithstanding the EMI improvement under the assumption of time-varying EMI, there are two similar results with the fixed EMI assumption. One is that TCU remains the important source of emissions of NH_3, NO_x, and SO_2. The other finding is that FIRE and services assume a growing portion of CO and VOC emissions.

5 Decomposition of the Emissions Inventory

5.1 Emission technology effect and production effect

The main purpose of the decomposition of emissions inventories is to analyze the relationship between the economic structural changes and emission-technology effect of the projected emission inventory. As expected, the simulations indicate that the Chicago economy as a whole will continue growing but the economic structure will continue to change in this region through 2050. These changes will be apparent in the changing demand for energy; the changes also reflect the different demand and supply relations among the economic sectors over time. On the other hand, technological change in emissions will shift energy usage in industries and consumers. Technological advances will result in a less polluting set of output across industries. At the same time, many policy instruments for environmental protection and regulation will have increased to achieve greater emission reduction since climate change and cleaner air are issues for political moment.

These two economic and environmental features are combined in the simulation results of future emission inventory in the previous section; no attempt was made to differentiate the effects of changes in economic structure and the evolution of emission technology in the Chicago area. To understand which factor plays a more significant role in changing the emission inventory now and in the future, the differences between structural changes in production and changes in emission technology affecting the emission coefficients will be separated. The production effect and emission technological effect are defined by the following relationship:

Production Effect = $PE_{jt} = (Q_{jt}*E_{kj99})-(Q_{j99}*E_{kj99})$ (18)

Technological Effect = $TCE_{jt} = (Q_{jt}*E_{kjt})-(Q_{jt}*E_{kj99})$ (19)

where:

Q_{jt} : Production in sector j in time t; Q_{j99} : Production in sector j in 1999; E_{kjt} : EMI of k pollutant in sector j in time t and E_{kj99} : EMI of k pollutant in sector j in 1999

Then, the total effect (TE) can be derived from the sum of production and technology effect:

(20)

Now it is possible to determine which effect is more influential in contributing to the total emission inventory by using a simple ratio of technology effect and production effect. It should be note that the technology effect does not show a positive value because varying EMI assumes that emission technology will be advanced in the future.

<<insert fig. 12 here>>

Figure 12 depicts the potential relationships. If the ratio of technology and production effect (hereafter called TCE/PE) is less than zero and greater than -1, an increasing trend of production makes the emission inventory grow more even though the developed emission technology affects the emission inventory. In the case where TCE/PE is between zero and 1, both technology and production effects contribute to decrease the emission inventory but the decreasing trend of production is more dominant than the enhanced technology effect. On other hand, if TCE/PE is greater than 1, the decreasing emission inventory is more affected by the technology effect than the falling level of production. In contrast, higher technology causes the emission inventory to decrease even though the level of production is increasing when the ratio of TCE and PE is less than -1.

<<insert table 4 here>>

Table 4 shows the classification of the decomposition effects according to the definition of the ratio between technology (TCE) and production effect (PE). Since all of time-varying EMI are assumed to be zero or negative, the focus will be on the two cases that are shaded in table 4. One is the case where emissions increase because the technology effect cannot prevail over the dominant production effect despite advanced technology (-1<TCE/PE ratio <0). The other one is where emissions decrease since the technology effect dominates the growing production effect (TCE/PE ratio <-1).

5.1 Results

With the detailed sectoral emission decomposition with 2050 projected emission inventory, the comparisons between the dominant production and technology effects are shown in tables 5 and 6. First of all, CX38 (Health care), CX33 (Motion picture and sound recording industries), CX46 (Federal government enterprise), CX40 (Art, entertainment and recreation), CX37 (Educational services), CX43 (Repair and maintenance), CX42 (Food services), CX41 (Accommodation Services), CX44 (Personal and Laundry services), CX26 (Air transportation), and CX34 (Finance and insurance) are categorized as the sectors that affect the increased CO emissions through dominant production effects. Some manufacturing sectors, for example, CX09 (Leather and leather products), CX10 (Lumber and wood products), and CX11 (Paper and allied products) play a significant role in increasing NO_x emissions. There is no sector in which the dominant production effect influences the NH_3 emission's increase in 2050. In general, the result with a dominant production effect could be interpreted as implying that growing production from some services and FIRE industries are responsible for increased future emissions regardless of their advanced technology effect.

<<insert tables 5 and 6 here>>

Meanwhile, with advanced technology, a lowered EMI yields decreased CO emissions in CX04 (utilities), CX35 (Real estate), CX08 (Apparel and textile products), CX09 (Leather and leather products), CX10 (Lumber and wood products), CX11 (Paper and allied products), CX15 (Rubber and miscellaneous plastic products), CX18 (fabricated metal products), CX24 (Wholesale trade), CX25 (Retail trade), CX32 (information), CX39 (social services), CX45 (membership organization), and CX47 (State and local government enterprise) although the production activity of those sectors will have increased by 2050 (first column in table 6).

For the case of all 7 pollutant emissions, CX08 (apparel and textile), CX15 (rubber and misc. plastic products), CX18 (fabricated metal products), CX25 (retail trade), CX35 (real estate), CX39 (social services), and CX45 (membership organization) are common sectors that demonstrate higher technology effects to reduce these emissions even though there will be increased production effects. Note that for CX04 (utilities) there is a significant technology effect on the decreased emission inventory of CO, SO_2, and VOC. Also CX35 (real estate) shows the highest technology effect on NO_x, NH_3, and PM 2.5, emissions than any other sector.

Even if the emissions' technology could be advanced through new technological progress and policy regulations that mandate lower levels of pollution, it is obvious that services and FIRE sectors produce more pollution indirectly because of their increasingly dominant role in the volume of production in the future Chicago economy according to the result of this decomposition analysis. Hence, it is important to highlight which economic activity is more responsive to decreases in the emission inventory associated with their emission technology progress. In particular, table 6 reveals that CX04 (utilities), CX05 (constructions), CX08 (apparel and textile), CX15 (rubber and misc. plastic products), and CX18 (fabricated metal products) will generate a large technology effect overall on the seven emission pollutants; these findings suggest that more direct approaches in technology development or policy instruments focused on these sectors would contribute most to the reduction of future emission pollutants in Chicago.

6 Conclusions

In order to analyze the issues of environmental impacts and economic structural change, an integrated econometric-emission model in continuous time has been developed to project future emissions to reflect Chicago regional changes in both emission generation and the structure of the economy. The Chicago Regional Econometric Input-Output Model (CREIM) was re-specified and re-estimated as a continuous-time model. Using this system, an economic-environment interface was created with two types of emission intensity (EMI), 1999 fixed EMI based on the 1999 National Emission Inventory (NEI) and a time-varying EMI, a measure that takes into account changes in environmental technology and policy. Although on-road mobile sources are a major contributor to total emissions, they were excluded in the estimated emission intensities in order to focus on the interaction between technological change and structural change in the Chicago economy. The CT-CREIM integrated econometric-environmental model provides the links to develop and interpret the complex demand-supply relationships with pollutant emissions.

By establishing the relationships between emissions and economic activity for each sector in this integrated model, the results indicate that resource, durable manufacturing and TCU sectors played dominant roles in overall pollution emissions in 1999. According to the forecasted emission under 1999 fixed EMIs, CO emissions produced from durable manufacturing and resources experience a considerable decrease while TCU remains the important contributor to emissions of NH_3, NO_x, and SO_2. Compared with the fixed EMI scenario, forecasted emissions under the assumption of time-varying EMIs show the trend that increased PM10, PM2.5 and VOC emissions are generated by resources but durable and non-durable manufacturing undergo a dramatic reduction in overall emissions. Based on these detailed sectoral emission projections, TCU dominates the production of NH_3, NO_x, and SO_2 emissions and FIRE and services should be considered as the indirect generation of CO and VOC emissions in the future. This finding only indicates that some polluting industry sectors reduce their direct emission and other non-polluting sectors such as FIRE and services increases their share of total emissions. Therefore, further attempts should be made to disaggregate their effects into direct and indirect effects on pollution generation in order to understand how the process of structural changes plays in transforming emission sources in the Chicago region.

One highlight of this analysis is the decomposition of the technology and production effects on future emission inventories. By differentiating structural changes in production from changes in emission technology affecting the emission coefficients, this analysis found that fast-growing production from services and FIRE industries account for a large share of the increased future emissions regardless of technological advances in pollution reduction. This finding suggests that services and FIRE industries are important indirect sources of emission pollution. In contrast, higher technology effects to reduce the emissions are found in CX04 (utilities), CX08 (apparel and textile), CX15 (rubber and misc. plastic products), CX18 (fabricated metal products), and CX35(real estate) even if their production effects increase.

The most important contribution of this study is the development of an integrated system that characterizes both the changing the structure of the economy and changes in emission intensity. However, the ability the model to support long-range emissions forecasting depends heavily on the stability of the estimated model and assumptions about the evolution of EMIs. This being so, future research should investigate the sensitivity of the model's stability to changes in specification or parameterization and alternative ways to represent emissions generation in the model.

References

Allen, R.G.D. (1965) *Mathematical Economics, 2nd Edition*, London, Macmillain & Company.

Arbia, G. and J.H. Paelinck (2003) "Spatial Econometric Modeling of Regional Convergence in Continuous Time," *International Regional Science Review*, 26: 342-362.

Babiker M.H., J.M. Reilly, M. Mayer, R.S. Eckasus, L.S. Wing and R.C. Hyman (2001) "The MIT Emissions Prediction and Policy Analysis (EPPA) Model: Revisions, Sensitivities, and Comparisons of Results," MIT Joint Program Report 71.

Bergstrom, A.R. (eds.) (1976) *Statistical Inference in Continuous Economic Models,* Amsterdam, North-Holland Publishing Company.

Briassoulis, H. (1986) "Integrated Economic-Environmental-Policy Modeling at the Regional and Multiregional Level: Methodological Characteristics and Issues," *Growth and Change*, 22-34

Conrad, K. and M. Schroder (1993) "Choosing environmental policy instruments using general equilibrium models," *Journal of Policy Modeling*, 15: 521-543

Conway, R.S. (1990) "The Washington Projection and Simulation Model: A regional interindustry econometric model," *International Regional Science Review*, 13, 141-156

Conway, R.S. (1991) "An empirical comparison of regional Multipliers,' in J.L. Dewhurst, G.J.D. Hewings and R.C. Jensen (eds.) *Regional Input-Output Modeling: New Developments and Interpretations*, Aldershot, Avebury, 178-195.

Donaghy, K.P. (2001) "Solution and econometric estimation of spatial dynamic models in continuous space and continuous time," *Journal of Geographical Systems*, **3**: 257-270.

Donaghy, K.P., N. Balta-Ozkan, and G.J.D. Hewings (2007) “Temporal disaggregation in a regional econometric input-output model,” *Economic Systems Research*, **19**:125-145.

Donaghy, K.P., and M. Plotnikova (2004) “Econometric estimation of a spatial dynamic model in continuous space and continuous time: an empirical demonstration,” in A. Getis, J. Mur, and H.G. Zoller (eds.), *Spatial Econometrics and Spatial Statistics,* New York, Palgrave, 104-131.

Feldman, S. J., D.McClain, and K.Palmer (1987) “Sources of structural change in the United States, 1963-1978: an input-output perspective,” *Review of Economics and Statistics*, 69: 503-510.

Forsund, F.R. (1985) “Input-output models. National economic models and the environment,” in A.V. Kneese and J.L. Sweeney (eds.), *Handbook of Natural Resource and Energy Economics*, vol 1, North Holland, Amsterdam.

Fritz, O., M. Sonis and G.J.D. Hewings (2002) “Direct and indirect industrial pollution generation: a field of influence approach,” in G.J.D. Hewings, M. Sonis and D. Boyce (eds.), *Trade, Networks and Hierarchies*, Heidelberg, Springer-Verlag.

Gandolfo, G. (1981) *Qualitative Analysis and Econometric Estimation of Continuous Time Dynamic Models*, Amsterdam, North-Holland Publishing Company.

Harvey, A.C. (1989) *Forecasting Structural Time Series Models and the Kalman Filter,* Cambridge, Cambridge University Press.

Hazilla, M. and R.J. Kopp (1990) “Social cost of environmental quality: a general equilibrium analysis,” *Journal of Political Economy*, 98(4): 853-873.

Hertel, T.W. and R. McDougall (2003) *GTAP Model Version 6.2*, Center for Global Trade Analysis, Purdue University

Hewings G.J.D. and R. Mahidhara (1996) “Economic impacts: lost income, ripple effects and recovery,” in S. Changnon (ed.) *The Great Flood of 1993*, Boulder, CO., Westview Press.

Hewings, G.J.D., M. Sonis, J. Guo, P.R. Israilevich, and G.R. Schindler (1998) “The hollowing-out process in the Chicago economy, 1975-2015,” *Geographical Analysis*, 30:217-233.

IPCC (intergovernmental panel on climate change) (2007) *Climate Change 2007: Climate Change Impacts, Adaptation and Vulnerability—Summary for Policy Makers, the Contribution of Working GroupII to the Fourth Assessment of the Intergovernmental Panel on Climate Change*, http://www.ipcc.ch/SPMavr07.pdf

Isard, W. (1972) *Ecologic-Economic Analysis for Regional Development*, Baltimore, Md., Johns Hopkins Press.

Israilevich, P.R. (2002) “Frame-Shifting in Regional General Equilibrium Models” In G.J.D. Hewings, M. Sonis and D. Boyce (eds.), *Trade, Networks and Hierarchies : Modelling Regional and Interregional Economies*, Heidelberg, Springer Verlag.

Israilevich, P.R., G.J.D. Hewings, G.R. Schindler and R. Mahidharha (1996), “The choice of input-output table embedded in regional econometric input-output models”, *Papers in Regional Science*, 75: 103-119.

Israilevich, P.R., G.J.D. Hewings, M. Sonis, and G.R. Schindler (1997), “Forecasting Structural Change with a Regional Econometric Input-Output Model,” *Journal of Regional Science*, 37: 565-590.

James, D.E. (1985), “Environmental economics, industrial processes and regional residuals models” In A.V. Kneese and J.L. Sweeney (eds.), *Handbook of Natural Resource and Energy Economics*, vol 1, NorthHolland, Amsterdam.

Jorgenson, D.W. and P.J. Wilcoxon (1990a) “Environmental regulation and US economic growth,” *Journal of Economics*, 21(2): 314–340.

Jorgenson, D.W. and P.J. Wilcoxon (1990b) “Intertemporal general equilibrium modelling of US environmental regulation,” *Journal of Policy Modelling*, 12(4): 714–744.

Ketkar, K.W. (1984) “Environmental protection policies and the structure of the US economy,” *Applied Economics*, 16: 237-256.

Lenzen, M, L. Pade and J. Munksgaard (2004) “CO_2 multipliers in multi-region input-output models,” *Economic System Research*, 16: 391-412.

Leontief, W.W. (1970), “Environmental repercussions and the economic structure,” *Review of Economics* *and Statistics*, 52: 262-271.

Leontief, W.W. and D. Ford (1972) "Air pollution and the economic structure : Empirical results of input-output computations," in A.Brody and A.P. Carter (eds.) *Input-output technique*, Amsterdam, North Holland.

Lesuis, P., F. Muller, and P. Nijkamp (1980) "An interregional policy model for energy-economic-environmental interactions," *Regional Science and Urban Economics*, 10(3): 343-370.

Meyer, B., C. Lutz, and I. Wolter (2004) "Economic Growth of the EU and Asia: A first forecast with the Global Econometric Model GINFORS," *Policy and Governance Paper Series*, No. 26, Tokyo, Keio University.

Munksgaard, J., K.A. Pedersen, and M.Wier (2000) "Impact of household consumption on CO_2 emissions," *Energy Economics*, 22: 423-440.

Munroe, D.K. G.J.D. Hewings and D. Guo (2007) "The role of intraindustry trade in interregional trade in the midwest of the US" In R.J. Cooper, K.P. Donaghy and G.J.D. Hewings (eds.), *Globalization and Regional Economic Modeling*, Heidelberg, Springer-Verlag.

NEI99 (http://www.epa.gov/ttn/chief/net/1999inventory.html).

Oosterhaven, J. and J.A. van der Linden (1997), "European technology, trade and income changes for 1975–85: an intercountry input–output decomposition," *Economic Systems Research*, 9: 393–411.

Oud J.H.L. and H. Folmer (2008) "A structural equation approach to models with spatial dependence," *Geographical Analysis* 40 (2), 152-66.

Pedersen, O.G. (1996), "Input-output analysis and emissions of CO_2, SO_2 and NO_X-linking physical and monetary data" In B. Madsen, C. Jensen-Butler, J.B. Mortensen, and A.M.B. Christensen (eds.), *Modelling the economy and the environment*, Berlin, Springer-Berlag.

Phillips, P.C.B. (1991), "Error correction and long-run equilibrium in continuous time," *Econometrica*, 59: 967-980.

Rhee, J.J. and J.A. Miranowski (1984) "Determination of income, production, and employment under pollution control: An input-output approach," *The Review of Economics and Statistics*, 57: 146-150.

Round, J. I. (1985) "Decomposing multipliers for economic systems involving regional and world trade," *Economic Journal*, 95: 383-399.

Sonis, M. and G.J.D.Hewings (1992) "Coefficient change in input-output models: Theory and applications," *Economic Systems Research*, 4: 143-157.

Sonis, M. and G.J.D.Hewings (1996) "Sources of structural change in input-output systems: A field of influence approach," *Economic Systems Research*, 8(1): 15-32.

Springer, K. (2002), *Climate Policy in a Globalizing World: A CGE Model with Capital Mobility and Trade*, Berlin, Springer-Verlag

Takayama, A. (1985) *Mathematical Economics*, Cambridge University Press.

Tao, Z., G.J.D. Hewings, and K.P. Donaghy (2010) "An Economic Analysis of Trends of Mid-Western US Pollutant Emissions from 1970 to 2000," *Ecological Economics*, 69: 1666-1674.

Tao, Z., A. Williams, K. Donaghy and G.J.D. Hewings (2007) "A socio-economic method for estimating future air pollutant emissions—Chicago case study," *Atmospheric Environment*, 41: 5398-5409.

Uno, K. (2002) "Energy projections: comparison of methodologies," in Uno, K. (eds.), *Economy-Energy-Environment Simulation: Beyond the Kyoto Protocol*, Berlin, Springer.

Wymer, C.R. (1972), "Econometric Estimation of Stochastic Differential Equation Systems", *Econometrica*, 40: 565-577

Wymer, C.R. (1993), "Estimation of Nonlinear Continuous-Time Models from Discrete Data" In P. Phillips and V. Hall. (eds.), *Models, Methods, and Application of Econometrics,* Oxford, Basil Blackwell

Wymer, C.R. (1997), "Structural Non-Linear Continuous-Time Models in Econometrics", *Macroeconomic Dynamics*, 1: 518-548

Wymer, C.R. (2004), *Systems Estimation and Analysis Programs (WYSEA)*, Auckland, New Zealand

Fig 1: The detailed structure of continuous time CREIM

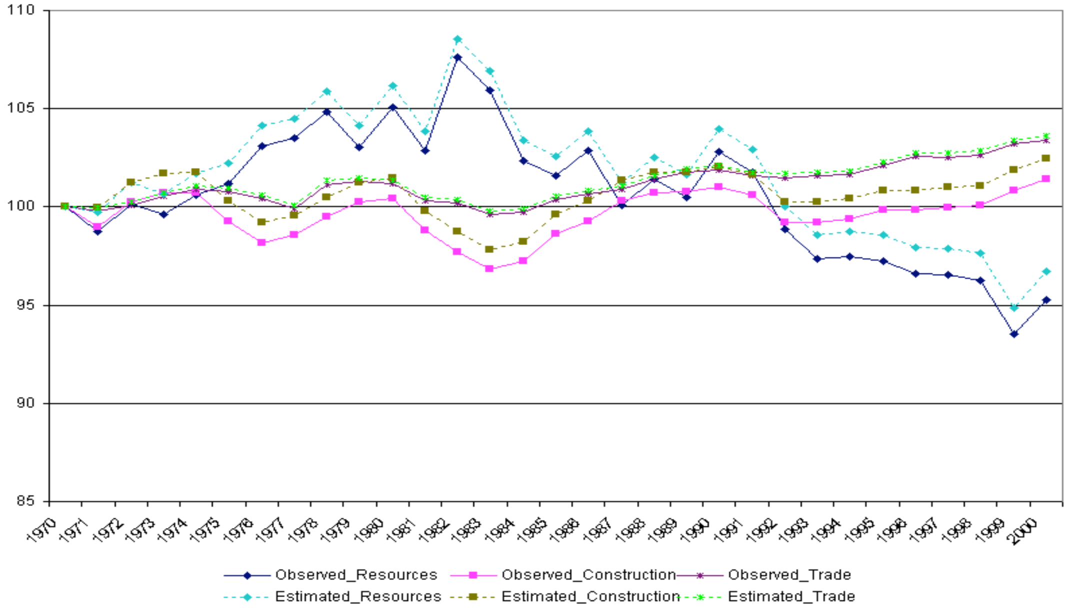

Fig. 2: Comparison of growth trend between observed and estimated output (Resources, Construction and Trade sector, 1970=100)

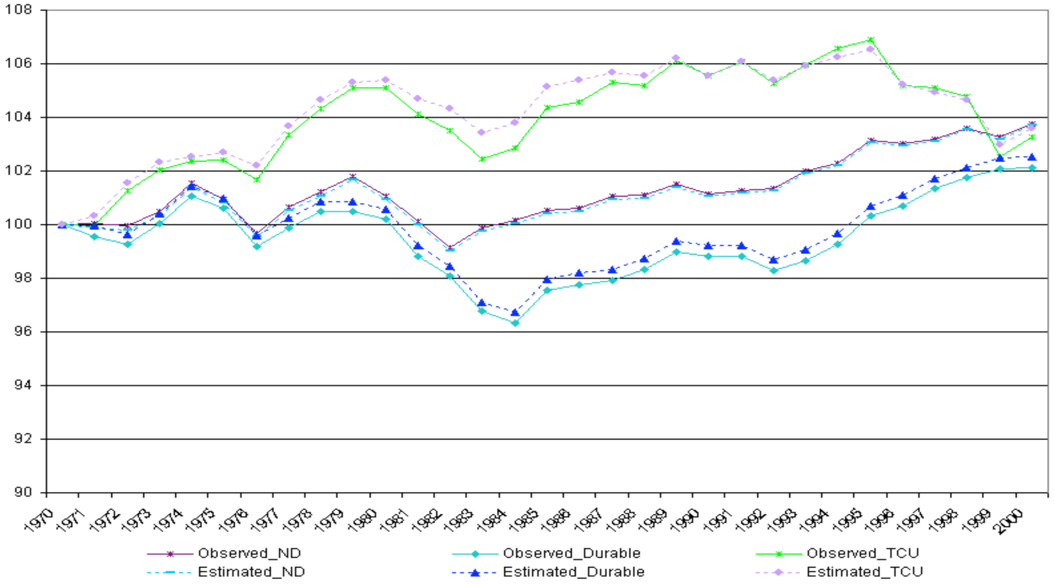

Fig. 3: Comparison of growth trend between observed and estimated output (ND, Durable, TCU sector, 1970=100)

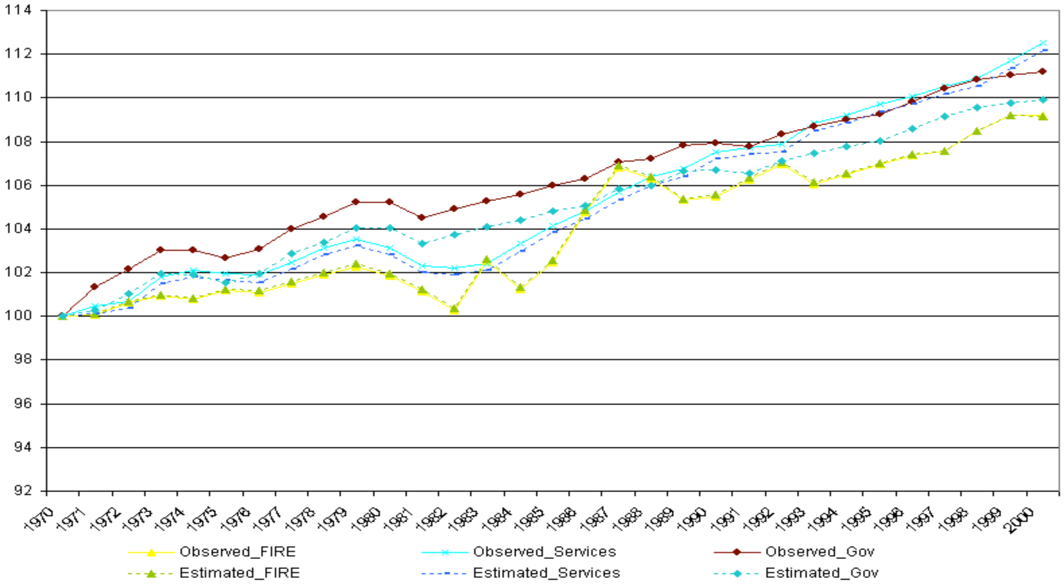

Fig. 4: Comparison of growth trend between observed and estimated output (FIRE, Services, Government sector, 1970=100)

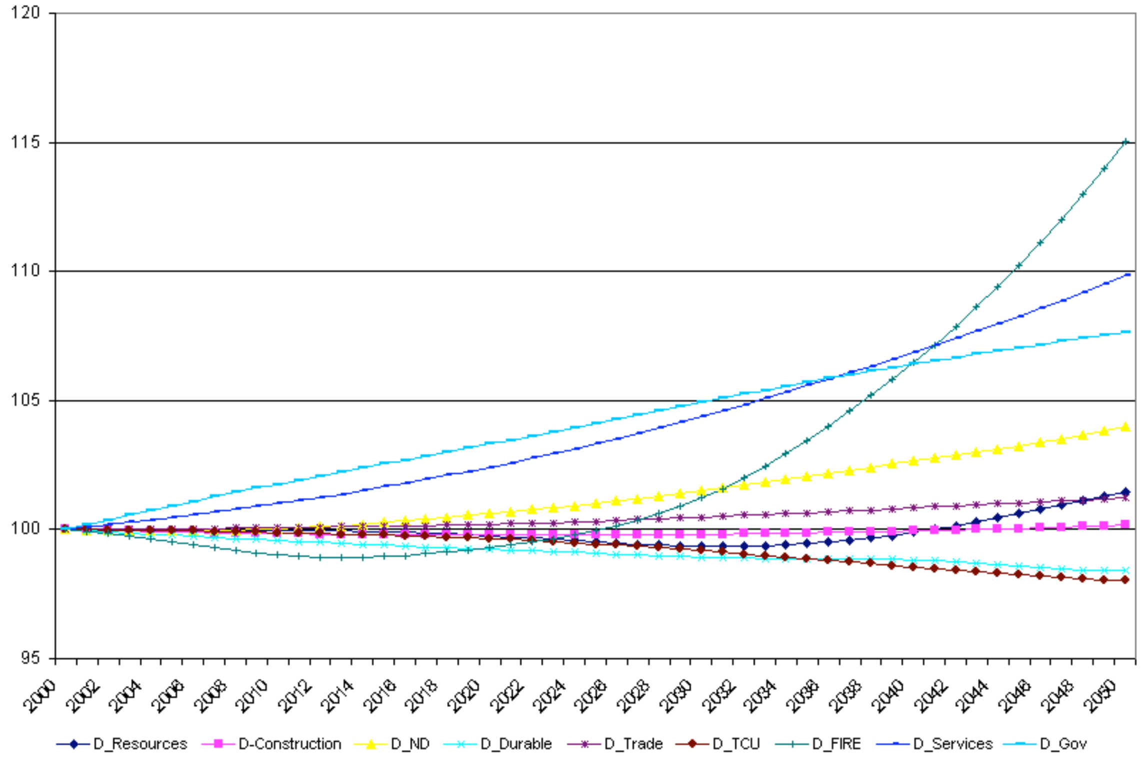

Fig. 5: Growth trend of out-of sample solution for output (2000=100)

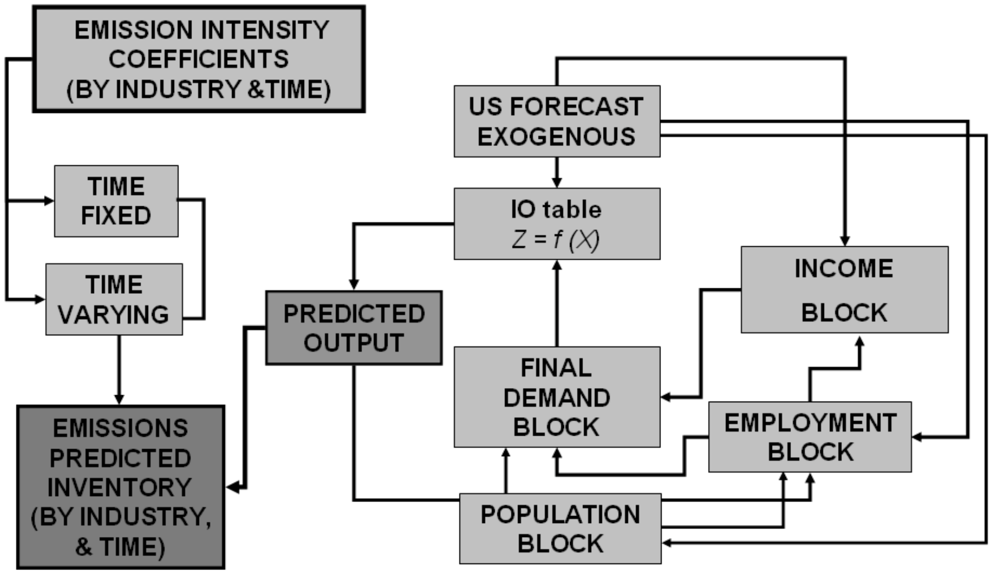

Fig. 6: Overview of the integrated econometric-emission modeling system

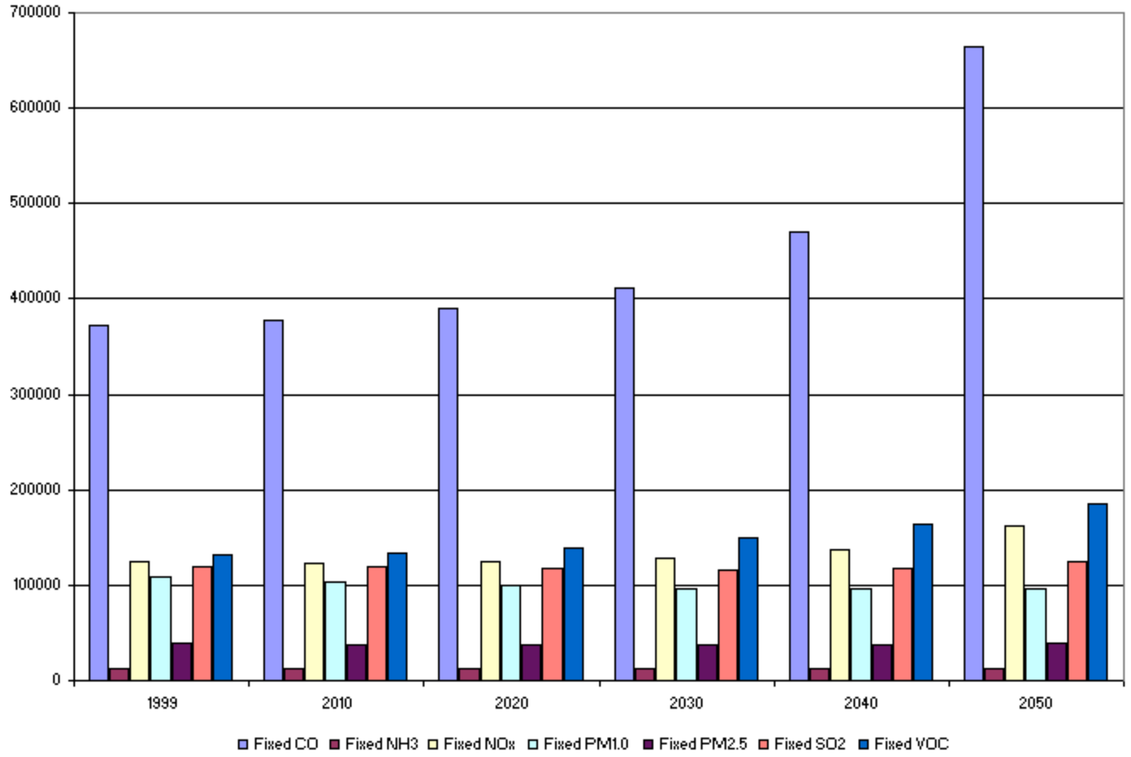

Fig. 7: Projection of seven emissions (tons) in the Chicago area under the fixed EMI

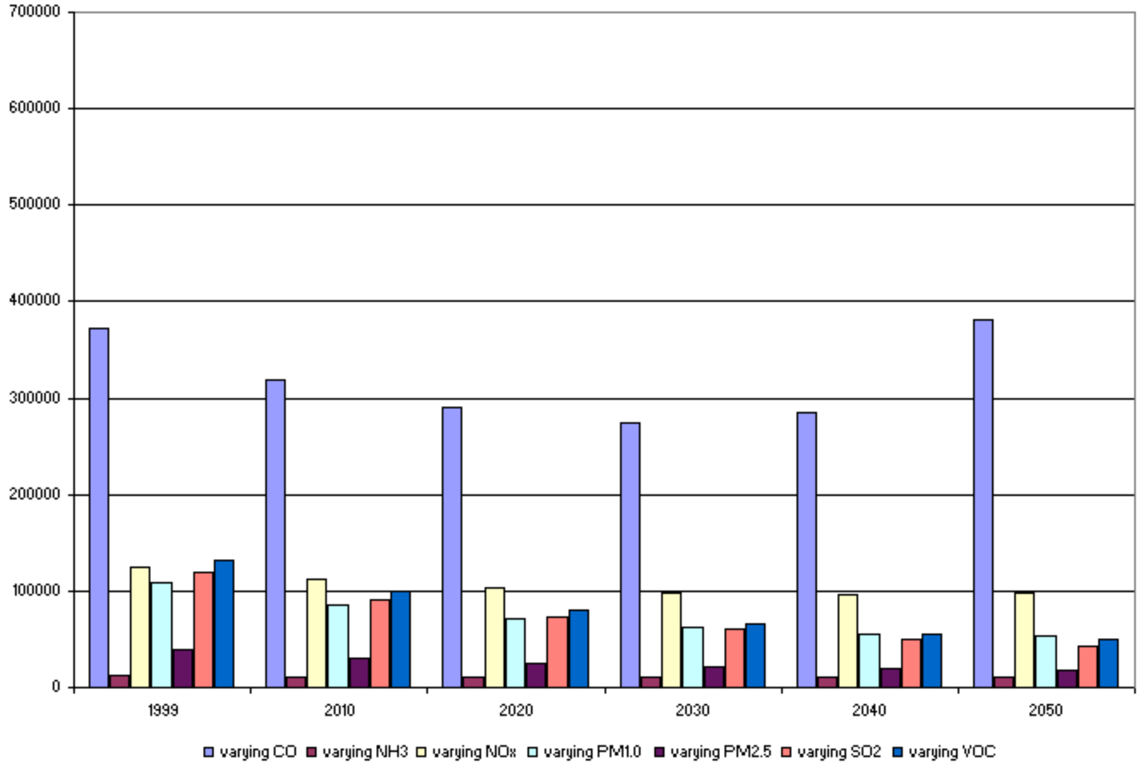

Fig. 8: Projection of seven emissions (ton) in the Chicago area under the time-varying EMI

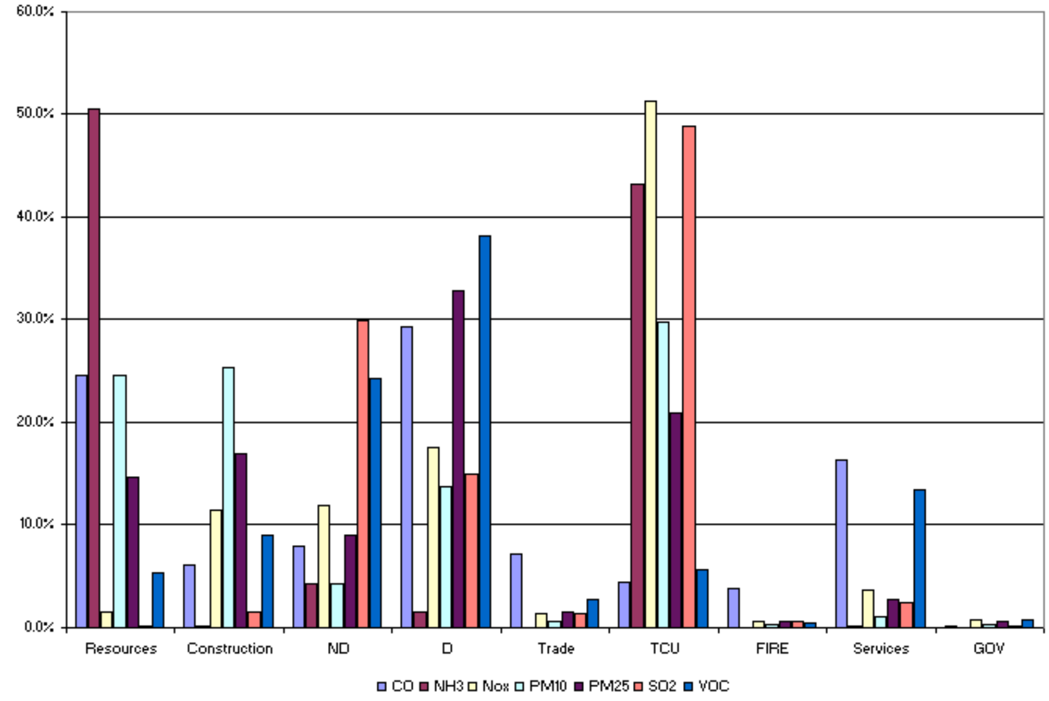

Fig. 9: Percentage distribution of 7 emission pollutants in base year (1999)

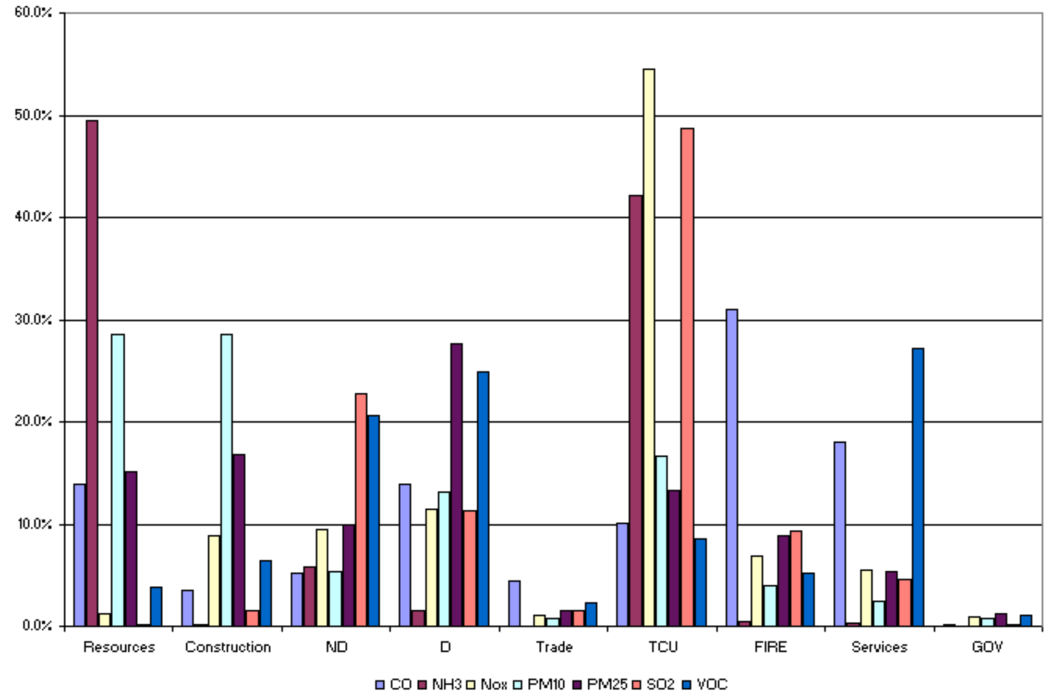

Fig. 10: Sectoral percentage of 7 emission pollutant in 2050 under the fixed EMI

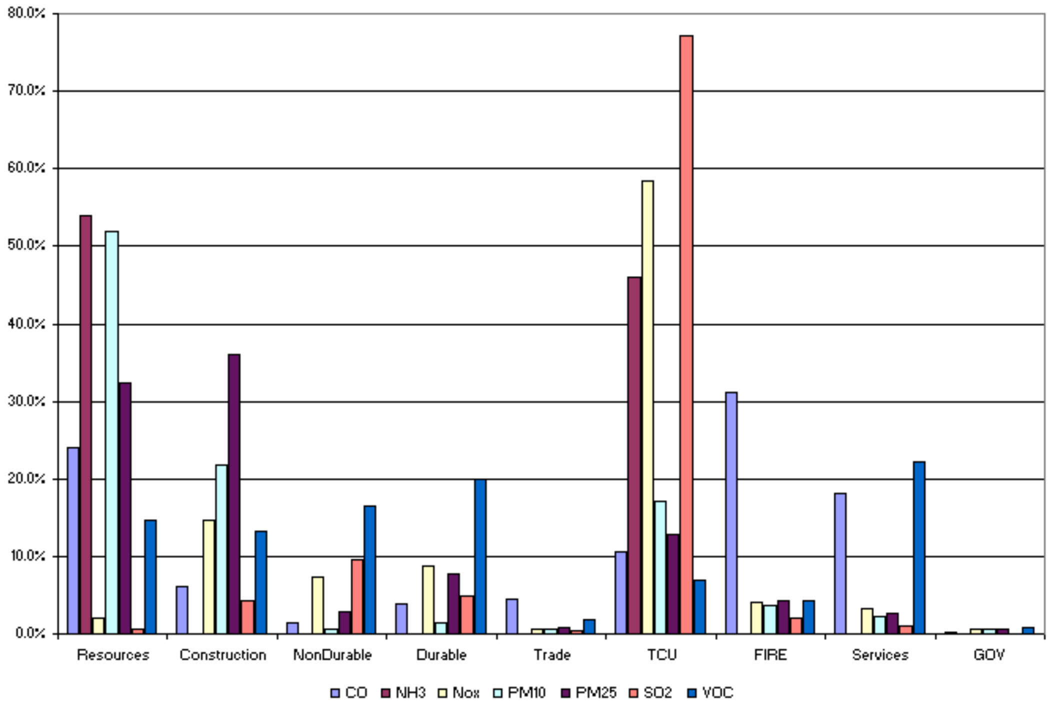

Fig. 11: Percentage distribution of 7 emission pollutants in 2050 under the time-varying EMI

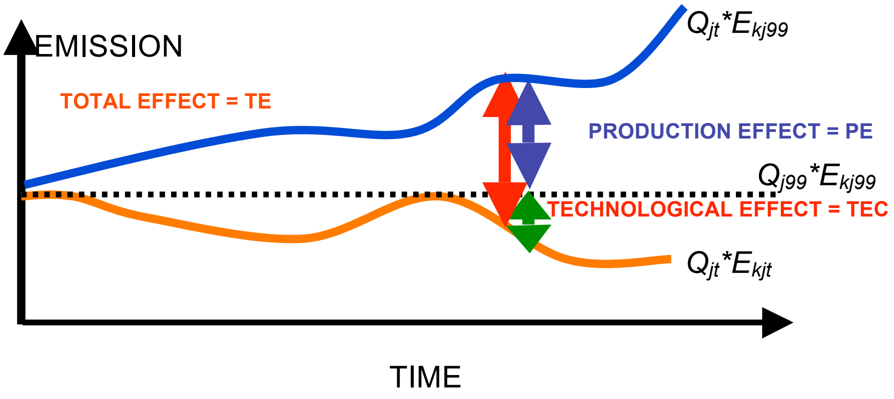

Fig. 12: Graphical decomposition of emission inventory

Table 1: In-Sample Forecasting Errors of the Estimated Output

	Observed		Simulated		Mean of Errors	Normalized RMSE
	Mean	Std. Dev'n	Mean	Std. Dev'n		
CX01	6.387840	0.312508	6.476969	0.001293	0.112766	0.049806
CX02	6.277977	0.387076	5.681334	0.000075	-0.677143	0.137717
CX03	7.013412	0.699505	6.665855	0.216918	-0.281396	0.108573
CX04	8.910463	0.205495	8.502822	0.000001	-0.410755	0.053742
CX05	9.935823	0.112135	9.812420	0.029700	-0.137180	0.019331
CX06	9.435423	0.185292	9.285486	0.000044	-0.177385	0.028263
CX07	5.179133	0.137655	4.855642	0.004081	-0.358681	0.078448
CX08	6.861352	0.175884	6.688479	0.196831	-0.152205	0.031346
CX09	5.431812	0.232009	5.288916	0.326272	-0.147441	0.064315
CX10	6.323547	0.122175	6.335195	0.024656	0.004204	0.017895
CX11	8.286292	0.105048	8.130700	0.030841	-0.176949	0.024052
CX12	9.147910	0.069685	9.064197	0.040835	-0.100626	0.016807
CX13	8.485364	0.315045	8.154482	0.007858	-0.388178	0.062181
CX14	9.257767	0.197613	9.021057	0.000027	-0.283094	0.039872
CX15	8.266818	0.368225	8.052862	0.136990	-0.274047	0.045789
CX16	7.397783	0.126611	7.345958	0.086626	-0.065330	0.024044
CX17	8.600601	0.274037	8.943430	0.002154	0.398542	0.054801
CX18	9.223180	0.096021	9.264224	0.000822	0.039870	0.011317
CX19	9.255457	0.298090	9.174487	0.047452	-0.132644	0.042559
CX20	9.383896	0.274129	9.225769	0.000884	-0.213132	0.041148
CX21	8.583331	0.313788	8.239241	0.002201	-0.404188	0.063751
CX22	7.578318	0.112803	7.307888	0.231641	-0.278283	0.042638
CX23	7.717590	0.050090	7.697480	0.010990	-0.031422	0.009977
CX24	10.293198	0.110411	10.113850	0.000002	-0.208833	0.023825
CX25	9.839345	0.097034	9.651247	0.040837	-0.215872	0.026614
CX26	8.583133	0.274716	8.420237	0.208009	-0.192502	0.025942
CX27	8.159620	0.079651	8.067058	0.028706	-0.107238	0.018165
CX28	5.821819	0.139585	5.670090	0.096731	-0.154815	0.039435
CX29	8.692577	0.119504	8.313626	0.146865	-0.408436	0.055637
CX30	6.308580	0.116929	6.249798	0.012305	-0.047938	0.020655
CX31	4.758786	0.499379	5.086768	0.451522	0.416610	0.168280
CX32	9.065914	0.266160	8.856970	0.106013	-0.267327	0.037896
CX33	7.028178	0.463498	6.780069	0.105582	-0.296482	0.070388
CX34	10.097889	0.395712	9.783757	0.180537	-0.375629	0.045789
CX35	9.660019	0.214611	9.530667	0.000714	-0.152640	0.028051
CX36	10.032803	0.509906	8.936335	0.000027	-1.229428	0.147180
CX37	8.028102	0.179294	7.889365	0.071925	-0.173321	0.028259
CX38	9.467018	0.321673	9.113597	0.093961	-0.395642	0.050498
CX39	7.322753	0.344819	6.808600	0.059709	-0.573756	0.105346
CX40	7.612142	0.367034	7.405184	0.111358	-0.279228	0.056933
CX41	7.626577	0.219598	7.359888	0.047962	-0.310638	0.050289
CX42	8.831879	0.177080	8.680299	0.064821	-0.181949	0.025262
CX43	8.509383	0.420159	8.504962	0.322716	-0.064855	0.019675
CX44	7.621232	0.120332	7.260127	0.206786	-0.389088	0.065912
CX45	8.081027	0.118887	8.092222	0.071850	-0.006324	0.010464
CXFG	7.164935	0.193000	7.04079	0.11692	-0.153257	0.024560
CXSL	7.752615	0.196951	7.65825	0.15712	-0.123279	0.017269

Table 2: 1999 fixed EMI in Chicago region

	Industry Sector	CO	NH_3	NO_x	PM10	PM25	SO_2	VOC
1	Livestock and Other Ag. Products	0.099	8.064	0.067	29.002	5.800	0.034	0.049
2	Agriculture, Forestry and Fisheries	319.62	0.015	4.981	0.984	0.904	0.464	24.555
3	Mining	1.184	0.001	0.763	6.934	1.716	0.102	0.164
4	Utilities	0.866	1.099	8.196	0.399	0.322	11.737	0.221
5	Construction	1.178	0.001	0.734	1.422	0.342	0.097	0.608
6	Food and Kindred Products	0.568	0.001	0.463	0.169	0.109	0.253	0.177
7	Tobacco Product Manufacturing	0.517	0.001	0.129	0.024	0.019	0.032	0.410
8	Apparel and Textile Products	0.525	0.001	0.129	0.034	0.027	0.064	0.254
9	Leather and Leather Products	0.533	0.001	0.155	0.032	0.027	0.033	0.480
10	Lumber and Wood Products	0.559	0.002	0.233	0.212	0.133	0.033	0.781
11	Paper and Allied Products	0.562	0.053	0.199	0.100	0.077	0.034	1.125
12	Printing and Publishing	0.518	0.001	0.123	0.026	0.024	0.037	0.481
13	Petroleum and Coal Products	0.794	0.086	1.460	0.245	0.204	9.792	3.864
14	Chemicals and Allied Products	1.437	0.002	0.332	0.152	0.122	0.159	0.774
15	Rubber and Misc. Plastics Products	0.553	0.002	0.148	0.059	0.045	0.034	0.771
16	Stone, Clay, and Glass Products	0.936	0.001	1.374	0.582	0.286	3.573	0.130
17	Primary Metals Industries	10.074	0.002	1.578	1.417	1.264	1.326	1.354
18	Fabricated Metal Products	0.589	0.002	0.202	0.067	0.057	0.048	1.792
19	Industrial Machinery and Equipment	0.529	0.001	0.148	0.031	0.028	0.036	0.285
20	Computer and other Electric product component manufacturing	0.520	0.013	0.129	0.043	0.038	0.043	0.649
21	Transportation Equipment Manufacturing	0.534	0.001	0.202	0.032	0.027	0.036	0.350
22	Furniture and Related Product Manufacturing	0.532	0.001	0.177	0.092	0.065	0.059	2.850
23	Miscellaneous Manufacturing	0.550	0.001	0.137	0.032	0.029	0.055	2.103
24	Wholesale Trade	0.662	0.000	0.042	0.019	0.016	0.044	0.065
25	Retail Trade	0.662	0.000	0.036	0.013	0.012	0.038	0.130
26	Air Transportation	1.479	0.000	0.929	0.029	0.021	0.087	0.293
27	Railroad Transportation and Transportation Services	0.466	0.000	3.416	0.094	0.086	0.208	0.152
28	Water Transportation	3.957	0.000	29.315	1.394	1.252	4.542	2.706
29	Truck Transportation and Warehousing	0.061	0.000	0.025	7.197	1.427	0.005	0.211
30	Transit and Ground Passenger Transportation	0.055	0.000	0.002	7.195	1.425	0.000	0.028
31	Pipeline Transportation	0.095	0.000	0.105	0.006	0.006	0.000	9.747
32	Information	0.055	0.000	0.003	0.006	0.006	0.000	0.004
33	Motion Picture and Sound Recording Industries	0.660	0.000	0.035	0.012	0.011	0.037	0.031
34	Finance and Insurance	0.661	0.000	0.036	0.012	0.011	0.037	0.031
35	Real Estate	0.670	0.000	0.047	0.014	0.012	0.041	0.032
36	Professional and Management services and other support services	0.665	0.000	0.049	0.014	0.013	0.043	0.034
37	Educational Services	0.787	0.001	0.357	0.037	0.031	0.200	0.042
38	Health Care	0.692	0.000	0.102	0.016	0.015	0.052	0.036
39	Social services	0.660	0.000	0.035	0.012	0.011	0.039	0.031
40	Arts, Entertainment, and Recreation	11.892	0.001	0.296	0.165	0.152	0.060	3.498
41	Accommodation Services	0.664	0.000	0.043	0.013	0.012	0.038	0.031
42	Food Services	0.660	0.000	0.035	0.012	0.011	0.037	0.031
43	Repair and Maintenance	0.661	0.000	0.037	0.016	0.014	0.037	0.849
44	Personal and Laundry Services	0.685	0.002	0.077	0.018	0.016	0.057	2.221
45	Memberships Organizations and Private Households	0.668	0.000	0.046	0.013	0.012	0.047	0.033
GE	Government enterprises	0.223	0.000	0.228	0.099	0.070	0.032	0.284

Table 3: Average annual EMI change rate (%) in the Chicago region

	CO	NH_3	NO_x	PM10	PM25	SO_2	VOC
Resources	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Construction	0.000	-5.644	0.000	-1.680	0.000	0.000	-1.173
Non Durable Manufacturing	-4.326	-14.669	-2.065	-4.713	-2.230	-3.747	-3.276
Durable Manufacturing	-2.490	-6.026	-0.554	-5.703	-4.882	-3.918	-2.613
Trade & Services	-1.070	0.000	-2.369	-1.655	-2.008	-4.292	-3.042

Table 4: The classification of decomposition effects

<table>
<tr><td colspan="3" rowspan="2"></td><td colspan="2">Production Effect (PE)</td><td rowspan="2"></td></tr>
<tr><td>Negative</td><td>Positive</td></tr>
<tr><td rowspan="3">Technology Effect (TCE)</td><td colspan="2">Zero</td><td>Emission ↓</td><td>Emission ↑</td><td>PE dominant</td></tr>
<tr><td rowspan="2">Negative</td><td>|TCE| > |PE|</td><td>Emission ↓</td><td>Emission ↓</td><td>TCE dominant</td></tr>
<tr><td>|TCE| < |PE|</td><td>Emission ↓</td><td>Emission ↑</td><td>PE dominant</td></tr>
</table>

Table 5: Emission inventory decomposition in 2050: sectors for a dominant production effect

CO	NO_x	NH_3	PM10	PM2.5	SO_2	VOC
CX38	CX43		CX33	CX44	CX34	CX44
CX33	CX42		CX46	CX26		CX26
CX46	CX41		CX40	CX34		CX34
CX40	CX11		CX37			
CX37	CX44		CX43			
CX43	CX26		CX42			
CX42	CX10		CX41			
CX41	CX09		CX44			
CX44	CX34		CX26			
CX26			CX34			
CX34						

Table 6: Emission inventory decomposition in 2050 : sectors for a dominant technology effect

CO	NO_x	NH_3	PM10	PM2.5	SO_2	VOC
CX04	CX35	CX35	CX18	CX35	CX04	CX04
CX18	CX18	CX18	CX35	CX18	CX35	CX35
CX35	CX08	CX05	CX05	CX08	CX18	CX18
CX08	CX32	CX08	CX08	CX32	CX08	CX05
CX32	CX39	CX39	CX32	CX39	CX39	CX08
CX39	CX25	CX25	CX39	CX25	CX25	CX32
CX25	CX45	CX45	CX25	CX45	CX45	CX39
CX15	CX47	CX38	CX15	CX47	CX47	CX25
CX11	CX38	CX33	CX11	CX15	CX38	CX45
CX45	CX33	CX15	CX45	CX38	CX33	CX47
CX10	CX46	CX40	CX10	CX33	CX46	CX38
CX09	CX40	CX37	CX09	CX46	CX40	CX33
CX47	CX37	CX11	CX47	CX40	CX37	CX46
	CX15	CX43	CX38	CX11	CX15	CX15
		CX42		CX37	CX11	CX40
		CX41		CX43	CX43	CX37
		CX10		CX10	CX42	CX11
		CX09		CX42	CX41	CX43
		CX44		CX09	CX10	CX42
		CX26		CX41	CX09	CX41
		CX34			CX44	CX10
					CX26	CX09