Disaggregating the Electricity Sector of China's Input Out table: Application to Environmental-Economic Life Cycle Analysis

S. Lindner[a1], J. Legault[b], D. Guan[c*]

a) Department of Land Economy, Cambridge University

b) Department of Engineering, Cambridge University, Trumpington Street, Cambridge, CB2 1PZ, UK

c) School of Earth and Environment, University of Leeds

Abstract

Missing process detail of sectors in Input-Output tables has been pointed out to be a limitation to using Input-Output Analysis (IOA) as an environmental-economic Life Cycle Analysis (EE-LCA) tool as it increases uncertainty of results. Often, economic sectors are compiled in a more aggregated form then environmental satellite accounts, and as Lenzen (2011) has pointed out it is superior for determining environmental multipliers to disaggregate economic data as opposed to aggregating the environmental datasets. In this paper we present data and methodology to disaggregate the electricity sector of China's national IO table, using as much external information as possible, into a transmission and distribution sector as well as 8 sub-sectors representing power plants. We determine sector specific electricity consumption mixes based on regional industry clusters and local electricity generation mixes. By multiplication with a CO_2 emissions satellite account we show the total embodied emissions in sectors' final demand in the disaggregated table. These results are compared with emissions intensity from a second disaggregation run in which the disaggregation criterion based on the national average electricity generation mix.

Keywords: Disaggregation, EE-LCA, Electricity Sector

1. Introduction

The mismatch of economic sector size in input-output (IO) tables and corresponding environmental satellite accounts is a problem IO practitioners often face in environmental-economic life cycle analysis (EE-LCA). During the stage of constructing an IO table it is common to merge sectors with similar production structure and output into one, but the data describing environmental factors (ie.: CO_2 emissions or water use) is available either in the original sector number, or they have a different sector classification altogether (Lenzen, 2011). Construction of IO tables relies on comprehensive surveying of sales and purchase patterns of industries, a time consuming and difficult process because most of this information is considered confidential. Industries with similar structure are aggregated because loss of detail during this step is often minimal for use of IO tables in economic analysis, outweighing the benefit gained from spending time and resources on more detailed industry surveys to produce a highly disaggregated table. However, for analysis of economic impacts on the environment using the Leontief framework the level of sector aggregation has an influence on the results (Su et al. 2010, Lenzen, 2011). Ferraro and Nhambiu (2009) mention missing process detail of sectors as a limitation of the IO framework as a LCA tool. He suggests combining approaches from purely process-based LCA tools with the Leontief framework whenever possible to do so. The result, a hybrid LCA model, adds more process information to the IO framework and thus enhances the suitability for economic-environmental life cycle analysis.

As mentioned in a paper by Lenzen (2011) aggregation of environmentally sensitive sectors has a more significant impact on the results of an EE-LCA than other sectors. Lenzen gives the example of aggregating a rice and wheat sector into one grain growing sector which may lead to under/overestimation of water use intensity in that sector because of the difference in water required per unit output of each individual sector. He concludes that results of EE-LCA analysis are more accurate when economic data is disaggregated as opposed to aggregating environmental accounts. For similar reason it is important to disaggregate the electricity production sector of the IO table into their individual power generation units. Clearly, the CO_2 emissions of one kilowatt hour (kwh) of electricity produced by a coal fired power station is much higher than a unit produced with wind power or a hydro power station. Adding process-detail to the power sector of a countries' IO table

[1] Corresponding Author: Soeren Lindner: sml51@cam.ac.uk

by disaggregating the sector into its generation components improves further environmental-economic analysis in which these tables are used. For instance, China's IO table is used in Multi-regional Input-Output (MRIO) models to analyse the emissions embodied in exports from China to the USA or European countries. By knowing the exact composition of electricity entering the production process for making goods and services in China emissions embodied in international trade can be quantified with more certainty (Su and Ang, 2010). But the issue of disaggregation also has relevance at the domestic level. China recently committed to a voluntary GHG emissions reduction plan which is implemented nationally across its industries. Disaggregation of the electricity sector can provide a more accurate picture of industry emissions levels, especially if regional factors like local electricity generation mixes and industry clusters are taken into consideration, and so results of IOA with a disaggregated electricity sector entry can be quite useful to policy makers.

The importance of disaggregating the electricity sector for EE-LCA has been mentioned by Marriot (2007), Turner et al. (2007), and Lindner et al. (forthcoming). The main obstacle to disaggregating the electricity sector is lack of detailed information about the make up of the new sectors and its purchase/sales patterns with other industries (which we call "common sectors"). In a previous paper we showed that disaggregation of the electricity sector in China is possible with only limited amount of data (in this case only the total output of the new sectors was known and weight factors were built based on output differences), but it was concluded that as much additional information as possible should be considered to make the disaggregation more accurate. For one, an improvement in accuracy would result in the IO table to resemble more closely the real economy it displays, but also results for CO_2 emissions intensities in an EE-LCA could potentially be improved. In the absence of reliable survey data for China's electricity sector several questions arise on how to disaggregate this sector: how can the input required by the new sectors from the common sectors in the economy be determined and what external data sets are available and useful? Secondly, how can we determine the new output of the disaggregated electricity generation sectors into the common sectors?

This paper serves two purposes. For one, it explores the range of suitable data and details needed for an accurate disaggregation of the Chinese electricity sector entry in the IO table. The data used includes specific costs for power plants, electricity prices, and province level data on spatial variation in electricity generation output and regional industry clusters. With this information two sets of weight factors are estimated to quantify output from new sectors into common sectors, and input from common sectors into new sectors (as well as input/output between new sectors). The second purpose is to analyse the effect of weight factor choice on sector level CO_2 emissions intensities. For this we create two disaggregation matrices that were derived with different sets of weight factors. We then take the Leontief inverse and multiply both matrices with a CO_2 satellite account which contains emissions vectors for each power generation plant type.

The paper is structured as follows: background and literature review on disaggregation and the specific case of China's electricity sector is given. Next, the methodology for disaggregation following Wolsky (1984) is explained and our technique for deriving weight factors is outlined. We then show results of the disaggregation exercise and compare emissions intensities of both disaggregated tables followed by a conclusion.

2. Literature Review

The relevant body of literature on sector disaggregation in IO tables broadly encompasses the following topics: there are a number of studies dealing with the "aggregation bias problem" (Kymn, 1990; Morimoto, 1970). Another set of studies solve disaggregation based on estimating input and output of new sectors with limited amount of information and data (Gillen and Guccione, 1990; Wolsky, 1984) Several authors analyse the mismatch of environmental satellite accounts and economic IO data, provide coping strategies or analyse the effect of sector aggregation on emissions embodied in production (Lenzen, 2011; Su et al., 2010).

A number of literature articles with focus on sector size in IO tables is actually about merging (aggregating) several industries into one as opposed to splitting a sector into several new ones (disaggregation) (Miller and Blair, 1985). Disaggregation always requires use of additional information, exogenous to what is given in the aggregated form of the IO table and is therefore a more complex task then aggregation. The problem of initial loss of information after aggregating sectors is termed the "aggregation bias problem" which has been discussed extensively in the literature (Fisher, 1986). The ideal set of information an IO practitioner needs to gather for a sector disaggregation includes total output of new sectors into the economy, the proportion of output of those sectors into other economic sectors, and vice versa their input. In case where survey data of companies and enterprises is not available to provide detailed information these inter-sectoral relationships in the IO matrix can be estimated with weight factors if the total output of new sectors is known. This is explained in figure 1. It shows a simplified form of disaggregation, where the last sector, C is disaggregated into c*1 and c*2. The blue arrow marks all possible output weights of new sectors into common sectors ($2n^2$ possibilities, where n = number of new sectors). Input weight factors need to be build to show the input from common sector A into c*1 and c*2, as well as B into c*1 and c*2. This is indicated by the red arrow. Both sets of weight factors also determine the allocation of intra-industry sales between sector C, marked by the dark shaded quadrant in the lower right hand side of the table.

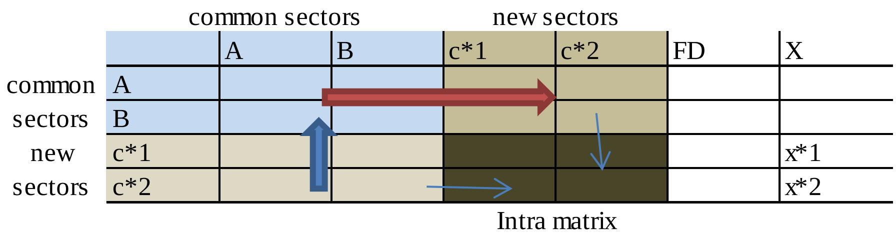

Figure 1: Schematic example of disaggregation an Input-Output table.

A general mathematical solution to such a problem was given by Wolsky (1984) (Wolsky, 1984). Lindner et al. (forthcoming) extend his approach to disaggregating one sector into an arbitrary number of new sectors (Lindner et al., forthcoming). Gillen and Guccione (1990) showed that disaggregation into sub-sectors is possible if input and output prices, gross output and final demand for the new sectors is available for in a period other than the base year. As such, they extend Wolsky's approach by including price information in the disaggregation method (Gillen and Guccione, 1990). Su et al. (2010) analysed the effect of sector aggregation on emissions embodied in trade between China and other countries. For the electricity sector they show how information on electricity consumption and prices can be used to obtain a more accurate estimate for disaggregating this sector (Su et al., 2010).

Other studies with a focus on disaggregation of the electricity production sector are Cruz, (2002 and 2004); Limmeechokchai and Suksuntornsiri, (2007); Shrestha and Marpaung, (2006); and Turner et al., (2007). These authors disaggregate the electricity sector in respective countries or regions of interest (Scotland in case of Turner et al., Portugal in Cruz (2002 and 2004) as well as Thailand and Indonesia in the other studies mentioned), by using different sets of data on electricity/utility companies or energy/electricity consumption of sectors. For example, in Turner et al. (2007) the information used is obtained directly from the Scottish energy companies and considered confidential, so only some results are published in their work. The main difference between the studies mentioned above is that both Cruz (2002) and Limmeechokchai and Suksuntornsiri (2007) use energy data and primary fuel inputs as a criteria for disaggregation. Cruz (2002) builds a hybrid unit input output model and disaggregates based on differences in fuel consumption of sectors. Turner et al. and Shrestha and Marpaung (2005) take a slightly different approach by disaggregating according to the fleet of power generating plants used for generating electricity. Instead of disaggregating the electricity sector based on input of primary energy, they disaggregate according to monetary/economic firm level data in the power production sector.

The latter approach is in essence followed in this paper, although we estimate the disaggregated table and do not use a full set of firm level data. Information available to us for building the estimation includes the mix of electricity generation by power plant type and industry output at the province level and cost data on operation and maintenance (O&M) of power plants. Based on the data a set of input and output weight factors are estimated. In a similar fashion this has been done in Marriott (2007), who disaggregates the electricity production sector of the US make and use tables (Marriott, 2007). He uses O&M costs of power generation plants to quantify and compare the input from common sectors to the new sectors. With this information he builds new supply chains for each type of power generation plant used to produce electricity in the US. Marriott's approach to modifying existing supply chains of all the common sectors, which are altered in the disaggregated table because electricity is supplied by several new sectors, is to develop a model that accounts for proximity of industries to power generation units. Assuming that industries use electricity from the closest source nearby, he derives sector-specific electricity consumption mixes. In our study the basic criteria for electricity sector disaggregation outlined in Marriott (2007) are adapted and applied to the case of China. Slight modifications to his methodology are made though. For example, we do not use the commodity by industry and industry by commodity tables of China (make and use tables) to perform the disaggregation, but instead directly disaggregate the national IO table of the year 2007. Also, instead of developing a linear logistic model to derive sector electricity consumption profiles we simply use differences in power generation mixes of the six electricity grid systems in China and an estimation of magnitude of industry output in these grids to build sector specific consumption profiles.

2.1 Regional electricity generation mix and industry clusters

In order to improve environmental analysis of production activities with the IO framework we need to move away from using a national electricity generation average as an estimation of input from the electricity production sector into all other sectors. Instead, sector specific consumption mixes should be developed. The CO_2 emissions associated with a unit of electricity of an economic sector depends on where this sector is located geographically and on the local power generation mix (Marriott, 2007). Especially in China it is very important to consider these regional factors. This has several reasons. For one, resource endowment is not evenly distributed between provinces (Wang and Chen, 2010). China is the largest coal producer in the world, but nearly 50% of the coal production is shared by only three provinces (Inner Mongolia, Shanxi and Shaanxi). The geographical distribution of hydropower and wind is very uneven as well (Liu et al., 2011; Meng et al., 2011) This leads to use of a different mix in electricity generation power plants across regions in China. Table 1 shows power generated by different technologies in each of the six independent electricity grids of China and we can see that carbon-free hydro electricity varies between 60.8 GW in Central China, to only 4.1 GW in North China. Table 2 shows the power generation mix in each grid as a percentile fraction and compares it with the national average. The information is taken from the Chinese Electricity Yearbook (NBS, 2008).

Table 1: The power generated in China's six electricity grids split by power plant type (2007):

Grid Region	Power generation by technology (GW)							
	Hydro	Coal Sub-c	Coal Super critical	Coal USC	NG	Nuclear	other	**Total**
North China	4.1	130.6	12.3	2.0	0.6	0.0	1.2	**150.1**
Central China	60.8	83.1	7.6	1.8	0.0	0.0	0.1	**152.4**
East	20.0	103.8	3.2	30.6	0.6	5.1	1.1	**164.8**
North East	6.6	56.1	4.9	0.0	0.5	0.0	1.7	**69.6**
South	40.9	36.4	6.0	0.0	0.7	3.8	0.3	**88.0**
Northwest	14.6	29.1	3.1	1.4	2.1	0.0	0.8	**51.0**
National Average	156.9	432.1	39.4	26.9	7.3	8.3	6.5	**675.9**

abbre.: coal sub-c = coal power plants with sub critical boiler type, Coal super critical = power plants with super critical boiler type, Coal USC = coal ultra super critical boiler type, NG = natural gas power plants. other = contains wind power and solar PV. Source: (NBS, 2008)

Table 2: Power generation in each grid expressed in percentale fractions (2007):

Electricity Generation in 6 operating power transmission and distribution networks in China								
%	Hydro	Coal Sub-c	Coal SC	Coal USC	NG	Nuclear	Wind	Solar Pv
North China	0.03	0.83	0.08	0.01	0.00	0.01	0.04	0.00
Central China	0.40	0.50	0.05	0.01	0.00	0.00	0.04	0.00
East	0.12	0.63	0.02	0.19	0.00	0.03	0.01	0.00
North East	0.09	0.81	0.07	0.00	0.01	0.00	0.02	0.00
South	0.47	0.41	0.07	0.00	0.01	0.04	0.00	0.00
Northwest	0.29	0.56	0.06	0.03	0.04	0.00	0.02	0.01
National Average	0.22	0.64	0.06	0.03	0.01	0.01	0.02	0.01

Source: (NBS,2007)

Secondly, a high disparity in socio-economic development exists between provinces. The rate of past economic growth in China has been spatially uneven, causing a high discrepancy in wealth and living standards between well developed provinces at the coast and underdeveloped provinces in the central- as well as western China (Zhang et al., 2011)). Regional economic disparity leads to different consumption patterns of goods and services between regions and specialization of some regional industries in production activities, resulting in industry clusters (Batisse and Poncet, 2004; Li and Xu, 2010). Thirdly, a combination of decentralization, inter-provincial competition, international trade and foreign direct investment has encouraged industry agglomeration and specialization of production activities among provinces (Gao, 2004). For instance, the coastal regions have a well developed manufacturing and service-oriented industry, whereas inland provinces are specialized in either agriculture or primary resource extraction (northwest), and provinces in the north are dominated by heavy industry. Uneven distribution of primary energy for power generation and industry specialisation have some important implications for the CO_2 emissions embodied in industrial production processes in China: specialization of some provinces in energy-intensive resource extraction or heavy industry, in contrast to a manufacturing and more service oriented industry in coastal provinces, leads to different GHG emissions profiles per province (Meng et al., 2011). Also, the fact that industries are not uniformly distributed across China, coupled with the regional difference in primary fuel mix used for electricity generation means that sectors probably do not consume the national average electricity mix across the country. This work examines the what extend these two factors vary and we analyse as well its effect on sector emissions levels.

3. Data requirement

Throughout the process of building the disaggregated IO model for China we use the following data:

- IO tables of 30 Chinese provinces of the year 2007 (NBS, 2010b). The tables are used to estimate level of regional industry concentration.

- Chinese national input-output table of 2007(NBS, 2010a). The table is in 42x42 sector format.

- Portfolio of power generation plants for all six power networks in China. Data is obtained from the Chinese Electricity Yearbook (NBS, 2008). The data is used in combination with provincial IO tables to estimate sector consumption profiles.

- Operation and management cost data (RMB/kwh) on power generation plants in China. These are taken from the book “Projected costs of generating electricity” (PCGE) issued by the International Energy Agency (IEA, 2010). The cost data is used to estimate proportional weight factors for the input of common sectors into new sectors.

- Estimates of electricity costs. The numbers are taken from the Electricity Yearbook of China.

- Emissions factors. Numbers are obtained from literature (Nsakala and Marion, 2001; Steen, 2001).

4. Methodology

4.1 Background on Disaggregation

A solution to disaggregating one sector into two has been described in Wolsky (1984) and extended to disaggregation into n-sectors by Lindner et al (forthcoming). We first review the basic methodology covering important aspects and then introduce new steps for disaggregating China’s electricity sector using a range of supporting information.

Recall that the Leontief framework relates output x_i, of goods produced by sector *i* to the sum of intermediate consumption, z, in the economy and an external final demand, f. It is assumed that industry flow from sector *i* to sector *j* depends linearly on the total output of sector *j*. We describe an economy with N+1 sectors as:

$$x_i = \sum_{j=1}^{N} z_{ij} + f_i \text{, for } i = 1 \text{ to } N + 1. \quad (1)$$

By denoting the ratio of sector *i* goods purchased by *j* to total output of sector *j* as the technical coefficient a_{ij} (1) is rewritten as

$$x_i = \sum_{j=1}^{N} a_{ij} x_{ij} + f_i \text{, for } i = 1 \text{ to } N + 1, \quad (2)$$

We present (2) in matrix form and invert to get the total requirements matrix:

$$\mathbf{x} = \left(\mathbf{I} - \mathbf{A}\right)^{-1} \mathbf{f} = \mathbf{Lf} \quad (3)$$

In the Leontief formulation (total requirement matrix) **I** describes the identity matrix of size N+1 x N+1 and **L** is the Leontief inverse formulation.

The Leontief framework can be extended to include environmental satellite accounts. Let e be a row vector of size N + n with N components of zero and n components of specific CO2 emissions per kwh of electricity output by power plant type (gCO2/kwh). In order to determine, ε , the emissions (gCO_2) per unit of RMB final demand, we multiply e with the total requirements matrix:

$$\boldsymbol{\varepsilon} = \mathbf{e}\left(\mathbf{I} - \mathbf{A}\right)^{-1} \tag{4}$$

Disaggregating a sector in the Leontief framework with only limited amount of information based on Wolsky is done by formulating an initial estimate for the unknown technical coefficients, A*, and final demand ratios for the new sectors. The coefficient matrix A* describes the same economy as A (an economy with N sectors), with the only difference that the last sector of the economy (N+1) has been disaggregated into *n* distinct sub-sectors. A weight factor is formed using the output ratio of the new sectors in relation to the aggregated sector they stem from. Usually, the total output of the new sectors is known, and since the output produced by the disaggregated sectors must be conserved we write:

$$w_k = x_{N+k}^{\ *}/x_{N+1}, \tag{5}$$

where w_k is the output of the k^{th} new sector and * denotes the disaggregated matrix. We call this factor the output factor. Knowing the output factor w_k leads to a set of 4 constraints describing the condition that final demand of new sectors must remain positive as well as that the amount of goods from common sectors to new sectors, new sectors to common sectors and input/output between new sectors in the intra-matrix must be conserved (see Wolsky, 1984 or Lindner et al. 2012). Every estimate for disaggregating one sector into several new sub-sectors needs to follow these constraints. When building such an estimate for disaggregation it is assumed that the new sectors in the economy have identical technologies and output to the other sectors are supplied in proportion to the output weights *w*.

The equations describing the estimate for disaggregation used in this paper are given in (6) to (9). We add a new weight factor, ρ , which describes the proportion of input from the common sectors, N, to the new sectors, k ($\sum \rho_k = 1$). We call this factor the input factor. The condition is that the sum of input from common sectors into new sectors must be equal to the input of the common sectors into the aggregated sector (N+1). This is described by equation (6):

$$\rho_k a^*_{i,N+n} = a_{i,N+1}, \text{ for } k = 1 \text{ to n, and } i = 1 \text{ to N} \tag{6}$$

Without this condition the input would stay fixed so that each common sector supplies the same proportion into the new sectors. In reality the money spent on operating a wind power plant will likely vary from the money spent on either a nuclear plant or coal fired power station. There are several variables determining the variation in supply to the electricity sector: besides output generated by the plants as a measure of sector “size” we need to consider operation and maintenance costs. Deriving the exact weight proportions for the input factor ρ is described in the next section. Equations (7) to (9) show the input relationship between new sectors and common sectors, the intra-matrix and the condition that final demand in the new sectors cannot be less than zero.

$$a^*_{N+k,i} = w_k a_{N+1,i}, \text{ for } k = 1 \text{ to } n \text{ and } i = 1 \text{ to } N, \tag{7}$$

$$a^*_{N+k,N+1} = a^*_{N+k,N+2} = \ldots = a^*_{N+k,N+n} = w_k a_{N+1,N+1}, \text{ for } k = 1 \text{ to } n, \tag{8}$$

$$b_k = w_k \frac{f_{N+1}}{x_{N+1}}, \text{ for } k = 1 \text{ to } n. \tag{9}$$

Note that the weight factors w_k only defines the proportion of supply from newly disaggregated sectors into the common sectors (row entry) and the input-output relationships of the intra-matrix. In the example of disaggregating the electricity sector into generation units the weight factor is usually determined by using the national average electricity generation mix. In the next section we introduce a method to determine the weight factor more accurately by taking data on regional variation in industry output as well as local electricity generation mixes.

4.2 Disaggregating China's Electricity Sector

4.2.1 Level of Disaggregation

Goal is to disaggregate sector entry 23, electricity production, heat and water distribution and supply in the national economic IO table (42 by 42 sectors) of China into 9 new sectors. The final product will be a 50x50 sector IO matrix for China. For the purpose of this exercise we move sector entry 23 to entry 42 in the IO table. Boundaries of disaggregation are set as follows: electricity production and distribution is first split into two separate sub-sectors, the transmission and distribution sector (T&D) and electricity production. The latter is further disaggregated into eight types of electricity generation: pulverized coal fired power (PCFP) stations with sub critical boiler type (sub-c), PCFP with super-critical boiler type (super-crit), PCFC with ultra-super critical boiler type (USC), wind power plants, solar power plants, nuclear power plants, hydroelectric power and natural gas power plants (NG plants). This is shown in Table 3, with the last column representing all new sectors in the IO table.

Table 3: Disaggregation of the electricity production and distribution entry

Sector entry 23 in 42x42 IO table of China		
Electricity production, transmission and distribution, heat and water supply	Electricity production	Pulverized coal plants (sub-c)
		PC coal plants (super-crit)
	transmission and distribution (T&D)	PC coal plants (ultra-super critical)
		Wind power plants
		Solar
		Nuclear power
		Hydro power
		Natural gas power plants
		T&D

It was agreed on this level of disaggregation in order to capture the major electricity production options with different CO2 emissions per unit output. The emissions factors (in grams of CO2/ kwh) are given in tables 4. We include the range of coal fired power stations with different boiler efficiency currently used in China because their emissions output varies as well (Ma, 2008). Although natural gas and solar power currently only contributes a minor fraction to China's national generation mix we also include these two plant types because all necessary data for disaggregation was available and because they will likely play a more dominant role in China's future generation mix (Wang and Chen, 2010). In case the disaggregated IO table of 2007 is used as a basis to estimate future IO tables then including these "future" generation options is vital. Ideally we would have also separated heat and water production and supply from the aggregated sector entry. Heat and hot water production and supply refers to co-generated heat power (CHP) from thermal plants and heat distribution networks like district heating. This form of heating is primarily used in the North and Northwest of China. However, we were unable to find data on O&M costs or investment costs of CHP plants and district heating lines in China. Therefore, this sub-sector remains aggregated in the electricity production sector.

Table 4: CO2 intensity of power plants

Technology	CO2 intensity (gCO2/kwh)
Hydroelectricity	18
Coal sub-c	1000
Coal super-c	900
Coal USC	750
Natural gas	400
Nuclear	45
Wind power	10
Solar PV	30

4.3 Disaggregating the electricity sector into production and supply:

The first level of disaggregation consists of splitting the aggregated sector into production and supply. This step can be understood as an adjustment to the inter-industry (z-) matrix before a more detailed disaggregation of the electricity production sector, based on the weight factors is done. We found no data detailing the input proportion of common sectors to T&D and production of electricity, or vice versa the proportion of monetary supply from T&D and production sector to other sectors in the economy. Hence, an assumption needs to be made. The Chinese electricity yearbook (NBS, 2008) lists the investment made into both sectors separately for the year 2007. This is shown in table 5:

Table 5: Investment in the power sector

Investment in Chinese power sector (bill. RMB)	
Total	549.29
Power generation	304.15
Transmission& Distribution	245.14

We see that about 45% of investment spending went to the supply and distribution of electricity. Since this is the only reliable number distinguishing the two sub-sectors we have to assume that industry input from all economic sectors into the two electricity sub- sectors is made according to the proportion of investment costs. Secondly, the output from both sectors into all other sectors is split in this proportion as well, and the same is done with the final demand. The result is a 43 x 43 sector IO table, and the electricity generation row and column entry contains 55% of monetary value of the previously aggregated sector.

4.4 Disaggregating the electricity generation sector

4.4.1 Deriving values for the input weight factors

The question is in what proportion are commodities from the common sectors in the economy bought by the newly disaggregated generation sectors? In the real economy it is probably not true that all common sectors supply their products in equal proportion to each new power generation sector. Thus, as stated in equation (6) we introduce a way to refine the disaggregation of the electricity production column entry by using the input factor ρ. Its purpose is to split the purchases of the electricity sector from common sectors into certain proportions to resemble purchases made by new sectors in a more accurate way. The factor for each sector is derived from taking the weighted sum of power plants' operation and maintenance (O&M) cost and annual electricity generation output. This is done according to the outline described in Marriot (2007). The argument is that allocation of industry input to the new power generation sectors should not solely be based on the electricity output of the new sectors, but also on how the money is spent within a year to generate said output. For example, an operator of a coal fired power station needs to buy fuel, whereas wind power plant operators do not. And there are other costs (materials, maintenance, waste disposal) that occur throughout a year and their magnitude varies among plant types. It is important to note that cost of construction, reflected in capital costs of power plants, is not considered in this exercise for distinguishing the supply. Construction is an economic activity within the construction sector of the IO table and so is therefore not included in the electricity sector (Marriot, 2007). If we were to consider construction of power plants we would have to disaggregate the construction sector as well.

O&M costs of power plants for China are taken from the IEA (2010). For each generating technology in the power sector the book gives a range of O&M costs in USD/kWh. These include fuel costs. We convert the costs into RMB/kWh using a currency conversion rate of 6.5 (as stated by the IEA). The price range is higher for technologies relying on fuels, like coal fired power stations and natural gas plants, due to price fluctuations of gas, coal and petroleum. Table 6 shows the results of the exercise by giving the medium, low and high values of O&M prices. Table 7 then shows the power generation mix in China for the year 2007 (NBS, 2008).

Table 6: Range of O&M costs by power plant

Electricity O&M prices by Generation type (RMB/kWh)			
Technology	Median	Low	High
Coal (SC)	11.2	9.5	12.9
Coal (USC)	12.3	10.3	14.3
Coal (sub-c)	8.5	7.5	9.5
Natural Gas	20.3	12.6	28.1
Nuclear	9.4	7.9	10.9
Hydroelectricty	13.4	12.0	14.8
Wind power	14.7	13.9	15.5
Solar PV	15.3	14.7	16.0

Source: (IEA, 2010)

Table 7: Electricity generation in China

Power generation mix in China 2007 (%)	
Coal (SC)	0.06
Coal (USC)	0.04
Coal (sub-c)	0.64
Natural Gas	0.01
Nuclear	0.01
Hydroelectricty	0.23
Wind power	0.01
Solar PV	0.00

Note: Solar = 0.003

Source: NBS (2008).

With both datasets we obtain input factors for supply of common sectors to the newly disaggregated sectors. The cost data of each power plant is weighted by multiplying it with its fraction in the national generation mix. Results are then normalized and expressed as a fraction of 1. In the results section this table is reported. But beforehand there are some exceptions that need to be considered. For example, all purchases from the common sector coal mining and processing (sector entry 2) are most likely entirely made by the three coal-fired power generation sectors. Likewise, output from gas production and supply is allocated entirely to the natural gas power plant sector. The assumption for allocating inputs petroleum processing and coking and crude petroleum and natural gas products across the generation types were taken from Marriot (2007).

4.4.2 Construction of the Intra matrix

The 2007 national IO table reveals that 11.3 billion RMB were spent in purchases from the electricity sector itself. This could be power purchased by utilities to cover supply shortfalls. We disaggregate this value to power purchases among the 9 new sectors, including T&D. We use the assumption made by Marriot (2007) that the intra-industry value is split among each entry in the new intra-matrix by multiplication with the row and column weight factor.

4.5 Deriving output weight factors

The question we try to answer in this section is in what ratio common sectors purchase electricity from the newly disaggregated generation sectors? We focus on equation (7) and explain how to derive the technical coefficient matrix, a*, adjusted for considering regional electricity generation mixes and industry clusters. The result of this exercise is a 8 x 41 sector matrix of technical coefficients showing the input of each new sector (8 electricity generation plants) into 41 common sectors. There will be 41 different sets of output weight ratios, wk, each set made up of 8 fractions of electricity input into a common sector that some up to 1, and hence meet the constraint given by Wolsky (1984). In other words, each sector in the national IO table is allocated a region specific electricity consumption mix.

1) We group the 30 province IO tables of China according to the electricity grid system they belong to. There are six grid systems in China and the grouping of provinces to each grid system is shown in Annex 1. In other words, the boundary chosen for determining regional electricity mixes is the electricity grid operating system. We chose this boundary because within provinces of a grid system considerable amount of electricity is traded, which has the effect that each province's electricity mix approaches the grid average mix.
2) In each of the six regions we extract the aggregated electricity sector row from the provincial IO tables (z-matrix) and add them together. As a result we obtain six 1 x 42 vectors showing the monetary input from the electricity sector to all common sectors in the grid. This regional electricity grid vector captures the different magnitude of electricity input to common sectors in the regions.
3) We compare the sum of the six regional electricity vectors with the value of electricity sector entry in the national IO table of China. There are some differences and the deviation is between 4 and 10% of the national IO table, but can be as high as 35% for some sectors. We normalize each regional electricity vector so that the sum of the six regional electricity vectors is equal to the row vector in the national table.
4) From the Chinese electricity yearbook and other literature sources we calculate the electricity generation mix for each grid system containing 9 generation units. This was shown in table 2 already. Each generation option in the six grids contributes a fraction of 1 to the total mix.
5) We multiply each regional electricity vector with the fraction of power plants available contributing to the region specific generation mix (shown in table 1). Results of this are grouped into 8 matrixes of the size 6 x 41. So each matrix shows monetary value of electricity input to the common sectors for each grid according to generation type.
6) The row sum of each matrix is divided by the total input of the aggregated electricity sector in the national table IO. As a result we obtain the 8x41 output weight factors which define the sector specific consumption mix of the common sectors.

We illustrate mathematically the combined effect of regional industry clusters and electricity generation mix on the consumption mix of common sectors in the national IO table. The following notation is adapted:

wk,(j) = percentage of total output of electricity generation sector type k, in region j.
Pi,(j) = percentage of total output of common sector produced in the jth region
N+1 = electricity sector of the national IO table to be disaggregated.
i = common sectors in the national IO table, where i = 1 to N.
Nr: number of regions
a: technical coefficient matrix of the aggregated table
a*: technical coefficient matrix of the disaggregated table
z = inter-industry matrix

We introduce additional constraints: the fraction of industry output from the common sectors produced in each region needs to sum up to 1 (to equal the output of the national table) and the fraction of regional electricity generation mix of power plant type k needs to sum up to 1 as well:

$$\sum_{j=1}^{Nr} P_{i,(j)} = 1, \ (10) \quad \text{and} \quad \sum_{j=1}^{Nr} w_{k,(j)} = 1, \qquad (11)$$

We can express the technical coefficient, *a*, of the aggregated matrix (left hand side of the equation) as the sum of inter-industry transfer *z* divided by total output in each of the 6 regions:

$$a_{N+1,\, i} = \frac{z_{N+1,i}}{x_{N+1}} = \frac{1}{x_{N+1}} \sum_{j=1}^{Nr} z_{N+1,(j)} , \qquad (12)$$

And since the output x*i (j)* of a common sector *i* in region *j* can be expressed as the sum of fraction P_i of national output x, we write:

$$z_{N+1,i(j)} = a_{N+1,i,(j)} x_{i,(j)} = a_{N+1,i,(j)} P_{i,(j)} x_i , \qquad (13)$$

so that equation (12) can be rewritten as:

$$a_{N+1,i} = \frac{1}{x_{N+1}} \sum_{j=1}^{Nr} a_{N+1,i,(j)} x_{N+1,i,(j)} = \frac{1}{x_{N+1}} \sum_{j=1}^{Nr} a_{N+1,i,(j)} P_{i,(j)} x_i = \sum_{j=1}^{Nr} a_{N+1,i,(j)} P_{i,(j)} \quad (14)$$

As an example, if we disaggregate the electricity sector into k sectors of electricity generation, we have:

$$a^*_{N+k,i} = \frac{z^*_{N+k,i}}{x^*_i} = \frac{1}{x^*_i} \sum_{j=1}^{Nr} z^*_{N+k,i,(j)} \approx \frac{1}{x_i} \sum_{j=1}^{Nr} z_{N+1,i.,(j)} w_{k,(j)} , \qquad (15)$$

The quantities $z_{N+1,i,(j)}$ and $w_{k(j)}$ can be determined for each region and since we know the total national output x_{N+1} we further write:

$$a^*_{N+k,i} \approx \frac{1}{x_i} \sum_{j=1}^{Nr} z_{N+1,i} w_{k,(j)} = \sum_{j=1}^{Nr} a_{N+1,i,(j)} P_{i,(j)} w_{k(j)}, \qquad (16)$$

From the last equation we can see that the departure of the coefficients $a^*_{N+k,i}$ from the national average of electricity generation input to industry sectors i can be attributed to two factors: the combined presence of regional industry clusters with regional electricity mix clusters and the difference in the regional industry efficiency from the national industry efficiency (i.e. the difference between the regional coefficients $a^*_{N+k,i}$ and the national coefficient $a_{N+1.i}$).

5. Results

5.1 Input and Output weight factors

In this section we present results of calculating the input weight factors, ρ, and output weight factors wk. Input weight factors were calculated using the low end and high end results the O&M data provided by the IEA (2011). We also calculated a median value and used this value during the actual disaggregation. This is shown in table 8.

Table 8: Input weight factors from common sectors to power generating sectors:

Input weight factors (%)			
Technology	Median	Low	High
Coal (SC)	0.07	0.06	0.06
Coal (USC)	0.05	0.04	0.04
Coal (sub-c)	0.54	0.48	0.44
Natural Gas	0.02	0.01	0.02
Nuclear	0.01	0.01	0.01
Hydroelectricty	0.30	0.28	0.23
Wind power	0.01	0.01	0.01
Solar PV	0.01	0.01	0.01

The input weight factors offer a first estimate on how to allocate supply from the common sectors to the disaggregated sectors. We notice that the factors differ from the fractions of electricity generation for power plants in the national mix. For instance hydroelectricity went up to 0.3 from 0.23 in the power mix, and coal fired power plants with sub-critical boiler moved down to 0.54. Coal-fired power stations with sub-critical boiler have lower O&M costs than hydroelectricity and this effect is weighted into the input factors.

The results for the manual allocation of supply from common sectors to newly disaggregated sectors are shown in table 9.

Table 9: Manual allocation of common sector's input to new sectors:

	Allocation across generation types							
common sector	Coal SC	Coal USC	Coal sub-c	NG plant	Nuclear	Hydroelectricity	Wind power	Solar pv
Coal mining and processing	0.11	0.08	0.81	0	0	0	0	0
Petroleum processing and coking	0.02	0.03	0.05	0.9	0	0	0	0
Transport and warehousing	0.11	0.08	0.81	0	0	0	0	0
Crude petroleum and natural gas products	0.02	0.03	0.05	0.9	0	0	0	0
Water production and supply	0.11	0.08	0.81	0	0	0	0	0
Gas production and supply	0	0	0	1	0	0	0	0

We also calculated new output weight factors which are based on our estimation of regional electricity consumption mixes per industry sector. The full table of output weights is given in the Appendix. In table 10 we only show 5 sectors and their deviation of electricity consumption compared to the national average. The minus sign indicates the consumption of electricity from a certain power plant type is less (in percentage points) than the national average. The calculation revealed that the pattern of electricity consumption by each industry is indeed different from the national average. In some cases, like wind power it can be as high as a magnitude of 1.7.

Table 10: comparison of national average with sector specific consumption mix:

Deviation of electricity consumption of four sectors from national generation average					
Technology	average (%)	Coal mining + processing	Chemicals	Metals smelting + pressing	Gas production and supply
Hydro	0.230	-44.6	-15.8	-12.8	-23.5
Sub-c	0.637	16.0	0.4	1.8	7.6
Super crit	0.060	16.8	-10.9	0.3	1.6
USC	0.040	-57.6	61.5	1.4	-16.7
NG	0.010	-6.6	-3.0	12.9	-32.6
Nuclear	0.010	-79.3	30.4	-17.5	-42.9
wind	0.010	199.9	109.7	152.9	175.6
solar pv	0.003	-66.2	-62.1	-52.1	-80.0

We construct the intra-matrix, distributing the value of intra-industry sales from the electricity to each new sector in the economy according to Marriot (2007). The full results, after disaggregation, are shown in table 11 and the monetary value is 10.000 RMB. Only parts of the disaggregated Chinese IO table are displayed in this paper, mainly due to the fact that a 50x50 sector excel matrix is difficult to show in third document. In the Annex, however, we show the 9 row and 9 column matrixes of the disaggregated electricity sector in the Chinese IO table, including final demand and total output of the new sectors.

Table 11: Intra-matrix of Chinese Disaggregated IO table:

	0.45	0.167	0.29	0.037	0.027	0.012	0.006	0.006	0.005
11.3000000 RMB	T&D	Hydro	Coal Sub-C	Coal SC	Coal USC	NG power	Nuclear	Wind power	Solar PV
T&D	22882500	8491950	14746500	1881450	1372950	610200	305100	305100	254250
Hydro	8491950	3151457	5472590	698227	509517	226452	113226	113226	94355
Coal Sub-c	14746500	5472590	9503300	1212490	884790	393240	196620	196620	163850
Coal SC	1881450	698227	1212490	154697	112887	50172	25086	25086	20905
Coal USC	1372950	509517	884790	112887	82377	36612	18306	18306	15255
NG power plant	610200	226452	393240	50172	36612	16272	8136	8136	6780
Nuclear	305100	113226	196620	25086	18306	8136	4068	4068	3390
Wind power	305100	113226	196620	25086	18306	8136	4068	4068	3390
Solar PV	254250	94355	163850	20905	15255	6780	3390	3390	2825

5.2 *CO_2 emissions intensity*

One aim of this work is to determine the effect of different weight factors used for disaggregation on results of emissions intensity, ε, of sectors in the economy. Using the final demand as stated in the Chinese IO table we compare the emissions embodied in one unit of final demand of two separate disaggregation runs. The first one, L1, uses the new set of weight factors which were determined as described in the previous section to disaggregate the row and column entry of the electricity sector. The other disaggregation run uses the national average electricity mix as weight factors to divide the row entry and for the division of supply from common sectors to new sectors (column entry) it was assumed that output is allocated in equal proportions to each generating sector (L2). We then build the Leontief inverse coefficient matrix of the disaggregated tables and multiply with a CO2 satellite account as described in equation (4). Results of both runs are shown below. Figure (1) shows the total emissions embodied in one unit of final demand for the 41 common sectors after using disaggregation run L1. Here we see the primary industry sector like resource extraction and mining as well as the metallurgy sectors having the highest emissions intensity whereas service oriented sectors (real estate, finance and insurance) have the lowest intensity.

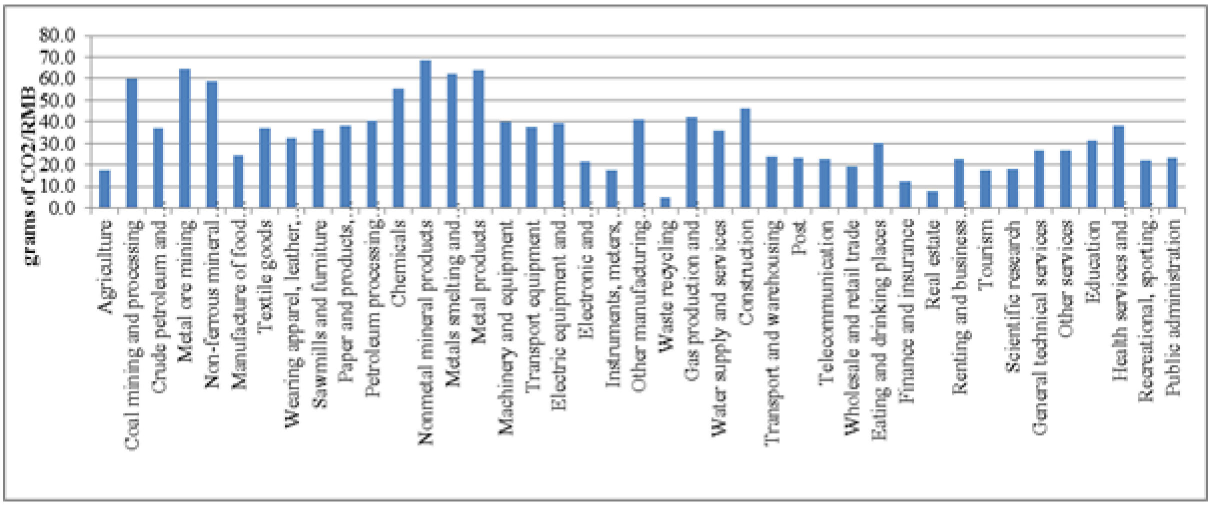

Figure 2. CO2 emissions intensity of 41 common sectors in the Chinese IO table.

The same results were produced using the assumption electricity is supplied to sectors according to the national average (L2). In the appendix we show a table listing emissions intensities of the new sectors. We compare both results in figure 2 by looking at the percentage deviation of L1 from L2. We see that the difference in emissions intensity is rather small: results of L1 fall between the range of plus or minus 4% of L2. In other words, despite using rather different weight factors not only between sectors in the L1 model run, but also between L1 and L2, the results of total emissions intensity among sectors varies considerably less.

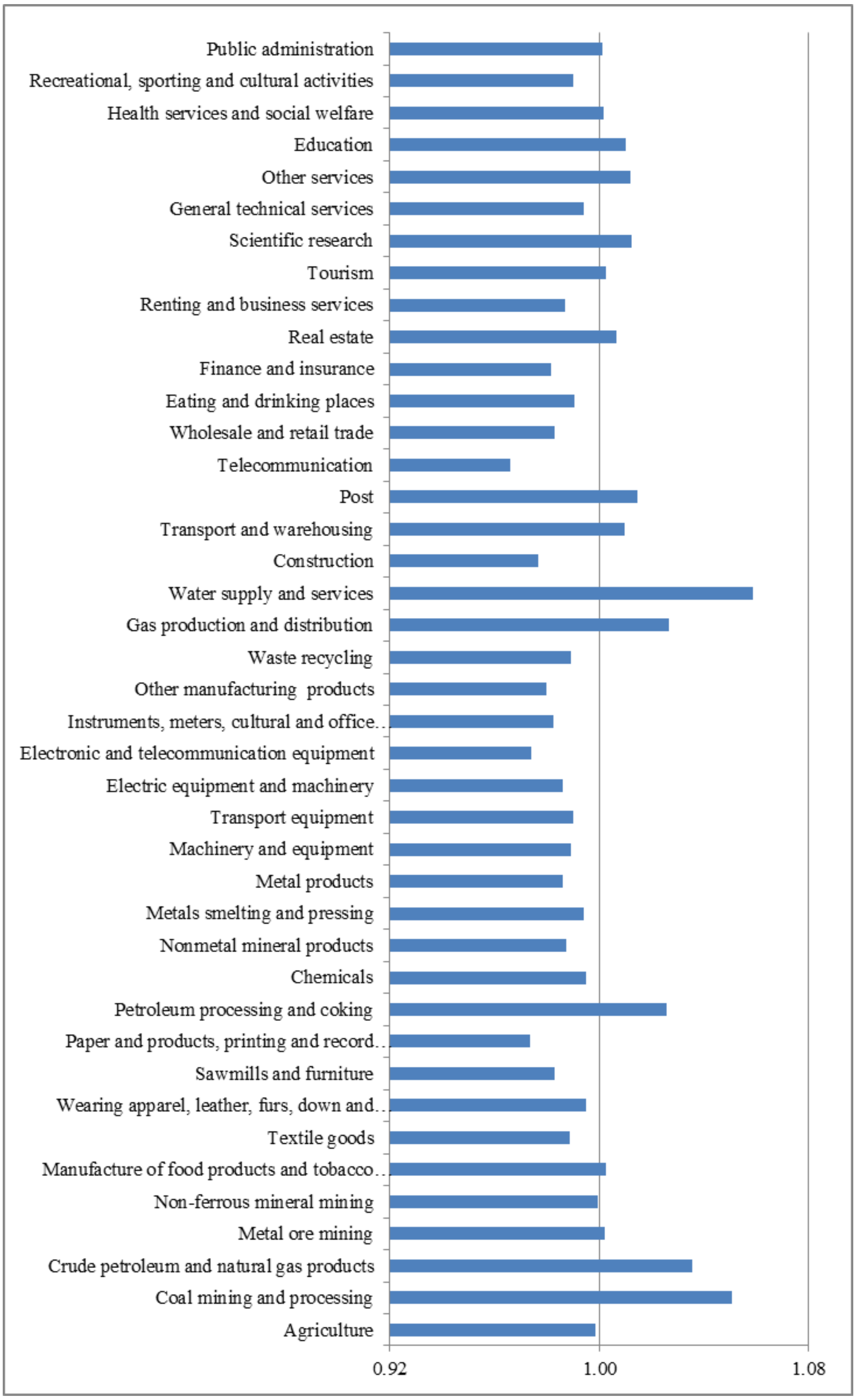

Figure 3: Difference in CO2 emissions intensity between 2 disaggregation model runs. 1 = no difference, < 1 = the emissions intensity of L2 is lower, > 1 = emissions intensity of L 2 is higher then L1.

Conclusion

The goal of this paper is to introduce data and a technique to disaggregate the electricity sector of Chinas' IO table. The argument for disaggregation is that it enables to add more process detail to some sectors in the IO table, and hence would make further use of the tables for EE-LCA more accurate. We perform two "runs" of disaggregation: one where weight factors to distinguish the new sectors are chosen based on a range of external information about the input/output relationship of the new sectors with common sectors, and one "run" where weight factor distinction is simply made on the national electricity generation average. Emissions intensities of both runs are compared.

We conclude that with the technique presented here disaggregation based on Wolsky's idea of developing an initial estimate that follows a set of constraints is possible even with more complex information to build the estimate. But due throughout the process one of the main goals of disaggregation, which is to decrease uncertainty of embodied emissions (for example in trade of goods and products), may actually be missed simply because the data used to estimate the weight factors already has a lot of uncertainty inherent. For example, the first step of disaggregation, the separation from T&D to the power generation units, is a very general guess based on investment costs simply because no other detailed data is available. Secondly, estimation of supply into new sectors from common sectors based on the O&M costs provided by the IEA contains uncertainty as well – simply because the O&M costs are estimations themselves. And thirdly, the technique of estimating sector consumption profiles with provincial IO tables also incorporates some error, varying from sector to sector. This has several reasons, some province level tables are not in the same level of quality than the national table, but also the provincial tables contain interprovincial exports/imports which ideally would have to be removed before comparing them with the national IO table. An improvement of the technique would be to account for uncertainty and error in the disaggregation by giving ranges for possible solutions of disaggregation. In Lindner et al. (forthcoming) the full range of possible solutions for the inverse coefficients in the disaggregated matrix was given. It is concluded that although we use more information to support a disaggregation in this paper, and therefore ideally we would place our estimate with more certainty in the space of all possible solutions for disaggregation, still the formulated estimate in this work has a considerable amount of uncertainty inherent. Therefore a range of disaggregation solutions should be provided even with more detailed data.

From the results of environmental analysis, in which we analysed the emissions embodied in one unit of final demand of the common sectors, we expected to see a difference between emissions intensities of sectors between both model runs. However, results indicate that the difference is less than 5% for all common sectors. This is likely due to the fact that we present the total embodied emissions which include the indirect emissions along the supply chain of sectors. Since each sector has a generic electricity consumption mix, accounting the emissions along the supply chain will necessarily result in the emissions intensity to approach the intensity of the national average. The effect of individual sector mixes on emissions intensity should be most visible when direct emissions are calculated, and decrease further down the supply chain. We conclude that using sector specific electricity consumption mixes are good to detect industry specific direct emissions, but not necessary for analysing indirect emissions because the emissions will approach the national average. From the viewpoint of environmental analysis it is also less important to accurately model the dertailed supply of common sectors into the new generating sectors, compared to estimating the input of generating sectors into common sectors. The input from common to new sectors in essence modifies the first layer of indirect emissions (electricity is sold to common sectors who produce goods that are sold again to the electricity generating sectors), and at that stage the emissions level are already approaching the national average.

Disaggregation is merely a step of improving quality of data to be used for future analysis. Given that an IO practitioner will likely weigh off the time invested in disaggregation and the benefit gained we suggest that disaggregation of the electricity based on weight factors that are built on using the national electricity generation average is satisfactory. For the compilation of the next IO tables of China we encourage to disaggregate the electricity sector before publication based on the firm level data that bodies of the Chinese Government may have access to.

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Appendix

1) Division of provinces into six electricity grids in China. Also shown are the percentage of powe generated with fossil fuels in each province (NBS, 2008).

Region	Provinces with more than 90% of power generation by fossil fuels	Provinces between 50 - 80% of power generation by fossil fuels	Provinces with less than 50% of power generation by fossil fuels
Central China		Henan, Hunan Jiangxi Chongqing	Hubei Sichuan
Eastern China	Shanghai Jiangsu Anhui	Fujian Zhejiang	
North East	Jilin, Heilongjiang Lianoning		
North West	Ningxia, Shaanxi	Gansu , Xinjiang	Qinghai
South China		Guizhou Guangdong	Yunnan Guangxi
North China Grid	Shanxi Shandong Beijing Inner Mongolia Tianjing Hebei		

2) Output weight for each common sector. Shown in the following table, split into three pieces, are the weight factors we determined to build sector specific electricity consumption profiles. All 8 weights add up to 1 for each sector.

2.1:

	National average	*Agriculture*	*Coal mining and processing*	*Crude petroleum and natural gas products*	*Metal ore mining*	*Non-ferrous mineral mining*	*Manufacture of food products and tobacco processing*	*Textile goods*	*Wearing apparel, leather, furs, down and related products*	*Sawmills and furniture*	*Paper and products, printing and record medium reproduction*	*Petroleum processing and coking*	*Chemicals*	*Nonmetal mineral products*	*Metals smelting and pressing*	*Metal products*
Hydro	0.23	0.19	0.13	0.15	0.19	0.19	0.18	0.20	0.19	0.24	0.24	0.18	0.19	0.21	0.20	0.20
Sub-c	0.64	0.67	0.74	0.72	0.67	0.66	0.68	0.63	0.65	0.63	0.61	0.68	0.64	0.64	0.65	0.62
Super crit	0.06	0.06	0.07	0.07	0.07	0.05	0.06	0.05	0.05	0.06	0.06	0.06	0.05	0.06	0.06	0.05
USC	0.04	0.03	0.02	0.01	0.02	0.05	0.03	0.08	0.07	0.03	0.05	0.03	0.06	0.04	0.04	0.08
NG	0.01	0.01	0.01	0.02	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.02	0.01	0.01	0.01	0.00
Nuclear	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.02	0.02	0.01	0.01	0.00	0.01	0.01	0.01	0.02
wind	0.01	0.02	0.03	0.02	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02
solar pv	0.003	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

2.2:

Machinery and equipment	Transport equipment	Electric equipment and machinery	Electronic and telecommunication equipment	Instruments, meters, cultural and office machinery	Other manufacturing products	Waste recycling	Gas production and distribution	Water supply and services	Construction	Transport and warehousing	Post	Telecommunication	Wholesale and retail trade	Eating and drinking places
0.20	0.20	0.22	0.24	0.22	0.23	0.20	0.18	0.18	0.28	0.18	0.15	0.23	0.22	0.21
0.63	0.65	0.61	0.59	0.61	0.59	0.63	0.69	0.69	0.58	0.68	0.72	0.61	0.64	0.65
0.05	0.06	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.06	0.07	0.06	0.06	0.06
0.06	0.05	0.07	0.08	0.07	0.09	0.09	0.03	0.03	0.04	0.04	0.02	0.04	0.04	0.03
0.02	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01
0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.00	0.00	0.00	0.01	0.01
0.02	0.02	0.02	0.01	0.02	0.01	0.02	0.03	0.02	0.02	0.03	0.02	0.02	0.03	0.02
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00

2.3:

Finance and insurance	Real estate	Renting and business services	Tourism	Scientific research	General technical services	Other services	Education	Health services and social welfare	Recreational, sporting and cultural activities	Public administration and other sectors	T&D
0.22	0.16	0.20	0.08	0.13	0.20	0.15	0.17	0.17	0.20	0.18	0.21
0.64	0.70	0.64	0.79	0.73	0.65	0.72	0.69	0.69	0.66	0.68	0.64
0.06	0.06	0.06	0.07	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
0.04	0.04	0.05	0.02	0.04	0.03	0.02	0.03	0.04	0.05	0.03	0.05
0.02	0.01	0.01	0.00	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01
0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01
0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

3. Difference of CO2 emissions intensities of new sectors from 2 disaggregation runs:

CO2 emissions intensities for new sectors from 2 model runs:			
	L1	L2	% difference
T&D	94.3	91.21	0.97
Hydroelectricty	197.4	166.22	0.84
Coal (sub-c)	1350.5	1339.11	0.99
Coal (SC)	1371.4	1294.45	0.94
Coal (USC)	1155.9	1076.96	0.93
Natural Gas	900.9	733.91	0.81
Nuclear	319.4	172.98	0.54
Wind power	496.5	245.78	0.50
Solar PV	485.1	231.85	0.48