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Energy Economics xx (2006) xxx–xxx

Energy Economics

www.elsevier.com/locate/eneco

The synthesis of bottom-up and top-down approaches to climate policy modeling: Electric power technology detail in a social accounting framework ☆

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Received 7 July 2004; accepted 11 June 2006

Abstract

"Hybrid" climate policy simulations have sought to bridge the gap between "bottom-up" engineering and "top-down" macroeconomic models by integrating the former's energy technology detail into the latter's macroeconomic framework. Construction of hybrid models is complicated by the need to numerically calibrate them to multiple, incommensurate sources of economic and engineering data. I develop a solution to this problem following Howitt's [Howitt, R.E., 1995. Positive Mathematical Programming, American Journal of Agricultural Economics 77: 329-342] positive mathematical programming approach. Using data for the U.S., I illustrate how the inputs to the electricity sector in a social accounting matrix may be allocated among discrete types of generation so as to be consistent with both technologies' input shares from engineering cost estimates, and the zero profit and market clearance conditions of the sector's macroeconomic production structure.

JEL classification: C680; Q400; Q540
Keywords: Energy modeling; Top-down; Bottom-up; Computable general equilibrium models; Electric power technologies

☆ This research was supported by U.S. Department of Energy Office of Science (BER) Grant No. DE-FG02-02ER63484. Dan Basoli provided expert research assistance. Errors and omissions remain the sole responsibility of the author.
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0140-9883/$ - see front matter
doi:10.1016/j.eneco.2006.06.004

1. Introduction

A crucial factor in mitigating future climate change is the expansion of energy supply technologies that have low or zero carbon dioxide (CO_2) emissions (IPCC, 2001). Computational policy models used to assess the climate implications of economic growth, energy use and GHG emissions represent these technologies in different ways, which has resulted in divergent predictions of the contributions of new energy sources – particularly renewables – to the future global energy supply. The main divide is between "bottom-up" engineering models, which simulate the interactions among the numerous individual energy technologies that make up the energy system of an economy, and "top-down" macroeconomic models, which simulate the effect on prices of the supply–demand interactions across the markets for all commodities, energy and non-energy alike.[1]

Attempts to reconcile these two approaches have focused on creating hybrid models which incorporate bottom-up technology detail within a top-down macroeconomic framework. The aim of this paper is to further this line of inquiry by developing a method for transparently integrating engineering data on technology detail into the macroeconomic accounts on which top-down models are empirically calibrated. I apply Howitt's (1995) positive mathematical programming (PMP) approach to data for the U.S. electric power sector to estimate the allocation of capital, labor, energy and material inputs among discrete activities and technologies in a way that is consistent with both the input shares implied by engineering cost data, and the conditions of zero profit and market clearance which define the sector's production structure from a macroeconomic perspective. The results demonstrate how the inconsistencies between engineering and macroeconomic data may be reconciled in a manner that is both transparent and portable among a variety of modeling applications.

The disparities in the structure and scope of bottom-up and top-down models imply that each has a comparative advantage in addressing complementary subsets of the research questions which arise in energy and climate policy analysis. Top-down models are a standard tool for assessing the macroeconomic costs of CO_2 abatement and its economy-wide feedbacks on prices, commodity and factor substitution, income and economic welfare. Bottom-up models are used to investigate the impacts of CO_2 emissions constraints on the portfolio of technologies that make up the supply and demand components of the energy system, in order to identify low-cost abatement opportunities or design technology-based subsidies or emission standards.

However, the results of these two approaches have tended to diverge, with top-down models typically indicating larger macroeconomic costs as the consequence of a given mitigation policy (NAS, 1991: 62; Grubb et al., 1993; Wilson and Swisher, 1993; IPCC, 2001). The origins of this

[1] Bottom-up models (e.g., MARKAL — Kypreos, 1998) are primal activity analysis simulations which solve for the levels of capacity of energy transformation and conversion technologies that minimize the cost of fulfilling demands for energy services. Energy demands are either specified exogenously or derived from simple aggregate macroeconomic models (e.g. Manne et al., 1995). Energy supplies emanate from a detailed model of the energy system which represents the capacities of and linkages among of a large set of discrete processes which transform primary energy resources into energy carriers, and convert these commodities into energy services that satisfy final demands. Top-down macroeconomic models come in two flavors: primal simulations of an aggregate Ramsey growth model with an environmental sector (e.g., DICE and RICE — Nordhaus and Boyer, 1999), and, more relevant to the subject matter of the present paper, primal–dual computable general equilibrium (CGE) simulations (e.g., EPPA — Paltsev et al., 2005). The latter solves for the set of commodity and factor prices and levels of industry activity and household income which clear all markets in the economy, given factor endowments, households' consumption technologies (specified by their utility functions) and industries' transformation technologies (specified by their production functions).

divide are by now well understood, with perhaps the biggest factor being bottom-up models' technological optimism about low-cost abatement potentials.[2]

Attempts to reconcile these differences have focused on the development of so-called "hybrid" models, which attempt to bridge the bottom-up/top-down divide by combining the detailed engineering specifications of energy supply technologies with the sector-wide nested production functions of CGE models.[3] Despite being the focus of much recent research (Boehringer, 1998; Boehringer et al., 2003; Frei et al., 2003; Kumbaroglu and Madlener, 2003; McFarland et al., 2004) this approach is still very much in its infancy. Perhaps the most important reason is the difficulty involved in constructing databases which integrate macroeconomic data with engineering detail in way that facilitates simple calibration of hybrid models.

To be consistent with bottom-up approaches, hybrid models' representation of the supplies of and the demands for energy commodities should faithfully reflect the engineering characteristics of different energy supply and conversion technologies. Simultaneously, to be consistent with top-down approaches, the activity levels and the input demands of the individual technologies introduced into hybrid models should match the inter-industry data employed in macroeconomic studies. The problem is that the engineering and the economic data are rarely consistent with each other. Thus, calibrating a model to faithfully capture both the aggregate and the disaggregate characteristics of energy's role in a CO_2 emission-constrained economy necessitates the balancing of competing demands. The current state of the technical art in this regard is more a matter of judicious assumptions and careful, manual calibration than systematic, replicable procedures.

It is in addressing this need for systematization that this paper makes its contribution. Its major advance is to simplify the calibration of hybrid models through the creation of a mathematical scheme that first reconciles and then integrates the kinds of engineering information used in bottom-up models with the macroeconomic data used to calibrate top-down models. This scheme is applied to the development of a hybrid model of the electric power sector in the U.S. using data which is readily available.

The methodology developed in the paper is deliberately simple, transparent, and above all, replicable, and, as far as the author is aware, represents the first completely general and robust scheme for calibrating hybrid energy policy simulations. This approach will benefit economists, engineers and modelers by speeding up the reconciliation of top-down and bottom-up data on the energy system of an economy, expediting comparisons of the effects of different relative price regimes on the structures of the costs of energy production, and, hopefully, facilitating the construction of hybrid models without tears.

The rest of the paper is organized as follows. Section 2 sets the stage by presenting simplified top-down and bottom-up models of the electric power sector, and using them to identify the challenges in

[2] The major differences between top-down and bottom-up models lie in their domains (economy-wide versus the energy system), solution concept (primal partial equilibrium versus primal–dual general equilibrium), scope for substitution (the demand influences of non-energy sectors and the supply influences of factor price changes versus discrete technology set), and inclusion of optimistic low-or negative-cost emission reduction possibilities (IPCC, 2001).

[3] This method may be contrasted with hybrid simulations such as MERGE (Manne et al., 1995) and MARKAL-MACRO (Kypreos, 1998). These are primal non-linear or mixed integer programming models in which a simple macroeconomic growth model drives increases in output and the demand for energy services, which is then satisfied by a technologically-detailed supply-side model of the energy system. Another approach is taken by Jacobsen (2000), who incorporates the diffusion of energy technologies of different vintages, each with a different level of energy efficiency, into a top-down macro-econometric model. Schäfer and Jacoby (2005) and Boehringer and Rutherford (2005) use yet a third approach of soft-linking a bottom-up engineering model and a top-down CGE model, using the latter's price and quantity allocations as boundary conditions for the former's optimization problem.

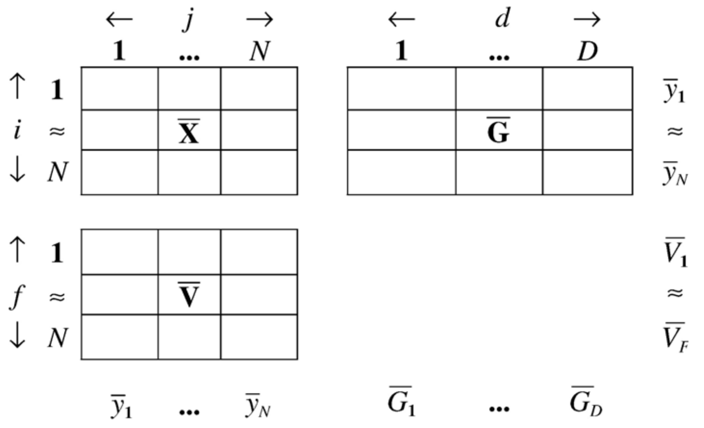

Fig. 1. Schematic of the social accounting matrix.

reconciling the data and algebraic relationships that underlie each of them. The meat of the paper is in Section 3, which presents a realistic top-down model of the electric power sector, outlines the engineering data with which, in a perfect world, its macroeconomic relationships should be consistent, and develops the calibration procedure for establishing consistency between the two. Section 4 describes the data for the U.S. electric power sector, and the engineering and economic calculations necessary to re-cast this information into a format suitable for reconciliation. The results are analyzed and discussed in Section 5. Section 6 concludes by briefly discussing the methodology's usefulness in constructing CGE models with technology detail.

2. Reconciling top-down and bottom-up approaches to modeling the electricity sector

2.1. Using social accounting matrices to calibrate a top-down production structure

The first step in constructing a hybrid model is to define the macroeconomic framework into which technology detail is to be incorporated. The framework that is typically employed is the array of inter-industry demands for inputs and supplies of outputs. This information is tabulated in a social accounting matrix (SAM), which forms the basis for numerically calibrating the production and demand functions in CGE models.

A SAM is a snapshot of the flows of value in an economy in equilibrium at a particular point in time, and is shown schematically in Fig. 1.[4] The economy represented therein possesses N industry sectors, F non-reproducible primary factors, and D categories of final uses by households. Each industry (indexed by $j=1,\ldots, N$) is assumed to produce a single commodity (indexed by $i=1,\ldots, N$) by combining portions of its own and other sectors' outputs as intermediate inputs with inputs of primary factors (e.g. labor and capital, indexed by $f=1,\ldots, F$). The output of each industry satisfies both other sectors' demands for intermediate goods and households' final uses (e.g. consumption and saving, indexed by $d=1,\ldots, D$). The corresponding flows of economic value, which are recorded in the currency of the benchmark year, are tabulated in the SAM's three data matrices: an $N\times N$ commodity-by-industry matrix of inter-industry

[4] For more in-depth discussions of SAMs and their use in CGE modeling, see King (1985), Kehoe (1998), Rutherford and Paltsev (1999) and Sue Wing (2004).

transactions ($\bar{\mathbf{X}}$), an $F \times N$ matrix of value-added activities by industry ($\bar{\mathbf{V}}$), and an $N \times D$ commodity-by-use matrix of final demand activities ($\bar{\mathbf{G}}$).

The organization of these data reflects the principle of double-entry book-keeping. For each industry or commodity in the SAM, the sum of the cells across a row, which reflects the total value of sales of product, is equal to the sum of the cells down the column corresponding to the same activity, which reflects the total value of inputs to production. These totals give the gross output of the commodity or sector in question, and the equality of the row and column sums reflects the properties of constancy of returns to scale and perfect competition in production, which imply that the value of commodity output is equal to the sum of the values of the inputs use in its production (Sue Wing, 2004). Thus, focusing narrowly on the electric power sector (ELEC), the value of that industry's output, $\bar{y}$, is equal to the sum of the entries down its column, or the sum of the inputs of the i intermediate goods, $\bar{\mathrm{x}}$, and the f primary factors, $\bar{\mathrm{v}}$, to the production of electricity:

$$\bar{\mathrm{y}}(\mathrm{ELEC}) = \sum_i \bar{\mathrm{x}}(i,\ \mathrm{ELEC}) + \sum_f \bar{\mathrm{v}}(f,\ \mathrm{ELEC}). \tag{1}$$

Now consider the use of these data to specify a production function for the electric power sector in a typical top-down climate policy model (Goulder, 1995), shown diagramatically in Fig. 2(a).

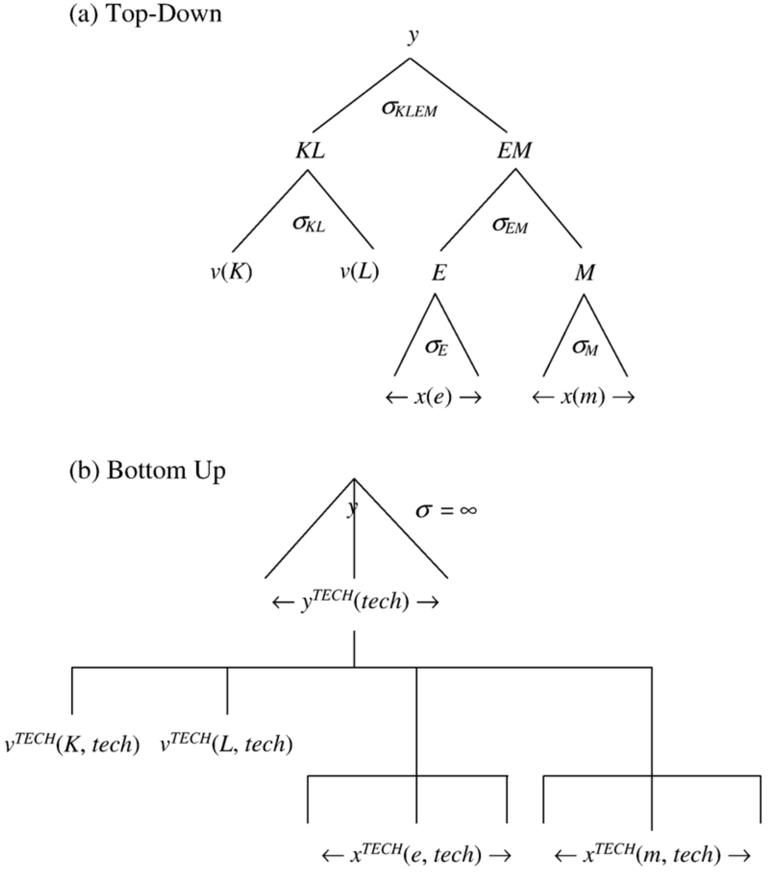

Fig. 2. The structure of production in top-down and bottom-up models (a) top-down; (b) bottom-up.

Assume that there are two factors of production: labor L and capital $K(f=L, K)$, and several intermediate inputs to production that can be partitioned into two subsets: energy commodities (typically, fuels such as coal, oil and gas) $e \subset i$ and materials $m \subset i (i=e, m)$. The diagram shows a nested structure of production in which each node of the tree represents the output of its constituent constant elasticity of substitution (CES) production functions, and the branches denote the inputs to these production functions. Starting at the top of the tree, output y is a CES function of a composite of labor and capital inputs (KL) and a composite of energy and material inputs (EM). KL represents the value added by primary factors' contribution to production, and is a CES function of inputs of labor $v(L)$ and capital $v(K)$. EM represents the value of intermediate inputs' contribution to production, and is a CES function of two further composites, E which is itself a CES function of energy inputs $x(e)$, and M, a CES function of material inputs $x(m)$.

At each level of the nested structure in Fig. 2(a), numerical calibration of the technical coefficients of the production functions is determined by the corresponding elasticities of substitution, σ, and the shares of value of the corresponding inputs in the value of output, recorded in the SAM. Thus the relationship between KL, $v(L)$ and $v(K)$ is determined by σ_{KL} and the elements of the column of $\overline{V}$ that corresponds to the electric power sector. E and M are specified as numerical functions of $x(e)$ and $x(m)$ by the elasticities σ_E and σ_M, respectively, along with their corresponding subsets of the elements in the appropriate column in $\overline{X}$. And, once the value of the input bundle EM is pinned down as a function of E, M and σ_{EM}, the output of the electric sector y can be calibrated as a function of KL, EM and σ_{KLEM}. In employing the SAM to calibrate the production structure, zero profit must be maintained for the sector as a whole as well as for each of its sub-components. Thus, letting $\overline{E}$, $\overline{M}$, $\overline{\mathrm{KL}}$ and $\overline{\mathrm{EM}}$ denote the benchmark values of the energy, material, capital-labor and energy-material composites, respectively, equivalence between the value of output and the value of inputs at each level of Fig. 2(a) implies that Eq. (1) may be disaggregated into the following components:

$$\overline{\mathrm{y}} = \overline{\mathrm{KL}} + \overline{\mathrm{EM}}, \quad \overline{\mathrm{KL}} = \overline{\mathrm{v}}(K) + \overline{\mathrm{v}}(L), \quad \overline{\mathrm{EM}} = \overline{\mathrm{E}} + \overline{\mathrm{M}}, \quad \overline{\mathrm{E}} = \sum_e \overline{\mathrm{x}}(e) \text{ and } \overline{\mathrm{M}} = \sum_m \overline{\mathrm{x}}(m).$$

2.2. A bottom-up production structure: calibration difficulties

From a bottom-up perspective, the previous section represents an overly simplistic characterization of the way in which the production of electric power is actually organized. In the engineering view, electricity output is generated from a number of discrete technologies, each with its own distinct characteristics, for example by a coal technology that combines primary factor inputs of labor and capital with intermediate inputs of coal, by a gas technology from inputs of labor, capital and natural gas, and similarly for petroleum, hydropower, nuclear fission, etc. Fig. 2 (b) shows this alternative production structure, in which there are a number of supply technologies, indexed by tech, each of which produce a single homogeneous commodity, and are therefore perfectly substitutable for one another ($\sigma=\infty$). The level of output of each technology, $y^{\mathrm{TECH}}(\mathrm{tech})$, is a Leontief fixed-coefficients transformation of technology-specific components $v^{\mathrm{TECH}}(L, \mathrm{tech})$, $v^{\mathrm{TECH}}(K, \mathrm{tech})$, $x^{\mathrm{TECH}}(e, \mathrm{tech})$ and $x^{\mathrm{TECH}}(m, \mathrm{tech})$ of the inputs to the electric sector of labor and capital and energy and non-energy intermediate commodities.

In order to use the macroeconomic data in the SAM to numerically calibrate the production structure in Fig. 2(b), one would require data on the benchmark values of the output of and inputs to each technology: $\bar{y}^{TECH}$, $\bar{x}^{TECH}$ and $\bar{v}^{TECH}$. Following the top-down example, the zero profit conditions for the sector and for each technology are:

$$\bar{y} = \sum_{tech} \bar{y}^{TECH}(tech) \tag{2}$$

and

$$\bar{y}^{TECH}(tech) = \sum_{e} \bar{x}^{TECH}(e, tech) + \sum_{f} \bar{v}^{TECH}(f, tech), \tag{3}$$

respectively. However, if we want to disaggregate the monolithic electric power sector into discrete technologies there are additional conditions which must be satisfied. In particular, the value of each input to the different technologies should sum to the value of its input to the sector, resulting in the market clearance conditions for factors

$$\bar{v}(f) = \sum_{tech} \bar{v}^{TECH}(f, tech), \tag{4a}$$

and for intermediate energy and material inputs

$$\bar{x}(e) = \sum_{tech} \bar{x}^{TECH}(e, tech) \tag{4b}$$

and

$$\bar{x}(m) = \sum_{tech} \bar{x}^{TECH}(m, tech). \tag{4c}$$

The foregoing procedure is equivalent to separating the electric power sector in the SAM into an array of column accounts, each of which records the inputs and output of the individual technologies which make up the sector. It is exactly the procedure that must be performed when calibrating hybrid CGE models, with one crucial difference: the values of $\bar{x}^{TECH}$ and $\bar{v}^{TECH}$ are not known to the modeler. The disaggregation procedure must therefore employ additional information on the input-using characteristics of the technologies that are represented, which for the most part are based on a mix of engineering data and assumptions.

Many CGE models for the analysis of energy and climate policy include future high-cost “backstop” technologies that are currently unprofitable and are inactive at initial relative prices, and therefore neither produce output nor absorb inputs in the benchmark dataset on which the model is calibrated (e.g., Goulder, 1995; Paltsev et al., 2005). These kinds of technologies are often included as production functions that are calibrated on engineering data. As relative prices change, either along the baseline solution trajectory in the case of dynamic models, or as a result of policy shocks, these technologies become active and begin demanding inputs and producing output. Such an approach is common in CGE simulations, as the inclusion of initially inactive technologies does not require the modeler to disaggregate the SAM.

By contrast, it is substantially more difficult for CGE modelers to incorporate the kind of energy system detail found in even simple bottom-up models, as this involves partitioning the SAM in accordance with estimates of the value of inputs to and the output of specific technologies which are active in the benchmark. Only a handful of studies have accomplished this feat, and their method of organizing their data and assumptions into a procedure for disaggregating the

SAM — which is the crucial element in the synthesis of top-down and bottom-up approaches-remains largely undocumented.

For example, Boehringer (1998) presents candidate SAMs in which the electric power sector is disaggregated using generic input shares and capacity constraints for a number of aggregate generation technologies.[5] But although the values of the input cost shares and the outputs of these technologies appear plausible, the paper provides no information about the procedure by which the shares and the assumed capacity bounds were employed to disaggregate the SAM. Similarly, Boehringer et al. (2003) present cost-share data for electricity generation technologies in Europe derived from a set of bottom-up studies (the IKARUS database), but give no details about how exactly these data are integrated into the SAMs used to calibrate that paper's multi-regional CGE model. McFarland et al. (forthcoming) introduced carbon-capture and sequestration and competitor electricity generation technologies as backstops into the MIT-EPPA model. But while these authors rigorously document both the bottom-up data and their use in calibrating individual technologies' production functions, they provide few specifics on how these data are used to separately account for technologies' inputs and outputs of the within the framework of the SAM.

2.3. The essence of the problem to be solved

The rest of the paper focuses squarely on the issue of how to disaggregate the SAM in a way that reflects the characteristics of bottom-up data. To understand the challenge in doing so, it is useful to return to Fig. 2(b). In this model, even if the shares of each technology in the total electric output of the benchmark year are known with certainty, it is by no means guaranteed that the input data will be consistent with the value shares of inputs for the electric power sector as a whole given in the SAM. A simple example makes this clear. Suppose that, as in Boehringer (1998), we calculate the shares of the different inputs in the value of output from engineering data, and the shares of the different technologies in electricity output from statistics on electricity generation. The result will be benchmark matrices of input shares for energy, materials and primary factors by technology: $\bar{\mathbf{s}}_E^{\mathrm{TECH}}$ (e, tech), $\bar{\mathbf{s}}_M^{\mathrm{TECH}}$ (m, tech) and $\bar{\mathbf{s}}_f^{\mathrm{TECH}}$ (f, tech), respectively, and the shares of technologies' outputs in the total output of the sector, given by the vector $\bar{s}_Y^{\mathrm{TECH}}$ $(tech)$. The benchmark values of the output of and inputs to each technology can then be recovered from Eqs. (2) and (3):

$$\bar{\mathrm{y}}^{\mathrm{TECH}}(\mathrm{tech}) = \bar{\mathbf{s}}_Y^{\mathrm{TECH}}(\mathrm{tech})\,\bar{\mathrm{y}}, \tag{5}$$

$$\bar{\mathrm{x}}^{\mathrm{TECH}}(e, \mathrm{tech}) = \bar{\mathbf{s}}_E^{\mathrm{TECH}}(e, \mathrm{tech})\,\bar{\mathrm{y}}^{\mathrm{TECH}}(\mathrm{tech}) \tag{6a}$$

$$\bar{\mathrm{x}}^{\mathrm{TECH}}(m, \mathrm{tech}) = \bar{\mathbf{s}}_M^{\mathrm{TECH}}(m, \mathrm{tech})\,\bar{\mathrm{y}}^{\mathrm{TECH}}(\mathrm{tech}) \tag{6b}$$

and

$$\bar{\mathrm{v}}^{\mathrm{TECH}}(f, \mathrm{tech}) = \bar{\mathbf{s}}_f^{\mathrm{TECH}}(f, \mathrm{tech})\,\bar{\mathrm{y}}^{\mathrm{TECH}}(\mathrm{tech}) \tag{6c}$$

However, there is no guarantee that the empirically-determined values of the input and output shares for the different technologies will be consistent with the market clearance conditions in Eqs. (4a) (4b) (4c). The source of this pathology is the doubly-constrained nature of the problem

[5] These data are also used in Frei et al. (2003).

of allocating technologies' inputs and outputs, where, for each primary factor or intermediate good, the sum of the values of its contributions across all technologies must equal its value in the SAM. The shares $\overline{s}^{\mathrm{TECH}}$ must then also satisfy:

$$\overline{\mathrm{x}}(e) = \sum_{\mathrm{tech}} \overline{\mathbf{s}}_E^{\mathrm{TECH}}(e, \mathrm{tech}) \boldsymbol{s}_Y^{\mathrm{TECH}}(\mathrm{tech})\, \overline{\mathrm{y}}\,, \tag{7a}$$

$$\overline{\mathrm{x}}(m) = \sum_{\mathrm{tech}} \overline{\mathbf{s}}_M^{\mathrm{TECH}}(m, \mathrm{tech}) \boldsymbol{s}_Y^{\mathrm{TECH}}(\mathrm{tech})\, \overline{\mathrm{y}}\,, \tag{7b}$$

and

$$\overline{\mathrm{v}}(f) = \sum_{\mathrm{tech}} \overline{\mathbf{s}}_f^{\mathrm{TECH}}(f, \mathrm{tech}) \boldsymbol{s}_Y^{\mathrm{TECH}}(\mathrm{tech})\, \overline{\mathrm{y}}\,. \tag{7c}$$

It would certainly be fortuitous if one could find statistics on technologies' shares of total generation and inputs' cost shares by technology, plug them into Eqs. (7a) (7b) (7c), and have the results magically satisfy the market clearance conditions. But in reality, inconsistencies among the different types of data mean that some adjustment of the shares will always be necessary. The essence of the problem of calibrating hybrid models is therefore to find a new set of technology share matrices $\mathbf{s}^{\mathrm{TECH}}$ whose elements satisfy Eqs. (7a) (7b) (7c) without taking on values that are not "too far" from their empirically-determined benchmark counterparts $\overline{\mathbf{s}}^{\mathrm{TECH}}$. The next section develops this intuition into a mathematically precise procedure, which is then applied to macroeconomic and engineering data for the U.S. electric power sector discussed in Section 4.

3. A model of the electric power sector

The electric power sector tabulated in the macroeconomic accounts is an aggregation of three distinct but related activities: electricity generation, transmission and distribution, and the overhead involved in administering the first two activities. This structure of production is shown in Fig. 3. In line with the process-oriented models of production discussed above, transmission and distribution (TD) and overheard (OH) be thought of as non-energy-using service activities, which can be modeled by production functions that combine inputs of primary factors and non-energy intermediate materials. Generation (GEN) is what most hybrid modeling studies seem to have in mind in the way they represent the electric power sector. This activity encompasses a number of discrete generation technologies, each of which can be modeled as a production function that combines inputs of labor, capital and fuel to produce electricity. As explained above, the problem of calibrating this structure on the data in the SAM is one of allocating proportions of each of the inputs $\overline{x}$ and $\overline{v}$ among elements of the set of activities act = {OH, TD, GEN}, and among elements of the set of generation technologies, in a way that reflects data from other sources on the input and output characteristics of different electricity supply technologies.

3.1. The top-down production structure

The first phase of the analysis is to specify the top-down zero-profit and market-clearance conditions which underlie the production structure in Fig. 3. Moving from top to bottom in the diagram, the first condition is the zero-profit constraint on the output of the sector as a whole,

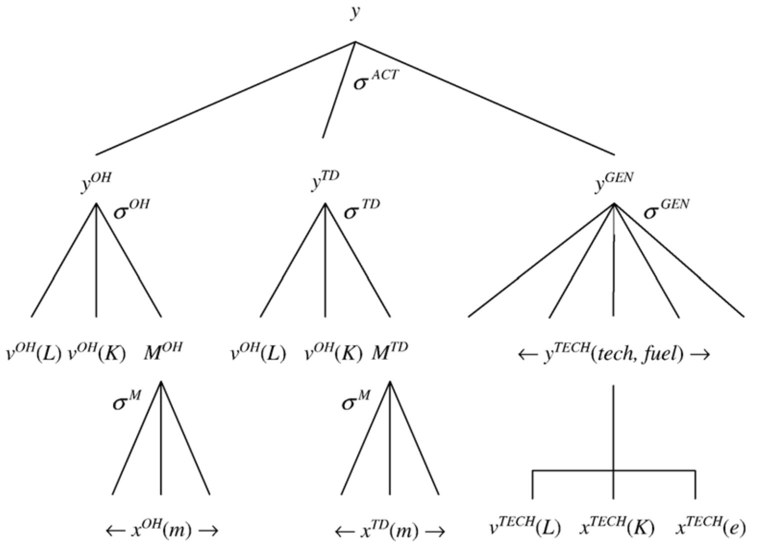

Fig. 3. The structure of p0roduction in a hybrid model of the electric power sector.

which equates the value of output of the electric power industry, $\overline{y}$, with the sum of the values of output of its constituent activities, y^{ACT}:

$$\overline{\mathrm{y}} = \sum_{\mathrm{act}} y^{\mathrm{ACT}}(\mathrm{act}). \tag{8}$$

The second condition is given by the market clearance constraints on the intermediate and primary factor inputs to activities:

$$\overline{\mathrm{x}}(i) = \sum_{\mathrm{act}} x^{\mathrm{ACT}}(\mathrm{act}, i) \tag{9a}$$

and

$$\overline{\mathrm{v}}(f) = \sum_{\mathrm{act}} v^{\mathrm{ACT}}(\mathrm{act}, f) \tag{9b}$$

Going one level deeper in the hierarchy, the third constraint is the zero profit condition for each activity, which equates the value of its output to the sum of the values of its constituent inputs, namely, the i intermediate goods, x^{ACT}, and f primary factors, v^{ACT}:

$$y^{\mathrm{ACT}}(\mathrm{act}) = \sum_{i} x^{\mathrm{ACT}}(\mathrm{act}, i) + \sum_{f} v^{\mathrm{ACT}}(\mathrm{act}, f). \tag{10}$$

A fourth constraint is market clearance in generation, the value of whose output must equal the sum of the value of output of its constituent generation technologies, y^{ACT}:

$$y^{\mathrm{ACT}}(\mathrm{GEN}) = \sum_{\mathrm{tech}} \sum_{\mathrm{fuel}} y^{\mathrm{TECH}}(\mathrm{tech}, \mathrm{fuel}). \tag{11}$$

Symmetrically, there is a fifth market clearance constraint that the value of each input to the generation as a whole must be equal to the sum of the uses of that input across all generation technologies:

$$x^{\mathrm{ACT}}(\mathrm{GEN}, i) = \sum_{\mathrm{tech}} \sum_{\mathrm{fuel}} x^{\mathrm{TECH}}(\mathrm{tech}, \mathrm{fuel}, i) \tag{12a}$$

and

$$v^{\mathrm{ACT}}(\mathrm{GEN}, f) = \sum_{\mathrm{tech}} \sum_{\mathrm{fuel}} v^{\mathrm{TECH}}(\mathrm{tech}, \mathrm{fuel}, f). \tag{12b}$$

Finally, moving down into the details of the individual technologies which comprise generation, the sixth constraint arises from the assumption that each technology earns zero profit, so that the value of output of each technology must equal the sum of the values of the inputs to it:

$$y^{\mathrm{TECH}}(\mathrm{tech}, \mathrm{fuel}) = \sum_{i} x^{\mathrm{TECH}}(\mathrm{tech}, \mathrm{fuel}, i) + \sum_{f} v^{\mathrm{TECH}}(\mathrm{tech}, \mathrm{fuel}, f). \tag{13}$$

3.2. Bottom-up detail

In the second phase we identify the sources of bottom-up detail with which the Eqs. (8) (9a) (9b) (10) (11) (12a) (12b) (13) should be consistent. The data which can be brought to bear in this process will vary according to the economy under consideration. For the U.S. there are three principal sources of information: the shares of inputs and output by generation technology, technologies' efficiency of converting thermal energy to electricity, and the distribution of inputs of capital to the electric sector's constituent activities. We describe these briefly below.

The first set of data is the technology share matrices of intermediate inputs, $\overline{\mathbf{s}}^{\mathrm{TECH}}(\mathrm{tech, fuel}, f)$, and primary factors, $\overline{\mathbf{s}}^{\mathrm{TECH}}(\mathrm{tech, fuel}, f)$, which are derived from engineering studies, and of the different technologies in the generation of electricity in the benchmark year recorded in the SAM, $\overline{\mathbf{s}}^{\mathrm{GEN}}(\mathrm{tech, fuel})$. Following Eqs. (5) and (6a) (6b) (6c), these data imply the following conditions:

$$y^{\mathrm{TECH}}(\mathrm{tech}, \mathrm{fuel}) = \overline{\mathbf{s}}^{\mathrm{GEN}}(\mathrm{tech}, \mathrm{fuel}) y^{\mathrm{ACT}}(\mathrm{GEN}), \tag{14}$$

$$x^{\mathrm{TECH}}(\mathrm{tech}, \mathrm{fuel}, i) = \overline{\mathbf{s}}^{\mathrm{TECH}}(\mathrm{tech}, \mathrm{fuel}, i) y^{\mathrm{TECH}}(\mathrm{tech}, \mathrm{fuel}), \tag{15}$$

and

$$v^{\mathrm{TECH}}(\mathrm{tech}, \mathrm{fuel}, f) = \overline{\mathbf{s}}^{\mathrm{GEN}}(\mathrm{tech}, \mathrm{fuel}, f) y^{\mathrm{TECH}}(\mathrm{tech}, \mathrm{fuel}). \tag{16}$$

The second, related set of information is engineering data on the first-law of thermal efficiency of the conversion of fossil fuels to electric power, and statistics on the prices of fuel inputs and the output of generation by technology. By the assumptions of the model in Fig. 3, fossil fuels are the only reproducible intermediate input to generation, with x^{TECH} and y^{TECH} capturing the values (i.e., price × quantity) of technologies' fossil fuel purchases and outputs. Empirical data on technologies' first-law efficiencies $\overline{\eta}^{\mathrm{TECH}}(\mathrm{tech, fuel})$ specify the ratio of the quantity of electricity output to the quantity of fossil fuel inputs, thereby linking the engineering estimates x^{TECH} and the statistics y^{TECH} with economic data on fossil fuel prices, $\overline{p}_E(e)$, and marginal costs of generation $\overline{p}_G(\text{tech, fuel})$ in the base-year:

$$\overline{\eta}^{\mathrm{TECH}}(\text{tech, fuel}) = \frac{y^{\mathrm{TECH}}(\text{tech, fuel})}{\overline{\mathrm{p}}_G(\text{tech, fuel})} \div \frac{x^{\mathrm{TECH}}(\text{tech, fuel}, e)}{\overline{\mathrm{p}}_E(e)}. \tag{17}$$

The final set of data relates to the distribution of primary factor and non-fuel intermediate inputs between the transmission and distribution and the overhead activities. The data described above determine only the characteristics of generation, therefore additional structure is necessary to characterize the allocation of inputs among the remaining activities. In particular, U.S. economic statistics record the distribution of several categories of fixed assets in different industries, which may be used to estimate the shares of capital input to different activities, $\overline{s}_K^{\mathrm{ACT}}$. These data specify an alternative, bottom-up version of Eq. (9b):

$$v^{\mathrm{ACT}}(\text{act}, K) = \overline{\mathrm{s}}_K^{\mathrm{ACT}}\, \overline{\mathrm{v}}(K) \tag{18}$$

Unfortunately, no such statistics are available on the inter-activity distribution of intermediate material inputs. The simplest assumption is to constrain TD and OH to exhibit the same intensity of use for each input in m, i.e.:

$$x^{\mathrm{ACT}}(\mathrm{OH}, m)/y^{\mathrm{ACT}}(\mathrm{OH}, m) = x^{\mathrm{ACT}}(\mathrm{TD}, m)/y^{\mathrm{ACT}}(\mathrm{TD}, m). \tag{19}$$

While admittedly a crude approximation, a condition of this nature is necessary given the lack of data — otherwise the system of estimating equations is not identified.

3.3. The calibration procedure

The problem of calibrating a hybrid model is to allocate the inputs in the SAM among the activities and technologies at the sub-sector level according to Eqs. (8) (9a) (9b) (10) (11) (12a) (12b) (13) in a way that simultaneously reflects the bottom-up information in Eqs. (14)–(19). Given that the aim of this exercise is to produce a CGE model database that embodies the details of specific technologies, the basis for the calibration procedure must be the primacy of the macroeconomic framework. Eqs. (8) (9a) (9b) (10) (11) (12a) (12b) (13) should therefore be regarded as constraints which must be satisfied with equality in order to maintain the row and column balance of the SAM. The problem is then one of specifying an allocation $\{y^{\mathrm{ACT}}, x^{\mathrm{ACT}}, v^{\mathrm{ACT}}, y^{\mathrm{TECH}}, x^{\mathrm{TECH}}, v^{\mathrm{TECH}}\}$ that meets these constraints with the smallest possible deviation from the benchmark shares $\overline{s}^{\mathrm{GEN}}$, $\overline{s}^{\mathrm{TECH}}$ and $\overline{s}_K^{\mathrm{ACT}}$in Eqs. (14–16) and (18), respectively, and the efficiency parameter $\overline{\eta}^{\mathrm{TECH}}$ in Eq. (17). This constrained minimization procedure falls within a class of econometric methods that Howitt (1995) has termed as positive mathematical programming.

All that remains is to specify the minimand, which is the criterion that captures the divergence between the allocation and the benchmark bottom-up information. The minimand is built up from a number of components. The first is the divergence of the elements x^{TECH}, v^{TECH} and y^{ACT} from the benchmark technology shares, quantified by the fractional deviations $\varepsilon^{\mathrm{TECH}}$ and $\varepsilon^{\mathrm{GEN}}$ of technologies' inputs from the input share data and of their outputs from the statistics on shares of generation, respectively:

$$\varepsilon^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel},i)=\frac{1}{\overline{\mathrm{s}}^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel},i)}\left(\frac{x^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel},i)}{y^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel})}\right)-1, \tag{20}$$

$$\varepsilon^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel},f)=\frac{1}{\overline{\mathrm{s}}^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel},f)}\left(\frac{v^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel},f)}{y^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel})}\right)-1 \tag{21}$$

and

$$\varepsilon^{\mathrm{GEN}}(\mathrm{tech},\mathrm{fuel})=\frac{1}{\overline{\mathrm{s}}^{\mathrm{GEN}}(\mathrm{tech},\mathrm{fuel})}\left(\frac{y^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel})}{y^{\mathrm{ACT}}(\mathrm{GEN})}\right)-1. \tag{22}$$

The next component is the divergence of generation technologies' thermal efficiency implied by the elements $y^{\mathrm{TECH}}(\mathrm{tech, fuel})$ and $x^{\mathrm{TECH}}(\mathrm{tech, fuel}, e)$ from the engineering data $\overline{\eta}^{\mathrm{TECH}}$, as captured by the fractional deviation ε^{η}, which is derived from Eq. (17):

$$\varepsilon^{\eta}(\mathrm{tech},\mathrm{fuel})=\frac{1}{\overline{\eta}^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel})}\left(\frac{y^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel})}{\overline{\mathrm{p}}_{G}(\mathrm{tech},\mathrm{fuel})}\div\frac{x^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel},e)}{\overline{\mathrm{p}}_{E}(e)}\right)-1. \tag{23}$$

The final element is the divergence of the allocation of capital among activities $v^{\mathrm{ACT}}(K)$ from their benchmark shares of total sectoral capital input can be represented by the fractional deviation ε^{K}, which is derived from Eq. (18):

$$\varepsilon^{K}(\mathrm{act})=\frac{1}{\overline{\mathrm{s}}_{K}^{\mathrm{ACT}}(\mathrm{act})}\left(\frac{v^{\mathrm{ACT}}(K)}{\overline{\mathrm{v}}(K)}\right)-1. \tag{24}$$

The calibration problem is therefore one of minimizing the sum of the squares of the error terms in Eqs. (20)–(24):

$$\begin{aligned}\min\mathrm{SSE}=&\sum_{\mathrm{tech}}\sum_{\mathrm{fuel}}\left[\varepsilon^{\mathrm{GEN}}(\mathrm{tech},\mathrm{fuel})\right]^2+\sum_{\mathrm{tech}}\sum_{\mathrm{fuel}}\sum_{i}\left[\varepsilon^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel},i)\right]^2\\&+\sum_{\mathrm{tech}}\sum_{\mathrm{fuel}}\sum_{f}\left[\varepsilon^{\mathrm{TECH}}(\mathrm{tech},\mathrm{fuel},f)\right]^2+\sum_{\mathrm{tech}}\sum_{\mathrm{fuel}}\left[\varepsilon^{\eta}(\mathrm{tech},\mathrm{fuel})\right]^2\\&+\sum_{\mathrm{act}}\left[\varepsilon^{K}(\mathrm{act})\right]^2\end{aligned} \tag{25}$$

subject to the constraints of Eqs. (8–13) and (19). The procedure is implemented as a non-linear program (NLP) in GAMS (Brooke et al., 1998) and solved using CONOPT version 3 (Drud, 1985, 1994, 1997).[6] The model code is given in an appendix.[7]

[6] This model belongs to a class of methods for matrix balancing that has long been studied in operations research (e.g., Schneider and Zenios, 1990).

[7] The results generated by the code in the appendix differ slightly from those in the paper as the latter employ a SAM with higher numerical precision (six significant digits).

4. The data

To operationalize the methodology described above we need three types of information: macroeconomic data on the value of inputs and output of the electric power sector, statistics on the output of electricity by type of generation technology, and information on the characteristics of the technologies used to generate electricity. This section discusses each of these in detail.

4.1. A social accounting matrix for the U.S. in the year 2000

The primary dataset is a U.S. social accounting matrix (SAM) for the year 2000, which was constructed using the SAM for 1999 published by the Bureau of Economic Analysis (BEA). The basic data comes from the BEA's 92-sector "Make of Commodities by Industries" and "Use of Commodities by Industries" tables for 1999, from which an initial SAM was constructed using the industry technology assumption (see e.g. Reinert and Roland-Holst, 1992). Its components of value added were disaggregated using data on industries' shares of labor, capital, taxes and subsidies in GDP published by BEA. The resulting benchmark flow table was then scaled to approximate the U.S. economy in the year 2000 using the growth rate of real GDP from 1999–2000 (3.75%), deflated to year 2000 using the GDP deflator from the NIPAs.

The 92-sector SAM was aggregated into nine industry groupings. In line with the goal of providing a detailed representation of the energy sectors, the disaggregation scheme contains five energy industries: coal, crude oil and gas mining, natural gas distribution, petroleum refining and electric power. The remaining industry sectors are highly aggregate in character: agriculture, energy intensive manufacturing (an amalgam of the pulp and paper, chemical, primary metal and non-metallic material products industries), other manufacturing sectors, transportation, services, and a composite of the remaining industries in the economy.

The economic accounts do not record the contributions to the various sectors of the economy of key natural resources that are germane to the climate problem. Sue Wing (2001) employs information from a range of additional sources to approximate these values as shares of the input of capital to the agriculture, oil and gas, mining, coal, and electric power, and rest-of-economy industries. Applying these shares allows the value of natural resource inputs to be disaggregated from the factor supply matrix $\overline{\mathbf{v}}$, with the value of capital being decremented accordingly.

The final SAM, shown in Fig. 4, provides the macroeconomic data base in which the column account representing the electric power sector is to be disaggregated. It defines the values of the output of the electric power sector, $\overline{\mathrm{y}}$, as well as the inputs of intermediate goods, $\overline{\mathrm{x}}$, and primary factors, $\overline{\mathrm{v}}$, to electricity production, which serve as the control totals for the constrains on the calibration procedure.

4.2. Electricity generation and fuel use statistics

Net electricity generation by technology is computed from the EIA Utility Form 906 database on net generation, fuel consumption, fuel stocks, prime mover and fuel type for the year 2000. The results, which define the technology share matrix, $\overline{\mathbf{s}}^{\mathrm{GEN}}$, are shown in Table 1. The technology data contain two classes of coal-fired generation (steam turbines, ST, and combined-cycle, CC), five classes of petroleum-and natural gas-fired generation (internal combustion engines, IC, combustion turbines, CT, and gas turbines, GT, in addition to ST and CC), and six carbon-free renewable electricity technologies. Table 2 shows the fossil fuel heat input by technology, also computed from

	Coal	Electricity	Gas	Agriculture	Crude oil & gas	Refined petroleum	Energy intensive manufacturing	Manufacturing	Transportation	Services	Rest of the economy	Final uses	Total
Coal	0.24	1.45	0.00	0.00	0.00	0.00	0.22	0.06	0.01	0.06	0.13	0.12	2.29
Electricity	0.05	0.08	0.03	0.28	0.12	0.17	1.38	2.35	0.28	6.45	0.46	12.82	24.47
Gas	0.00	0.53	2.28	0.04	0.45	0.25	0.82	0.73	0.06	1.22	0.21	4.18	10.76
Agriculture	0.00	0.01	0.00	7.03	0.00	0.01	0.17	14.88	0.01	3.07	0.72	3.46	29.37
Crude oil & gas	0.00	0.02	4.80	0.00	2.68	8.38	0.94	0.02	0.03	0.06	0.04	-6.10	10.86
Refined petroleum	0.07	0.24	0.04	0.47	0.07	1.75	0.63	0.61	2.43	2.41	1.73	7.93	18.10
Energy intensive mfg.	0.10	0.12	0.02	1.42	0.29	0.51	17.43	29.83	0.18	6.81	9.47	6.64	72.82
Manufacturing	0.34	0.35	0.05	3.16	0.18	0.19	5.51	91.16	2.28	43.48	24.57	161.42	332.69
Transport.	0.16	0.95	0.13	0.88	0.12	0.78	3.55	7.68	9.80	8.30	2.98	23.92	59.24
Services	0.39	2.27	0.74	4.78	3.99	2.26	10.78	49.31	11.17	240.36	25.59	573.46	925.08
Rest of the economy	0.02	2.51	1.11	0.40	0.52	0.35	3.51	4.97	2.60	24.81	2.69	194.57	238.06
Labor	0.44	4.42	0.43	4.19	0.67	1.14	16.13	84.31	19.03	353.96	111.49		596.21
Capital	0.17	8.39	0.87	7.67	0.84	2.11	10.81	41.03	9.79	187.89	66.51		336.07
Resources	0.11	0.44	0.00	0.16	0.69	0.00	0.00	0.00	0.00	0.00	7.39		8.79
Taxes	0.20	2.69	0.26	0.63	0.26	0.20	0.94	5.77	1.71	47.31	1.26		61.23
Subsidies	0.00	0.00	0.00	-1.72	0.00	0.00	0.00	0.00	-0.13	-0.82	-17.19		-19.87
Total	2.29	24.47	10.76	29.37	10.86	18.10	72.82	332.69	59.24	925.08	238.06	982.42	

Value added = GDP = 9.82 Trillion dollars. Gross Output = 17.24 Trillion dollars
Source: Bureau of Economic Analysis; author's calculations and assumptions

Fig. 4. Year 2000 social accounting matrix for the U.S. (2000 dollars $\times 10^{10}$).

the Form 906 data. The data in Table 1, when divided by these values, gives an estimate of the gross thermal efficiency by technology, $\overline{\eta}^{\mathrm{TECH}}$.

4.3. Bottom-up characteristics of electric generation technologies

Electric power generation technology characteristics are from the assumptions to the annual energy outlook (AEO — DOE/EIA, 2003a) and are reproduced in Table 3:

- The average size of a generation unit (size) in kW of capacity
- The total capital (overnight) cost of the unit (k) per kW
- Variable *O&M* per kWh of output (uvom) and fixed *O&M* per kW of capacity (ufom), and
- The average heat rate (hrt)

Table 1
Net electricity generation (10^{12} kWh) in 2000 by technology and fuel

Technology	Oil	Coal	Gas	Natural resources
Nuclear	–	–	–	0.2482
Hydro	–	–	–	0.7054
Geothermal	–	–	–	0.0006
Wind	–	–	–	7.8×10^{-6}
Solar	–	–	–	2.5×10^{-8}
Biomass	–	–	–	0.0010
Internal combustion	0.0013	–	0.0005	–
Gas turbine	0.0052	–	0.0216	–
Steam turbine	0.0619	1.6973	0.2076	–
Combustion turbine	0.0010	–	0.0505	–
Combined cycle	0.0002	0.0019	0.0069	–

Source: EIA Form 906 data and author's calculations.

Table 2
Heat input (10^{12} kWh) in electricity generation in 2000 by technology and fuel

Technology	Oil	Coal	Gas
Internal combustion	0.0045	–	0.0017
Gas turbine	0.0229	–	0.0860
Steam turbine	0.1919	5.2613	0.6845
Combustion turbine	0.0035	–	0.1367
Combined cycle	0.0005	0.0050	0.0136

Source: EIA Form 906 data and author's calculations.

The table includes additional assumptions about the capacity factors (cf) of different technologies and the average price of different fuels (p_F) in the year 2000, both drawn from a variety of sources.

Table 3
Electric power technology characteristics

Technology	size	kcost	uvom	uvom	hrt	cf	p_E
	Size[a] (mW)	Overnight costs[a] ($2000/kW)	Variable *O&M*[a] ($2000 mills/kWh)	Fixed *O&M*[a] ($2000/kW)	Heat rate[a] (btu/kWh)	Capacity factor[b]	Fuel price ($2000/million btu)
New scrubbed coal	600	1127.34	3.00	23.95	9000	0.85	1.20[c]
IGCC	550	1335.42	1.99	32.94	8000	0.85	1.20[c]
Conv. gas/oil combined cycle	250	523.62	1.99	11.98	7500	0.91	4.24[d]
Adv. gas/oil combined cycle	400	593.96	1.99	9.98	7000	0.91	4.24[d]
Conv. combustion turbine	160	399.55	4.00	9.98	10,939	0.92	4.24[d]
Adv. combustion turbine	230	449.37	3.00	7.98	9394	0.92	4.24[d]
Fuel cells	10	2087.64	19.96	6.98	7500	0.87	4.30[c]
Adv. nuclear	1000	2068.10	0.42	57.13	10,400	0.85	1.95[e]
Distributed generation/base	2	785.43	5.99	13.47	9400	0.86	4.30[c]
Distributed generation/peak	1	942.71	5.99	13.47	10,400	0.05	4.30[c]
Biomass	100	1722.27	2.89	44.88	8911	0.80	1.25[f]
MSW/landfill gas	30	1426.27	0.01	96.15	13,648	0.90	–
Geothermal	50	1725.21	0.00	70.09	32,320	0.95	–
Wind	50	979.83	0.00	25.50	10,280	0.40	–
Solar thermal	100	2534.08	0.00	47.78	10,280	0.42	–
Solar PV	5	3824.56	0.00	9.83	10,280	0.30	–
New hydro[g]	50	3370.18	2.09	7.52	10,280	0.45	–
Existing hydro[h]	50	390.35	2.09	7.52	10,280	0.45	–

[a] DOE/EIA (2003a) Table 40.
[b] DOE/EIA (1999) Table C4; Hamachi et al. (2003) Table 1; DOE/EIA (2003a) Table 73 and text.
[c] DOE/EIA (2003b) Table 4.5.
[d] Average of (DOE/EIA, 2003b) petroleum and natural gas costs per Btu.
[e] NEA (1994) Fig. 6.6 (PWR fuel cycle with direct disposal) at 8% interest rate, deflated.
[f] Haq (2002).
[g] Derived from parameter estimates in Hall et al. (2003) assuming a unit size approximately equal to their sample mean.
[h] Same as new hydro except overnight costs less Hall et al. (2003) dam and powerhouse construction costs.

These data are used to compute the benchmark unit characteristics of the different electricity generation technologies, shown in Table 4. These are:

- Each unit's average annual output (q)
- Its variable and fixed operation and maintenance (*O&M*) costs (vom and fom, respectively), which, following McFarland et al. (2004), are assumed to consist entirely of labor, and make up its annual labor cost (lcost).[8]
- Its annual cost of capital (kcost), equal to plant overnight costs that are levelized using assumptions of an interest rate (r) of 10% and a term (T) of 15 years, [9] and
- Annual cost of inputs of fuel (fcost)

The costs of labor, capital and fuel determine the benchmark shares of fuel, capital and labor input in the cost of generation. Together, these determine the total generation cost (gcost), which along with q gives the average cost of generation p_G.

Two further pre-processing steps are necessary to prepare these data for use in the calibration exercise. The first is to match the AEO technologies to the technology classes used to tabulate the EIA Form 906 data on actual net electricity generation. The matching process is by no means foolproof, as there is the inevitable need to make assumptions about the similarity between the technologies in the two classification schemes. For some technologies, there is a clear one-to-one relationship between the categories in Tables 1 and 2) and those in 3 and 4 (e.g., coal ST and CC technologies, as well as CT and nuclear and renewable generation). For the others, the match was made based on judgments of the similarity between the attributes of the AEO and Form 906 technology categories. For CC and GT technologies, it was assumed that higher thermal efficiency and lower fuel requirements resulted when they were fired with natural gas as opposed to oil, resulting in a smaller share of fuel in total costs for the former. The "advanced" combined-cycle and gas-turbine AEO technologies that exhibit this characteristic were thus matched with gas-fired generation, and their "conventional" counterparts were matched with oil. IC and ST technologies' characteristics were assumed to be the same as the combustion turbine. In with the previous assumption about thermal efficiencies, it was assumed that oil-fired generation was better represented by conventional CT and gas-fired technologies by advanced CT.

The final step is to specify the shares of "fuel" in the value of total output of the carbon-free technologies in Table 4. These generate electricity from inputs of so-called "fixed-factor" energy resources, principally land area with incident insolation or atmospheric boundary-layer flow in the cases of solar and wind, topographically-determined hydrostatic potential in the case of hydroelectricity, or geologically-determined hot dry rock in the case of geothermal energy. A key limitation is the dearth of data on the value of these inputs, which not separately recorded in conventional accounts but are lumped together with overnight (construction) costs. Their value is thus estimated as a share of levelized capital input. In the absence of additional information, it is assumed that the share of the value of fixed-factor energy resources in the input of broad capital is roughly similar among all technologies, leading to benchmark shares of 20% of total costs, similar to the cost shares of fuel inputs computed for nuclear and biomass generation.

[8] In reality, fixed and variable O&M both comprise labor and intermediate materials. The simplifying assumption of attributing O&M entirely to labor is made because of the lack of data on intermediate inputs to generation.

[9] The average bank prime interest rate (http://www.federalreserve.gov/releases/h15/data/a/prime.txt) was 9.23% in 2000. In tests of robustness of these assumptions, simultaneously reducing r to 8% and lengthening T to 30 years significantly reduced both capital's cost share and the overall cost of generation. However, doing so ignores the empirical regularity of the term structure of interest rates. Kahn (1995) discusses the range of plausible assumptions about electric power project financing parameters.

Table 4
Quantities and costs of inputs and output, and initial input cost shares for electric power technologies

Technology	q[a]	vom[b]	fom[c]	fcost[d]	kcost[e]	lcost[f]	gcost[g]	p_G[h]	s_F	s_K	s_L
	Annual electric output (GWh)	Total variable *O&M* ($2000 million)	Total Fixed *O&M* ($2000 million)	Fuel cost ($2000 million)	Levelized capital cost ($2000 million)	Labor cost ($2000 million)	Total generation cost ($2000 million)	Average generation cost (2000 cents/kWh)	Fuel cost share	Capital cost share	Labor cost share
New scrubbed coal	4467.60	13.40	14.37	48.25	87.07	27.77	163.09	3.65	0.30	0.53	0.17
IGCC	4095.30	8.16	18.12	39.31	94.54	26.28	160.14	3.91	0.25	0.59	0.16
Conv. gas/oil combined cycle	1992.90	3.97	2.99	63.38	16.85	6.97	87.20	4.38	0.73	0.19	0.08
Adv. gas/oil combined cycle	3188.64	6.35	3.99	94.65	30.58	10.35	135.58	4.25	0.70	0.23	0.08
Conv. combustion turbine	1289.47	5.15	1.60	59.81	8.23	6.75	74.79	5.80	0.80	0.11	0.09
Adv. combustion turbine	1853.62	5.56	1.84	73.84	13.30	7.39	94.54	5.10	0.78	0.14	0.08
Fuel cells	76.21	1.52	0.07	2.46	2.69	1.59	6.74	8.84	0.36	0.40	0.24
Adv. nuclear	7446.00	3.13	57.13	136.14	266.21	60.26	507.67	6.21	0.29	0.58	0.13
Distributed generation/base	15.07	0.09	0.03	0.61	0.20	0.12	0.93	6.16	0.66	0.22	0.13
Distributed generation/peak	0.44	0.00	0.01	0.02	0.12	0.02	0.16	35.85	0.12	0.77	0.10
Biomass	700.80	2.03	4.49	7.81	22.17	6.51	36.49	5.21	0.21	0.61	0.18
MSW/landfill gas	236.52	0.00	2.88	–	5.51	2.89	8.39	3.55	0.00	0.66	0.34
Geothermal	416.10	–	3.50	–	11.10	3.50	14.61	3.51	0.00	0.76	0.24
Wind	175.20	–	1.27	–	6.31	1.27	7.58	4.33	0.00	0.83	0.17
Solar thermal	367.92	–	4.78	–	32.62	4.78	37.40	10.16	0.00	0.87	0.13
Solar PV	13.14	–	0.05	–	2.46	0.05	2.51	19.11	0.00	0.98	0.02
New hydro	197.10	0.46	0.38	–	21.69	0.83	22.52	11.43	0.00	0.96	0.04
Existing hydro	197.10	0.46	0.38	–	2.51	0.83	3.35	1.70	0.00	0.75	0.25

[a] $q = \text{size} \times \text{cf} \times (24\text{ h/day}) \times (365\text{ days/year})$.
[b] $\text{vom} = q \times \text{uvom}$.
[c] $\text{fom} = \text{size} \times \text{ufom}$.
[d] $\text{fcost} = q \times \text{hrt} \times p_F$.
[e] $\text{kcost} = r \times \text{size} \times k/(1 - e^{-rT})$, $r = 10\%$, $T = 15$ years.
[f] $\text{lcost} = \text{vom} + \text{fom}$.
[g] $\text{gcost} = \text{fcost} + \text{kcost} + \text{lcost}$.
[h] $p_G = \text{gcost}/q$.

Table 5 shows the final benchmark technology-specific cost shares that result from these assumptions, which define the parameters $\overline{s}^{\mathrm{TECH}}(\mathrm{tech},\ \mathrm{fuel},\ i)$ and $\overline{s}^{\mathrm{TECH}}(\mathrm{tech},\ \mathrm{fuel},\ f)$. In comparison with Boehringer (1998: Table 2) and Frei et al. (2003: Table 3), the estimates in Table 5 allocate larger shares of total costs to inputs of labor and fuel, and a smaller share to capital, except in the case of coal technologies.

4.4. Disaggregated capital input by activity

Bottom-up shares of capital by activity were derived using data on the values of current-cost net stocks and depreciation of over sixty different classes of capital assets in the electric utility industry from the BEA Tangible Wealth Survey (Herman 2000). Each asset class was allocated to OH, TD or GEN by assigning to it a subjective probability of belonging to one or more of these activities. The probability weights are shown in Table 6. Capital input to each activity was computed by summing up the value of depreciation, and the value of the stock multiplied by the rate of interest for each asset, and then summing over all classes of assets. The shares of each activity in the resulting value of total capital input define the vector $\overline{\boldsymbol{s}}_K^{\mathrm{ACT}}$.

5. Results and discussion

The model in Section 3 is initialized and run using the data in Section 4. Its solution generates the disaggregated representation of the electric power sector in Table 7, dividing the sector's

Table 5
Benchmark cost shares and unit output costs for electric power technologies

Technology	Unit cost (2000 ¢/kWh)	Factor inputs		Fuel inputs				AEO technology
		Labor	Capital	Coal	Oil	Nat. gas	Nat. res.	
A. Coal								
ST	3.65	0.17	0.53	0.30	–	–	–	New scrubbed coal
CC	3.91	0.16	0.59	0.25	–	–	–	Integrated coal-gasification combined cycle
B. Petroleum								
IC	5.80	0.09	0.11	–	0.80	–	–	Conv. combustion turbine
GT	5.80	0.09	0.11	–	0.80	–	–	Conv. combustion turbine
ST	5.80	0.09	0.11	–	0.80	–	–	Conv. combustion turbine
CT	5.80	0.09	0.11	–	0.80	–	–	Conv. combustion turbine
CC	4.38	0.08	0.19	–	0.73	–	–	Conv. gas/oil combined cycle
C. Natural gas								
IC	5.10	0.08	0.14	–	–	0.78	–	Adv. combustion turbine
GT	5.10	0.08	0.14	–	–	0.78	–	Adv. combustion turbine
ST	5.10	0.08	0.14	–	–	0.78	–	Adv. combustion turbine
CT	5.10	0.08	0.14	–	–	0.78	–	Adv. combustion turbine
CC	4.25	0.08	0.22	–	–	0.70	–	Adv. gas/oil combined cycle
D. "Fixed-factor" energy resources								
Hydro	1.70	0.25	0.55	–	–	–	0.20[a]	Existing hydro
Nuclear	6.21	0.13	0.58	–	–	–	0.31	Advanced nuclear
Wind	4.33	0.17	0.63	–	–	–	0.20[a]	Wind
Biomass	5.21	0.18	0.61	–	–	–	0.21	Biomass
Geothermal	3.51	0.24	0.56	–	–	–	0.20[a]	Geothermal
Solar	14.64	0.07	0.73	–	–	–	0.20[a]	50–50 avg. of solar thermal and photovoltaic

[a] Assumed shares of fixed-factor energy resource inputs.

Table 6
Estimates of benchmark capital input to activities

Asset class	BEA year 2000 data[a]		Probability			Disaggregated stocks[a]			Disagg. depreciation[a]			Disagg. capital input[a,b]		
	Stock	Deprec.	OH	TD	GEN	OH	TD	GEN	OH	TD	GEN	OH	TD	GEN
Computers and software[c]	5266	2190	0.5	–	0.5	2633	–	2633	1095	–	1095	1358	–	1358
Communication equipment	6514	761	0.3	0.3	0.3	2171	2171	2171	254	254	254	471	471	471
Instruments	14,914	2119	0.5	–	0.5	7457	–	7457	1060	–	1060	1805	–	1805
Photocopy and related equipment	943	192	1.0	–	–	943	–	–	192	–	–	286	–	–
Office and accounting equipment	181	58	1.0	–	–	181	–	–	58	–	–	76	–	–
Nuclear fuel rods	6323	1734	–	–	1.0	–	–	6323	–	–	1734	–	–	2366
Other fabricated metal products	7735	747	–	–	1.0	–	–	7735	–	–	747	–	–	1521
Steam engines	33,558	1755	–	–	1.0	–	–	33,558	–	–	1755	–	–	5111
Internal combustion engines	669	147	–	–	1.0	–	–	669	–	–	147	–	–	214
Metal working machinery	1845	228	–	–	1.0	–	–	1845	–	–	228	–	–	413
Special industry machinery, n.e.c.	2285	246	–	–	1.0	–	–	2285	–	–	246	–	–	475
General industrial machinery	12,325	1386	–	–	1.0	–	–	12,325	–	–	1386	–	–	2,619
Electrical transmission and distrib.	108,604	5479	–	1.0	–	–	108,604	–	–	5479	–	–	16,339	–
Trucks, buses, and truck trailers	9214	1880	0.5	0.5	–	4607	4607	–	940	940	–	1401	1401	–
Autos	1982	587	1.0	–	–	1982	–	–	587	–	–	785	–	–
Aircraft	472	53	1.0	–	–	472	–	–	53	–	–	100	–	–
Furniture[d]	2818	342	1	–	–	2818	0	0	342	0	0	624	0	0
Farm tractors	300	48	0.5	0.5	–	150	150	–	24	24	–	39	39	–
Construction tractors	1058	182	0.3	0.3	0.3	353	353	353	61	61	61	96	96	96
Agricultural mach., ex. tractors	28	4	0.5	0.5	–	14	14	–	2	2	–	3	3	–
Construction mach., ex. tractors	9107	1463	0.3	0.3	0.3	3035	3035	3035	488	488	488	791	791	791
Service industry machinery	1106	178	1.0	–	–	1106	–	–	178	–	–	289	–	–
Household appliances	7	1	1.0	–	–	7	–	–	1	–	–	2	–	–
Other electrical equipment, n.e.c.	424	85	0.3	0.3	0.3	141	141	141	28	28	28	42	42	42
Other nonresidential equipment	363	56	0.5	0.5		182	182		28	28	–	46	46	–
Industrial buildings	2790	86	0.5	–	0.5	1395	–	1395	43	–	43	183	–	183
Office buildings	1793	41	1.0	–	–	1,793	–	–	41	–	–	220	–	–
Electric light and power	545,380	11,368	–	0.5	0.5	–	272,690	272,690	–	5684	5684	–	32,953	32,953
Total	778,004	33,416	–	–	–	31,440	391,947	354,615	5474	12,987	14,955	8,618	52,182	50,416

[a] Million 2000 dollars.
[b] Input = Depreciation + $r \times$ Stock, $r = 10\%$.
[c] Composite of mainframe computers, personal computers, computer printers, computer terminals, computer tape drives, computer storage devices, integrated systems, prepackaged software, custom software and own-account software.
[d] Composite of household furniture and other furniture.

244.7 billion dollar gross output into 26.9 billion dollars of tax payments, and 19.3 billion of overhead, 124.4 billion of transmission and distribution, and 74.1 billion of generation activities.[10] Comparison of the row totals with the relevant column in the SAM in Fig. 4 confirms that the allocation procedure preserves the row balance necessary for market clearance at the macro level. Overhead activities use 9% of the sector's labor, 8% of its capital, and 13% of its input of intermediate non-fuel commodities. Transmission and distribution employs 66% of the labor, 48% of the capital and 87 of intermediate materials. Generation accounts for 24% of labor, 44% of capital, and, by construction, none of the sector's non-fuel intermediate inputs and all of its inputs of fuel and fixed-factor energy resources.

Of the technologies comprising generation, coal is the largest with 62% of the value of that activity, followed by nuclear and hydro with 15 and 11%, natural gas and oil with 9 and 4%, and renewables making up less than one-tenth of 1%. The importance of coal technologies is also evident from their command of the inputs to generation, with coal, gas and oil accounting for 65, 24 and 11% of the total value of fossil fuels, respectively. In terms of the distribution of labor inputs to generation, coal accounts for 62%, followed by hydro with 18%, nuclear with 13%, gas with 5% and oil with 2%. Similarly, the lion's share of capital input to generation goes to coal, which accounts for 67%, followed by hydro with 18%, nuclear with 13%, gas with 5% and oil with 2%. Finally, even though renewables are relatively resource-intensive technologies, their output is so small that virtually all of the fixed-factor energy resource is concentrated in the two large-scale non-fossil technologies, nuclear (65%) and hydro (35%).

The technology cost shares that are implied by this allocation are shown in Table 8, which may be contrasted with those in Table 3 of Boehringer et al. (2003). In addition to their greater technology detail the current estimates differ from Boehringer et al.'s in a number of ways. That study assumes a nesting structure similar to Fig. 2(b), which treats each technology as a composite of OH, TD and GEN with intermediate non-fuel commodities as inputs. The input cost shares for coal-fired technologies are roughly similar (taking into account this study's classification of *O&M* as labor), but those for oil-and gas-fired technologies differ radically. While oil and gas generation's labor-cum-material shares are similar, the present results impute the lion's share of their costs of to fuel, as opposed to Boehringer et al.'s attribution of 50–60% of costs to capital. For nuclear, capital's share is also smaller in the present results, reflecting the disaggregation of physical plant and equipment from fixed-factor energy resources. Our labor share is also much larger, partially reflecting the value that Boehringer et al. allocated to that technology's material inputs. Lastly, this pattern of differences is similar for hydro and wind, except that Boehringer et al. did not specify material inputs to these technologies. Here too, cost shares are lower for capital (even when resources are included) and higher for labor.

This comparison raises an important point, which, although implicit in the inter-regional differentiation of the cost share estimates in the Boehringer et al. study, is not emphasized there. It is that technologies' input cost share parameters may far less generic-in the sense of being engineering characteristics of the technologies themselves — than bottom-up studies appear to acknowledge. Rather, as argued throughout this paper, the values of these parameters are significantly influenced by the ruling relative prices in the particular economy in which the technologies are operated by cost-minimizing producers. The implication is that a given technology's input cost coefficients may well

[10] Bounds on the error components ε were added to improve the numerical stability of the optimization problem. Bounding the magnitude of the error terms on generation end thermal efficiency to 45%, and those on technologies' inputs and activities' shares of capital to 25%, resulted in convergence to an interior solution with maximum reduced costs of less than 10^{-7} in fewer than 120 iterations.

Table 7
The main result: disaggregation of the electric power sector

	OH	TD	GEN																		Total
			Coal		Natural gas					Petroleum					Non-fossil						
			ST	CC	IC	GT	ST	CT	CC	IC	GT	ST	CT	CC	Hydro	Nucl.	Wind	Solar	Bio.	Geo.	
1	–	–	1.446	0.001	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	1.448
2	0.011	0.073	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.084
3	–	–	–	–	0.001	0.06	0.327	0.123	0.014	–	–	–	–	–	–	–	–	–	–	–	0.526
4	0.002	0.013	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.015
5	0.003	0.021	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.024
6	–	–	–	–	–	–	–	–	–	0.004	0.018	0.212	0.003	3.6×10^{-4}	–	–	–	–	–	–	0.238
7	0.016	0.105	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.121
8	0.047	0.303	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.350
9	0.127	0.819	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.945
10	0.304	1.962	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	2.265
11	0.337	2.175	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	2.512
12	0.406	2.934	0.67	8.110^{-4}	1.3×10^{-4}	0.005	0.032	0.013	0.002	4.8×10^{-4}	0.002	0.024	3.4×10^{-4}	3.3×10^{-5}	0.195	0.138	3.9×10^{-6}	1.8×10^{-7}	6.5×10^{-4}	3.8×10^{-4}	4.422
13	0.674	4.037	2.446	0.003	2.2×10^{-4}	0.008	0.056	0.023	0.005	5.9×10^{-4}	0.002	0.029	4.1×10^{-4}	6.7×10^{-5}	0.451	0.651	1.5×10^{-5}	1.9×10^{-6}	0.002	8.8×10^{-4}	8.389
14	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0.153	0.288	4.6×10^{-6}	5.1×10^{-7}	7.6×10^{-4}	3.1×10^{-4}	0.442
Total	1.927	12.441	4.562	0.005	0.002	0.072	0.416	0.160	0.020	0.005	0.021	0.266	0.004	4.6×10^{-4}	0.798	1.077	2.3×10^{-5}	2.6×10^{-6}	0.004	0.002	21.781
GEN			4.567		0.669					0.296					1.880						7.413

Inputs: 1. Coal, 2. Electric Power, 3. Natural Gas, 4. Agriculture, 5. Crude Oil and Gas, 6. Petroleum, 7. Energy Intensive Manufacturing., 8. Other Manufacturing, 9. Transportation, 10. Services, 11. Rest of the Economy, 12. Labor, 13. Capital, 14. Natural Resources.

Table 8
Estimated input cost shares by technology

Technology	Factor Inputs	Fuel Inputs				
	Labor	Capital	Coal	Oil	Nat. Gas	Nat. Res.
A. Coal						
ST	0.15	0.54	0.32	–	–	–
CC	0.16	0.58	0.26	–	–	–
B. Petroleum						
IC	0.09	0.11	–	0.80	–	–
GT	0.08	0.09	–	0.83	–	–
ST	0.09	0.11	–	0.80	–	–
CT	0.09	0.11	–	0.81	–	–
CC	0.07	0.15	–	0.78	–	–
C. Natural gas						
IC	0.07	0.12	–	–	0.80	–
GT	0.07	0.1	–	–	0.83	–
ST	0.08	0.13	–	–	0.79	–
CT	0.08	0.14	–	–	0.77	–
CC	0.08	0.23	–	–	0.69	–
D. "Fixed-factor" energy resource						
Hydro	0.24	0.56	–	–	–	0.19
Nuclear	0.13	0.61	–	–	–	0.27
Wind	0.17	0.63	–	–	–	0.20
Solar	0.07	0.73	–	–	–	0.20
Biomass	0.18	0.61	–	–	–	0.21
Geothermal	0.24	0.56	–	–	–	0.20

differ from one economy to another. This possibility should give model-builders pause before simply borrowing cost-share estimates from prior studies when data are available that are specific to the economy under investigation. The methodology developed here thus provides a useful tool for comparing how the distribution of technologies' input costs varies among economies with significant differences in the relative prices of capital, labor and fuels.

One potential caveat is that the heterogeneity in our estimated cost shares may be less a function of the broader economy's dominance over the energy system and more an artifact of the errors introduced by the calibration procedure. While it is important to consider the magnitude and distribution of the errors, the general agreement between our estimates and the bottom-up information on which the calibration procedure is based suggests that it is the patterns in the underlying data which are driving inter-technology differences in our estimates of input characteristics. Table 9 provides an assessment of the performance of the calibration procedure, showing that the allocation of inputs by technology generally reflects the engineering data to a reasonable degree of accuracy. The input share errors ε are all under 10% for fossil fuel and natural resource inputs (with the exception of nuclear power) and under 15% for labor. There are significant problems, however, in the capital allocations for oil- and natural gas-fired gas turbines (26 and 16%, respectively), and oil-fired combined-cycle technologies (23%). Nevertheless, the errors in allocating capital by activity (ε^K) are all less than 2%.

The match between the distribution of electric output and technologies' benchmark generation shares is also generally good. The errors $\varepsilon^{\mathrm{GEN}}$ are under 10% with the exceptions of gas-fired combustion turbines (10%), and especially steam turbines (43%). However, these technologies together make up less than 9% of the total kWh of electric output, which reduces the likelihood that the overall impact of these errors is severe. But by the same token, the comparatively small

Table 9
The performance of the calibration procedure

Technology	Inputs				Generation			Thermal efficiency		
	ε^{TECH}(%)				Quantity (10^{12} kWh)		ε^{GEN}	η (%)		ε^{η}
	Fuel	Labor	Capital	Nat. res.	Predicted	Actual	(%)	Predicted	Actual	(%)
A. Coal										
ST	5.7	−13.7	1.2	–	1.810	1.697	6.7	35.4	32.3	9.8
CC	5.3	−0.6	−2.1	–	0.002	0.002	0.0	39.9	37.8	5.5
B. Natural Gas										
IC	3.1	−7.4	−13.0	–	5.1×10^{-4}	5.1×10^{-4}	−0.1	35.8	29.8	20.4
GT	6.2	−14.9	−25.9	–	0.021	0.022	−4.7	34.8	25.1	38.6
ST	1.0	−2.8	−3.8	–	0.118	0.208	−43.2	36.6	30.3	20.5
CT	−0.8	1.7	3.3	–	0.045	0.051	−10.3	37.2	37.0	0.6
CC	−1.6	0.1	0.4	–	0.007	0.007	−1.0	50.1	50.7	−1.2
C. Petroleum										
IC	0.2	−0.7	−0.8	–	0.001	0.001	0.2	30.7	30.2	1.7
GT	3.7	−13.1	−16.0	–	0.005	0.005	0.6	29.6	22.9	29.4
ST	0.0	−0.3	0.2	–	0.066	0.062	7.1	30.7	32.3	−4.8
CT	1.0	−3.4	−4.2	–	9.8×10^{-4}	9.8×10^{-4}	0.1	30.4	28.0	8.9
CC	7.2	−9.8	−23.4	–	1.5×10^{-4}	1.5×10^{-4}	0.0	41.7	32.7	27.6
D. "Fixed-Factor" Energy Resource										
Hydro	–	−2.4	2.6	−4.2	0.681	0.705	−3.4	–	–	–
Nuclear	–	−1.6	4.3	−14.8	0.251	0.248	1.1	–	–	–
Wind	–	–	–	–	7.6×10^{-6}	7.8×10^{-6}	–	–	–	–
Biomass	–	–	–	–	2.5×10^{-7}	2.5×10^{-7}	–	–	–	–
Geothermal	–	–	–	–	0.001	0.001	–	–	–	–
Solar	–	–	–	–	6.5×10^{-4}	6.5×10^{-4}	–	–	–	–

error in coal steam turbine output (6.7%) is much more consequential, given that this technology accounts for over 56% of total kWh produced.

There is far less consistency between the first-law efficiencies of conversion implied by the data and those implicit in the model's allocation. For half of the fossil fuel technologies, the errors ε^{η} are on the order of 20–30%. Moreover, the predicted efficiencies consistently over-estimate the benchmark bottom-up values. The likely explanation for this phenomenon is systematic bias in the efficiency metric used to calibrate the allocation. The numerator of $\overline{\eta}^{TECH}$ tabulates plants' generation not only for dispatch or spinning reserves but also for periods of standby operation, throughout which their thermal efficiencies are significantly lower than their "nameplate" heat rates might suggest. Although the failure of either the economic data or the allocation mechanism to capture this phenomenon remains a puzzle, the predicted efficiencies are in any case all within plausible ranges, which inspires confidence in the veracity of the results.

Finally, the number of bottom-up technologies and associated characteristics, the dearth of information on the range of uncertainty in the values of these parameters, as well as the variety of potential matches between the AEO and the Form 906 technologies, all make a full-blown sensitivity analysis prohibitively complicated, and in any case too lengthy, to include here. Tests of robustness focused on examining the sensitivity of the calibration procedure to the key assumptions of capital amortization and fixed-factor supply and demand.[11] Varying the interest

[11] The results of these tests are available from the author upon request.

rate and payback period in the calculation of technologies' levelized capital costs was found to induce substantial changes in the benchmark cost shares and the resulting allocation of inputs, but only when the cost of capital was significantly reduced below the base-case level.[12] Other, more reasonable parameter combinations caused shifts in the cost shares and the allocation of less than 10%.

The performance of the model was also relatively insensitive to varying assumptions about both the natural resource supply in the SAM and the cost shares of fixed-factor inputs to renewables. Doubling and halving both the assumed resource cost shares or the resource supply in the SAM exerted only a small influence on either the allocation of intermediate goods or the output levels of fossil fuel technologies. However, they substantially affected both the allocation of primary factor inputs among, and the predicted levels of output of, carbon-free technologies. Moreover, for the two large-scale non-fossil technologies hydro and nuclear, in no case were the combined errors in the share of generation smaller than in the base case, which further strengthens the case for the robustness of the allocation in Table 7. Nevertheless, this result also highlights the need for improved estimates of the value of these resource inputs in the macroeconomic accounts, and for disaggregation of their contribution to technologies' fixed and variable costs in bottom-up data.

6. Conclusion

This paper has developed a procedure for disaggregating the top-down macroeconomic representation of the electric power sector in a SAM for the U.S. into specific electricity supply technologies in a manner that is consistent with these technologies' bottom-up engineering characteristics. Starting with a SAM-based top-down model of the electric power sector and cost shares derived from engineering data, a calibration procedure was developed that apportioned inputs to the electric power sector in the SAM among discrete generation technologies by minimizing the deviation of the allocation of inputs from that implied by engineering cost shares, subject to the zero-profit and market-clearance constraints of the sector's macroeconomic production structure. The results demonstrate the success of this approach, on one hand emphasizing its robustness to variations in the assumptions employed in constructing the data, and on the other the ability to assimilate and reconcile disparate, inconsistent sources of data in a manner that is both transparent and replicable.

Still, much can be done to refine the approach developed here. One important limitation of the paper is its focus on the point estimates generated the calibration procedure while paying too little attention to uncertainties in the activity totals in the top-down model or input cost shares of the bottom-up data. Methodologically, this shortcoming may be addressed by the use of more sophisticated matrix-balancing techniques such as maximum-entropy methods (Golan et al., 1996; Robinson et al., 2001) to estimate confidence bounds on the allocation. But the key prerequisite to this work will be the development of improved bottom-up and top-down datasets to which the procedure in the paper can be applied, perhaps relying on multiple data points over a number of years, but most crucially with a better resolution the value of inputs of fixed-factor primary energy resources to nuclear, hydro and renewable technologies.

Finally, it is natural to ask how the results developed here can be used. The answer to this question is given in a companion article (Sue Wing, in press), which constructs a hybrid model of the U.S. economy which is calibrated to the data in Fig. 4 and Table 7, and compares its response to

[12] This was found for $r = 8\%$ and $T = 30$ years.

emission taxes with that of an identical top-down model that contains no technology detail. Future work will also illustrate how these benchmark data can be used to incorporate technology detail into a fully dynamic general equilibrium simulation of the kind described in Sue Wing and Popp (2006).

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