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Changes in China's Energy Intensity: Origins and Implications for Long-Term Carbon Emissions and Climate Policies

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A key environmental challenge facing all developing countries is the need to reduce the intensity with which energy is used by industry. In the 1980s and 1990's, China saw a dramatic decline in the energy intensity of its economy. However, between 2000 and 2005, the country's energy intensity flattened out and even rose slightly. Since 2005, it has started to drop again. Now, a new EEPSEA report has looked at why these changes have taken place and assessed their significance for future energy policy.

The study is the work of Jing Cao and Mun S. Ho from the School of Economics and Management, Tsinghua University, Beijing, and Harvard University. It finds that technological improvements drove the sustained decline in China's overall energy intensity before 2000. By the years 2000/2002, technological progress had peaked and no other factors were driving improvements – hence the flattening out of energy intensity. After 2005, new strict energy intensity policies reversed the energy intensity trend, but this change has mainly been restricted to the coal sector. In light of these findings, the study projects how energy intensity might change in the future and finds that a carbon tax would be the most cost-effective way of cutting the environmental and social costs of industry and reducing a wide range of pollutants.

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CHANGES IN CHINA'S ENERGY INTENSITY: ORIGINS AND IMPLICATIONS FOR LONG-TERM CARBON EMISSIONS AND CLIMATE POLICIES

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EXECUTIVE SUMMARY

Since the economic reforms that began in 1978, China has experienced a dramatic decline in energy intensity but in 2002 it flattened out and even rose slightly. There have been considerable debates about the origins of this dramatic decline in energy intensity before the year 2000: is this decline mostly due to changes in the composition of economic activity? (structural change) or is it mostly due to changes in technology? (energy per ton of steel, for example). However, very few studies have examined the slightly rising energy intensity trend for the post-2000 period. In this report, we use a new time-series input-output data set from 1981– 2007 to decompose the reduction in energy use into technical change and various types of structural change, including changes in the quantity and composition of imports and exports. We use two different decomposition methodologies: Structural Decomposition Analysis (SDA) and Index Decomposition Analysis (IDA) methods. Based on these estimates of changes in energy intensity, we project Autonomous Energy Efficiency Improvement (AEEI) parameters in forecasting future capital, labor and energy input shares of output for each industry. We then construct a recursive-dynamic computable general equilibrium (CGE) model of the Chinese economy to analyze both command-and-control policies and carbon taxes, and provide policy recommendations on how China could pursue a more sustainable development trajectory to deal with greenhouse gas emissions.

1.0 INTRODUCTION

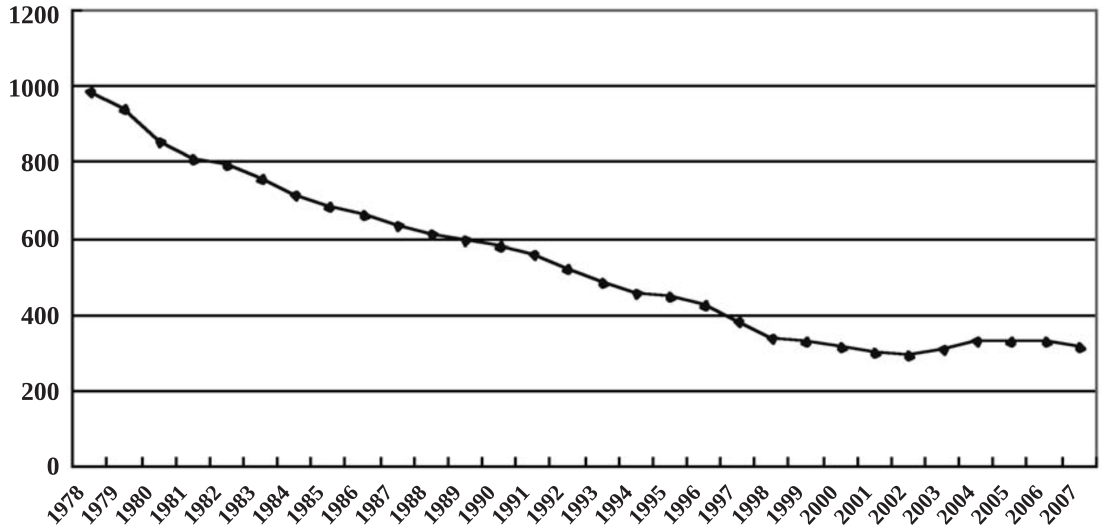
1.1 Problem Description

In many developing or transitional economies, energy consumption typically grows faster than GDP or final economic output during the period of industrialization, motorization, and urbanization. This is due to rising capital-labor ratios, increasing use of commercial energy, and the construction of modern infrastructure (Lin and Polenske, 1994; Lin 1994). However China, the biggest transitional and developing economy in the world, followed a strikingly opposite pattern of consumption up until the year 2000. China had an average annual growth rate of 9.7% from 1978 to 2000, but commercial energy consumption per unit of GDP declined by about two thirds. After 2000, the rate of declining energy intensity slowed down or even slightly rose in certain years (Figure 1).

Much of this energy comes from fossil fuels and China's carbon intensity (carbon emissions per unit of GDP) followed a sharply falling trend up to 2000. However, given the size of the economy and the rapid growth of GDP, it is now estimated that Chinese arbon emissions have surpassed the U.S. to become the biggest carbon emitter in the world[1]. Given the reversal of the downward trend after 2000, the growth of Chinese CO_2 emissions now dominate the growth in global CO_2 emissions. Figure 2 shows the annual carbon emissions from fossil fuels and cement production in the major carbon-emitting countries. China follows a trend similar to other non-Annex I countries up until the early 2000s, but after 2002 the growth of carbon emissions increased dramatically, much faster than all the developed and other non-Annex I countries. Understanding these trends is important for discussing the future path of emissions and control policies.

[1] See, for example, the estimates by the Netherlands Environmental Assessment Agency: http://www.pbl.nl/en/publications/2009/Global-CO2-emissions-annual-increase-halves-in-2008.html

Figure 1: China's energy intensity (measured in kg coal equivalent to thousand YUAN, 2005), 1978 – 2007

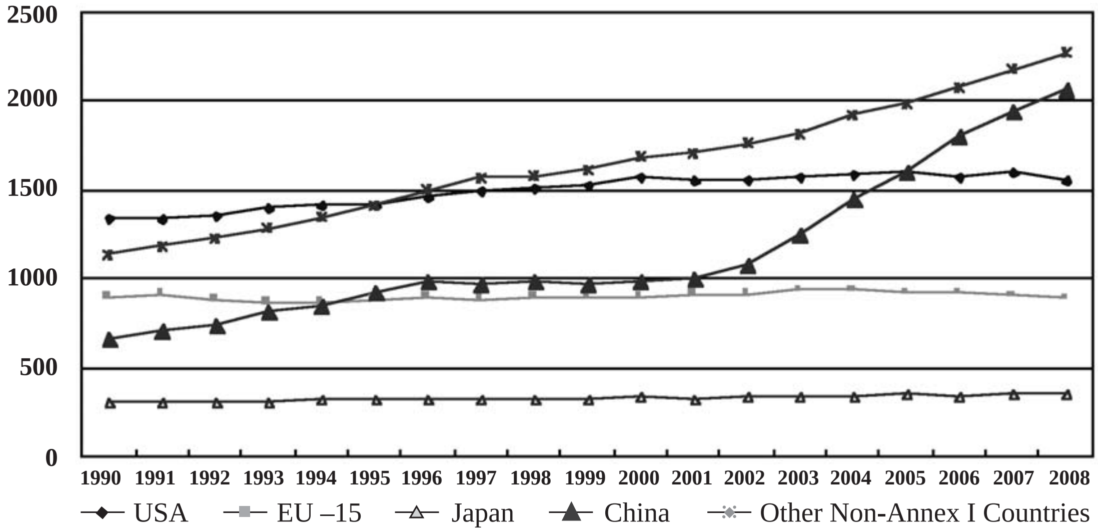


Sources: *Sinton (2005) China Energy Databook (version 6); China Energy Statistical Yearbook; Data of Gross Domestic Product of China: 1952 – 2004;* and *China Statistical Abstract: 2007* (GDP data reflects the national revision in 2006). Note: energy consumption here only includes commercial energy and excludes biomass and firewood.

In its 11th Five-Year Plan (2006), the Chinese government set a target to reduce energy intensity by 20% during 2006 – 2010. Prior to the world economic crisis of 2008, the dramatically faster growth in total energy use and carbon emissions after 2001 (see Figures 1, 2 and 3) indicated to many that it would be very difficult to meet this target. China failed to reach the energy saving and environmental protection targets set out in the 10th Five-Year Plan, as discussed in Cao et al. (2009). Although the government has asserted that the target in the 11th Five-Year Plan is a "mandatory" objective, the likelihood of reaching it attracted a lot of discussion in both academic and policy forums prior to the global slowdown. To assess this, it is necessary to understand the nature of past changes in energy intensity. This paper examines the change in aggregate energy intensity (the energy-GDP ratio) by decomposing it into structural change and change in energy efficiency at the industry level. This industry level efficiency change includes the effect of substitution among inputs due to changes in prices, and changes due to technical progress. Structural change includes the reallocation of capital and labor across industries due to the changes in the composition of final demand (composition of consumption, investment and exports).

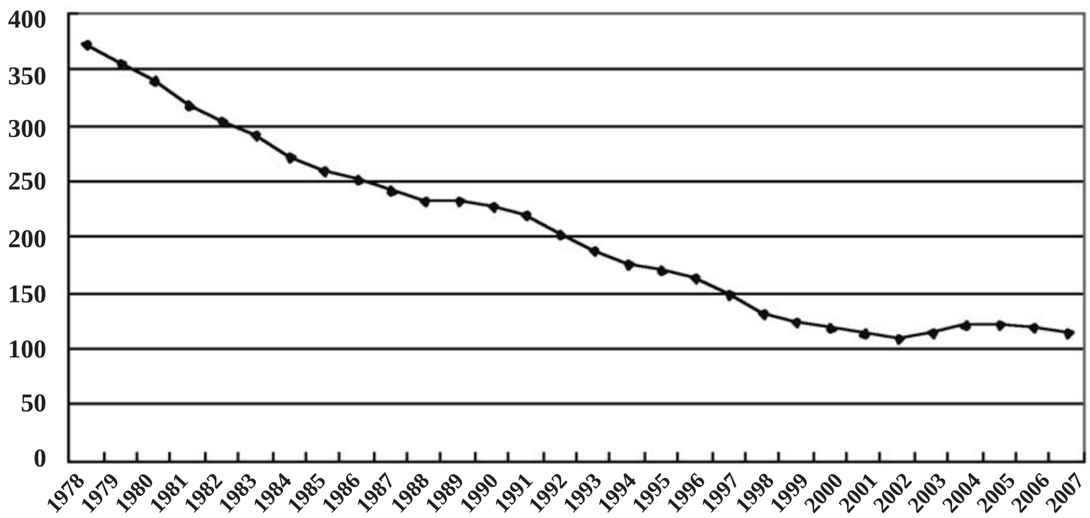
A comprehensive analysis of climate change policies should include some understanding of future greenhouse gas emissions (GHGs). Projections of long-term emissions of GHGs require a projection of the level of economic activity, the distribution of resources among the various industries, and the demand for fossil fuel by these industries. Given this complexity there is little consensus on the projection of long-term emissions. The main sources of uncertainty are the modeling of technical progress and the modeling of substitution.

Figure 2: CO_2 emissions from fossil fuel use and cement production in major countries, 1990 – 2008 (in million tons of carbon)



Source: EDGAR 4.0 (JRC/PBL, 2009) (1990-2005); Energie/energy: International Energy Agency (IEA), 2008 (1990-2006); BP, 2009 (2006-2008 trend).

Figure 3: China's carbon intensity (measured in tons of carbon dioxide per thousand YUAN, 2005), 1978 - 2007



Sources: Carbon emission data was collected from the Energy Research Institute (ERI) of the National Development and Reform Commission (NDRC), and was originally based on IEA estimates.

In many integrated assessment models or environmental-economic models, the technological changes of energy use per unit output (i.e. changes over time not due to price effects) are typically represented as following some exogenous path of Autonomous Energy Efficiency Improvement (AEEI). By exogenous we mean that the rate of technical progress does not depend on any variable determined within the model, such as levels of output or prices[2]. Some models implement this by having a declining trend in the coefficients on coal, oil and gas use in the production functions.

[2] An alternative formulation would have endogenous technical progress where higher prices of energy, say, would lead to a faster rate of innovation in energy-saving processes. Another case is where research and development expenditure leads to a faster rate of progress. These effects are distinct from the more familiar substitution between capital and energy in a given period due to changes in the prices of capital and energy.

Other models specify two techniques – clean and conventional – and change the share of the clean one over time. For example, in Edmonds and Reilly (1985) and many intertemporal CGE models for climate policy analysis, coefficients on energy use in industrial production functions were constructed to decline according to the inverse of an index of energy-saving technological progress.

In this research project, we first decomposed the change in aggregate energy intensity into the contributions of structural change and change in energy efficiency at the industry level. Then we used the estimates of the rate of change of input intensities in individual sectors to project the change in the AEEI parameters in our economic growth model. In this paper we compare two types of climate policies: command-and-control mandates on energy conservation, and market-based policies such as energy taxes. In the current (11th) Five-Year Plan, the first policy option – command-and-control energy targets – is being implemented by the National Development Reform Commission (NDRC). However, the latter policy option is under discussion for future implementation

1.2 Review of Energy Intensity Decomposition Literature

There is extensive literature which uses decomposition analysis to study the changes in Chinese energy intensity, the changes in carbon dioxide intensity and other related indicators in the past two decades (for example: Huang, 1993; Sinton and Levine, 1994; Lin and Polenske, 1995; Garbaccio, Ho and Jorgenson, 1999; Zhang, 2003, Fisher-Vanden et al., 2003; Ma and Stern, 2007). Most of these studies examine the energy intensity trend for the pre-2000 period, and conclude that the most important factor for the sharp decline in energy intensity is technical change, and there is some disagreement about the role of structural change. Many find that structural change only plays a minor role in reducing energy intensity, Garbaccio, Ho and Jorgenson (1999), and Ma and Stern (2007) even estimated that structural change increased energy use. On the other hand, the World Bank (1994, 1997) asserted that structural change was the major factor in the declining energy intensity trend. That conclusion was drawn from earlier work conducted by the Energy Research Institute (ERI) of the National Development and Reform Commission (NDRC) (Wang and Xin, 1989).

Ma and Stern (2007) is the only study among those listed above that examined energy intensity in the post-2000 period. Ma and Stern concluded that the increasing trend after 2000 was mainly explained by negative technological progress. However, Ma and Stern based their study only on 10 aggregate sectors, or aggregated to primary, secondary and tertiary sectors. They used the Index Decomposition Analysis (IDA) approach, due to a lack of time-series input-output tables, for a more robust Structural Decomposition Analysis (SDA)[3]. In addition, as Garbaccio, Ho and Jorgenson (1999) pointed out, most of the controversies rest on the level of aggregation used. Thus, if the sectors are aggregated at a high level, structural changes below that level may be wrongly attributed to technical changes. Similarly, both Sinton and Levine (1994) and Fisher-Vanden et al. (2003) found that the explanatory power of structural change rises as the sectoral disaggregation becomes finer. Thus, in this study we use a more robust decomposition method based on a time-series of input-output tables for 1980– 2005 for 33 sectors in China.

[3] We explain these different decomposition methods in the Research Methods section.

The changes in the economy post-2000 may have been of a very different nature compared to the earlier period of declining energy intensity. Environmental and other regulations may have limited the potential for technical improvements at the industry level; improvements in household incomes may have exceeded some threshold that dramatically changed the rate of automobile and electricity use.

Our goal is to examine the historical trend and patterns in energy and carbon intensity, focusing carefully on the changes in the post-2000 era. We believe that this is useful information for policy analysts to parameterize their models, as well as for government energy planning. This should help project the trend of technical change and also shed some light on future carbon emissions and other local pollutants, such as particulate matter and sulfur dioxide. Given the widespread concern about the quality of data on output and prices from different sources, we also conducted several decomposition methods, including the Divisa-index SDA approach, and LDA approaches, to see if there was a common pattern from these different methods and data sources.

1.3 Autonomous Energy Efficiency Improvement (AEEI)

As noted above, most top-down energy use or climate policy models have an exogenous Autonomous Energy Efficiency Improvement (AEEI) parameter to project exogenous improvements in energy per unit of output. The value chosen is about 1% per year (Weyant, 1999). The basic idea is to sketch a declining trend in the coefficients on energy use in the production function, with the AEEI parameter being the rate of the decline (Sue Wing and Eckaus, 2005). In most of these macro-economic models the AEEI is set to one common parameter for all industries for generating the future trajectories of energy use and carbon emissions. Such an approach is understandable given the lack of estimates, however, this "one-size-fits-all" parameter has some weaknesses.

Base-year bias: many models calibrate the AEEI parameters by retaining the characteristics of the base year when forecasting the future. However, without decomposing the origins of the aggregate efficiency improvement, the fixed calibrated AEEI tends to maintain the ratio of energy use to overall economic output and the initial industry structure of the economy. This is due to the absence of mechanisms to allow the different rates of improvement that we actually observe in the data.

Inappropriate use of developed-country estimates: In much climate policy modeling, long-term energy intensity (E/GDP) is modeled to decline at about 1% per year, which is roughly the average of US performance over the past 200 years (Grubler, 1998). However, future growth in energy and emissions intensities may differ significantly from historical time series. Even for the United States, Manne and Richels (1990) pointed out that there is no well-established empirical basis for such a coefficient for energy efficiency improvement. Hogan and Jorgenson (1991) also argue that the AEEI may actually be negative. In addition, there is no obvious reason for the US historical experience to be replicated in today's developing or transitional economies.

In this study we decomposed the trend in aggregate energy-output ratio by sector to identify the sources of the aggregate AEEI. We want to understand the magnitude of the contributions from intra-sector intensity reductions driven by the substitution of various inputs, such as embodied energy-saving technologies, disembodied technological progress, and structural change. Based on our empirical decomposition results, we estimated the values of the AEEI parameter for China, and then applied these parameters to an economic growth model for climate policy analysis.

1.4 Significance of this Study

As the largest developing country in the world, and a country experiencing dramatic change and economic growth, China is expected to consume a large and rapidly rising share of the world's energy. This trend is viewed with alarm by anyone worried about the sustainability of such economic development. China's energy intensity had been declining for 20 years, since the economic reforms of 1978. However, this frugal pattern may have reversed since 2002, causing analysts to raise the previous high projection even further. How the Chinese government can reverse this rise in energy intensity, or at least lower the growth rate, i.e. how it can achieve its 20% reduction target, as stated in the 11th Five-Year Plan, and reduce carbon emissions in the future, is becoming a crucial question. In particular, should the government follow a command-and-control policy, such as the energy conservation mandates currently used in the 11th Five-Year Plan, or alternatively, should economic incentive-based policies – such as energy or carbon taxes – be used? These questions are the focus of our study. We provide a methodological framework for energy intensity decomposition, and for projecting future energy use and carbon emissions using industry-level estimates of improvements in energy use. In the process we provide a new set of AEEI estimates by detailed sectors for other analysts to use in their models.

2.0 RESEARCH OBJECTIVES

2.1 General Objective

The general goal of this project is to understand the proximate reasons for past changes in aggregate energy intensity and to use the estimates of the contribution of these various factors to project future energy consumption and emissions if past policies are maintained. With these estimates of past energy use we also analyzed the effects of other policies in reducing energy use and emissions to meet China's sustainable development targets.

2.2 Specific Objectives

The specific objectives were:

- To reconcile energy use and production data in value terms in the time-series of input-output tables (1980 – 2005) prepared by the National Bureau of Statistics (NBS) with price and quantity data. (Our research team is involved in a project compiling a consistent time-series of I-O tables with collaborators from the NBS, Beihang University, and The Conference Board).
- To apply the Structural Decomposition Analysis (SDA-Divisa) method for energy intensity using the above set of matched data on output and consumption, and to apply other index decomposition methods to check the robustness of the results. We related the decomposition results and energy intensity trends to major macroeconomic events and changes in reform policies.
- Based on the above decomposition results, to work out a strategy for constructing the AEEI parameters to forecast future energy consumption, carbon emissions, and energy intensity by sector to 2030, and to use this as the reference, or "business-as-usual" scenario for further policy analysis.
- To analyze two alternative policy options: command-and-control policies versus economic-incentive-based taxation policies, such as taxes imposed on energy use. Finally, based on these policy simulations, we compared the pros and cons of the two alternative policy options, and then we discussed what lessons there might be for climate change policy reform in the 12th Five-Year Plan.

3.0 RESEARCH METHODS

3.1 Data Preparation and Adjustments

As noted above, previous decomposition analysis of Chinese energy intensity change has either used input-output tables from two benchmark years or has used annual data for gross output and energy input only. In this study, we used an annual series of input-output tables. This data set, covering the period 1980 – 2005, was a preliminary version of estimates made by a group led by the National Accounts Department in the National Bureau of Statistics (NBS) and Ren Ruoen of the School of Economics and Management, Beihang University, in collaboration with Dale Jorgenson (Harvard University) and Bart van Ark (The Conference Board, New York)[4]. This is the first study to use this unique data set for energy decomposition analysis.

Our data covered a newly revised data set covering the period 2000 – 2005, after the NBS adjusted the GDP level. A new GDP series I-O table was revised upward so that the GDP adjustments in major service sectors could be incorporated. Therefore the entire series was used in this report.

3.1.1 Capital Input

We measured capital input in a way that took into account the heterogeneity of the capital assets, from long-lived buildings to short-lived computers. Capital input for industry j, K_{jt}, was defined as the Tornqvist index (the Divisia method) of three types of assets: structures, equipment and auto vehicles:

$$d \ln K_{jt} = \sum_k \bar{v}^j_{Kkt} d \ln K_{jkt} \qquad \text{(Equation 1)}$$

where the value shares are given by:

$$\bar{v}^j_{Kkt} = \frac{1}{2}(v^j_{Kkt} + v^j_{Kkt-1})$$

$$v^j_{Kkt} = \frac{p^j_{Kkt} K_{jkt}}{\sum_k p^j_{Kkt} K_{jkt}} \qquad (j = 1, 2, \ldots, 33;\ k = \text{structures, equipment, auto vehicles})$$

P^j_{Kkt} denotes the rental price of capital asset k in industry j and is derived from data on operating surplus and depreciation. K_{jkt} is the stock of capital of type k and is derived from data on investment in asset k. The measurement of capital input is discussed at length by Ren and Sun (2005).

[4] An earlier version of this work is described in Cao et al. (2009). Van Ark and The Conference Board also aim to supplement these input-output estimates with data on capital and labor input in order to conform to the requirements of a large international project to study productivity, the *Productivity in the European Union* (EU KLEMS) project. This is described at www.euklems.net.

3.1.2 Labor Input

Labor input was measured in a way that also accounted for the heterogeneity of workers, from high-wage, educated, experienced workers to young, less educated workers. The details are in Yue et al. (2005). Briefly, the workers were cross-classified by gender, age and educational attainment. The labor data was compiled from the 1982, 1990 and 2000 Population Censuses, and the 1987 and 1995 Sample Population Surveys. Labor costs were estimated from household surveys of income distribution, the China Household Income Project (CHIP) survey. Our index of labor input in industry j, L_{jt}, was a Tornqvist index over the various types of labor:

$$d\ln L_{jt} = \sum_{l} \bar{v}_{Llt}^{j} d\ln L_{jlt} \qquad \text{(Equation 2)}$$

where the value shares are:

$$\bar{v}_{Llt}^{j} = \frac{1}{2}(v_{Llt}^{j} + v_{Llt-1}^{j})$$

$$v_{Llt}^{j} = \frac{p_{Llt}^{j} L_{jlt}}{\sum_{l} p_{Llt}^{j} L_{jlt}} \qquad \text{(j=1,2,…, 33; l=cross classification of gender, age, education)}$$

P_{Llt}^{j} denotes the price of labor of type *l* in industry *j*, and L_{jlt} denotes the hours worked by type *l*.

3.1.3 Output and Intermediate Inputs

Ren et al. (2005) describe how they constructed a time-series of input-output tables for 33 industries in nominal terms covering the period 1981 – 2000. These were derived by revising the benchmark tables for 1981, 1987, 1992 and 1997 to the latest definitions based on the *System of National Accounts* (SNA). They also constructed price indices for the output of the 33 industries since they were not compiled by any statistical agency in China. These value and price data were then used to construct indexes of sectoral output and intermediate inputs.

The I-O tables give us the value of each of the 33 intermediate input, and capital and labor inputs into each of the 33 industries. The energy input index for industry *j*, E_{jt}, is the Tornqvist aggregate over the five energy commodities (e = coal mining, oil and gas mining, petroleum and coal products, electric utilities, gas utilities) while the material input index, M_{jt}, is an aggregate over the remaining *i*=1, 28 commodities:

$$d\ln E_{jt} = \sum_{e} \bar{v}_{Eet}^{j} d\ln E_{jet}$$

$$d\ln M_{jt} = \sum_{i} \bar{v}_{Mit}^{j} d\ln M_{jit} \qquad \text{(Equation 3)}$$

where

$$\bar{v}_{Eet}^{j} = \frac{1}{2}(v_{Eet}^{j} + v_{Eet-1}^{j}) \qquad \bar{v}_{Mit}^{j} = \frac{1}{2}(v_{Mit}^{j} + v_{Mit-1}^{j})$$

$$v_{Eet}^{j} = \frac{p_{Eet}^{j} E_{jet}}{\sum_{e} p_{Eet}^{j} E_{jet}} \qquad v_{Mit}^{j} = \frac{p_{Mit}^{j} M_{jit}}{\sum_{i} p_{Mit}^{j} M_{jit}}$$

3.2 Decomposition Analysis of the Change in Energy Intensity (1981 – 2005)

Decomposition analysis has been extensively applied in energy research, in particular in interpreting the factors affecting aggregate energy intensity, or energy-related carbon emissions. However, there is little consensus on a decomposition methodology and results vary depending on the methods, in addition to the differences due to data sources and sample periods. Here we used three decomposition techniques on the Chinese data to shed some light on these methodological issues, and tried to look for a convenient approach to use the decomposition results to adjust AEEI parameters in our CGE model.

Up to now, two major types of decomposition method have been extensively used: Structural Decomposition Analysis (SDA) and Index Decomposition Analysis (IDA). Structural Decomposition Analysis is based on input-output tables, so it captures both direct and indirect effects. An increase in the demand by households for motor vehicles has a direct effect on the output of motor vehicles, but producing more vehicles requires more steel and the production of steel requires motor vehicles, thus there is an indirect effect due to the increase in household demand. Given the structural details in the input-output table that allow us to distinguish between GDP (the sum of value added) and the sum of industry gross output, SDA is able to distinguish between a range of technical effects and structural effects that are not possible in the IDA model (Ma and Stern, 2007). Index Decomposition Analysis usually considers only industry gross output and defines aggregate output as the sum of industry output. More specifically, the IDA analyzes effects from changes in the structure of production, while SDA typically analyzes the technology effects in production that arise from changes in the input requirement matrix and the structural effects from the changes in the composition of GDP (final demand) (Wadeskog and Palm, 2003). Structural Decomposition Analysis almost exclusively works with levels, while IDA can work with levels, intensities, or elasticities. In terms of time frames, SDA typically corresponds to the availability of I-O tables, which are only available for benchmark years, while IDA is less demanding in terms of data and easier to implement for time-series analysis (Wadeskog and Palm, 2003).

Another key issue was the choice of index, such as the Laspeyres Index, with fixed base year weights, or the Divisia Index, with moving weights. In this study, our preferred methodology used an SDA approach based on input-output tables, similar to the I-O-based studies introduced by Lin and Polenske (1995) and Lin (1996). Following Garbaccio, Ho and Jorgenson (1999) we did not use fixed base year weights, but used the Divisia Index.

3.3 Method 1: Structural Decomposition Analysis (SDA)

Our method was similar to that used in Garbaccio, Ho and Jorgenson (1999) and Liu, Ang, and Ong (1992). A summary description of our method is given here[5]. Unlike the above studies we were able to apply the methodology to a sequence of annual tables, rather than two sporadic base and end years. This was especially useful when matching our decomposition results with the actual policies implemented in particular years or with particular energy-saving strategies – so we had a more accurate estimate of the impact of past policies, allowing for a better discussion of future energy-saving programs or policy options. It was also helpful to further divide the whole period into sub-periods based on structural breaks.

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[5] Our discussion and notation follows Miller and Blair (1985), however, here we only use the activity matrix A instead of the "use" and "make" matrices separately.

Let $\mathbf{A_t}$ denote the input-output matrix at time t (with *n* sectors), $\mathbf{y_t}$ the vector of final demand and $\mathbf{x_t}$ the vector of industry gross output (both of length n). The sum of intermediate demand and final demand equals the supply of the output:

$$\mathbf{A_t x_t} + \mathbf{y_t} = \mathbf{x_t} \qquad \text{(Equation 4)}$$

The sum of the values of the *n* commodities in the final demand vector gives us GDP. From equation 4 we get the well known Leontief inverse which gives us the level of industry output required to supply the vector **y**:

$$\mathbf{x_t} = (\mathbf{I} - \mathbf{A_t})^{-1}\mathbf{y_t} \qquad \text{(Equation 5)}$$

It is useful to decompose final demand to the main components:

$$\mathbf{y_t} = \mathbf{c_t} + \mathbf{v_t} + \mathbf{g_t} + \mathbf{e_t} - \mathbf{i_t} = \mathbf{y_t^d} - \mathbf{i_t} \qquad \text{(Equation 6)}$$

where $\mathbf{c_t}$ is household consumption, $\mathbf{v_t}$ is investment, $\mathbf{g_t}$ is government consumption, $\mathbf{e_t}$ is exports and $\mathbf{i_t}$ is imports. The second equality in equation 6 expresses net final demand as the difference between the gross domestic demand and imports.

In addition, the use of commodities (u_t) can be written as domestic production plus imports less exports:

$$\mathbf{u_t} = \mathbf{x_t} + \mathbf{i_t} - \mathbf{e_t} \qquad \text{(Equation 7)}$$

We can also rewrite $\mathbf{y_t}$ as a share vector of total demand, or GDP, (Y_t):

$$\mathbf{y_t} = \gamma_t Y_t \qquad \text{Where } \gamma_t = (\gamma_{1t}, ..., \gamma_{nt})' \qquad \text{(Equation 8)}$$

The output equation 5 can thus be rewritten as:

$$\mathbf{x_t} = \mathbf{G_t y_t} = \mathbf{G_t}\gamma_t Y_t \qquad \text{(Equation 9)}$$

where $\mathbf{G_t} = (\mathbf{I} - \mathbf{A_t})^{-1}$ is the Leontief inverse, the "commodity total requirements matrix"

Writing this out explicitly for the output of industry *j*:

$$x_{jt} = \sum_i G_{jit}\gamma_{it}Y_t \qquad \text{(Equation 10)}$$

Combining this with equation 7, the rate of change in the use of commodity *j* is:

$$\dot{u}_{jt} = \sum_i \dot{G}_{jit}\gamma_{it}Y_t + \sum_i G_{jit}(\dot{\gamma}_{it}^d - \dot{\gamma}_{it}^m)Y_t + \sum_i G_{jit}\gamma_{it}\dot{Y}_t + \dot{i}_{jt} - \dot{e}_{jt} \qquad \text{(Equation 11)}$$

The Tornqvist discrete time approximation of the integral of equation 11 gives
(see Garbaccio, et al. (1999) equation 20):

$$\begin{aligned}\ln\frac{u_{jt}}{u_{j,t-1}} &= \sum_i \tfrac{1}{2}(w_{i,t-1} + w_{i,t})\ln\frac{G_{jit}}{G_{ji,t-1}} + \sum_i \tfrac{1}{2}\Big(w_{i,t-1}\frac{\gamma_{i,t-1}^d}{\gamma_{i,t-1}} + w_{it}\frac{\gamma_{it}^d}{\gamma_{it}}\Big)\ln\frac{\gamma_{it}^d}{\gamma_{i,t-1}^d} \\ &+ \left[-\sum_i \tfrac{1}{2}\Big(w_{i,t-1}\frac{\gamma_{i,t-1}^m}{\gamma_{i,t-1}} + w_{it}\frac{\gamma_{it}^m}{\gamma_{it}}\Big)\ln\frac{\gamma_{it}^m}{\gamma_{i,t-1}^m}\right] + \sum_i \tfrac{1}{2}(w_{i,t-1} + w_{it})\ln\frac{Y_t}{Y_{t-1}} \\ &+ \tfrac{1}{2}(w_{j,t-1}^m + w_{jt}^m)\frac{i_{jt}}{i_{j,t-1}} - \tfrac{1}{2}(w_{j,t-1}^e + w_{jt}^e)\frac{e_{jt}}{e_{j,t-1}} + R_u\end{aligned} \qquad \text{(Equation 12)}$$

where the d superscript denotes domestic, and m denotes import, and the shares are:

$$w_{it} = \frac{G_{jit}\gamma_{it}Y_t}{u_{jt}}, \quad w^m_{jt} = \frac{i_{jt}}{u_{jt}}, \quad w^e_{jt} = \frac{e_{jt}}{u_{jt}}$$

and R_u is the approximation residual. When j = coal, for example, we may interpret the above equation as expressing the change in coal use as the sum of the change in technique, the change in the composition of domestic demand, the change in the composition of imports, the growth of GDP, and the change in the level of coal imports and exports. Note that the GDP term on the right-hand side may be simplified using equation 10 to:

$$\sum_j \tfrac{1}{2}(w_{j,t-1} + w_{jt}) \ln \frac{Y_t}{Y_{t-1}} = \tfrac{1}{2}\left(\frac{x_{j,t-1}}{u_{j,t-1}} + \frac{x_{jt}}{u_{jt}}\right) \ln \frac{Y_t}{Y_{t-1}}$$

We also wanted to decompose the change in the intensity of energy use (energy per unit of GDP). Rewriting equation 12 by moving the GDP term to the left-hand side, and denoting the change in intensity of commodity j by $\breve{u}_{jt}$, we get:

$$\begin{aligned}
\breve{u}_{jt} &= \ln \frac{u_{jt}}{u_{j,t-1}} - \tfrac{1}{2}\left(\frac{x_{j,t-1}}{u_{j,t-1}} + \frac{x_{jt}}{u_{jt}}\right) \ln \frac{Y_t}{Y_{t-1}} \\
&= \sum_i \tfrac{1}{2}(w_{i,t-1} + w_{it}) \ln \frac{G_{jit}}{G_{ji,t-1}} + \sum_i \tfrac{1}{2}\left(w_{i,t-1}\frac{y^d_{i,t-1}}{y_{i,t-1}} + w_{it}\frac{y^d_{it}}{y^d_{i,t-1}}\right) \ln \frac{y^d_{it}}{y^d_{i,t-1}} \\
&\quad + \left[-\sum_i \tfrac{1}{2}\left(w_{i,t-1}\frac{y^m_{it}}{y_{i,t-1}} + w_{it}\frac{y^m_{it}}{y_{it}}\right) \ln \frac{y^m_{it}}{y^m_{i,t-1}}\right] \\
&\quad + \tfrac{1}{2}(w^m_{j,t-1} + w^m_{jt}) \frac{i_{jt}}{i_{j,t-1}} + \left[-\tfrac{1}{2}(w^e_{j,t-1} + w^e_{jt}) \frac{e_{jt}}{e_{j,t-1}}\right] + R_u
\end{aligned} \qquad \text{(Equation 13)}$$

When j = coal, for example, equation 13 may be interpreted as saying that the change in the intensity of coal use can be attributed to the following five factors[6].

1) Changes in technology as represented by changes in the **G** matrix.
2) Changes in final demand patterns for domestic goods as represented by changes in the share vectors (γ^d).
3) Changes in the pattern of imports (γ^m).
4) Changes in the level of imports of commodity j.
5) Changes in the level of exports of commodity j.

[6] See the discussion in Garbaccio, Ho and Jorgenson (1999) for their equation 27.

Before applying the above decomposition equation let us summarize the main features of Chinese energy use. Table 1 gives an overview of the domestic output of China's primary energy and secondary energy sectors. We can see that China kept a real GDP growth rate of about 10% from 1981 – 2005, while coal, crude petroleum and gas, and refining petroleum only increased at 5%, giving the decline in energy intensity. Electricity growth was slightly slower than GDP growth at 9.1% per year, compared to 10.1%. However, during the most recent period (2000 – 2005), the overall growth rate of coal, oil, gas and electricity was close to real GDP growth with some energy sectors, such as natural gas and electricity, even exceeding the GDP growth rate. Thus overall energy intensity did not go down as in the earlier period, but was flat or slightly increased. In order to use the SDA method, we collected more data in addition to the I-O tables – industry output prices, export and import prices and quantities for all energy commodities.

As equation 13 suggests, we conducted a decomposition analysis for each of the energy types: coal, crude petroleum and gas, hydroelectricity, electric power (non-hydro), and refined petroleum. The hydroelectric sector is part of the power generation sector in the input-output tables described in the data section above, and we disaggregated it so that we had an explicit hydro industry. We did this in order to be able to isolate the contribution of the main sources of primary energy – coal, crude oil, natural gas, and hydro. Nuclear power and biomass were still very small sources of electricity from 2000 to 2005, so we did not separate them.

The results of our decompositions of changes in energy use per YUAN of GDP are reported in Tables 2, 3, 4, 5 and 6. The decompositions were performed using the input-output tables from 1981 to 2007 described above. The first column of numbers is the overall change in the use of each type of energy per YUAN of GDP for each year. The next six columns of numbers correspond to the terms on the right-hand side of equation 13, breaking down the change in the energy-output ratio into the five components and the approximation residual. Since China has substantially revised its GDP value, so the data set we have has a gap before and after the year 2000, where the NBS had a consistent national account measurement after 2000 based on the NBS official 2002 benchmark I-O table definition and 2004 census data. For the period before the year 2000, the NBS also revised the whole time series and adjusted the service sector based on 2004 census information. However all the pre-2000 figures are based on a 1997 I-O benchmark, so there is still a gap between the 1981 – 1999 and 2000 – 2007 data, so we divided our sample into two sub-samples for analysis.

Table 1: Domestic Output of Energy Sectors (1981– 2005)

Year	Primary Energy			Secondary Energy			
	Coal	**Crude Petroleum**	**Natural Gas**	**Hydro-Electricity**	**Total Electricity**	**Refined Petroleum**	**GDP* Bil. 2000**
	(mil.SCE)	**(mil.SCE)**	**(mil.SCE)**	**(Twh)**	**(Twh)**	**(mil. SCE)**	**(YUAN)**
1981	432.2	118.9	16.9	65.6	309.3	105.8	1613.0
1982	457.4	117.3	15.9	74.4	327.7	106.8	1759.8
1983	490.0	119.5	16.2	86.4	351.4	113.9	1951.6
1984	533.9	123.4	16.5	86.8	377.0	117.0	2248.2
1985	581.2	131.1	17.2	92.4	410.7	121.1	2551.7
1986	612.8	139.1	18.3	94.5	449.5	130.2	2776.3
1987	660.1	147.3	18.5	100.0	497.3	137.2	3098.3
1988	708.6	159.0	19.0	109.2	545.2	143.6	3448.4
1989	736.7	165.8	20.0	118.4	584.8	149.8	3589.8
1990	752.1	163.8	20.3	126.7	621.2	152.4	3726.2
1991	789.8	177.5	21.4	125.1	677.6	162.2	4069.1
1992	826.4	191.0	21.0	132.5	753.9	171.9	4646.9
1993	866.5	211.1	22.3	151.8	837.3	182.3	5297.4
1994	920.5	213.6	23.4	167.4	928.1	183.5	5991.4
1995	978.6	229.6	23.9	190.6	1007.7	199.1	6644.5
1996	1037.9	250.1	26.8	188.0	1080.0	212.4	7308.9
1997	988.0	281.1	30.2	196.0	1134.5	231.9	7988.6
1998	920.2	284.3	31.0	208.0	1166.2	232.5	8611.7
1999	924.8	302.5	29.0	203.8	1239.3	251.3	9266.2
2000	939.4	321.4	32.0	222.4	1355.6	279.8	10044.6
2001	955.1	327.9	36.3	277.4	1480.8	282.8	10958.7
2002	1006.4	355.2	39.2	288.0	1654.0	295.6	12054.5
2003	1196.9	388.5	44.1	283.7	1910.6	326.9	13272.0
2004	1381.9	453.2	51.9	353.5	2203.3	379.3	14652.3
2005	1552.6	471.8	61.6	397.0	2500.3	398.3	16381.3
Growth (81-05)	*5.47%*	*5.91%*	*5.53%*	*7.79%*	*9.10%*	*5.68%*	*10.14%*
Growth (81-00)	*4.17%*	*5.37%*	*3.40%*	*6.64%*	*8.09%*	*5.25%*	*10.10%*
Growth (00-05)	*10.57%*	*7.98%*	*14.01%*	*12.29%*	*13.02%*	*7.32%*	*10.28%*

Sources: *Chinese Statistical Yearbook*, *Chinese Energy Yearbook*, and author's calculations.
GDP*: computed from our time-series input-output table, so there are some discrepancies compared with the official NBS yearbook statistics.
SCE: Standard Coal Equivalent

Consistent with the overall energy intensity trend in Figure 1, there was a general intensity decline between 1981 and 1999 for the five types of primary energy, followed by rising intensity between 2001 and 2005. In the following discussion we will try to understand the links between actual macroeconomic and energy policy changes and our energy intensity decomposition factors.

3.3.1 Coal

In terms of coal, technical change is the main factor that explains the overall intensity changes during our samples. Except for the period from 1992 to 1996, when Chinese macroeconomics expanded with inefficient investment, overall the coal mining industry improved its technological progress over the whole period from 1982 – 2002. However, during 2002 – 2005 the trend reversed until 2005 – 2007 when China implemented its 20% energy intensity reduction target in the 11th Five-Year Plan. Part of the reason for the trend reversal from 2002 to 2005 was that in the 10th Five-Year Plan China faced huge demand from infrastructure development. With big profits in iron, steel, cement and the chemical industries, small-scale inefficient firms were built up quickly to meet the surge in demand but the level of technology actually declined substantially, eventually leading to the failure to reach the environmental target set for 10th Five-Year Plan. After 2005, China imposed some stringent policies in energy-intensive sectors – mainly in the coal mining and electricity sectors – for example shutting down inefficient coal mines and power plants, and listing the achievement of energy saving and environmental targets as important performance indicators for local government. Thus we observe substantial energy intensity improvement after 2005.

In terms of changes in demand patterns for the coal sector, we can see that except for some periods, such as 1987 – 1989, 1992 – 1993 and 1997 – 1998, the demand pattern in general shifted positively towards a cleaner consumption structure. Coincidently, these special periods all correspond to major reforms or events, such as Deng's trip south, which foreshadowed the start of SOE (State-Owned Enterprises) reform in 1992, the Asian economic crisis in 1997, and the Yangtze River floods of 1998. So we can see inefficiencies before these historical moments and big improvements following them. Similarly, for the period 2001 – 2005 we can see that inefficiencies arose due to a huge surge in demand for housing and real estate development. The 11th Five-Year Plan energy policy also reversed the negative demand trend.

Imports and exports play important roles after 1991, though they are not as important as technological change and demand patterns. For the sub-periods of 1994 – 1998 and 2001 – 2005 we can see that import patterns play a positive role in energy intensity reduction, however after 2005 although overall energy intensity declined the trend of coal importation was reversed, thus dragging down progress in energy conservation. On the other hand, China's coal exports increased substantially during 2002 – 2004 then contracted again after 2004, reflecting changes in both domestic and world coal markets.

3.3.2 Crude Petroleum and Gas

We can see that during the pre-2000 period, crude petroleum and gas had similar effects to coal but after 2002 inefficiencies in technology and in demand, partly due to a surge in demand for automobiles in China, was reflected in the trend reversal. We also found big changes between 1992 – 1993 and 1997 – 1998. Part of the reason for this may have been due to macro events, though data issues could be another reason for outliner estimates. We observed a big improvement in efficiency between 2000 and 2002, however this trend was reversed after 2002 and got even worse after the 11th Five-Year Plan, because there is only an overall energy efficiency target, which encourages a shift in the use of coal to oil, and there was no policy to curb automobile use. Import and export patterns and level changes were key factors affecting overall energy intensity for crude oil, and imports played a much more important role than exports. This trend became more prominent in the post-2000 period, shedding light on the challenges ahead in improving oil efficiency and curbing vehicle emissions.

Tables 4, 5 and 6 show the decomposition results for hydroelectricity, electricity power (non-hydro) and refined petroleum. Except for hydroelectricity, both the electricity (non-hydro) and refined petroleum results suggest that intensity in 2005 – 2007 basically followed the trend of 2002 – 2005, and that the post-2000 trend is quite different from the pre-2000 trend. Since 2004, electricity demand has faced a shortage, with two-digit GDP growth, meanwhile the coal price and electricity price are managed by the NDRC, thus a low electricity price leads to excess demand. In some areas, such as Guangdong Province, inefficient oil-fired power plants have been put into production again with local government subsidies to support the electricity shortage. These partly offset the government's efforts in terms of the small unit power plant shutdown policy and the energy saving target policy.

Table 2: Decomposition of change in energy use per unit of GDP (SDA method): Coal

Of which:

Overall change per YUAN of GDP		Technical change	Change in demand patterns	Change in import patterns	Change in quantity of imports	Change in quantity of exports	Residual
Type of energy							
Coal							
Pre-2000							
1981-1982	0.1237	0.1301	0.0153	-0.0029	-0.0013	-0.0049	-0.0127
1982-1983	-0.0043	-0.0485	0.0472	0.0136	0.0003	0.0040	-0.0209
1983-1984	-0.0926	-0.0849	-0.0180	0.0297	-0.0011	-0.0058	-0.0125
1984-1985	-0.1679	-0.1875	0.0045	0.0445	-0.0099	-0.0087	-0.0109
1985-1986	-0.0473	-0.0625	-0.0004	-0.0081	0.0039	-0.0107	0.0305
1986-1987	-0.0834	-0.0876	-0.0345	-0.0048	0.0002	0.0017	0.0416
1987-1988	0.0734	0.0454	0.0298	-0.0098	-0.0007	-0.0044	0.0130
1988-1989	0.1578	0.1288	0.0598	0.0027	-0.0030	0.0064	-0.0369
1989-1990	-0.0302	0.0503	-0.0289	0.0161	-0.0007	-0.0182	-0.0487
1990-1991	-0.0590	-0.0291	-0.0206	0.0044	0.0036	-0.0088	-0.0085
1991-1992	-0.1021	-0.0885	-0.0176	0.0168	-0.0016	-0.0120	0.0008
1992-1993	0.1138	0.1185	0.0138	-0.0045	0.0036	0.0246	-0.0422
1993-1994	-0.1096	0.0274	-0.0934	0.0314	-0.0022	-0.0122	-0.0606
1994-1995	0.0206	0.0348	-0.0006	-0.0225	-0.0005	0.0027	0.0067
1995-1996	0.1472	0.1563	0.0279	-0.0085	-0.0052	-0.0003	-0.0231
1996-1997	-0.0578	-0.0093	-0.0606	-0.0178	0.0066	-0.0002	0.0234
1997-1998	0.0121	-0.0544	0.0704	-0.0138	0.0009	0.0013	0.0077
1998-1999	-0.1210	-0.0645	-0.0545	0.0164	0.0002	-0.0010	-0.0177
Post-2000							
2000-2001	-0.0659	-0.0318	-0.0141	0.0053	0.0005	-0.0228	-0.0030
2001-2002	0.0142	-0.0739	0.1057	-0.0231	0.0060	0.0033	-0.0039
2002-2003	0.0585	0.2064	-0.1236	-0.0617	0.0005	-0.0022	0.0390
2003-2004	0.0613	0.1612	0.0856	-0.0602	0.0083	-0.0109	-0.1227
2004-2005	0.0962	0.1521	-0.0364	-0.0092	0.0057	0.0013	-0.0174
2005-2007	-0.1391	-0.2615	-0.1225	0.0552	0.0078	0.0012	0.1806

Table 3: Decomposition of change in energy use per unit of GDP (SDA method): Crude Petroleum and Gas

Overall change per YUAN of GDP		Of which: Technical change	Change in demand patterns	Change in import patterns	Change in quantity of imports	Change in quantity of exports	Residual
Type of energy							
Crude Petroleum and Gas							
Pre-2000							
1981-1982	-0.0585	-0.0762	-0.0286	-0.0083	0.0000	-0.0076	0.0622
1982-1983	-0.0954	-0.0550	-0.0180	0.0071	0.0000	-0.0274	-0.0022
1983-1984	0.0393	0.1213	0.0298	0.0273	0.0000	-0.0698	-0.0693
1984-1985	-0.4092	-0.2353	-0.1600	0.0500	0.0000	-0.0121	-0.0519
1985-1986	0.0192	-0.0235	-0.0080	-0.0024	0.0000	0.0599	-0.0069
1986-1987	-0.0517	-0.0024	-0.1157	-0.0033	0.0000	0.0780	-0.0083
1987-1988	-0.0679	-0.1213	-0.0638	0.0083	0.0000	0.0585	0.0504
1988-1989	0.0897	0.0495	0.0486	0.0095	-0.0041	0.0158	-0.0298
1989-1990	0.0427	0.0750	0.0818	0.0477	-0.0173	-0.0474	-0.0972
1990-1991	0.0977	0.0300	0.0657	0.0553	-0.0491	0.0109	-0.0150
1991-1992	0.0600	0.1311	-0.0373	0.0391	-0.0556	0.0042	-0.0215
1992-1993	0.1472	0.2754	-0.0776	-0.0141	-0.0129	0.0201	-0.0437
1993-1994	0.0757	0.1858	-0.0077	0.0886	-0.0708	-0.0075	-0.1126
1994-1995	-0.0964	-0.1805	0.0320	0.0158	-0.0245	-0.0134	0.0741
1995-1996	-0.0240	-0.1175	0.0448	-0.0536	0.0340	-0.0128	0.0812
1996-1997	0.0459	0.0997	0.0238	0.0477	-0.0514	-0.0404	-0.0335
1997-1998	0.4860	0.5364	0.1083	-0.0935	0.0490	0.0332	-0.1474
1998-1999	0.0668	0.1130	-0.0162	0.0324	-0.0205	0.0151	-0.0570
Post-2000							
2000-2001	-0.1225	-0.0245	-0.1519	0.0893	-0.0383	0.0145	-0.0117
2001-2002	-0.0684	-0.0376	0.0017	-0.0030	-0.0121	0.0017	-0.0191
2002-2003	0.1377	0.1621	0.0754	-0.2177	0.1604	-0.0039	-0.0386
2003-2004	0.1174	0.1175	0.0556	-0.2112	0.1541	0.0050	-0.0036
2004-2005	0.1391	0.1145	-0.0078	-0.0568	0.0865	-0.0110	0.0137
2005-2007	0.2729	0.2032	-0.1082	0.0301	0.1612	0.0039	-0.0173

Table 4: Decomposition of change in energy use per unit of GDP (SDA method): Hydroelectricity

Overall change per YUAN of GDP		Of which: Technical change	Change in demand patterns	Change in import patterns	Change in quantity of imports	Change in quantity of exports	Residual
Type of energy							
Hydroelectricity							
Pre-2000							
1981-1982	0.0499	0.1277	-0.0624	-0.0047	0.0000	0.0000	-0.0107
1982-1983	0.0390	0.0405	0.0281	0.0155	0.0000	0.0000	-0.0452
1983-1984	-0.2041	-0.2133	-0.0352	0.0368	0.0000	0.0000	0.0076
1984-1985	-0.1059	-0.1336	0.0377	0.0486	0.0000	0.0000	-0.0587
1985-1986	-0.1435	-0.2078	-0.0089	-0.0036	0.0000	0.0000	0.0767
1986-1987	-0.0555	-0.0735	-0.0162	-0.0039	0.0000	0.0000	0.0382
1987-1988	-0.0443	-0.1124	0.0119	-0.0161	0.0000	0.0000	0.0723
1988-1989	0.1336	0.1731	0.0073	-0.0009	0.0000	0.0000	-0.0458
1989-1990	0.0945	0.2118	-0.0291	0.0211	0.0000	0.0000	-0.1093
1990-1991	-0.0584	-0.0477	-0.0064	0.0141	0.0000	0.0000	-0.0184
1991-1992	-0.0191	0.0008	0.0021	0.0241	0.0000	0.0000	-0.0460
1992-1993	0.0205	0.0234	0.0246	-0.0032	0.0000	0.0000	-0.0243
1993-1994	0.0652	0.1306	-0.0251	0.0398	0.0000	0.0000	-0.0801
1994-1995	0.0526	0.0508	0.0233	-0.0274	0.0000	0.0000	0.0059
1995-1996	-0.0557	-0.1061	-0.0043	-0.0162	0.0000	0.0000	0.0709
1996-1997	0.0472	0.0458	0.0079	-0.0134	0.0000	0.0000	0.0069
1997-1998	0.3030	0.4625	0.0175	-0.0131	0.0000	0.0000	-0.1640
1998-1999	-0.1031	-0.1980	0.0733	0.0197	0.0000	0.0000	0.0020
Post-2000							
2000-2001	0.1151	0.1385	-0.0274	0.0046	0.0000	0.0000	-0.0007
2001-2002	-0.0948	-0.0762	-0.0051	-0.0174	0.0000	0.0000	0.0039
2002-2003	0.0819	0.0087	0.1410	-0.0615	0.0000	0.0000	-0.0064
2003-2004	0.2990	0.2754	0.0815	-0.0479	0.0000	0.0000	-0.0100
2004-2005	-0.0504	-0.0207	-0.0151	-0.0061	0.0000	0.0000	-0.0084
2005-2007	-0.2630	-0.2067	-0.1546	0.0491	0.0000	0.0000	0.0491

Table 5: Decomposition of change in energy use per unit of GDP (SDA method): Electricity Power (non-hydro)

		Of which:					
Overall change per YUAN of GDP		Technical change	Change in demand patterns	Change in import patterns	Change in quantity of imports	Change in quantity of exports	Residual
Type of energy							
Electricity Power (non-hydro)							
Pre-2000							
1981-1982	0.2012	0.2433	0.0137	-0.0055	-0.0004	-0.0309	-0.0191
1982-1983	-0.0267	-0.0056	-0.0108	0.0093	-0.0014	0.0042	-0.0223
1983-1984	-0.0374	0.0557	-0.0538	0.0274	-0.0053	-0.0192	-0.0422
1984-1985	-0.4301	-0.4095	-0.0602	0.0679	-0.0409	-0.0206	0.0333
1985-1986	0.0305	0.0882	0.0063	0.0014	-0.0050	0.0110	-0.0715
1986-1987	-0.1782	-0.1408	-0.0647	-0.0025	-0.0048	0.0018	0.0330
1987-1988	0.0543	-0.0539	0.0031	0.0331	-0.0490	0.0185	0.1026
1988-1989	0.0854	0.0521	0.0627	0.0092	-0.0066	0.0033	-0.0353
1989-1990	0.0578	-0.0612	0.1544	0.0458	-0.0408	-0.0270	-0.0135
1990-1991	0.1813	0.1340	0.0835	0.0163	-0.0234	-0.0066	-0.0224
1991-1992	-0.0825	-0.0228	-0.0608	-0.0191	0.0177	0.0003	0.0021
1992-1993	0.1704	0.2632	-0.0412	-0.0042	-0.0062	0.0204	-0.0616
1993-1994	-0.0922	0.0379	-0.0768	0.0160	0.0041	-0.0203	-0.0530
1994-1995	-0.0064	-0.0173	-0.0022	0.0039	-0.0295	0.0017	0.0370
1995-1996	-0.0250	-0.0801	0.0226	0.0007	-0.0178	-0.0063	0.0559
1996-1997	0.0368	0.0714	-0.0168	0.0126	-0.0291	-0.0145	0.0132
1997-1998	0.3179	0.4482	0.0388	-0.0532	0.0366	0.0097	-0.1624
1998-1999	0.0541	0.1269	-0.0287	0.0194	-0.0077	-0.0027	-0.0531
Post-2000							
2000-2001	-0.0784	0.0016	-0.0873	0.0180	-0.0088	-0.0007	-0.0013
2001-2002	0.0092	0.0017	0.0144	-0.0586	0.0540	0.0000	-0.0024
2002-2003	0.0796	0.1574	0.0776	-0.0722	0.0134	-0.0205	-0.0760
2003-2004	0.0991	0.0964	0.0894	-0.0920	0.0492	-0.0148	-0.0292
2004-2005	0.1075	0.1369	-0.0209	-0.0169	0.0237	-0.0127	-0.0026
2005-2007	0.1853	0.0920	-0.0668	0.0768	0.0002	-0.0011	0.0842

Table 6: Decomposition of change in energy use per unit of GDP (SDA method): Refined Petroleum

Of which:

Overall change per YUAN of GDP		Technical change	Change in demand patterns	Change in import patterns	Change in quantity of imports	Change in quantity of exports	Residual
Type of energy							
Refined Petroleum							
Pre-2000							
1981-1982	-0.0310	0.0271	-0.0623	-0.0047	-0.0005	0.0000	0.0093
1982-1983	-0.0345	-0.0518	0.0281	0.0155	-0.0002	0.0000	-0.0260
1983-1984	-0.1631	-0.1604	-0.0351	0.0367	-0.0005	0.0000	-0.0038
1984-1985	-0.0767	-0.0978	0.0376	0.0484	-0.0041	0.0000	-0.0608
1985-1986	-0.0660	-0.0962	-0.0088	-0.0035	0.0001	0.0001	0.0423
1986-1987	-0.0031	0.0080	-0.0162	-0.0039	0.0000	0.0000	0.0090
1987-1988	-0.0389	-0.1048	0.0119	-0.0161	0.0000	0.0000	0.0702
1988-1989	0.1210	0.1560	0.0073	-0.0009	0.0000	0.0000	-0.0413
1989-1990	0.0847	0.1981	-0.0291	0.0211	0.0000	0.0000	-0.1055
1990-1991	0.0205	0.0665	-0.0064	0.0141	0.0000	0.0000	0.0537
1991-1992	0.0289	0.0726	0.0021	0.0241	0.0000	0.0000	-0.0699
1992-1993	0.0041	-0.0014	0.0246	-0.0032	0.0000	0.0000	-0.0159
1993-1994	0.0666	0.1328	-0.0251	0.0398	0.0000	0.0000	-0.0809
1994-1995	-0.0013	-0.0335	0.0233	-0.0274	0.0000	0.0000	0.0363
1995-1996	0.0278	0.0205	-0.0043	-0.0162	0.0000	0.0000	0.0277
1996-1997	0.0440	0.0571	0.0080	-0.0135	0.0000	0.0000	-0.0077
1997-1998	0.2702	0.4145	0.0176	-0.0132	0.0000	0.0002	-0.1490
1998-1999	0.0139	-0.0242	0.0739	0.0198	0.0000	-0.0017	-0.0538
Post-2000							
2000-2001	-0.0185	0.0045	-0.0275	0.0046	0.0000	-0.0007	0.0006
2001-2002	-0.0213	-0.0002	-0.0051	-0.0175	0.0002	0.0002	0.0012
2002-2003	0.2419	0.1664	0.1416	-0.0617	0.0002	-0.0002	-0.0045
2003-2004	0.2216	0.1973	0.0816	-0.0480	0.0001	0.0006	-0.0101
2004-2005	-0.0428	-0.0187	-0.0151	-0.0061	0.0004	-0.0004	-0.0029
2005-2007	0.1865	0.2491	-0.1540	0.0490	-0.0002	-0.0003	0.0429

Note: change in import pattern and change in quantity of export are calculated as

$${}_{i}\ \tfrac{1}{2}\left(w_{i,t-1}\frac{y^{m}_{it}}{y_{i,t-1}}+w_{it}\frac{y^{m}_{it}}{y_{it}}\right)\ln\frac{y^{m}_{it}}{y^{m}_{i,t-1}} \text{ and } \tfrac{1}{2}\left(w^{e}_{j,t-1}+w^{e}_{jt}\right)\frac{e_{jt}}{e_{j,t-1}}$$

, respectively.

3.4 Method 2: Index Decomposition Analysis (IDA)

The second method used was Index Decomposition Analysis (IDA), described in Ma and Stern (2007). This method uses a time series data set from the NBS's final energy use by sector data, and the sector gross output and price data from the I-O data set. In the NBS framework, the aggregate economy is first divided into primary, secondary and tertiary industries. The mining, manufacturing, utilities and construction sectors can be found within the secondary industry category. Then there are sub-sectors within these areas; within manufacturing, for example, there are sub-sectors such as food manufacturing, tobacco, textiles, etc.

Instead of calculating separate decompositions for coal, oil and gas, as in the previous SDA method, here we added the units of energy (in Standard Coal Equivalents, SCE) from all the primary sources to give the total energy consumption of the target of interest. The target may be the total economy, however, here we focused on the mining, manufacturing and utilities sectors only because they have the most reliable data. Let E_{mk} denote the energy in SCE from fuel m used in the *k*-th sub-sector, and Q_k the output. The total energy used in the sub-sector was: $E_k = \sum_m E_{mk}$ and its energy intensity is: $I_k = E_k / Q_k$

Aggregate energy use is $E = \sum_k E_k$, aggregate output is $Q = \sum_k Q_k$ and the overall, or total, energy intensity is thus $I_{tot} = E/Q$. The IDA method expresses the overall energy intensity as a function of the fuel shares in each sector and sector output shares of aggregate output:

$$I_{tot} = \sum_i \sum_j \sum_k \sum_m F_m I_k S_k S_j S_i \qquad \text{(Equation 14)}$$

I_{tot} – overall energy intensity;

F_m – share of fuel m in total energy consumption of the *ijk*-th sub-sector (E_{mk}/E_k); m = coal, oil, gas, hydro;

I_k – energy intensity in the *ijk*-th sub-sector;

S_k – output share of the *ijk*-th sub-sector in the *ij*-th sector;

S_j – output share of the *ij*-th sector in the *i*-th industry;

S_i – output share of the *i*-th industry in the overall economy.

The overall energy intensity can be decomposed as a summation of each of the sub-sectors of the major sectors in the economy. As Ma and Stern (2007) suggest, a Logarithmic Mean Divisa Index (LMDI) would avoid the unexplained residual in the SDA methods, and is not path-dependent so that one can choose any two years for comparison. Differentiating equation 14 with respect to time, and using the logarithmic mean weight scheme, we have:

$$\begin{aligned}\Delta I_{tot} &= \sum_i \sum_j \sum_k \sum_m L(w_{ijkm_{t-1}}, w_{ijkm_t}) \ln\left(\frac{F_{m_t}}{F_{m_{t-1}}}\right) + \sum_i \sum_j \sum_k \sum_m L(w_{ijkm_{t-1}}, w_{ijkm_t}) \ln\left(\frac{I_{k_t}}{I_{k_{t-1}}}\right) \\ &+ \sum_i \sum_j \sum_k \sum_m L(w_{ijkm_{t-1}}, w_{ijkm_t}) \ln\left(\frac{S_{k_t}}{S_{k_{t-1}}}\right) + \sum_i \sum_j \sum_k \sum_m L(w_{ijkm_{t-1}}, w_{ijkm_t}) \ln\left(\frac{S_{j_t}}{S_{j_{t-1}}}\right) \\ &+ \sum_i \sum_j \sum_k \sum_m L(w_{ijkm_{t-1}}, w_{ijkm_t}) \ln\left(\frac{S_{i_t}}{S_{i_{t-1}}}\right) \\ &= \Delta I_{fls} + \Delta I_{tec} + \Delta I_{strss} + \Delta I_{strs} + \Delta I_{stri}\end{aligned} \qquad \text{(Equation 15)}$$

Where $w_{ijkm} = F_m I_k S_k S_j S_i$ and $L(w_{ijkm_{t-1}}, w_{ijkm_t})$ is the logarithmic mean weight:

$$L(w_{ijkm_{t-1}}, w_{ijkm_t}) = \frac{w_{ijkm_t} - w_{ijkm_{t-1}}}{\ln(w_{ijkm_t}) - \ln(w_{ijkm_{t-1}})} \qquad \text{(Equation 16)}$$

That is, the aggregate intensity change, ˘ I_{tot}, is decomposed to five factors:

ΔI_{fls} – intensity change due to fuel substitution;

ΔI_{tec} – technological change;

ΔI_{strss} – structural shift at sub-sector level;

ΔI_{strs} – structural shift at sector level;

ΔI_{stri} – structural shift at industry level.

Our analysis focused on the industrial sector only, this included mining, manufacturing, electric power and hot water utilities; we ignored agriculture and services here. That is, the overall energy intensity in this section is not the economy-wide energy intensity of the previous section using the SDA, but merely the secondary industries. In terms of equation 14 we do not need the S_i term, and in equation 15 there is no ˘ I_{stri} term. We also just focused on total energy use in each sub-sector, ignoring the reallocation among fuel types. The fuel substitution effect was folded into the technological change term. Thus, we focused on the following three factors:

ΔI_{tec} – technological change;

ΔI_{strss} – structural shift at sub-sector level;

ΔI_{strs} – structural shift at sector level.

The I-O data set described earlier includes a version with 62 sub-sectors, with 52 of these in the mining/manufacturing/utilities group. This gives us the output of the 52 sub-sectors for each year between 1993 and 2005. *The Chinese Energy Statistical Yearbook* (CESY) gives final energy use for 39 sub-sectors within Industry (Tables 5 – 3 of CESY 2007). Final energy use includes the combustion of fossil fuels and electricity but excludes biomass and energy embodied in intermediate inputs. Combining the output and energy use data gives us information for 39 sub-sectors.

Table 7 gives the results of the above IDA method of decomposing energy intensity changes in the mining, manufacturing and electricity power sectors. The industrial energy intensity drops very quickly during 1982 – 1987 and 1990 – 1994. Overall, due to the data difference, the IDA decomposition results in some years are quite different from the SDA methods. But for 2005 – 2007, the general trend is consistent for all the sectors using both methods. We can see that for the coal sector there were inefficiencies during 2000 – 2005 but with the 11th Five-Year Plan there was an efficiency improvement in 2005 – 2007. However for other energy sectors, we did not observe this effect, which suggests that our energy conservation mostly focused on coal use only, thus the overall intensity decline from 2005 to 2007 was still very limited.

Table 7: Decomposition of change in energy use per unit of GDP (IDA method)

	Energy intensity change	Technical change	Structural change	Residual	Energy intensity change	Technical change	Structural change	Residual	Energy intensity change	Technical change	Structural change	Residual	Energy intensity change	Technical change	Structural change	Residual	Energy intensity change	Technical change	Structural change	Residual
	Coal				**Crude Petroleum**				**Refined Petroleum**				**Electricity Utilities**				**Gas Utility**			
1981-1982	0.108	1.236	-1.128	-0.001	-0.030	0.150	-0.184	0.004	0.238	0.654	-0.416	0.000	0.019	1.032	-1.012	-0.001	0.014	0.937	-0.921	-0.001
1982-1983	-0.042	-1.124	1.083	0.000	-0.064	-0.126	0.061	0.000	-0.009	-0.537	0.528	0.000	-0.037	-1.215	1.178	0.000	-0.036	-1.087	1.051	0.000
1983-1984	-0.115	-0.108	-0.006	0.000	0.059	0.195	-0.136	0.000	0.009	-0.029	0.038	0.000	-0.146	-0.297	0.151	0.000	-0.112	-0.244	0.132	0.000
1984-1985	-0.197	-0.319	0.122	0.000	-0.321	-0.116	-0.204	-0.001	-0.352	-0.382	0.029	0.001	-0.093	-0.187	0.093	0.000	0.156	0.067	0.089	0.000
1985-1986	-0.043	0.068	-0.111	0.000	-0.043	0.534	-0.577	0.000	0.069	0.072	-0.003	0.000	-0.054	-0.057	0.003	0.000	0.035	0.031	0.005	0.000
1986-1987	-0.074	0.109	-0.163	-0.020	-0.058	0.100	-0.058	-0.099	-0.129	-0.071	-0.056	-0.002	0.017	0.046	-0.028	-0.002	-0.019	0.001	-0.019	-0.001
1987-1988	0.086	0.055	0.027	0.005	-0.079	-0.019	-0.016	-0.044	-0.022	-0.027	0.004	0.002	-0.032	-0.118	0.086	0.000	0.163	0.088	0.073	0.002
1088-1989	0.129	-0.075	0.204	0.000	0.073	-0.230	0.303	0.000	0.032	-0.048	0.080	0.000	0.115	0.004	0.111	0.000	0.119	0.004	0.115	0.000
1989-1990	0.000	-0.063	0.062	0.000	0.097	-0.391	0.488	0.000	-0.080	-0.130	0.049	0.000	0.086	0.079	0.007	0.000	0.097	0.096	0.001	0.000
1990-1991	-0.036	0.106	-0.142	0.000	0.075	-0.067	0.141	0.000	0.105	0.131	-0.026	0.000	0.037	0.011	0.025	0.000	0.058	0.037	0.021	0.000
1991-1992	-0.098	-0.005	-0.093	0.000	0.052	0.245	-0.193	0.000	-0.041	-0.013	-0.028	0.000	0.033	0.065	-0.032	0.000	-0.057	-0.061	0.003	0.000
1992-1993	0.128	0.182	-0.059	0.005	0.201	0.483	-0.281	-0.001	0.237	0.276	-0.051	0.013	0.036	0.113	-0.080	0.003	0.146	0.191	-0.051	0.006
1993-1994	-0.033	-0.097	0.035	0.028	0.050	0.109	-0.063	0.004	-0.051	-0.043	-0.013	0.005	0.020	-0.051	0.065	0.005	-0.155	-0.205	0.053	-0.002
1994-1995	0.038	0.086	-0.047	0.000	-0.143	-0.164	0.022	0.000	0.009	0.075	-0.066	0.000	-0.009	0.085	-0.094	0.000	-0.044	0.050	-0.094	0.000
1995-1996	0.150	0.230	-0.080	0.000	-0.068	-0.133	0.065	0.000	-0.037	-0.055	0.018	0.000	0.042	0.010	0.032	0.000	0.060	0.027	0.033	0.000
1996-1997	0.010	0.083	-0.073	0.000	0.069	0.081	-0.012	0.000	0.075	0.080	-0.005	0.000	0.059	0.083	-0.024	0.000	0.066	0.060	0.006	0.000
1997-1998	-0.041	0.628	-0.669	0.000	0.494	1.053	-0.558	-0.001	0.334	0.699	-0.364	0.000	0.284	0.736	-0.452	0.000	0.201	0.656	-0.456	0.000
1998-1999	-0.057	-1.015	0.958	0.000	0.061	0.090	-0.028	0.000	0.067	-0.295	0.363	0.000	-0.041	-0.383	0.342	0.000	0.021	-0.341	0.362	0.000
2000-2001	-0.045	0.075	-0.121	0.000	-0.087	0.871	-0.958	0.000	-0.004	0.023	-0.027	0.000	0.007	-0.026	0.033	0.000	0.006	0.016	-0.010	0.000
2001-2002	-0.083	-0.023	-0.050	-0.010	-0.080	-0.027	-0.004	-0.049	0.013	0.000	0.011	0.002	0.010	0.006	0.003	0.001	-0.013	-0.045	0.028	0.004
2002-2003	0.256	0.051	0.205	0.000	0.129	-0.610	0.738	0.000	0.155	0.146	0.009	0.000	0.197	0.231	-0.034	0.000	0.111	0.017	0.094	0.000
2003-2004	0.173	-0.089	0.257	0.005	0.111	-0.320	0.430	0.001	0.093	-0.134	0.224	0.003	0.238	-0.059	0.282	0.016	0.137	-0.038	0.174	0.001
2004-2005	0.123	0.210	-0.096	0.008	0.129	-0.043	0.154	0.017	0.126	0.114	-0.009	0.021	-0.019	-0.024	0.002	0.003	0.068	0.060	0.001	0.007
2005-2007	-0.240	0.502	-0.818	0.076	0.189	0.929	-0.788	0.048	0.122	0.396	-0.364	0.090	0.275	0.886	-0.534	-0.077	0.274	0.538	-0.441	0.177

The caveats for the IDA methods rely on its decomposition of sector classifications at different layers and data is extracted from very different sources, so its results are less reliable than the SDA method. In summary, when we conclude the total energy intensity change, we can see that both methods show that after the year 2000 there is a reverse trend. Changes in technology and the pattern of demand both play important roles here, and sometimes both have opposite effects.

3.5 Method 3: Simple Index

Most energy decomposition studies use the SDA or IDA methods implemented here. However, the results from these decomposition techniques are difficult to use to specify AEEI parameters that could be incorporated into CGE models. Therefore, we also used a simple decomposition technique suggested by Wing and Eckaus (2004 and 2005) to apply a simpler index for linking with our CGE model.

Let the energy used in industry *i* in period t be E_{it}, the output be Y_{it}, and the aggregate energy use be E_t^*. Aggregate energy intensity is a weighted sum of the sectoral intensities:

$$\frac{E_t^*}{Y_t^*} = \left[\prod_{i=1}^{N} \phi_{i,t} \left(\frac{E_{it}}{Y_{it}}\right)\right]^{1/N} \qquad \text{(Equation 17)}$$

where $\frac{E_t^*}{Y_t^*}$ is the overall energy intensity, N is the total number of sectors which include the primary, manufacturing and tertiary sectors, and $\phi_{i,t}$ is the weight of industry i given by the ratio of its share of GDP to its share of total energy use $(\frac{Y_{it}/Y_t^*}{E_{it}/E_t^*})$ and $\left(\frac{E_{it}}{Y_{it}}\right)$ is the energy intensity of each sector *i*. Taking the time derivative of equation 17 in logarithms, we have:

$$\frac{\partial}{\partial t}\ln\left(\frac{E_t^*}{Y_t^*}\right) = \underbrace{\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial t}\ln\phi_{i,t}}_{\Phi^*} + \underbrace{\frac{1}{N}\sum_{i=1}^{N}\frac{\partial}{\partial t}\ln\left(\frac{E_{it}}{Y_{it}}\right)}_{\Psi^*} \qquad \text{(Equation 18)}$$

The change in overall energy intensity can be decomposed as two parts:

1) Structural change effects: the average of changes in industries' contributions to aggregate energy intensity, denoted as Φ^*;
2) Intensity change effects: the average of changes in energy intensity within industries, such as input substitution, pure technology progress with fixed amounts of inputs, denoted as Ψ^*.

We combined our time-series 1981 – 2007 I-O tables with the physical units of energy used by five energy industries: coal, oil and gas mining, hydro, the refining sector (processing of petroleum, coking, nuclear fuel, etc.), and electricity. Figure 4 presents the estimated structural change effects (Φ^*) and intensity change effects (Ψ^*) of coal use in China. Figure 5 shows the estimated structural change effects (Φ^*) and intensity change effects (Ψ^*) of crude oil and natural gas in China. For coal use, we can see that the overall change in energy intensity ($\Phi^* + \Psi^*$) is negative in most years except 2003–2005. The improvement in energy efficiency is mostly attributed to changes in technology – we can see that in only 6 out of 24 years the intensity change effects were positive, and for about half of the years the structural change effects are positive. Although this is only the energy change for coal use, considering coal use accounts for about 70% of total energy use in China, it is not surprising that the coal result alone coincides with the total energy intensity trend in Figure 1. For crude oil and natural gas, we see similar overall trend changes, though structural changes and technology changes are more volatile than coal use, except during 2005 – 2007.

The detailed results of coal intensity decomposition in the mix of industries within the large sectors is shown in Figures 6 and 7, both are in terms of coal consumption. We can see that structural composition changes and energy intensity changes vary substantially across different sectors. For example, in most energy-intensive industries and service industries, the origins of coal intensity decline can be attributed to within-industry intensity changes. In fact, we can also see that for energy-intense sectors and service sectors, the effects of the changing composition of industry increase the use of energy. However, for agriculture and other manufacturing, the effects of changing industrial composition may exceed the energy intensity changes within the industry, and both effects are working in the same direction, reinforcing the decline in overall energy intensity. From 2003 – 2005, within-industry energy intensity changes were smaller in all the four major sectors: agriculture, energy-intensive sectors, other manufacturing, and service sectors. This explains why overall energy intensity flattens out after 2003, especially the improvement from the structural change, which is almost flat for most sectors when compared to 1981 levels. From 2005 to 2007, we can see that within-sector intensity change improved substantially for coal use, however this, for the most part, was offset by the structural change in the opposite direction. Therefore, overall the aggregate intensity change was still quite limited.

In summary, our paper obtained similar results to many previous energy intensity decomposition studies for China for the pre-2000 era. For example, using a discrete SDA method, Lin and Polenske (1995) suggested that the origin of the energy intensity decline between 1981 and 1987 was technology change, rather than final demand changes. In addition, with an improved SDA method and updated I-O data for 1987 and 1992 tables, Garbaccio and Ho (1999) also suggested that technology change within sectors accounted for most of the fall in the energy-output ratio, and pointed out that structural change increased the use of energy. Zhang (2003) used the Laspeyres Index to calculate the energy intensity decomposition for China's manufacturing sectors for 1990 – 1997, and suggested that technology change was the most important reason. Ma and Stern (2006) used the Logarithmic Mean Divisia Index (LMDI) to study the energy intensity trend for 1980 – 2003. They focused on the post-2000 period and suggested that the increased energy intensity could be attributed to negative technology change and that within-sector energy input substitution and structural change played very minor roles. In this study, we applied three decomposition techniques, all suggesting that real technology change after 2002 is limited, however for 2005 to 2007 the trend seems to reverse to some degree, most prominently in the coal sector.

Figure 4: Contribution of structural change and intensity change to change in aggregate energy intensity in the coal sector, 1981 – 2007

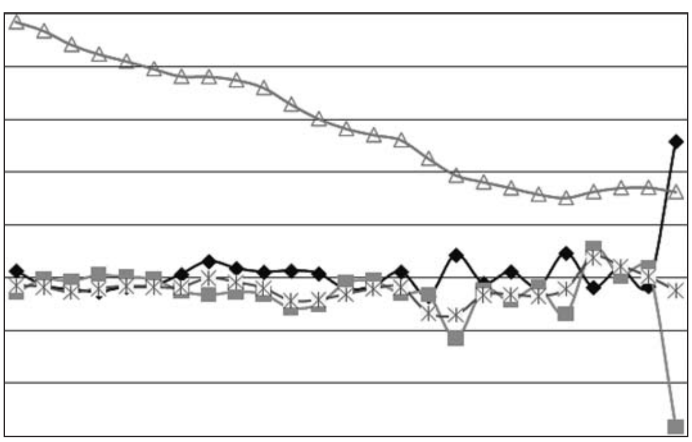


Figure 5: Contribution of structural change and intensity change to change in aggregate energy intensity in the crude oil and natural gas sectors, 1981 – 2007

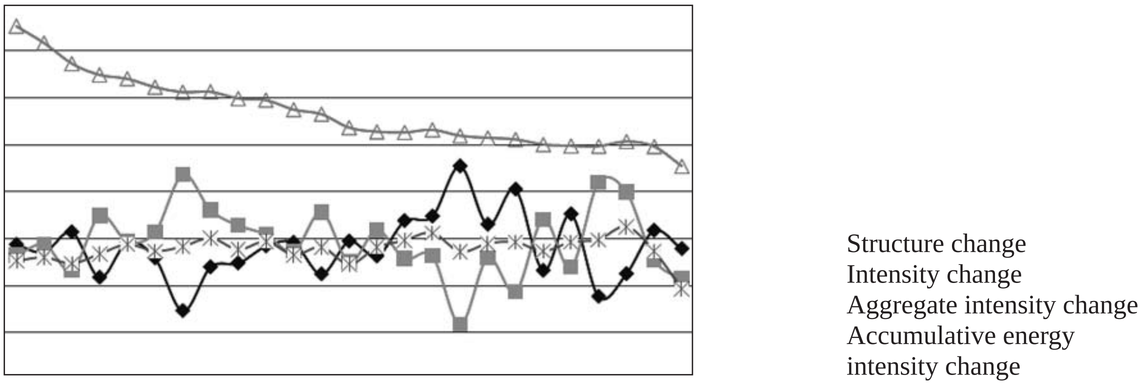
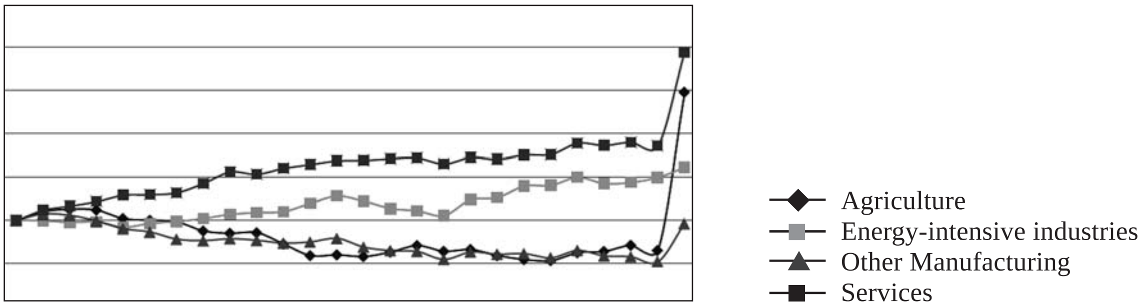
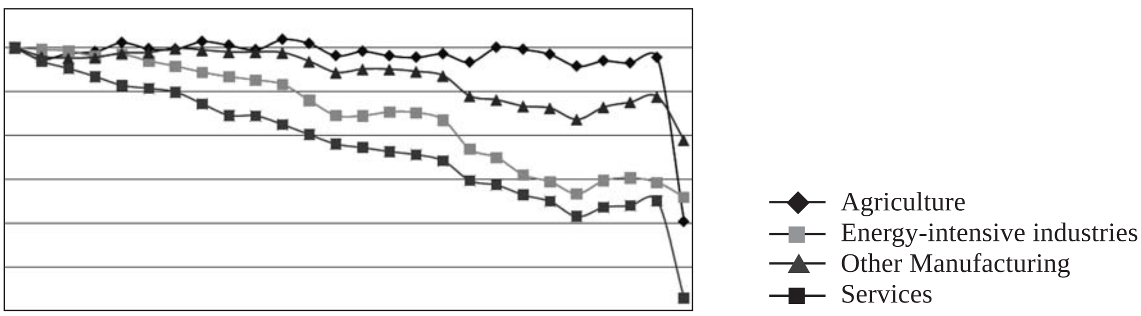


Figure 6: Effects of changing industrial composition by sectors, coal use, 1981 – 2007



(Percentage change from 1981 level)

Figure 7: Within-industry energy intensity change, coal use, 1981 – 2007



(Percentage change from 1981 level)

4.0 ENERGY INTENSITY DECOMPOSITION, ENERGY USE PROJECTIONS AND ENVIRONMENTAL POLICY ANALYSIS

We now turn to the question of what these results imply for the projection of energy use and carbon emissions in the long-term future, especially how the energy intensity decomposition results for the historical data can be of some use to the CGE model analysis and policy simulations. At the moment, most CGE models normally assume one-size-fits-all AEEI parameters to indicate the autonomous energy efficiency improvement, that is, all the countries and most models use the same common parameter, assuming AEEI shows a 1% improvement every year.

It has long been understood that AEEI is not a simple factor, but a shorthand approximation of several complicated processes, such as: energy-saving technological progress that uses less energy with given fixed inputs; shifts in the composition of energy mix; shifts in the composition of the economy that demand less energy use (i.e. structural changes); relevant policy effects, such as environmental policies that restrict the use of fossil fuels; research and development and technological diffusion; or simply removing market barriers to more advanced energy-saving technologies (Williams 1987, 1990; Williams et al. 1987, Weyant, 2000, Wing and Eckaus, 2005).

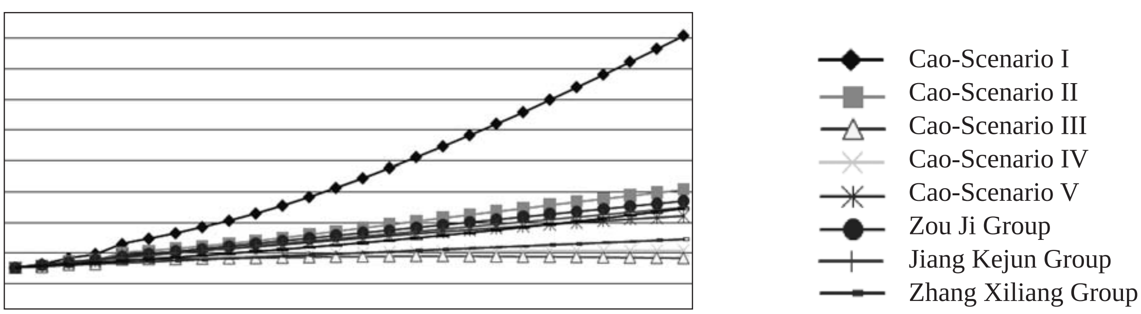
In this study, we conducted a number of numerical experiments to shed some light on various future energy use and carbon emission scenarios. The scenarios are described in Table 8.

Table 8: Experiments with the CGE model AEEI scenarios

Scenarios	Growth Rate of AEEI
I	No AEEI improvements
II	1% per year
III	Average annual rate of overall energy intensity change $(\Phi^* + \Psi^*) = 0.0476$, 1981 – 2007
IV	Average annual rate of overall energy intensity change $(\Phi^* + \Psi^*) = 0.0229$, 2000 – 2007
V	Average annual rate of overall energy intensity change $(\Phi^* + \Psi^*) = 0.0177$, 2000 – 2005

First, we considered a scenario where we assumed no AEEI at all in a control experiment, that is only the benchmark I-O table was used in our simulations. Secondly, we adopted the most common assumption in energy modeling, that is to assume that the AEEI shows a 1% improvement for each sector every year. Thirdly, following the Wing and Eckaus study of 2005, and based on our energy intensity studies above, we assumed that the AEEI parameters incorporated both structural and intensity change factors, and we used different sample periods 1981– 2007, 2000 –2007 and 2000 – 2005 results for our sensitivity analysis to forecast carbon emissions using our CGE model. Note the difference from other carbon emission forecasts, which focus on empirical estimation techniques – here we conducted a sensitivity analysis on AEEI parameters, then ran our CGE model in order to obtain a forecast of carbon emissions. From 2000 – 2005 our overall intensity change (1.77%) was only slightly higher than the one-size-fits-all AEEI (of 1%). If we incorporate the 11th Five-Year Plan period after 2005, then overall intensity from 2000 – 2007 was about 2.29%, and if we consider the overall AEEI for 1981 – 2007, then technology progress stands at 4.76%.

Figure 8: Range of uncertainties in model projections (Carbon emission forecasts)



Carbon emissions (in million tC)

Figure 8 shows our forecast of China's future energy use and carbon emissions up until 2030. Without any improvement in AEEI, we can see that energy use and carbon emissions will increase six-fold by 2030. If we adopt the common AEEI assumption (1% per year), then both energy use and carbon emissions will be cut by more than half. If we base our AEEI assumption on data from 2000 – 2005, our carbon emissions forecast is similar to EIA (2008), Zou Ji's group at Renmin University, and ERI Jiang Kejun's group results. If we assume 2000 – 2007 and 1981 – 2007 results, our forecast is much lower than most other groups at the "business-as-usual" level. During 2000 – 2005 there was no important energy policy in place and after 2005 China imposed a very stringent energy intensity target policy. Therefore, we think that an overall AEEI of 1.7% is more reliable in the business-as-usual scenario and is mostly consistent with other modeling groups' results, so we have used this as our central estimate in the following policy analysis, while using other scenarios to test for sensitivity and robust checks.[7]

4.1 An Overview of the Chinese Economy-Energy-Environment CGE Model

To have a better and more reasonable forecast of future energy use and carbon emissions in China, we incorporated the results of the previous section into a recursive-dynamic CGE model of the Chinese economy[8]. In the following section, we will describe the economic module and the environmental module respectively.

4.1.1 Economic Module

Production

The production technology is a nested Cobb-Douglas production function:

$$QI_{jt} = g(j,t)KD_{jt}^{\alpha_{Kj}} LD_{jt}^{\alpha_{Lj}} TD_{jt}^{\alpha_{Tj}} E_{jt}^{\alpha_{Ej}} M_{jt}^{\alpha_{Mj}} \quad \text{(Equation 19)}$$

where is *g(j,t)* the technical progress term that assumes rapid technology progress at the beginning, followed by a decrease in growth rate, and eventual stabilization at a steady state. When analyzing the impacts of policies, the Cobb-Douglas production function is sometimes more flexible than other function forms, such as the Constant Elasticity of Substitution (CES) function, or translog functions. Considering that there are no reliable econometric estimates for such functions, we have used the calibrated Cobb-Douglas parameter in our model, and leave alternative models of function forms for future work. However, this assumption may underestimate policy impacts on the economic system or overestimate energy reduction or environmental performance.

Household

The representative household drives utility from the consumption of commodities, supplies an inelastic supply of labor input in production, and owns a share of the capital stock; it also receives lump-sum transfers and interests on its public debts. For the recursive property, the representative household makes exogenous savings decisions that are transformed into investment in the subsequent period.

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[7] Scenario I assumes no efficiency improvement and structural shift, so it is not realistic. In the uncertainty analysis on environmental policies we drop this scenario as upper bound but pick the 1% AEEI assumption as upper bound for energy use and carbon emissions.

[8] A detailed description of the Chinese CGE model is given in Appendix 1.

Capital and Investment

The Chinese capital stock was modeled in two parts: the first part is the share of planned capital, from the centrally-planned economy, because some state-owned enterprises receive favorable investment funds directly from the state budget; the second part is market capital, the rental price of which is equal to the marginal product of capital input. Both types of capital are evolved with investment accumulation and depreciation.

Pre-Existing Taxation

The model includes a variety of pre-existing taxes, such as: taxes on production; taxes on consumption; subsidies for production and consumption; and tariffs and subsidies on exports. With tax reform in 1994, the Chinese taxation system has moved to a broader tax base and a value-added tax covers all the industrial sectors, commerce, enterprise profits tax, and sales tax.

International Trade

This model assumed imperfect substitution among goods originating from China and those from the rest of the world. The demand for imported goods was derived from a CES aggregation of domestic and imported goods. The current account and government debts were set as exogenous. Although at this stage of our CGE model development such a strong assumption was not quite realistic, we focused on calibrating the 2005 – 2008 current account, and we were only concerned with short-medium-run simulation results, mitigating the effects of such modeling weaknesses. Our policy was focused on the domestic, so changes in imports and exports were not quite as important for our purposes. In addition, our domestic policy changes only brought about second-order bias when we compared with the benchmark case.

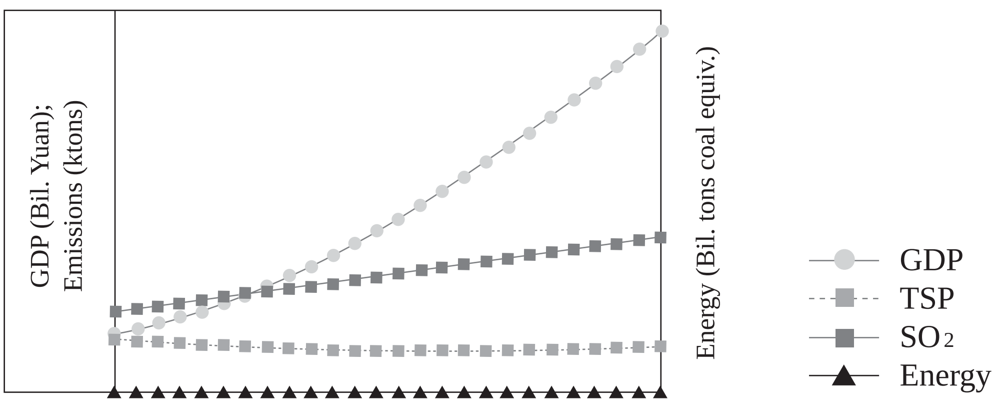
Market Clearing

All market prices in the model were endogenous and adjusted to clear the market for goods and factors. In addition, the government debt balance, trade balance, and savings-investment balance were combined in order to complete the model. The Walras Law was checked to test the market clearing.

Calibration

To improve the robustness of the model, a critical step after setting up the model was to calibrate parameters in the recursive CGE model so that it could successfully "replicate" the benchmark year of 2002 for China. But, different to the previous version, the energy input share parameters were based on our empirical work on energy intensity decomposition. Figure 9 shows the projected GDP, energy use and pollution trends from 2005 to 2030.

Figure 9: GDP, energy and emissions projected in the base case (Scenario VI)



4.1.2 Environmental Module

One advantage of our CGE model lies in its integrated structure; both economics and energy/pollution/health modules are used for analyzing the benefits and costs of environmental policies. More specifically, the China CGE model has developed a methodology and data base that provide a tractable link between emissions and human exposure, which is incorporated into an environmental damage model that estimates health damage by industry. In estimating the cost and benefit of environmental policies, many previous studies have dealt only with the direct costs of pollution control, such as the cost of scrubbers. In contrast, our CGE modeling approach also identified the indirect, general equilibrium costs. The overall flowchart of this integrated approach is summarized in Table 9.

Table 9: Pollution Impact Pathways and Analysis

1	Economic activity and fossil fuel use to pollutant emissions
2	Emissions to concentrations
3	Concentrations to human exposure
4	Exposure to health impacts
5	Valuation of health impacts
6	Marginal damage by industry and fuel type
7	Benefit-cost analysis of command-and-control and energy taxes based on marginal damage

Step 1. From economic activity and fossil fuel use to pollutant emissions

In our integrated economy-environment model for China, the economic component generated the level of output for 33 industries and the household sector. The input demand functions of the model generated the consumption of fossil fuels – coal, oil and gas – or each industry, which in turn generated the emissions of pollutants. The focus was on three pollutants: TSP, SO_2 and NO_x. Emissions may come from either the combustion of fossil fuels or from production processes. Only NO_x emissions from the transportation sector were considered, because there were no estimates for the other sectors at the time of either study. The emissions of the three pollutants were linked to fossil fuel combustion by emission coefficients (e.g. tons of TSP per ton of coal). The damage due to particulate matter depends crucially on the size of the particles, with fine particles going deep into the lungs. PM_{10} denotes particles smaller than 10 microns, and $PM_{2.5}$ denotes those finer than 2.5 microns. However, comprehensive data for China was only available for TSP. Therefore the emission coefficients were calibrated to the official national TSP data and converted to PM_{10} equivalents.

Step 2. From emissions to concentrations

Although different industries clearly produce different levels of emissions and emissions per dollar of output, it may be less obvious that each ton of emissions from different industries produces a different level of damage. This is due to numerous factors, including differences in meteorology, smokestack characteristics, proximity to dense populations, and distributions of particle size. The modeling of atmospheric transport is a large field of study involving complex atmospheric chemistry. In this interim report we used our previous Harvard-Tsinghua study to calibrate our emission-concentration relationships. The detail of this work is explained in Ho and Jorgenson (2007a, 2007b). Our results have been calibrated to two basic air dispersion models. The first used a relatively simple model for dispersion within 50 km, and the second used a more sophisticated model for regional dispersion of up to 3,000 km. We used this model to calculate the dispersion of pollutants for a sample of sources and, as explained in Step 3, the concentration estimates were combined with population maps.

Step 3. From concentrations to human exposure

In this step, we applied the "intake fraction" *(iF)* methodology described by Levy and Greco (2007) which allowed the Harvard-Tsinghua study to estimate human exposure to all national sources. The *iF* from a particular source is the fraction of a pollutant emitted that is eventually inhaled by people before it is dissipated. This method calculates the *iF*s using the air dispersion models and population maps for a small sample of sources and then extrapolates to other emission sources. This extrapolation is done using regressions of the *iF*s on a small set of key characteristics, such as a source's stack height and emission characteristics, average wind speed, population within 10 km and total population in the domain. The *iF* estimates for China were obtained by running the air dispersion models over a fine population grid for a sample of sources. The resulting pollution concentrations were then regressed on the key characteristics described above. We then turned to national data sets for the four highly polluting industries and selected a national sample of plants.

Step 4. From exposure to health impacts

This part of the analysis relied on air pollution epidemiology to identify concentration-response coefficients (e.g. the percentage increase in death rates per g/m^3 increase in the PM_{10} concentration). Levy and Greco (2007) summarized the few epidemiological studies for China and compared them to estimates for other countries. They described how most of the studies for the U.S.A., which has much lower levels of pollution, attributed most of the health effects to PM concentrations and a statistically insignificant amount to SO_2 (Levy and Greco, Table 4.5, p135, in Ho and Nielsen, 2007, *Clearing the Air, the Health and Economic Damages of Air Pollution in China)*. However, because the Chinese studies also found statistically significant contributions from SO_2, we have included effects from both types of pollutants. After considering all the studies, we used concentration-response estimates for "acute mortality" of 0.03% per g/m^3 of PM_{10} and 0.03% per g/m^3 of SO_2. Based on the mortality rate in China, we estimated that these values of the concentration-response are equivalent to 1.92 deaths per million people per year per g/m^3 increase in concentration of PM_{10} and SO_2.

Step 5. Valuation of health effects

After the health impacts have been estimated, they need to be monetized in order to compare the benefits of pollution reduction with the cost of pollution reduction policies. The central concept in this analysis is the value of a statistical life (VSL), which is the willingness to pay (WTP) divided by the change in risk. We expressed the value of the change in the number of cases of illness and mortality in terms of Yuan, the Chinese currency. The VSL ranges from a modest YUAN 0.26-0.51 million from Hammit and Zhou (2005) to over YUAN 1.4 million from the World Bank (2008). In our study we conducted sensitivity analysis to compare various environmental policies due to the uncertainty of VSL estimations.

The estimated valuations for the other health effects listed in Table 10 are based on the World Bank (2007) and ECON (2000), and are mostly from studies of Western countries. The top two values of morbidity risks are for chronic bronchitis and respiratory hospital admissions.

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Table 10: Estimates of the value of a statistical life in Chinese studies

Study	**Million YUAN**
Wang and Mullahy (2006)	0.30 – 1.25
Zhang Xiao (2002)	0.24 – 1.70
Hammitt and Zhou (2005)	0.26 – 0.51
Krupnick et al. (2006)	1.40

Source: World Bank (2007)

4.2 Environmental Policy Analysis (Command-and-Control vs. Economic-Incentive-Based Instruments)

When reconciling economic growth and environmental protection, the Chinese government has made a great deal of effort to achieve certain growth rate targets, such as 8% this year (2009). However, in recent years, environmental concerns have been increasingly incorporated into China's planning process at both national and local levels, and targets for pollution control are being set parallel with the the growth rate target. For example, in the area of environmental protection, the National Economic and Social Development 11th Five-Year Plan has set a 20% energy intensity reduction, a 10% SO_2 reduction, and a 10% reduction in COD. These targets were ratified by the Fourth Plenary Session of the 10th National People's Congress in March 2006, and can be seen as an attempt to maintain rapid growth while accommodating increased concern for environmental sustainability.

The 11th Five-Year Plan, covering the years 2006 – 2010, assumed that China's economy is now market-driven, and targets are now specified as either "expected" or "compulsory." Expected targets are those that are anticipated to be achieved through market forces, with the government providing overall macroeconomic stability and the necessary regulatory institutions. Compulsory targets are those that are imposed by central government, with enforcement the responsibility of central government agencies and local governments (Fan 2006; You 2007). Of the compulsory targets, half are directly related to energy and the environment. This plan contains only five targets: three for water quality and two for air, including a 10% reduction in SO_2 emissions and a 20% reduction in energy intensity. The sulfur target is modest, perhaps due to poor performance under the 10th Environmental Protection Plan, which covered the years 2001 – 2005, which was set at 10% below the 2000 level of emissions but was exceeded by more than 40%. The energy efficiency target is very ambitious, reflecting a number of growing concerns in central government. Among these concerns is energy security, as China has been forced to import increasing amounts of oil and natural gas and more recently has also been a net importer of coal (Oster and Davis 2008).

In this study we focused on two typical command-and-control policies in the 11th Five-Year Plan: a technological mandate policy that requires the installation of fluidized gas desulfurization (FGD) equipment in the electricity sector; and a mandate policy to shut down small-scale coal-fired power plants. More specifically, the first policy requires the installation of 167 GW of new FGD equipment in existing power generation units.[9] The adoption of this equipment is expected to result in a reduction of 5.4 million tons of emissions. The second policy is a shutdown of 50 GW of small-scale power generation units during the time span of the plan (2006– 2010). The expected net reduction in SO_2 emissions from this policy is 2.1 million tons. Base year (2005) emissions levels, 2010 business-as-usual (BAU) emissions projections, and the 2010 Five-Year Plan targets are shown in Table 11.

Table 11: SO_2 emissions targets for the 11th Five-Year Plan

	2005	**2010 BAU Baseline**		**2010 Target**		
	mil. tons	**mil. tons**	**Change from 2005**	**mil. tons**	**Change from 2005**	**Change from BAU**
Power Sector	13.3	18	35%	10	-25%	-44%
All Other Sectors	12.2	13	+6%	13	+6%	0%
Total	**25.5**	**31**	**+19%**	**23**	**-10%**	**-26%**

Source: JES (2007)

Table 12: Cost structure for thermal power plants, 2005 (YUAN per kWh)

Costs	**Large Plants**	**Small Plants**		
		Total	**Coal**	**Diesel**
Average Total Cost	0.250	0.704		
Operating & Maintenance Cost	0.057	0.068		
Fuel Costs	0.153	0.596	0.230	2.520

Source: Energy Research Institute

Alternatively, we think that China is ready to impose a new market incentive-based tax or cap-and-trade instruments. In our model, we used a carbon tax to represent this portfolio of policies. We assumed that the tax was imposed on the carbon contents of fossil fuel consumption. Based on a recent Ministry of Finance Carbon Tax study, it is likely that such a tax on fossil fuel will be implemented in the 12th Five-Year Plan or the 13th Five-Year Plan. In fact Chinese energy tax, in the form of the "resource tax", is already undergoing a major reform process to substantially raise its current tax rate to reflect the environmental externality cost. In our study, we assumed a fiscal neutral carbon tax, that is the revenue is either transferred to households as a lump sum, or is used to reduce other pre-existing distorted taxes in the current fiscal structure.

[9] All new power plants are required to install FGD equipment.

In summary, we wanted to compare two different policies: command-and-control policies (FGD, shutdown, and combined 11th FYP FGD and shutdown policy), and a carbon tax (recycled with lump-sum transfer, or recycling other distorted taxes). We assumed that both kinds of policies were imposed from the first year of the 11th Five Year Plan (2006), then we compared their cost-effectiveness and economic impacts with regard to each carbon emission scenario specified in previous sections of this report.

4.2.1 FGD Installation Policy under the 11th Five-Year Plan

At the end of 2005, FGD equipment had been installed on 46.2 GW of coal-fired electricity generation capacity – 12 % of the total. In order to meet the SO_2 reduction target stated in the 11th Five-Year Plan, an additional 167 GW of FGD equipment is scheduled to be installed on existing power generation units by 2010. Moreover, all new power generation units constructed during the 11th Five-Year Plan – estimated in the JES (2007) at 250 GW of capacity – are mandated to have FGD equipment. Thus, if the FGD policy is fully implemented, there will be a total of 463.2 GW of FGD equipment installed on coal-fired power plants by the end of 2010. The IEA's reference scenario (IEA 2007) projects total coal-fired electricity generation capacity at 547 GW in 2010. This means that FGD would be installed in almost 85% of total coal-fired power plant capacity.

The costs of the FGD installation policy can be divided into two types: direct and economy-wide. The direct costs of the FGD policy include the capital costs of the FGD equipment and its operation and maintenance costs, which include additional electricity for the operation of the equipment and so an increase in fuel inputs. Capital costs for FGD units manufactured in China have fallen by more than half since the 1990s as domestic firms have learned to produce this new technology. These costs now range from 150 YUAN per kW for a 600 MW plant to 180 YUAN per kW for a 100 MW plant. As the cost of constructing a 600 MW plant without FGD is approximately 4,000 YUAN per kW, the addition of FGD equipment represents a 3.8% increase in capital costs. The unit operating cost of the FGD equipment (per ton of SO_2 removed) depends on the size of the plant and the sulfur content of the coal used, and ranges from 1,244 YUAN per ton of SO_2 for a 100 MW plant to 800 YUAN per ton for a 1,000 MW plant (for coal with a sulfur content of 1%). Low sulfur coal raises the cost per ton removed, from 1,020 YUAN per ton for 1% sulfur coal to 1,840 YUAN per ton for 0.5% sulfur coal. The Chinese Academy for Environmental Planning (CAEP 2007) reports that coal with a sulfur content of less than 0.5% makes up 30% of coal combusted in the power sector, with coal with a sulfur content of 0.5-1% making up another 35%. Averaging over plant sizes and coal types, CAEP estimates that running FGD equipment raises operating costs by 2.4%. In terms of the price of delivered electricity, which includes transmission costs, the additional cost of running FGD equipment is only 1.5%.

Using our CGE model, we modeled the impact of FGD policy as a negative productivity shock in the production function, that is, to raise electricity prices, by 0.25% in 2006, rising to 0.94% in 2010. Given our unit elasticity assumption, this reduced overall electricity use by approximately the same (absolute) percentage as the rise in price. The higher cost of electricity led to a small decline in the output of energy-intensive industries such as chemicals, non-metal mineral products, and primary metals. The use of FGD also increased the amount of coal required to generate a kWh of deliverable electricity. However, this was offset by the reduction in demand for electricity and the reduction in demand for coal by energy-intensive industries, which led to a small net decline (0.08%) in coal consumption in 2010.

As Table 13 shows, this small negative productivity shock resulted in a slight decline in GDP, with corresponding reductions in the consumption and investment components of GDP. The negative shock gave rise to larger impacts on consumption, while most other indicators, such as impacts on CO_2, TSP, SO_2 and NO_x were similar in the first year or last year. The GDP loss ranged from -0.10% in 2010, corresponding to the central AEEI assumption specified in the previous sections. The impacts on CO_2 and PM are less significant, and there was no revenue collected for the government to reduce other distortions.

4.2.2 Shutting Down Small-Scale Power Plants under the 11th Five-Year Plan

At the end of 2005, almost one third of China's thermal power generation capacity was provided by small-scale power generation units, where small-scale is defined as a unit with a capacity of less than 100 MW.[10] Most of these small-scale units are coal-fired, but some are oil and diesel units serving localities which have in the past experienced severe electricity shortages. These small units are generally inefficient in their use of energy and highly polluting. However, as they have been seen to be providing local benefits, they have continued to operate. With the emphasis on energy efficiency and pollution control in the 11th Five-Year Plan, 50 GW of small-scale power plants have been targeted for closure by the end of the plan (2010).

Table 12 shows the cost structure for thermal power plants. The average total cost per kilowatt hour for small plants is almost three times higher than for large plants. The greatest contributor to this cost is the higher fuel requirements needed to produce a kilowatt hour of electricity. Diesel-fired plants are particularly inefficient.

Implementing the small unit shutdown policy requires replacement capacity to be built. However, as the policy is being implemented gradually over the five years of the plan, the individual units that are shutdown are proportionately small and have a wide geographical spread. Also, the electricity connected to the grid is fungible so the actual cost of replacement capacity is an average of all new capacity installed over the plan period. The direct cost of the shutdown policy would then be equal to the cost of producing the replacement electricity, less the operating and maintenance costs that would have been incurred by operating the small units and the decommissioning costs.[11]

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[10] The NDRC's Energy Research Institute estimates that in 2006 there was about 115 GW of capacity provided by coal- and oil-fired units under 100 MW, out of a total of 391 GW of thermal-fired capacity.

[11] The location of the replacement plants may also mean higher transmission costs.

The decommissioning costs could include the shutdown of the small plants themselves and perhaps the retraining and relocating of displaced workers. The value of any scrap materials and the land the plant was located on should be accounted for as negative costs. Although estimation of the total direct costs of the shutdown of these very heterogeneous units is difficult, limited analysis indicates that when high fuel costs and the value of freed-up land are fully accounted for, the total direct costs of the shutdown policy are negative – even without taking into account the environmental benefits. The environmental benefits of the small unit shutdown policy are substantial. Based on a previous study, it is estimated that the shutdown of 50 GW of small units would save almost 30 million tons of coal over the 11th Five-Year Plan period. The annual reduction in SO_2 emissions from the policy would be about 2.1 million tons.

The second column in Table 13 shows the effects of such a shutdown policy on the economic and environmental variables. We can see that the effects on SO_2 are higher than the FGD mandates, in fact due to the inefficient small scale and higher fuel use, we can see that the positive impacts are the biggest of all of the policies. This shows that in some circumstances command-and-control policies are important because they can prevent the market's myopic perspective on investment, encouraging investment in larger and more environmentally-friendly technologies, thus requiring government intervention to mitigate market failure. Column 3 shows the effects of the combined FGD and shutdown policy, which can be used to approximate China's 11th FYP measures on SO_2 controls. Therefore the impact on SO_2 emissions is very significant, while impacts on CO_2, TSP, and NO_x are quite limited.

4.2.3 Hypothetical Carbon Tax Policies

The alternative policy instrument we picked was the imposition of a carbon tax on energy use. The carbon tax policy is currently being debated in China, compared to an emissions trading policy, and has not yet been implemented by the Chinese government, except for the installation of a new gasoline tax to replace road tolls, which started in January 2009. So it is interesting to ask questions about the potential role of this alternative economic incentive-based tax policy – whether it is more cost-effective than the currently implemented command-and-control options listed above, and how this alternative tax policy differs in terms of influence on energy use, and technology choices within and across sectors. In particular, should this alternative tax policy be recommended to reach a new energy-intensity target in the next (12th) Five-Year Plan?

In this report, we experimented with a carbon tax policy of 100 YUAN per tC on coal, crude oil and natural gas, depending on their carbon content. A carbon tax encourages a switch from polluting coal to cleaner oil and gas, and a substitution of capital for energy. Although it is not a first-best policy, such a tax in general could still generate substantial reductions in pollution.

Table 13: Effects of environmental policies on the economy and environmental performance (in percentages)

	Assumption: reform starts in 2006 and effects in year 2010				
	C&C – FGD policy	**C&C – shutdown policy**	**C&C – combined policy**	**Carbon tax with lump-sum transfer (100 YUAN per tC)**	**Carbon tax with reduced distorted tax (100 YUAN per tC)**
GDP	-0.100	0.732	0.656	-0.129	0.025
Consumption	-0.094	0.479	0.436	0.169	-0.086
Investment	-0.083	1.114	1.137	-0.162	0.379
Coal use	-0.159	-5.478	-5.558	-14.402	-14.167
Oil use	-0.062	-0.447	-0.475	-2.577	-2.368
CO_2 emissions	-0.143	-4.567	-4.638	-12.199	-11.970
Primary TSP from combustion	-0.138	-1.057	-1.162	-12.458	-12.381
SO_2 emissions	-9.184	-16.096	-16.164	-13.077	-12.884
NO_X emissions (transportation)	-0.080	0.353	0.313	-2.231	-1.931
Premature deaths	-4.234	-6.784	-6.891	-11.482	-11.657
Value of health damages	-3.943	-5.718	-6.277	-11.763	-11.574
Change in other tax rates	0.000	0.000	0.000	0.000	3.030
Reduction in damages/GDP	-0.002	-0.0021	-0.002	-0.004	-0.004
Pollution tax/total tax revenue	0.000	0.000	0.000	2.390	2.880

The model was first simulated with the existing tax rates to obtain a base case growth path. We then simulated the carbon tax in the counterfactual case to be compared to the base case. In this experiment, we assumed revenue neutral carbon tax reform, that is, the collected carbon tax revenue would be returned to industries by cutting their VAT and business taxes and other fees.

As shown in the fourth and fifth columns of Table 13, the carbon tax caused coal use to fall by about 14% in 2010 and crude oil use to fall by 2.4-2.6%. Because the policy raises coal prices and petroleum product prices, the major users of these fossil fuels increase their output prices, causing a reduction in demand for energy-intensive goods. The imposition of fuel taxes caused changes in output mix and fuel switching that reduced both primary combustion PM emissions by 12.4-12.5% and SO_2 emissions by 12.9-13.1% in 2010. The modest tax on oil reduced transportation output and NO_x emissions by only 1.9-2.3%.

So, compared with command-and-control policies, a carbon tax can deal with multiple pollutants and be more effective in reducing overall health damages, at similar macro costs. We can also see that, in the case of carbon tax, the impacts on GDP are small overall, though the magnitude depends on how revenue is recycled. The GDP impacts are positive in the reduced distorted tax scenario, however this slightly hurt households but compensated firms with capital tax and VAT tax reductions. For recycling with a lump-sum transfer to households, households were better off with a slight decline in investment. In our simulations, carbon tax at 100 YUAN per tC brought in 2.4-2.9% in revenue, which is a modest tax revenue source for the government to spend on compensating negatively-affected coal miners, or on reducing pre-existing capital and VAT taxes, or in investing in low-carbon research and development technologies, etc.

In our study we also conducted a robust sensitivity check using different AEEI assumptions. We found that our policy simulations were not sensitive to the changes in the benchmark cases due to various AEEI results – the signs and magnitudes of policy impacts on GDP, consumption, investment and environmental performance were quite similar in all the scenarios.

5.0 CONCLUSION

In this study we used time-series input-output tables and corresponding physical energy use statistics by sector to decompose China's sectoral energy intensities, by adopting several decomposition techniques. Based on the energy intensity decomposition, we forecast future energy use and carbon emissions based on various AEEI assumptions. Then we compared our results to other studies and used a central AEEI estimate for China to conduct climate policy analysis. The main results of this study may be summarized as follows.

Firstly, during the 1980s and 1990s, technological changes played a very important role in explaining the sustained decline in overall energy intensities, while structural shifts played very limited roles. In many industries China's productivity and technological progress was lower than that of developed countries. After economic reform it was easier to catch up with productivity, allowing sustained efficiency improvement within industries. However, after sustained improvement over a 20-year period, by the year 2000 there was a steady decline in the role of technology progress in energy intensity decomposition, and structural change had not yet taken a dominant role. Stringent energy intensity policy after 2005 seemed to revert the energy intensity trend, but most of these efforts have been mainly in the coal sector.

Secondly, based on our energy intensity decomposition using different decomposition techniques, we extracted some useful information for specifying AEEI parameter assumptions. We used the common AEEI assumption for comparison, that is, a "one-size-fits-all" parameter that assumes that all sectors show a 1% improvement in energy efficiency each year. Our studies suggested that, for a transitional economy such as China, a parameter set at 1% is neither accurate nor generates trajectories of energy use and carbon emissions that are consistent with the historical trend. Thus, based on past energy intensity decomposition studies, we tried different AEEI scenarios and then, using our CGE model, we forecast future energy use and carbon emissions. In general, our model projection range was consistent with several other modeling groups in China, especially using the low AEEI parameter at 1.7%. These carbon emissions and low-carbon pathway studies were conducted by Tsinghua Zhang Xiliang's group, the ERI's modeling group, and Renmin University Zouji's modeling group. Though all three were based on bottom-up technology models, similar to the macro model, our projections linked historical energy intensity decomposition to derive AEEI parameters, then used a top-down CGE model to simulate future carbon emission trends.

Thirdly, based on the different AEEI estimates and different energy use and carbon emission projections, we used a recursive CGE model to analyze the economy-wide impacts of two alternative policies:

1) An existing command-and-control policy used widely in the 11th Five-Year Plan, FGD policy in the electricity sector and shutdown policy for small-scale power plants; and

2) A carbon tax of 100 YUAN per tC imposed on fossil fuel use with two different revenue recycling regimes. Our model showed that assumptions of future energy use and carbon emissions only slightly affected the model results, however, in general, the signs and magnitude of policy effects held in all the simulations. Thus the changes in the projections of the base case model only brought second order bias, thus we can trust the robustness of the CGE model on policy analysis even with various AEEI parameter assumptions.

Finally, by comparing the command-and-control policies and the carbon tax we found that the carbon tax was more cost-effective in terms of reducing a wide range of pollutants, while command-and-control technology mandates usually only imposed big cuts in one pollutant. Our model showed that technology mandates would bring negative macro costs, however sometimes command-and-control policies, such as shutting down inefficient small-scale power plants and replacing them with large-scale efficient power plants, could have both economic and environmental effects on correcting the myopia of investment distortions and market failures. In both command-and-control policies no revenue could be utilized to reduce other distortions, for example fiscal distortions in the pre-existing world or research and development investment in low-carbon technologies. In addition, our experiments showed that a carbon tax was more efficient for reducing carbon emissions and had great potential to bring other co-benefits to public health. Thus, in general, the carbon tax was superior to the command-and-control policies, if we take into account both economic and environmental net benefits, and can be used to reconcile both local environmental protection and climate change challenges.

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