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General Equilibrium, Electricity Generation Technologies and the Cost of Carbon Abatement

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General Equilibrium, Electricity Generation Technologies and the Cost of Carbon Abatement

Bruno Lanz* and Sebastian Rausch†

Abstract

Electricity generation is a major contributor to carbon dioxide emissions, and a key determinant of abatement costs. Ex-ante assessments of carbon policies mainly rely on either of two modeling paradigms: (i) partial equilibrium models of the electricity sector that use bottom-up engineering data on generation technology costs, and (ii) multi-sector general equilibrium models that represent economic activities with smooth top-down aggregate production functions. In this paper, we examine the structural assumptions of these numerical techniques using a suite of models sharing common technological features and calibrated to the same benchmark data. First, our analysis provides evidence that general equilibrium effects of an economy-wide carbon policy are of first-order importance to assess abatement potentials and price changes in the electricity sector, suggesting that the parametrization of Marshallian demand in a partial equilibrium setting is problematic. Second, we find that top-down technology representations produce fuel substitution patterns that are inconsistent with bottom-up cost data, mainly because of difficulties in capturing the temporal and discrete nature of electricity generation by means of aggregate substitution elasticities. Our analysis highlights the difficulty to parameterize numerical models used for policy projections, and suggests that the integration of a bottom-up electricity sector model into a general equilibrium framework provides an attractive structural alternative for ex-ante policy modeling.

Contents

1. INTRODUCTION

Electricity generation is a significant contributor to carbon dioxide (CO_2) emissions, and potentially has an important role in abatement efforts. The current research paradigm for ex-ante carbon policy assessment mainly involves two classes of models (Hourcade *et al.*, 2006, e.g.,). On

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the one hand, technology-rich 'bottom-up' models provide a detailed representation of generation technologies and the overall electricity system. By construction, these models are partial equilibrium, and typically include no or very limited interactions with the macroeconomic system. On the other hand, economy-wide 'top-down' models represent sectoral economic activities and electricity generation technologies through aggregate production functions. While these models are designed to incorporate general equilibrium effects, smooth aggregate production functions are not well suited to capture the temporal and discrete nature of technology choice.[1]

Given the shortcomings of each model class, the integration of bottom-up technology representation and economy-wide interactions is the subject of a large literature. In so-called 'hybrid' models, the combination of the two models either fail to achieve overall consistency (Hofman and Jorgenson, 1976; Hogan and Weyant, 1982; Drouet *et al.*, 2005; Jacoby and Schäfer, 2006), or complement one type of model with a 'reduced-form' representation of the other, thereby lacking structural explicitness (Messner and Schrattenholzer, 2000; Bosetti *et al.*, 2006; Manne *et al.*, 2006; Strachan and Kannan, 2008). An alternative and more recent approach is to directly embed a set of discrete generation technologies into a top-down model (Sue Wing, 2006; Boehringer and Rutherford, 2008). Under this approach, however, the representation of technological detail significantly increases the dimensionality of the model, thus severely constraining large-scale applications. Finally, a decomposition algorithm by Boehringer and Rutherford (2009) employs an iterative solution procedure between the top-down and bottom-up model components, overcoming issues of dimensionality and model complexity. This approach has been successfully implemented in Sugandha *et al.* (2009). Despite the large literature documenting efforts to reconcile top-down and bottom-up modeling paradigms, there is no quantitative evidence on the relative merits of either of the two approaches or on the benefits of model integration.

The objective of this paper is to examine the implications of top-down and bottom-up modeling approaches for the assessment of economy-wide carbon policies, and explore the sensitivity to different structural assumptions concerning electricity supply and demand. As it is impossible to derive general qualitative propositions for such an issue, we employ a suite of numerical partial equilibrium (PE) and general equilibrium (GE) models that share common technological features and are calibrated to the same benchmark equilibrium. Our benchmark model consistently integrates a bottom-up technology representation of the electricity sector within a general equilibrium setting based on the decomposition method by Boehringer and Rutherford (2009). The economy-wide component is based on a static version of the MIT U.S. Regional Energy Policy (USREP) model, a multi-sector multi-region numerical general equilibrium model designed to analyze climate and energy policy in the U.S. (Rausch **et al.**, 2010a, 2010b). Electricity production is represented by a multi-region load-dispatch model based

[1] Another issue with top-down representations of the electricity sector is the violation of basic energy conservation principles away from the benchmark calibration point (see Sue Wing, 2008).

on a comprehensive database of electric generators from the Energy Information Administration (EIA, 2007a), and features detailed plant-level information on the generation costs and capacity, fuel switching capabilities, and season-specific load profiles.[2]

Our results are as follows. First, we find that general equilibrium income and substitution effects induced by an economy-wide carbon policy are of first-order importance to evaluate the response of the electricity sector, as changes in electricity prices and abatement potentials are largely driven by both the slope and the location of the demand schedule. Following the suggestion in an early and influential article by Hogan and Manne (1977), we explore whether price elasticities of electricity demand simulated from a GE model can approximate general equilibrium effects in a partial equilibrium setting. However, we find that such a modeling strategy is not sufficient to approximate the results one would get with an integrated model. For example, we calculate that general equilibrium effects mitigate electricity price increases by up to 20% in the case of even moderate carbon prices of around \$25 to \$50 per metric ton of CO_2.

Our second set of results relates to the representation of electricity generation technologies in general equilibrium top-down models. Our analysis suggests that top-down technology representations produce fuel substitution patterns that are inconsistent with bottom-up cost data, mainly because of difficulties to capture the temporal and discrete nature of electricity generation by means of aggregate substitution elasticities. In addition, top-down representation of electricity markets imply that the price of electricity reflects the total carbon content of generation. This contrasts with real markets (and the bottom-up approach), where the carbon price is reflected in the electricity price through the carbon content of the marginal producer at a given point in time (Stavins, 2008). We quantify these differences by implementing two widely adopted top-down technology specifications based on nested constant-elasticity-of-substitution (CES) functions (Paltsev *et al.*, 2009; Bovenberg and Goulder, 1996). We find that on the national level structural assumptions about the technology representation translate into welfare costs estimates that differ by as much as 60% for an emissions reduction target of 20%. Regional discrepancies are of the same order of magnitude depending on the initial stock of electric generation technologies.

On a more general level, our findings demonstrate the significance of structural assumptions embedded in top-down and bottom-up modeling approaches for the assessment of carbon and energy policies. Our analysis is thus beneficial to modelers and those who make use of model results as it contributes to an improved understanding of the theoretical and methodological basis for carbon policy assessment with large-scale simulation models. Moreover, we argue that an integrated approach that overcomes limitations inherent in each modeling paradigm can provide a

[2] One major advantage of an integrated approach is the possibility to represent highly detailed assumptions about the market structure in the electricity sector while still capturing general equilibrium effects. In a companion paper (Lanz and Rausch, 2011), we incorporate cost-of-service regulation at the operator level and imperfect competition in wholesale markets to investigate the implications of market structure for the design of carbon pricing policies. To facilitate the comparison of top-down and bottom-up approaches, the present analysis, however, assumes marginal cost-pricing and perfect competition in the electricity sector.

fruitful avenue for enhancing tools for policy analysis.

The remainder of this paper proceeds as follows. Section 2 provides an overview of the economy-wide model and describes the top-down and bottom-up representation of the electric power sector. Section 3 describes the integrated economic-electricity model and issues related to the implementation of the integration algorithm. Section 4 investigates the importance of general equilibrium factors and the implications of top-down versus bottom-up technology representation for carbon policy assessment. Section 5 concludes.

2. ANALYTICAL FRAMEWORK

This section presents the different components of our numerical modeling framework. We first provide an overview of the economy-wide model, and then describe the top-down and bottom-up models of electric generation technologies.

2.1 The U.S. Regional Energy Policy Model

The economy-wide model is based on a static version of the MIT U.S. Regional Energy Policy model (Rausch *et al.*, 2010a,b), a multi-region and multi-sector general equilibrium model for the U.S. economy. USREP is designed to assess the impacts of energy and GHG control policies on regions, sectors and industries, and different household income classes. It is built on state-level data for the year 2006 that combines economic Social Accounting Matrix (SAM) data from from the IMPLAN data set (Minnesota IMPLAN Group, 2008) with physical energy and price data from the State Energy Data System (EIA, 2009b). The model is written in the GAMS software system, formulated with the MPSGE modeling language (Rutherford, 1995, 1999) and solved with the PATH solver (Dirkse and Ferris, 1995) for mixed complementarity problems (MCP). As a detailed description of the model is provided in Rausch *et al.* (2010b), including a full algebraic characterization of equilibrium conditions, we here only give a brief overview of key model features.

The structure of the model is summarized in **Table 1**. Much of the sectoral detail in the USREP model is focused on providing a more accurate representation of energy production and use as it may change under policies that would limit greenhouse gas emissions. Here we group economic sectors as either energy demand sectors or energy supply and conversion sectors. Energy demand sectors include five industrial and three final demand sectors. Each industrial sector interacts with the rest of the economy through an input-output structure, where each sector uses outputs from other sectors, and its output is then used by other sectors, for final demand or is exported. The energy sector encompasses fossil energy production, as well as electricity production (including generation, transmission and distribution activities). Energy supply and conversion sectors are modeled in enough detail to identify fuels and technologies with different CO_2 emissions. The model describes production and consumption sectors as nested Constant Elasticity of Substitution (CES) production functions (or the Cobb-Douglas and Leontief special cases of the CES). The nesting structure and parametrization for each production and consumption activity is described in detail in Rausch *et al.* (2010a).

Table 1. USREP Model Details.

Sectors	Regions[a]	Production Factors
Industrial sectors	California ISO (CA)	Capital
Agriculture (AGR)	Northwest Power Pool (NWPP)	Labor
Services (SRV)	Mountain Power Area (MOUNT)	**Resource factors**
Energy-intensive products (EIS)	Texas (ERCOT)	Coal
Other industries products (OTH)	Southwest Power Pool (SPP)	Natural gas
Transportation (TRN)	Midwest ISO (MISO)	Crude oil
Final demand sectors	Southeast Power Pool (SEAST)	Hydro
Household demand	PJM Interconnection (PJM)	Nuclear
Government demand	New York ISO (NY)	Land
Investment demand	New England ISO (NENGL)	
Energy supply and conversion		
Fuels production		
Coal (COL)		
Natural gas (GAS)		
Crude oil (CRU)		
Refined oil (OIL)		
Electric generation, transmission and distribution		

Notes: [a]Specific detail on regional grouping is provided in Figure 1.

A single representative household in each region is endowed with labor, capital, and industry-specific natural resources. The government is modeled as a passive entity which collects taxes and spends revenue on goods and transfers to households. Tax rates are differentiated by region and sector, and include both federal and state taxes.[3] The demand for investment is driven by savings, which enter directly into the utility function and makes the consumption-investment decision endogenous.

The regional structure of the model is based on the geographical segmentation of electric power markets. This segmentation is mainly driven by available transmission capacity and by the evolving regulatory status of the electricity sector (Joskow, 2005).[4] We approximate the geographical structure of electricity markets by grouping states into ten regions. The resulting regional aggregation is shown in **Figure 1**, and region acronyms are listed in Table 1. Labor is assumed to be fully mobile across industries in a given region but is immobile across U.S. regions, while capital is mobile across regions and industries.

[3] The USREP model includes ad-valorem output taxes, corporate capital income taxes, and payroll taxes (employers' and employees' contribution). In addition, IMPLAN data has been augmented by incorporating tax data from the NBER TAXSIM tax simulator to represent marginal personal income taxes. The detailed representation of taxes captures the effects of tax-base erosion following a GHG pricing policy.

[4] Figure A1 in Appendix A provides a current map of integrated electricity markets.

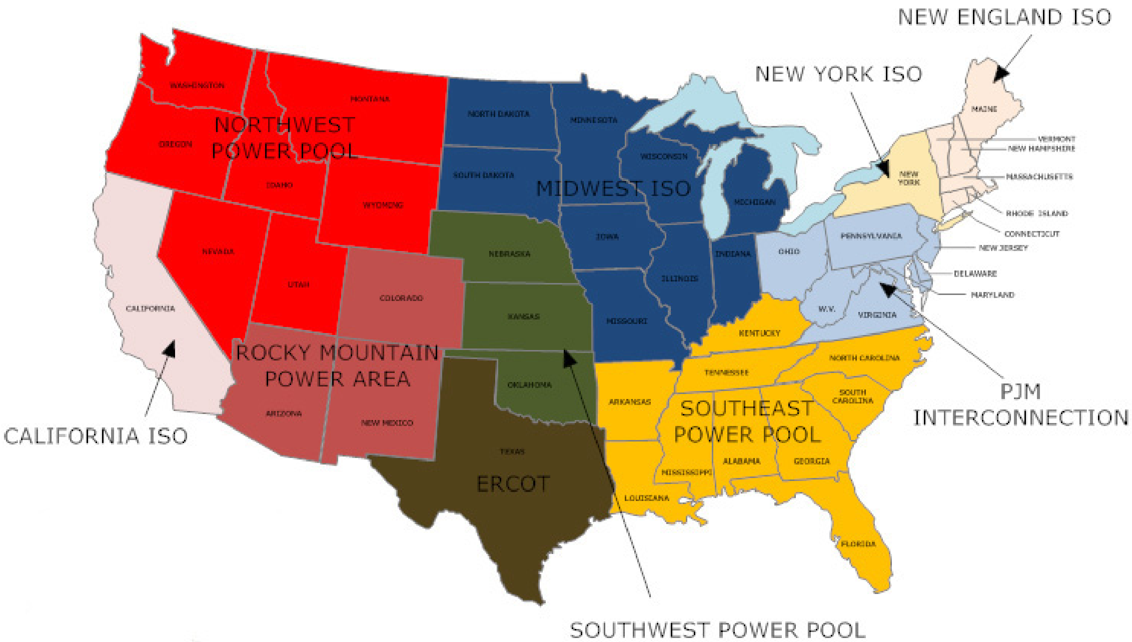

Figure 1. Regions in the Integrated Economic-Electricity Model.

All goods represented in the model are tradable and, depending on the type of commodity, we distinguish three different representations of intra-national regional trade. First, bilateral flows for all non-energy goods are represented as Armington goods (Armington, 1969), where like goods from other regions are imperfectly substitutable for domestically produced goods. Second, domestically traded energy goods, except for electricity, are assumed to be homogeneous products, i.e. there is a national pool that demands domestic exports and supplies domestic imports. This assumption reflects the high degree of integration of intra-U.S. markets for natural gas, crude and refined oil, and coal. Third, we differentiate three regional electricity pools that are designed to provide an approximation of the three asynchronous interconnects in the U.S.: the Eastern Interconnection, Western Electricity Coordinating Council (WECC), and the Electric Reliability Council of Texas (ERCOT).[5] We assume that within each regional pool traded electricity is a homogeneous good.

Foreign closure of the model is determined through a national balance-of-payments (BOP) constraint. Hence, the total value of U.S. exports equals the total value of U.S. imports accounting for an initial BOP deficit given by 2006 statistics. The BOP constraint thereby determines the real exchange rate which indicates the endogenous value of the domestic currency vis-a-vis the foreign currency. The U.S. economy as a whole is modeled as a large open economy by specifying elasticities for world export demand and world import supply functions. Thus, while

[5] In terms of the regional aggregation described in Figure 1, the Eastern Interconnection thus comprises SPP, MISO, SEAST, PJM, NY, and NENGL, and the WECC comprises CA, NWPP, and MOUNT.

we do not explicitly model other regions, the simulations include terms of trade and competitiveness effects of policies that approximate results we would get with a global model.

2.2 Top-Down Modeling of the Electricity Sector

The top-down approach for modeling electricity generation in energy-environment general equilibrium models typically involves a representative firm in each region chooses a profit-maximizing level of output. In our setting, production technologies involve energy (E), capital (K), labor (L), and material inputs (M_j) from other sectors indexed by $j \in \{$*Agriculture, Services, Energy-Intensive, Other Industries, Transportation*$\}$, subject to technological, institutional and resource constraints. Production technologies are described by nested CES production function, and markets are competitive. In the following, we describe the representation of the nesting structure and lay out equilibrium conditions for electricity generation. The nesting structure that we adopt and values for the free elasticity parameters are provided in **Figure 2** and **Table 2**, respectively.

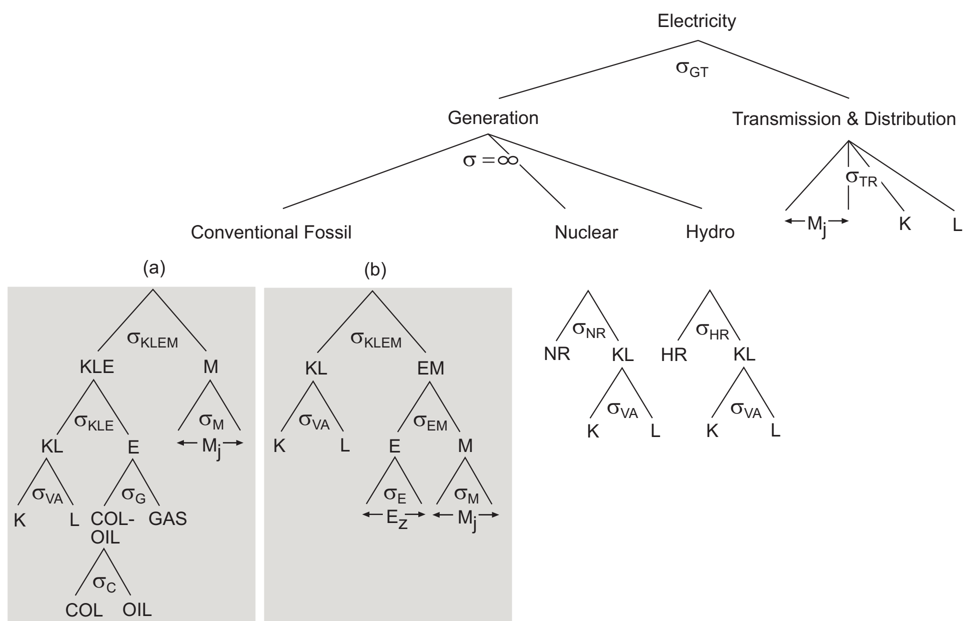

Figure 2. Top-Down Production Structure of Electricity Sector.

Electricity for end-use demand combines electricity generated with *Transmission & Distribution* services, which themselves are a CES composite of capital, labor, and material inputs. Electric current from different sources is modeled as a homogeneous commodity (as indicated by an infinite elasticity of substitution in the nest labeled *Generation*), and production from *Conventional Fossil*, *Nuclear*, and *Hydro* is resolved at the sub-sector level to separately identify inputs and outputs, and to reflect the characteristics of each technology. Electricity produced from nuclear and hydro power relies on capital and labor, and a technology- and region-specific resource factor (NR and HR) that is assumed to be in fixed supply. The elasticity

Table 2. Elasticity Parameters for Top-down Representation of Electricity Sector.

Parameter	Description	Value[a] (a)	Value[a] (b)
Elasticity of substitution			
σ_{KLEM}	Capital-labor and energy-materials bundle	0	0.70
σ_{KLE}	Energy and value-added	0.40	–
σ_{E}	Energy inputs	–	0.97
σ_{M}	Material inputs	0	0.60
σ_{EM}	Energy and materials bundle	–	0.70
σ_{G}	Coal/oil and natural Gas	1.00	–
σ_{C}	Coal and oil	0.30	–
σ_{GT}	Generation and transmission & distribution	0	0
σ_{TR}	Inputs in transmission & distribution bundle	0	0
σ_{VA}	Capital and labor	1.00	1.00
Elasticity of supply			
η_{NR}	Nuclear resource	0.25	0.25
η_{HR}	Hydro resource	0.50	0.50

Notes: [a]Values shown in columns (a) and (b) refer to elasticity parameters used on the nesting structure shown in Panel (a) and (b) in Table 2, and are taken from the MIT EPPA model (Paltsev *et al.*, 2009) and Bovenberg and Goulder (1996), respectively.

of substitution between the resource factor and value-added bundle is calibrated to match observed price elasticities of supply reported in Table 2.[6]

For fossil-based electricity, we implement two different nesting structures widely that are adopted in the literature. The nesting structure labeled (a) in Figure 2 is in line with Rausch et al. (2010b), Paltsev *et al.* (2009) and Boehringer *et al.* (2010). The nesting structure labeled (b) is based on Bovenberg and Goulder (1996), and has been used for policy analysis in Sue Wing (2006). Elasticities values for each nesting structure are shown in Table 2, and are taken from the MIT EPPA model (Paltsev *et al.*, 2009) and Bovenberg and Goulder (1996), respectively.

Under the nesting structure (a) electricity produced from fossil fuels combines materials and a capital-labor-energy composite in a Leontief nest ($\sigma_{KLEM} = 0$). Generation from coal, oil, and gas technologies are not represented separately but are instead treated via substitution between fuels. This has the implication of limiting the substitution possibilities among fuels, thus representing their unique value for peaking, intermediate, and base load. For example, even if gas

[6] Following Rutherford (1998), the elasticity of substitution between value-added and the resource factor in the nuclear sector can be calibrated according to $\sigma_{NR} = \eta_{NR} \frac{\theta_n}{1-\theta_n}$ where θ_n is the value share of resource costs. A similar formula is used to calibrate σ_{HR}, the elasticity of substitution between value-added and the resource factor in the hydro sector.

generation becomes much more expensive than coal or nuclear, this structure will tend to preserve its use. This is consistent with gas technology being adequate for peak load supply, since building capacity of nuclear and coal for peak demand would mean large amounts of capital would be idle much of the time.

The nesting structure (b) follows the same logic but allows for direct substitution between all fossil fuels (E_z, $z = \{$*Coal, Oil, Natural Gas*$\}$). Moreover, the value added bundle here trades off with an energy-materials composite whereas under the nesting structure (a) capital-labor can be substituted directly for composite energy. A key difference between both structures is that (b) allows for a higher degree of substitutability between materials M and energy E, i.e. $\sigma_{EM} > 0$, whereas under (a) materials enter in fixed proportions, i.e. $\sigma_{KLEM} = 0$. This implies that if energy prices rise relative to material costs, generation costs will be higher under structure (a) compared to (b).

Given this structure, the agent's interactions generate a set of supply and demand schedules, and interactions among these agents determine equilibrium values of the endogenous variables listed in **Table 3**. In equilibrium, the cost minimizing behavior and the price-taking assumption imply that zero-profit and market clearing conditions exhibit complementary slackness with respect to activity levels and market prices, respectively (Mathiesen, 1985; Rutherford, 1995). Hence, zero-profit conditions for fossil and non-fossil electricity generation determine the respective activity levels:[7]

$$-\Pi^{\text{NF}} \geq 0 \quad \perp \quad \text{ELE}^{\text{NF}} \geq 0 \tag{1}$$

$$-\Pi^{\text{F}} \geq 0 \quad \perp \quad \text{ELE}^{\text{F}} \geq 0 \tag{2}$$

where Π^{NF} and Π^{F} denotes the unit profit function for each type of generation technology, and the $\perp$ operator indicates the complementary relationship between an equilibrium condition and the associated variable.

Unit profit functions for electricity generation from non-fossil fuel sources, indexed by $NF = \{Nuclear, \; Hydro\}$, can be derived based on the dual cost minimization problem of individual producers. Given the CES nesting structure reported in Figure 2 these can be written as:

$$\Pi^{\text{NF}} = P^{\text{ELE}} - \left(\theta^{\text{NF}} \left(\frac{P^{\text{NF}}}{\theta^{\text{NF}}} \right)^{1-\sigma_{\text{NF}}} \right.$$
$$\left. + (1-\theta^{\text{NF}}) \left[\left(\frac{P^K}{(1-\theta^{\text{NF}})\theta_K^{\text{NF}}} \right)^{\theta_K^{\text{NF}}} \left(\frac{P^L}{(1-\theta^{\text{NF}})(1-\theta_K^{\text{NF}})} \right)^{(1-\theta_K^{\text{NF}})} \right]^{1-\sigma_{\text{NF}}} \right)^{1/(1-\sigma_{\text{NF}})}$$

[7] For notational convenience, we suppress the region index and focus on an algebraic characterization of the production structure shown in Panel (a), Figure 2. Also, we abstract here from generation and transmission costs that are modeled as a simple fixed coefficient (Leontief) technology.

Table 3. Equilibrium Variables Related to Electricity in Top-Down Representation.

Activity variables	
$\mathrm{ELE}^{\mathrm{NF}}$	Electricity generation from non-fossil technologies
$\mathrm{ELE}^{\mathrm{F}}$	Electricity generation from fossil fuels
D^{ELE}	Demand for electricity
S^j , D^j	Supply and demand for commodity j in non-electricity sectors
L , D^{L}	Labor supply and demand in non-electricity sectors
K , D^{K}	Capital supply and demand in non-electricity sectors
S^{z} , D^{z}	Supply of and demand for fuel z in non-electricity sectors
S^{NF}	Supply of technology-specific resource
Price variables	
P^{ELE}	Price index for electricity generation
P^j	Price index non-energy commodity j
P^{L}	Wage rate
P^{K}	Rental price for capital
P^{z}	Price index for fossil fuel z
P^{NF}	Price index for technology-specific resource NF

where θ^{NF} is the benchmark cost share of the fixed input in the non-fossil generation technology and θ_K^{NF} is the cost share of capital in the value-added subnest.

Using a similar notation, and given the Leontief structure in the top-nest of electricity generation, the unit profit function for electricity generation from conventional fossil fuels is:

$$\Pi^{\mathrm{F}} = P^{\mathrm{ELE}} - \left(\theta^{\mathrm{KLE}} P^{\mathrm{KLE}} + (1-\theta^{\mathrm{KLE}}) \sum_j \theta^j P^j\right)$$

where θ^{KLE} is the benchmark cost share of the capital-labor-electricity (KLE) composite, and θ^j is the benchmark cost share of commodity *j*. The cost of a unit of KLE is given by:

$$P^{\mathrm{KLE}} = \left\{\theta^{\mathrm{E}} \left(\frac{P^{\mathrm{E}}}{\theta^{\mathrm{E}}}\right)^{1-\sigma_{\mathrm{KLE}}} + (1-\theta^{\mathrm{E}}) \left[\left(\frac{P^K}{(1-\theta^{\mathrm{E}})\theta_K^{\mathrm{E}}}\right)^{\theta_K^{\mathrm{E}}} \left(\frac{P^L}{(1-\theta^{\mathrm{E}})(1-\theta_K^{\mathrm{E}})}\right)^{(1-\theta_K^{\mathrm{E}})}\right]^{1-\sigma_{\mathrm{KLE}}}\right\}^{1/(1-\sigma_{\mathrm{KLE}})}$$

where θ^E is the cost share of the composite fuel cost and θ_K^{E} is the cost share of capital in the value-added subnest. The unit profit function of the fossil-based generation is completed by the composite cost-minimizing unit fuels costs:

$$P^E = \left\{\theta^{\mathrm{GAS}} \left(\frac{P^{\mathrm{GAS}}}{\theta^{\mathrm{GAS}}}\right)^{(1-\sigma_{\mathrm{G}})} + (1-\theta^{\mathrm{GAS}}) \left[\theta^{\mathrm{COL}} \left(\frac{P^{\mathrm{COL}}}{\theta^{\mathrm{COL}}(1-\theta^{\mathrm{GAS}})}\right)^{(1-\sigma_{\mathrm{C}})} + (1-\theta^{\mathrm{COL}}) \left(\frac{P^{\mathrm{OIL}}}{(1-\theta^{\mathrm{COL}})(1-\theta^{\mathrm{GAS}})}\right)^{(1-\sigma_{\mathrm{C}})}\right]^{\frac{(1-\sigma_{\mathrm{G}})}{(1-\sigma_{\mathrm{C}})}}\right\}^{1/(1-\sigma_{\mathrm{G}})}$$

with respective baseline cost share parameters.

For a given region, equilibrium interactions of the electricity sector with the rest of the economy can be fully described by a set of market clearing conditions. We begin with the market clearing condition for electricity:

$$\mathrm{ELE}^{\mathrm{F}} + \sum_{\mathrm{NF}} \mathrm{ELE}^{\mathrm{NF}} = \mathrm{D}^{\mathrm{ELE}} \quad \perp \quad P^{\mathrm{ELE}}\,. \tag{3}$$

The demand for inputs can be derived by applying the envelope theorem (Shephard's Lemma), so that the market clearing for non-energy commodity j is given by:

$$S^j = D^j + \overline{\mathrm{ELE}}^{\mathrm{F}} \frac{\partial \Pi_{\mathrm{F}}}{\partial P^j} \quad \perp \quad P^j \tag{4}$$

where a variable with a bar denotes its benchmark value.

The regional labor market is in equilibrium if:

$$L = D^L + \overline{\mathrm{ELE}}^{\mathrm{F}} \frac{\partial \Pi_{\mathrm{F}}}{\partial P^L} + \overline{\mathrm{ELE}}^{\mathrm{NF}} \sum_{\mathrm{NF}} \frac{\partial \Pi_{\mathrm{NF}}}{\partial P^L} \quad \perp \quad P^L\,, \tag{5}$$

and the market clearance condition for capital is:

$$\sum_{\mathrm{r}} K_{\mathrm{r}} = \sum_{r} D^K_r + \overline{\mathrm{ELE}}^{\mathrm{F}}_r \frac{\partial \Pi_{\mathrm{F}}}{\partial P^K} + \overline{\mathrm{ELE}}^{\mathrm{NF}}_r \sum_{\mathrm{NF}} \frac{\partial \Pi_{\mathrm{NF}}}{\partial P^K} \quad \perp \quad P^K\,. \tag{6}$$

Similarly, the market for fossil fuel z and technology-specific resources is in balance if:

$$S^{\mathrm{z}} = D^{\mathrm{z}} + \overline{\mathrm{ELE}}^{\mathrm{F}} \frac{\partial \Pi_{\mathrm{F}}}{\partial P^{\mathrm{z}}} \quad \perp \quad P^{\mathrm{z}} \tag{7}$$

$$S^{\mathrm{NF}} = \overline{\mathrm{ELE}}^{\mathrm{NF}} \frac{\partial \Pi_{\mathrm{NF}}}{\partial P^{\mathrm{NF}}} \quad \perp \quad P^{\mathrm{NF}}\,. \tag{8}$$

Finally, the income of the representative household is given by:

$$M = P^K \overline{\mathrm{K}} + P^L \overline{\mathrm{L}} + \sum_{NF} P^{NF} \overline{\mathrm{R}}^{NF} + TR\,. \tag{9}$$

where M denote income and comprises revenues derived from capital, labor and natural resources endowments, as well as government transfers (*TR*).

2.3 Bottom-Up Modeling of the Electricity Sector

The bottom-up approach exhibits two key differences as compared with the top-down representation of electricity generation. First, the bottom-up model uses a cost-based description of discrete generation technologies to determine the least-cost utilization that meets the demand, whereas the top-down representation uses smooth (nested) CES functions where the share parameters are calibrated to match the benchmark value market shares. Second, the bottom-up approach features a finer time resolution, dividing the year into load blocks to capture observed fluctuations of the physical demand for electricity. This reflects the limited substitution possibilities of electricity generated at two different times in the year, since neither the supply of electricity nor the demand for electricity services can easily be shifted across time.[8]

Our bottom-up representation of the electricity sector, a partial equilibrium multi-region load-dispatch model for the continental U.S., is conceptually close to a static version of a MARKAL (MARKet ALlocation) model, a widely used normative framework for optimal resource allocation, originally developed by the International Energy Agency (Fishbone and Abilock, 1981). The model is based on a comprehensive data set of more than 16,000 electricity generators that were active in 2006 (EIA Form EIA-860, 2007a) containing information on the capacity, generation technology and energy sources. The list of generation technologies and fuels included in the model are displayed in **Table 4**. Generators are characterized by a constant marginal generation cost and maximum output in each time period.[9]

Marginal costs of generators include two main components. First, we use variable operation and maintenance (O&M) costs from EIA (2009a). These costs are specific to combinations of technology and fuel, and includes labor, capital, material and waste disposition costs per unit of output. The second cost component is fuel specific, and contingent on generator-specific technology, as reported in EIA (EIA Form EIA-860, 2007a), generators can use up to three different fuels. The choice of fuel is thus endogenous, and depends on the prevailing fuel prices, including differences in carbon intensity when a carbon price is levied on carbon emissions. We use data on state-level fuel prices for 2006 (EIA, 2009c). The second determinant of the fuel cost is the efficiency of the plants, which we derive by matching generators to plant level data on fuel consumption and net electricity output (EIA Form EIA-920, 2007b).

In the benchmark, the electricity demand by region (in MWh) is directly taken from the augmented SAM data that underlies the USREP model and that incorporates information about physical energy quantities. We then share out the demand across three seasons (summer, winter and fall/spring) with region-specific data (EIA Form EIA-920, 2007b), and into three load blocks (peak, intermediate and base-load) with region and season-specific load distribution data (EIA, 2009a).

In order to keep simulations comparable across modeling frameworks, the market structure is akin to that of the top-down representation, and in each region and time period generators are assumed to be price-takers. The market value of electricity generated, which we refer to as the wholesale price (net of transmission and distribution costs), varies in each region, season and load

[8] First, the costs of storing electric current are essentially prohibitive, so that electricity must be produced "on demand". Second, the demand for electricity services varies over time through stable (although uncertain) factors, like the hours with natural light or the weather conditions.

[9] For technologies with relatively low generation costs, we impute capacity factors from data on observed output (EIA Form EIA-920, 2007b). Indeed, technologies such as nuclear, hydro, wind and solar can be seen as "must-run" technologies, in the sense that they are typically used at their effective capacity in each period (Bushnell *et al.*, 2008).

Table 4. Generation Technologies and Fuel Mapping between Economy-wide and Electricity Sector Model.

Technologies

Combined Cycle, Combustion Turbine, Hydraulic Turbine, Internal Combustion Engine, Photovoltaic, Steam Turbine, Wind Turbine

Fuels

Coal:

Anthracite and Bituminous Coal (BIT), Lignite Coal (LIG), Coal-based Synfuel (SC), Sub-bituminous Coal (SUB), Waste and other Coal (WC)

Natural Gas:

Blast Furnace Gas (BFG), Natural Gas (NG), Other Gas (OG), Gaseous Propane (PG)

Oil:

Distillate Fuel Oil (DFO), Jet Fuel (JF), Kerosene (KER), Residual Fuel Oil (RFO)

Exogenous:

Agricultural Crop (AB), Other Biomass (gas, liquids, solids) (OB), Black Liquor (BLQ), Geothermal (GEO), Landfill Gas (LFG), Municipal Solid Waste (MSW), Nuclear Fission (NUC), Petroleum Coke (PC), Other wastes (OWH), Solar (SUN), Wood and Wood Waste (WDS), Wind (WND), Hydroelectric (WAT)

Table 5. Equilibrium Variables Related to Electricity in Bottom-up Model.

Activity variables	
$\mathrm{ele}_{\mathrm{t}}^{\mathrm{g,z}}$	Electricity generation for generator g, fuel z and load block t
$d_{\mathrm{t}}^{\mathrm{ele}}$	Electricity demand in load block t
d^{z}	Demand for fuel z
Price variables	
p_t^{ws}	Wholesale price of electricity generation in load block t
p^{ele}	Consumer price for electricity generation
p^{z}	Price of fuel z
μ_t^{g}	Fixed capacity rents for generator g and load block t

block according to the generation costs of the marginal producer.

Akin to the top-down representation, the model is formulated as a MCP and we now lay out the equilibrium conditions for the bottom-up representation of the electricity sector. Endogenous variables are listed in **Table 5**, where we denote respective counterparts to the top-down representation with corresponding lower case variables and list.[10]

Electricity output at each generator g and load block t exhibits complementarity slackness with the zero profit condition:

$$-\pi_{\mathrm{t}}^{\mathrm{g,z}} \geq 0 \quad \perp \quad \mathrm{ele}_{\mathrm{t}}^{\mathrm{g,z}} \geq 0 \tag{10}$$

[10] As above, we omit the region index and we abstract from generation and transmission costs.

where the unit profit function is given by:

$$\pi_{\mathrm{t}}^{\mathrm{g,z}} = p_t^{\mathrm{ws}} - c^{\mathrm{g}} - p^{\mathrm{z}}\gamma^{\mathrm{g}} - \mu_t^{\mathrm{g}}$$

and where c^{g} denotes variable O&M costs of generation and γ^{g} is a measure of the fuel requirements per unit of output. Note here that generators able to use multiple fuels always use their capacity at the lowest possible cost, and since fuel prices are determined on a yearly basis, it is always optimal for producers to use only the cheapest fuel for generating electricity across all load blocks.

The wholesale price of electricity in each load block is the complementary variable to the market clearance equation:

$$\sum_{g,z} \mathrm{ele}_{\mathrm{t}}^{\mathrm{g,z}} = d_{\mathrm{t}}^{\mathrm{ele}} \quad \perp \quad p_t^{ws}\,. \tag{11}$$

In this setting, all submarginal generators earn scarcity rents $\mu_{\mathrm{t}}^{\mathrm{g}}$ measuring the value of the installed generation capacity per unit of output. The rents are the multiplier associated with the per period capacity constraints:

$$\kappa_{\mathrm{t}}^{\mathrm{g}} \geq \sum_{z} \mathrm{ele}_{\mathrm{t}}^{\mathrm{g,z}} \quad \perp \quad \mu_{\mathrm{t}}^{\mathrm{g}} \geq 0 \tag{12}$$

where $\kappa_{\mathrm{t}}^{\mathrm{g}}$ is the maximum output of generator g in a given time period.

By construction, the bottom-up model is not calibrated to a benchmark dataset, but rather optimizes the utilization of available capacity in order to meet the electricity demand. The benchmark output $\overline{\mathrm{ele}}_{\mathrm{t}}^{\mathrm{g,z}}$ and price $\overline{p}_{\mathrm{t}}^{\mathrm{ws}}$ are determined by solving equations (10) through (12) given observed demand $\overline{d}_{\mathrm{t}}^{\mathrm{ele}}$ and fuel prices $\overline{p}^{\mathrm{z}}$. The regional fuel mix predicted by the model ($\hat{s}^z$) is reported in **Table 6** and closely matches observed values (s^z).[11]

The response of the model to a carbon policy is driven by three mechanisms. First, fuel costs are increased according to fuel-specific CO_2 emission coefficients (EIA, 2008). Second, we add structure on the electricity demand response. Since a wide majority of electricity consumers are charged near constant yearly retail price (despite substantial time variations on the wholesale market), we assume that the generation costs passed forward to the consumers is an output-weighted yearly average of the wholesale price in each load block t:

$$p^{\mathrm{ele}} = \frac{1}{\sum\limits_{\mathrm{g,z,t}} \mathrm{ele}_{\mathrm{t}}^{\mathrm{g,z}}} \sum_{\mathrm{g,z,t}} p_{\mathrm{t}}^{\mathrm{ws}} \mathrm{ele}_{\mathrm{t}}^{\mathrm{g,z}}\,. \tag{13}$$

[11] As a formal goodness of fit measure, we compute the coefficient of determination $R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2}$, where y_i is observed outcome, $\hat{y}_i$ is the prediction from the model, and $\bar{y}$ is average observed outcome. The R^2 with respect to the predicted output by fuel and by region yields is above 95%, and around 90% for the regional output per generation technologies.

Table 6. Observed (s^z) and Predicted ($\hat{s}^z$) Fuel Mix (% of Total Regional Electricity Output).

Regions	Coal		Natural gas		Nuclear		Hydro		Other	
	s^z	$\hat{s}^z$	s^z	$\hat{s}^z$	s^z	$\hat{s}^z$	s^z	$\hat{s}^z$	s^z	$\hat{s}^z$
CA	7.2	8.4	46.6	46.4	13.8	14.3	20.9	20.8	11.4	10.1
ERCOT	31.7	32.7	53.5	53.7	11.8	10.7	0.2	0.1	2.8	2.8
MISO	68.6	69.0	5.3	5.1	22.6	21.4	1.6	1.8	1.9	2.7
MOUNT	56.6	56.3	26.7	26.4	11.2	12.5	4.2	4.1	1.2	0.8
NENGL	14.8	15.2	39.8	40.5	27.8	27.6	7.1	6.6	10.5	10.0
NWPP	34.5	34.8	14.5	14.4	2.9	3.0	45.4	44.6	2.7	3.2
NY	14.7	14.0	29.4	31.5	29.5	29.0	19.1	18.4	7.2	7.1
PJM	64.9	63.8	6.7	6.6	25.0	23.7	1.4	1.1	2.1	4.8
SEAST	50.8	48.0	19.2	19.7	22.5	22.6	2.5	2.7	5.0	7.1
SPP	59.7	59.3	24.4	25.4	12.9	12.4	0.7	1.0	2.4	1.9
US	49.1	48.2	20.4	20.9	19.4	18.9	7.1	7.0	3.9	5.0

This can be interpreted as if the prices transmitted to consumers were updated once a year to reflect changes in generation costs. The demand schedule is assumed to feature a constant price elasticity and is calibrated to the benchmark consumer price of electricity $\overline{p}^{\text{ele}}$ and to the benchmark demand $\overline{d}^{\text{ele}}$:

$$d_{\text{t}}^{\text{ele}} = \overline{d}_{\text{t}}^{\text{ele}} \left(\frac{p^{\text{ele}}}{\overline{p}^{\text{ele}}} \right)^{\epsilon} \tag{14}$$

where $\epsilon < 0$ is the regional price elasticity of demand, parameterized with price elasticities shown in **Table 7**. Besides econometric estimates based on Bernstein and Griffin (2005), we use simulated price elasticities that are derived from the economy-wide model, hence providing a local approximation of general equilibrium demand response. The difference between estimated and simulated elasticities reflects variations of ceteris paribus assumptions, i.e. while estimated elasticities describe the slope of a given demand curve, simulated elasticities incorporate general equilibrium determinants of demand that affect the slope and location of the demand schedule for a given change in price.

The third response of the system occurs through changes on the fuel markets, with fuel prices responding to changes in the choice of the generation technologies. Defining the demand for fuel z as:

$$d^{\text{z}} = \sum_{\text{g,t}} \gamma^{\text{g}} \text{ele}_{\text{t}}^{\text{g,z}} , \tag{15}$$

we assume a set of constant elasticity supply schedules calibrated to the benchmark fuel price and demand, so that the inverse supply function is:

$$p^{\text{z}} = \overline{p}^{\text{z}} \left(\frac{d^{\text{z}}}{\overline{d}^{\text{z}}} \right)^{\frac{1}{\eta^{\text{z}}}} \tag{16}$$

Table 7. Regional Price Elasticities for Fuel Supply and Electricity Demand.

Region	**Electricity demand elasticities**		**Fuel supply elasticities: Simulated values** [b]	
	Econometric estimates [a] ($\hat{\epsilon}_r$)	**Simulated values** [b] ($\tilde{\epsilon}_r$)	**Coal** ($\tilde{\eta}_r^{\text{coal}}$)	**Natural gas** ($\tilde{\eta}_r^{\text{natural gas}}$)
CA	-0.25	-0.47	0.01	0.02
ERCOT	-0.15	-0.43	0.01	0.04
MISO	-0.14	-0.24	0.03	0.01
MOUNT	-0.20	-0.37	0.01	0.02
NENGL	-0.19	-0.72	0.01	0.01
NWPP	-0.23	-0.43	0.09	0.01
NY	-0.10	-0.17	0.01	0.01
PJM	-0.22	-0.23	0.04	0.01
SEAST	-0.25	-0.32	0.05	0.01
SPP	-0.15	-0.50	0.01	0.01

Notes: [a]Econometric estimates from Bernstein and Griffin (2005), point estimates averaged across end-use demands. [b]Simulated from the USREP model.

where $\eta_{\mathrm{r}}^{\mathrm{z}} > 0$ is the regional supply price elasticity for fuel z. We include a supply function as in (16) for coal and natural gas as for these fuels certain regions are characterized by large market shares. The local price elasticities are simulated from the economy-wide model and reported in Table 7. Overall, the change in the demand from the electricity sector has a relatively small impact on the market price for coal, and an even smaller impact on the natural gas market. For all other fuels, the electricity sector is assumed to be a price-taker, i.e. $\eta^{\mathrm{z}} = \infty$.

3. RECONCILING TOP-DOWN AND BOTTOM-UP

Our integrated framework comprises the following two sub-models: (1) the economy-wide USREP model with *exogenous* electricity generation that is parameterized with the benchmark input demand from the bottom-up model, and (2) the bottom-up load-dispatch electricity model with electricity demand and fuel supply functions locally calibrated with top-down quantities and prices.[12] We use a block decomposition algorithm based on Boehringer and Rutherford (2009) to solve the two modules consistently. The algorithm involves an iterative procedure between both sub-models solving for a mutually consistent general equilibrium response in both sub-models.

A schematic overview of the steps is presented in **Figure 3**. The first step (grey shaded box) for implementing the decomposition procedure by Boehringer and Rutherford (2009) in an

[12] In principle, a bottom-up representation of the electricity sector can be integrated directly within a general equilibrium framework by solving Kuhn-Tucker equilibrium conditions, that arise from the bottom-up cost-minimization problem, along with general equilibrium conditions describing the top-down model (Boehringer and Rutherford, 2008). In applied work, this approach is infeasible due to the large dimensionality of the bottom-up problem. Moreover, the bottom-up model involves a large number of bounds on decision variables, and the explicit representation of associated income effects becomes intractable if directly solved within a general equilibrium framework.

applied large-scale setting is the calibration of the two models to a consistent benchmark. Initial agreement in the benchmark is achieved if benchmark bottom-up electricity sector outputs and inputs over all regions and generators are consistent with the aggregate representation of the electricity sector in the SAM data that underlies the general equilibrium framework. This step is necessary to ensure that in the absence of a policy shock iterating between both sub-models always returns the no-policy benchmark equilibrium. Violation of this initial condition means that any simulated policy effects would be confounded with adjustments triggered by initial data inconsistencies between the two sub-models.

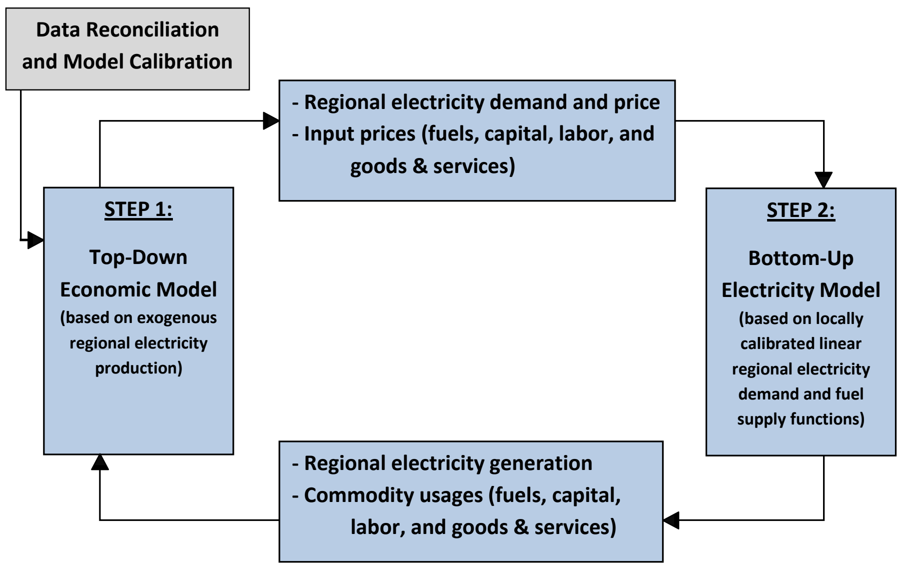

Figure 3. Iterative Steps in Decomposition Algorithm.

To produce a micro-consistent benchmark data that integrates the disaggregated electricity sector, we apply a two-step procedure that (1) generates bottom-up data from a no-policy solution of the bottom-up model that is benchmarked to macroeconomic electricity demand, and that (2) accommodates bottom-up electricity data by adjusting the SAM data subject to equilibrium consistency constraints. Appendix B provides a detailed description of the steps involved.

Turning to the solution algorithm, each iteration comprises two steps. Step 1 solves a simplified version of the top-down model with exogenous electricity production where electricity sector output and input demands are parameterized based on the previous solution of the bottom-up model. The subsequent solution of the bottom-up electricity model in Step 2 is based on a locally calibrated set of linear demand functions for electricity. The key insight from Boehringer and Rutherford (2009) is that a Marshallian demand approximation in the electricity sector provides a good local representation of general equilibrium demand, and that rapid convergence is observed as the electricity sector is small relative to the rest of the economy. We find that convergence speed can be increase further if a linear approximation of fuel supply is included in the bottom-up model that is successively re-calibrated on the basis of top-down equilibrium fuel prices.

The following subsections provide a formal description of the decomposition technique based on the notation developed in Section 2 and discuss the convergence behavior of the algorithm.

3.1 Formulation of the Integrated Model

We first turn to the specification of the economy-wide component in the integrated model. Let $n = 1, \ldots, N$ denote an iteration index. Electricity supply in the economy-wide model is exogenous and hence zero-profit conditions for the electricity generation activities and resource-specific market clearance can be dropped (equations 1, 2 and 8). Furthermore, the least-cost input requirement determined by solving the bottom-up model in iteration $(n-1)$ are used to parameterize the economy-wide model in (n) by replacing equations (3) to (7) with a set of modified market clearance conditions:

$$\sum_{g,z,t} ele_{\mathrm{t}}^{\mathrm{g,z}(n-1)} = \mathrm{D}^{\mathrm{ELE}(n)} \quad \perp \quad P^{\mathrm{ELE}(n)} \tag{3'}$$

$$S^{j(n)} = D^{j(n)} + \sum_{g,z,t} \phi_{\mathrm{g}}^{j} c^{\mathrm{g}}\, ele_{\mathrm{t}}^{\mathrm{g,z}(n-1)} \quad \perp \quad P^{j(n)}, \quad \forall j \tag{4'}$$

$$L^{(n)} = D^{L(n)} + \sum_{g,z,t} \phi_{\mathrm{g}}^{L} c^{\mathrm{g}}\, ele_{\mathrm{t}}^{\mathrm{g,z}(n-1)} \quad \perp \quad P^{L(n)} \tag{5'}$$

$$\sum_{\mathrm{r}} K_{\mathrm{r}}{}^{(n)} = \sum_{r} \left(D_{r}^{K(n)} + \sum_{g,z,t} \phi_{\mathrm{g}}^{K} c^{\mathrm{g}}\, ele_{\mathrm{t}}^{\mathrm{g,z}(n-1)} \right) \quad \perp \quad P^{K(n)} \tag{6'}$$

$$S^{\mathrm{z}(n)} = D^{\mathrm{z}(n)} + d^{\,\mathrm{z}(n-1)} \quad \perp \quad P^{\mathrm{z}(n)} \tag{7'}$$

where ϕ's denote the benchmark value share of capital, labor, and materials of variable O&M costs.[13] In addition, we modify the income balance (9) to include technology-specific rents arising from the limited capacity determined in iteration $(n-1)$:

$$M^{(n)} = P^{K(n)}\overline{\mathrm{K}} + P^{L(n)}\overline{\mathrm{L}} + \sum_{g,z,t} ele_{\mathrm{t}}^{\mathrm{g,z}(n-1)} \left(P^{\mathrm{ELE}(n)} p_{\mathrm{t}}^{\mathrm{ws}(n-1)} - c^{\mathrm{g}} P^{\mathrm{c}(n)} - \overline{p}^{\mathrm{z}} P^{z(n)} \gamma^{\mathrm{g}} \right). \tag{9'}$$

where the price of fuel z is defined using the mapping shown in Table 4, and the price for variable O&M costs is a composite index defined as $P^{\mathrm{c}(n)} = \sum_j \phi_j P^{j(n)} + \phi_L P^{L(n)} + \phi_K P^{K(n)}$. Note

[13] Transmission and distribution costs are assumed to add in a Leontief fashion to the marginal value of electricity (P^{ELE}) as determined by (3′).

that in this approach the electricity-sector output and inputs are valued at market prices, and hence we do not need to include capacity rents explicitly in the economy-wide model.

In the second step of the algorithm, the bottom-up demand and fuel supply schedules are linearized to locally approximate the demand response from the top-down model with simulated elasticity parameters ϵ_r and η_r^z. More specifically, the second step in iteration *n* involves re-calibrating the linear functions based on price and quantities derived from the top-down solution:

$$d_{\mathrm{t}}^{\mathrm{ele}\,(n)} = \overline{d}_{\mathrm{t}}^{\mathrm{ele}\,(n)} \left(1 + \epsilon \left[\frac{p^{\mathrm{ele}\,(n)}}{\overline{p}^{\mathrm{ele}\,(n)}} - 1 \right] \right) . \tag{14'}$$

Input prices in the bottom-up model are updated with candidate general equilibrium prices from the economy-wide model. Fuel prices are scaled with the corresponding top-down price index:

$$\overline{p}^{\mathrm{z}(n)} = \overline{p}^{\mathrm{z}(0)} P^{z\,(n)} ,$$

and the fuel supply schedule is re-calibrated with updated price and quantity information from iteration $(n-1)$:[14]

$$p^{\mathrm{z}(n)} = \overline{p}^{\mathrm{z}(n)} \left\{ 1 + \left[\frac{1}{\eta^{\mathrm{z}}} \left(\frac{d^{\,\mathrm{z}(n)}}{d^{\,\mathrm{z}(n-1)}} - 1 \right) \right] \right\} . \tag{16'}$$

Finally, the variable cost index is updated according to :

$$p^{\mathrm{c}(n)} = \sum_j \phi_j P^{j\,(n)} + \phi_L P^{L\,(n)} + \phi_K P^{K\,(n)} . \tag{17'}$$

The profit function in iteration n of the bottom-up model is thus given by:

$$c^{\mathrm{g}} p^{\mathrm{c}(n)} + p^{\mathrm{z}(n)} \gamma^{\mathrm{g}} + \mu_t^{\mathrm{g}} \geq p_t^{\mathrm{ws}(n)} \quad \perp \quad \mathrm{ele}_{\mathrm{t}}^{\mathrm{g,z}(n)} \geq 0 . \tag{10'}$$

Additional complexity arises from the fact that demand in the top-down model is defined on an annual basis whereas the bottom-up model distinguishes demand by season and load time. We reconcile both concepts by scaling intra-annual reference demand and price in the bottom-up model using the top-down index from iteration (n):

$$\overline{d}_{\mathrm{t}}^{\mathrm{ele}\,(n)} = \mathrm{D}^{\mathrm{ELE}\,(n)} \overline{d}_{\mathrm{t}}^{\mathrm{ele}\,(0)}$$

$$\overline{p}^{\mathrm{ele}\,(n)} = P^{\mathrm{ELE}\,(n)} \overline{p}^{\mathrm{ele}\,(0)}$$

where $\overline{d}_{\mathrm{t}}^{\mathrm{ele}\,(0)}$ and $\overline{p}^{\mathrm{ele}\,(0)}$ denote the no-policy benchmark value of electricity demand and the consumer price, respectively.

[14] The demand for fuel is not scaled due to the lack of an appropriate scaling variable from the top-down model, and we use the fuel demand from the previous iteration as the initial calibration point.

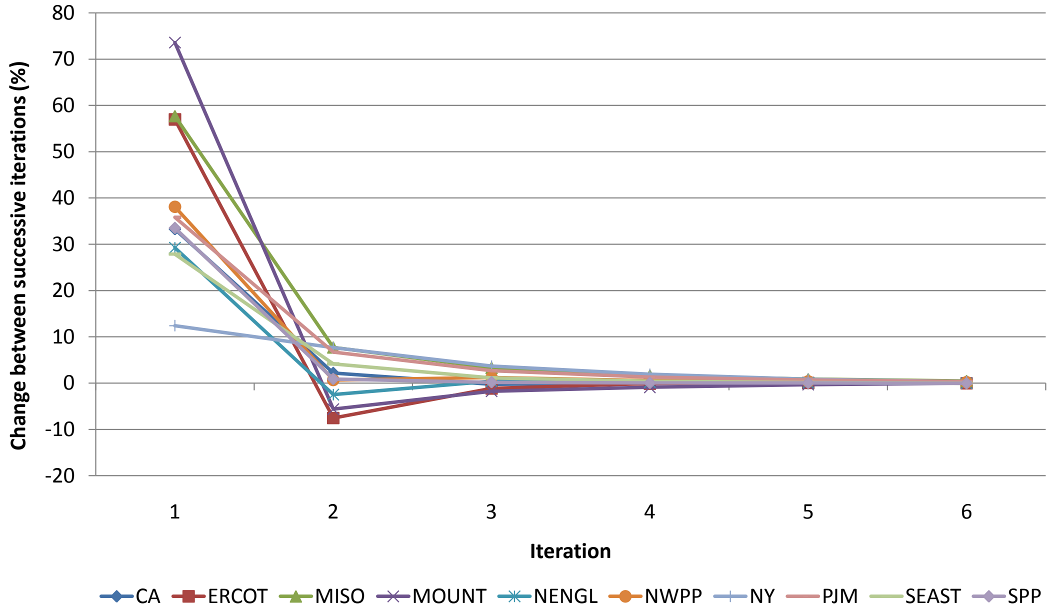

Figure 4. Convergence in Regional Consumer Price of Electricity.

3.2 Convergence Performance

This section provides evidence on the convergence performance of the solution algorithm. Overall we find that despite the complexity and dimensionality in both modules, the algorithm is robust and provides rapid convergence provided a good local approximation of demand elasticity is used to parameterize the bottom-up demand. Our convergence metric terminates the algorithm if the maximum deviation in decision variables between two successive iterations is less than one percent. **Figure 4** reports the percentage change in the consumer price of electricity following a $50 carbon tax across regions between two successive iterations. The largest adjustments take place in the first iteration, and for most regions, subsequent iterations of the algorithm only involve refinements of the supply system, resulting in much smaller changes in relative prices. For this particular policy shock, the algorithm achieves convergence after six iterations, and up to eight iterations were required for a carbon tax of $100. **Figure 5** shows the convergence in other top-down quantities (both in physical and value terms) and prices for the PJM region. Overall, convergence in input prices is rapid, with the price of coal requiring the largest adjustments.

Some additional remarks are in order. First, it is important to note the algorithm is robust with respect to the parametrization of the elasticities, and the final equilibrium allocation is independent of the chosen values. Our computational experience suggests that the algorithm always converged for values smaller than those obtained by simulation; for much higher values, some regions failed to achieved convergence. Second, we find that providing a good approximation of the top-down response through simulated elasticities is important to reduce the number of iterations needed for convergence. In particular, approximating the top-down response through fuel supply elasticities improves the convergence speed. Lastly, we find that it is sufficient to evaluate price elasticities of electricity demand at the initial equilibrium, and then use these values for subsequent iterations. In other words, convergence speed could not significantly

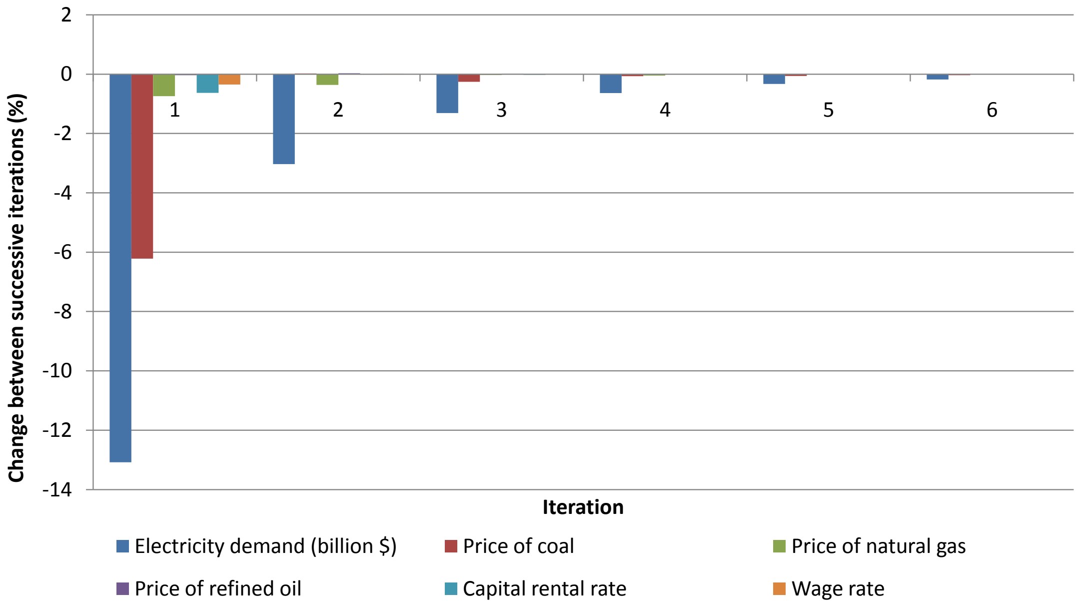

Figure 5. Convergence in Decision Variables.

be improved by evaluating elasticities at each iteration.

4. ELECTRICITY SECTOR MODELING AND THE COST OF CARBON ABATEMENT

This section examines the implications of top-down and bottom-up approaches to electricity sector modeling for the assessment of economy-wide carbon policies. We explore the sensitivity to different structural assumptions concerning electricity supply and demand by using a suite of models that share common technological features and are calibrated to the same benchmark equilibrium. The virtue of our integrated framework is that it can be used as a benchmark against which we can compare different versions of the stand-alone top-down and bottom-up models.

Our counterfactual imposes a national tax on CO_2 emissions in all regions and sectors of the economy.[15] We consider several tax levels: \$25, \$50, \$75, and \$100 per metric ton of CO_2 (in 2006\$). Throughout our analysis, we require revenue-neutrality by holding back a fraction of the revenue to offset losses in conventional (non-CO_2) tax revenue. Carbon revenue is returned as a lump-sum transfer to households on a per-capita basis.[16]

To motivate our analysis, we begin by assessing the size of emissions reductions in the electricity sector vis-à-vis other sectors and the general equilibrium impacts on factor and fuel markets. **Table 8** reports sectoral benchmark emissions, reductions, and factor and fuel price changes from the integrated model. In the benchmark, emissions from the electric power sector represent about 40% of total emissions. For carbon prices higher than \$50, the electricity sector

[15] Given the absence of uncertainty in our framework, an equivalent policy with the same environmental stringency could be implemented as a national cap-and-trade system.

[16] We do not attempt to approximate allocation rules that have been proposed by specific U.S. climate legislation but rather want to make the point that any comprehensive analysis needs to take into account the value of allowances.

Table 8. Integrated Model: Emissions Reductions and Price Impacts (% Change from BAU).

Tax level		**\$25**	**\$50**	**\$75**	**\$100**
CO_2 emissions reduction					
	Benchmark emissions (mmt)				
Agriculture	58.3	-18.0	-24.1	-28.1	-31.4
Services	172.3	-20.2	-33.0	-42.8	-49.9
Energy-intensive products	605.9	-19.4	-30.3	-38.4	-44.4
Other industries products	157.5	-21.4	-34.7	-44.2	-51.1
Transportation	2029.7	-6.4	-11.9	-16.5	-20.5
Electricity	2365.0	-9.8	-32.2	-54.0	-66.5
Price change					
Wage rate[a]		-0.4	-1.0	-1.8	-2.5
Capital rental rate		-0.5	-1.4	-2.4	-3.2
Coal[a] (producer price)		-1.2	-5.9	-12.4	-18.0
Natural gas[a] (producer price)		-1.7	-1.2	0.3	1.4
Welfare change		-0.1	-0.4	-0.9	-1.3

[a]Average change across regions.

yields the largest emissions reductions in absolute terms.

Changes in factor and fuel prices are substantial, with the capital rental and wage rate decreasing by -0.5% to -3.2% depending on the level of the carbon tax. Likewise, impacts on fuel prices exclusive of the carbon charge are significant, with a drop in the producer price of coal ranging from -1.2% to -18%. The producer price of gas increases slightly for higher carbon tax levels as the substitution from coal to gas increases demand. As a measure of economic costs, we report welfare change measured in equivalent variation as a percentage of full income.[17] Carbon price of \$25 and \$100 bring about welfare losses of about 0.1% and 1.3%, respectively.

Figure 6 shows the fuel mix in electricity generation derived from the bottom-up component of the integrated model. The key result is the gradual substitution from coal to natural gas.[18] For a \$25 carbon price, we observe a reduction in all technologies using fossil fuels. A small number of generators using coal with a high carbon content switch to use other types of coal or alternative energy sources. Fuel switching represents a significant flexibility mechanism which is reflected by a decline in the carbon intensity of coal generation of about 10%. As the carbon price increases, the change in relative fuel prices gradually makes natural gas generation more competitive compared to coal-fired generation. The decline in coal-based generation is therefore partly compensated by an increased utilization rate of the generators using natural gas. Overall, a \$25 carbon price induces a reduction of electricity consumption by about 10%, a \$50 price yields a 20% reduction, while for a price of \$100, demand declines by about 30%.

[17] Full income is the value of consumption, leisure, and the consumption stream from residential capital.

[18] Since carbon-neutral technologies (mainly nuclear and hydro) operate close to capacity in the benchmark, generation from these 'must run' technologies does not expand.

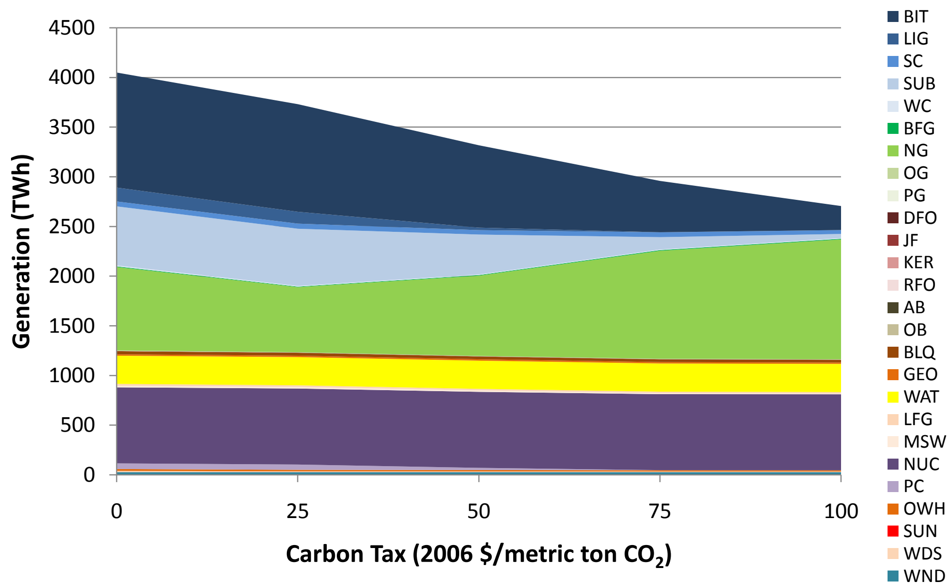

Figure 6. Electricity Generation by Fuel from the Integrated Model for Different Carbon Prices.

4.1 A Comparison of Partial and General Equilibrium Analysis

We first examine the reliability of partial equilibrium analysis as an approximate solution technique for assessing the impact of changes in the electricity sector. In our setting, there are two channels through which general equilibrium factors affect the bottom-up electricity model: (i) income and substitution effects that determine the location and slope of the electricity demand schedule, and (ii) fuel prices that influence generation costs. Note that in the partial equilibrium setting, the electricity sector model optimizes along a given demand curve and assumes constant fuel prices.

Table 9 reports changes in regional wholesale electricity prices (net of transmission and distribution costs) and demand reductions for a $50 carbon tax. We contrast results from the integrated GE model with three different versions of the PE bottom-up model:

- PE model parameterized with econometric estimates of the price elasticity of demand ($\hat{\epsilon}_r$), in column (1),
- PE model with price elasticities of demand simulated from the GE model ($\tilde{\epsilon}_r$), in column (2),
- PE model with price elasticities of demand simulated from the GE model ($\tilde{\epsilon}_r$) and fuel supply schedules parameterized with elasticities for coal and natural gas simulated from the GE model ($\tilde{\eta}_r^z$), in column (3).

Not surprisingly, a $50 carbon tax leads to substantial increases in regional electricity prices across all models. Since the carbon tax is reflected in the electricity price through the carbon intensity of the marginal generator, the key driver for regional variations in price increases is the relative generation cost of the marginal fuel in the pre- and after-tax equilibrium. MISO, for example, has a large stock of efficient coal-fired plants and faces relatively low benchmark coal prices, making coal the marginal technology across all load blocks. The $50 carbon price does not

Table 9. Partial (PE) and General Equilibrium (GE) Estimates of Regional Electricity Prices and Demands for a $50 Carbon Tax.

Region	PE electricity model			GE model
	(1)	(2)	(3)	(4)
	Estimated demand elasticities[a]	**Simulated demand elasticities and no fuel price response**[b]	**Simulated demand elasticities and fuel price response**[c]	**Endogenous general equilibrium response**
Change in electricity price (in % relative to BAU)				
MISO	77.9	75.3	75.0	67.0
MOUNT	52.4	51.0	51.3	49.4
PJM	53.8	53.6	53.5	43.6
NWPP	43.3	40.1	39.4	37.9
CA	39.8	35.7	35.4	31.0
ERCOT	39.0	33.4	33.3	29.8
SEAST	41.4	36.2	36.4	28.9
SPP	47.0	46.0	45.7	28.3
NENGL	31.9	28.5	28.4	26.6
NY	33.3	33.0	32.9	25.3
Change in electricity demand (in % relative to BAU)				
MISO	-7.8	-12.4	-12.4	-25.8
MOUNT	-8.1	-14.0	-14.1	-16.3
PJM	-9.0	-9.2	-9.2	-17.9
NWPP	-7.9	-13.4	-13.2	-21.2
CA	-8.0	-13.3	-13.2	-17.9
ERCOT	-5.1	-12.3	-12.4	-14.7
SEAST	-9.2	-11.3	-11.2	-14.5
SPP	-4.8	-13.2	-13.2	-17.8
NENGL	-5.1	-16.5	-16.5	-20.0
NY	-2.8	-4.7	-4.7	-11.4
US	-7.8	-11.7	-11.6	-18.1

Notes: [a]PE model with estimated price elasticities for electricity demand ($\hat{\epsilon}_r$) and exogenous fuel prices ($\eta_r^z = \infty$). [b]PE model with simulated price elasticities for electricity demand ($\tilde{\epsilon}_r$) and exogenous fuel prices ($\eta_r^z = \infty$). [c]Similiar to (b) but PE model here also includes constant-elasticity fuel supply schedules for coal and gas with simulated supply price elasticities ($\tilde{\eta}_r^z$).

lead to a significant reordering of technologies in the supply schedule, and the price increase is the largest among all regions. In MOUNT and PJM, coal is also the predominant marginal fuel in the benchmark, but generation from natural gas expands significantly under the carbon tax, therefore mitigating the price increase. Regions such as CA, ERCOT, NENGL, and NY are characterized by a relatively large share of natural gas in the benchmark, and they experience relatively modest price increases.

Comparing projected electricity prices from the PE models and the integrated GE model, it is evident that the PE models suggest higher price increases. The main reason for this is that the PE models do not capture shifts and changes in the slope of the electricity demand schedule. Indeed, reduced income due to lower factor prices and substitution away from electricity towards other

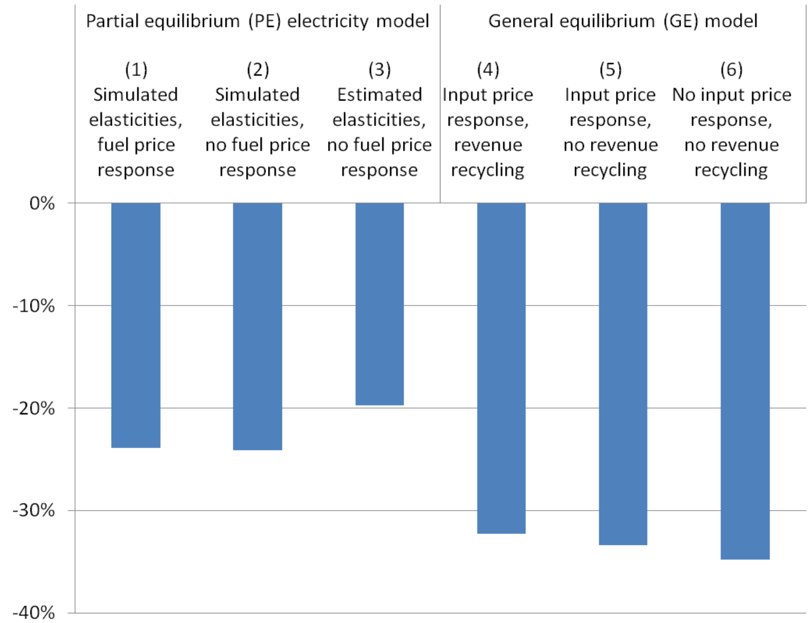

Figure 7. Model Comparison of U.S. CO_2 Emissions Reductions from Electricity Generation for $50 Carbon Tax (relative to BAU).

goods and services induce a structural change in electricity demand rather than a movement along the demand schedule. The PE model based on econometrically estimated elasticities generates the largest price increases. Differences with the integrated GE framework range from around 3% for MOUNT to 20% for SPP. When using simulated price elasticities that locally approximate the demand response of the GE model, the PE estimates for all regions are somewhat closer to those from the GE case. Including a fuel supply response in the PE model has only a minor effect, reflecting the small impact of the electricity sector on the markets for coal and natural gas.

While overall price differences across models are relatively modest, the step function representation for supply implies that shifts in the demand are not necessarily reflected in price changes.[19] In fact, demand reduction suggested by the PE models (see bottom panel of Table 8) grossly underestimate the change in demand suggested by the general equilibrium framework. Averaged across all regions, the PE models estimate demand reductions that are 35% to 58% smaller than the GE estimate. At the regional level, and across different PE models, estimates are 13% to 75% lower than those from the GE case.

Figure 7 provides a comparison of PE and GE models in terms of country-wide emissions reductions from the electricity sector. The pattern of emissions reductions for the three different PE models (columns 1-3) and the integrated model (column 4) mirrors the pattern of electricity demand reductions. Thus, for the purpose of approximating emissions reductions, a PE approach

[19] Moreover, the price signal is a weighted average over different time periods, which further tends to smooth out intra-annual price differences.

can be a poor tool. To further explore the scope and magnitude of GE effects, we run two additional versions of the integrated GE model where we do not recycle the carbon revenue (column 5), and where, in addition, input prices to the electricity sector are kept constant (column 6). In both cases, emissions reductions are slightly larger compared to (4) as reduced income lowers consumer demand and keeping input price constant implies higher generation costs. Overall, Figure 7 suggests that economy-wide income and substitution effects on electricity demand are of first-order importance. Comparing the 'simple' PE model (3) with the full GE model (4), we find that emissions reductions are 38% larger in the GE case. Evaluated at a carbon price of \$50 per metric ton, this is equivalent to \$17.7 billion worth of carbon revenue (or allowance value).

In summary then, the different parameterizations of the PE model seem to provide unreliable approximations of general equilibrium projections. If the goal is to approximate price changes, the performance of the PE framework can be improved if price elasticities are based on a local approximation of the GE model. However, PE analysis uniformly diverges with regard to changes in the electricity demand and CO_2 emissions.

4.2 Top-Down and Bottom-Up Technology Representation and the Cost of Carbon Abatement

This section explores the implications of top-down and bottom-up approaches to electricity sector modeling for the assessment of CO_2 mitigation policy. We consider three versions of the model outlined in Section 2 :

- GE model with top-down representation of electricity generation, based on nesting structure (a),
- GE model with top-down representation of electricity generation, based on nesting structure (b),
- GE model with integrated bottom-up representation of electricity generation.

All three models are benchmarked to the same fuel mix in electricity generation, so that any differences in the model response can be attributed to the specific structural technology representation.

Figure 8 shows U.S. electricity generation from coal and natural gas for different carbon prices.[20] For a carbon price of \$25, the bottom-up representation suggests a decline in generation from coal and natural gas. This is mainly due to a demand reduction, as the small change in relative generation costs has almost no influence on the ordering of technologies in the supply schedule. In contrast, with either top-down representation, coal generation sharply decreases and generation from natural gas slightly increases. This effect is a consequence of using aggregate

[20] We focus on the change in fossil fuel generation, and in particular on the substitution between coal and natural gas, because (i) the shares of nuclear and hydro remain almost constant and (ii) other fuels have relatively small market shares.

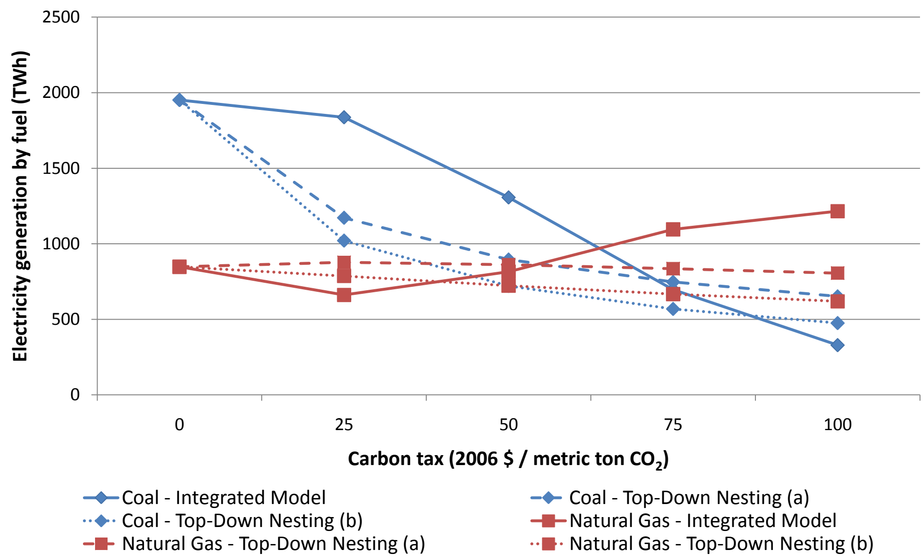

Figure 8. Top-down vs. Bottom-up Comparison of U.S. Electricity Generation from Coal and Natural Gas.

CES functions to characterize electricity generation, as changes in relative fuel prices trigger a movement along the smooth production possibility frontier even for low tax levels. Furthermore, in the top-down approach the price of electricity reflects the total carbon content of generation, so that the demand response is larger than in the bottom-up approach.

For carbon prices above $25, the differences in the substitution pattern persist. The bottom-up version predicts that coal-fired generation declines steadily while electricity from natural gas gradually expands with an increasing carbon price. The distinct increase in electricity generated from gas is possible because all regions have idle generation capacity for natural gas. In contrast, the two top-down models show a virtually constant generation from natural gas, while the decline in coal-fired electricity gradually flattens out. The main driver of this effect is a low elasticity of substitution between coal and gas preventing a significant increase in the generation from natural gas.[21]

A key aspect of top-down models is that the nesting structure and elasticity parameters are typically identical across regions while the response of the integrated model depends on the benchmark fuel costs and stock of available generation technologies. **Figure 9** reports differences between models in regional emissions reductions for a $50 carbon price. Averaged across all regions, emissions reductions in the integrated model are 23% and 31% lower than under the top-down representations (a) and (b), respectively. Differences in emissions reductions are most striking in regions with a large share of coal-fired generation (SPP, PJM, SEAST, and MOUNT),

[21] Both top-down approaches produce relatively similar substitution patterns, but the decline in coal-based generation is more pronounced for nesting structure (b) relative to (a). The latter assumes a smaller elasticity of substitution between energy and material inputs.

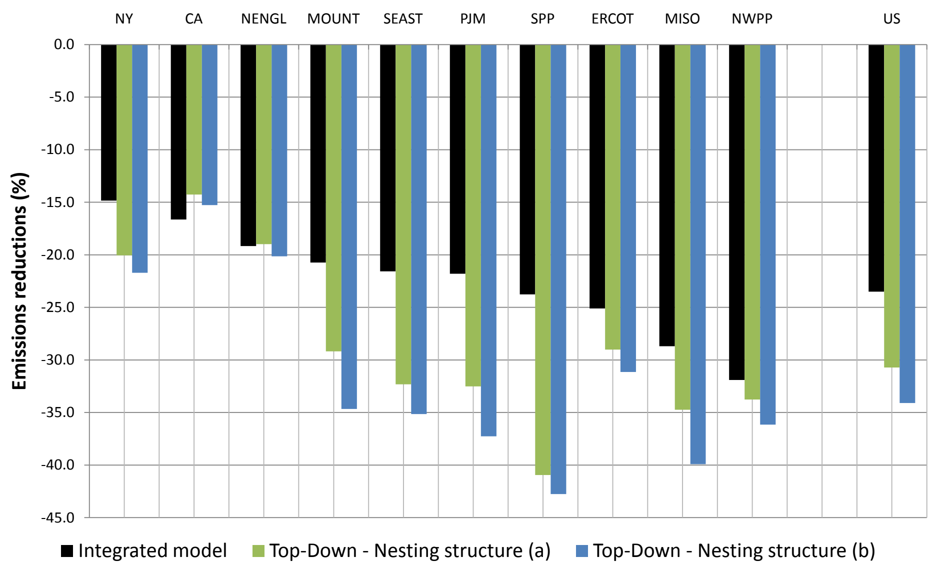

Figure 9. Model Comparison of Regional CO_2 Emissions Reductions for a $50 Carbon Tax (All Sectors).

for which the top-down models suggest large emissions reductions.[22] Regions using a larger share of natural gas generation in the benchmark (CA, NENGL, NY, and ERCOT) have similar emissions reductions for all modeling approaches. Note also that, among the two top-down models, differences in emissions reductions are largest in regions using a large share of coal in the benchmark, illustrating the sensitivity of the parametrization in top-down nesting structures.

Figure 10 shows the U.S. welfare cost and emissions reductions for the three models. Each locus has one marker for each carbon price level ($25, $50, $75, and $100) and thus provides a mapping between emissions reductions and welfare costs for the different modeling frameworks. The advantage of this graphical presentation is that policy costs across different models can be compared for the same environmental impacts.

For economy-wide abatement levels below 10%, results from the three models are virtually identical. For a 20% abatement level, welfare costs from the bottom-up approach are about 40% and 60% higher than those from the top-down structure (a) and (b), respectively. For higher abatement levels, the welfare difference between bottom-up and top-down approaches is even more pronounced. Furthermore, the marginal abatement costs (as measured by the carbon price) for a given emissions reduction differ widely across models. A $75 carbon tax imposed under the top-down structure (b) yields a welfare cost of about -0.8% and a decline in emissions of 40%. For the bottom-up approach and the top-down nesting structure (a), the same carbon abatement level would be achieved with a carbon price of $100, which is associated with a welfare cost of -1.2%, a difference in welfare cost of about 50%. Differences between the bottom-up approach

[22] The only exception is MISO, where the integrated model suggest a very large increase of generation costs and in turn a large demand reduction (see Table 9).

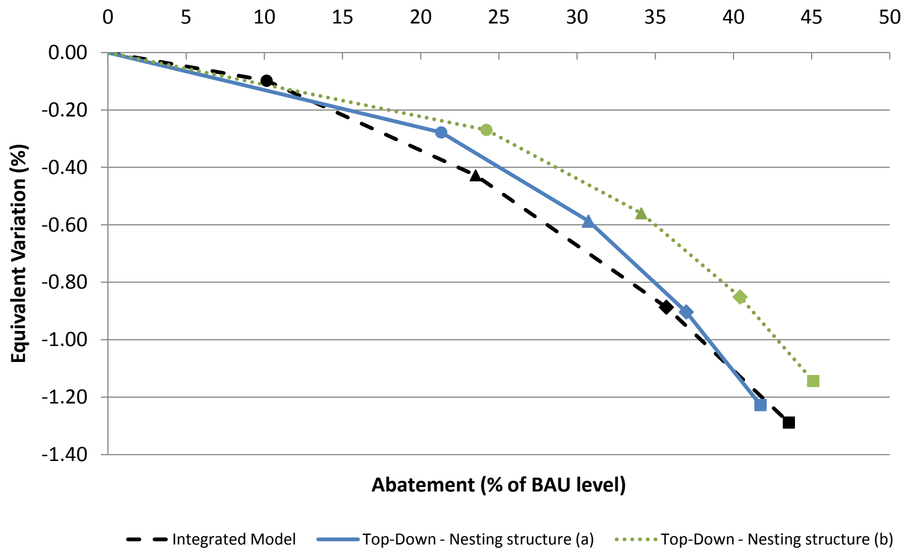

Figure 10. Model Comparison of Welfare Costs and Emissions Reductions for U.S.

and the top-down structure (b) are smaller, especially for emissions reductions above 30%.

At the regional level, we report results for three representative regions to illustrate the large heterogeneity across model outcomes even though the benchmark data is the same (**Figure 11**). First, the solid lines for ERCOT are almost identical across models, as they all suggest a large decline in coal-fired generation and a small increase in natural gas—most of the abatement here is driven by the demand response. This situation is similar for MISO. Second, NENGL generates little electricity from coal, and the top-down representation suggests much higher abatement costs in the electricity sector, as compared to the bottom-up representation. This situation is similar for CA, NY and NWPP.[23] Finally, SPP has a large share of coal in the benchmark, and the bottom-up approach suggests that generation from natural gas expands. Here, abatement costs in the electricity sector are higher under the bottom-up representation. This situation is similar for PJM, SEAST and MOUNT.

Two general conclusions can be drawn from this model comparison. First, the choice of bottom-up or top-down technology representation for the electricity sector has a large effect on the estimated cost and environmental effects of carbon policies. The differences implied by these structural assumptions would seem to go beyond the model uncertainty that is typically borne out by parametric sensitivity analysis. Second, given the significant discrepancies across model outcomes, in particular at the regional level, our analysis reveals the difficulty in parameterizing a top-down technology representation of the electricity sector. While simulating elasticities from a bottom-up model may be one potential avenue to address this issue, approximating the multi-dimensional and discontinuous response of a bottom-up model by means of highly

[23] Note that for a $25 carbon price, the integrated model suggests a positive welfare impact for NENGL which is due to the redistribution of allowances.

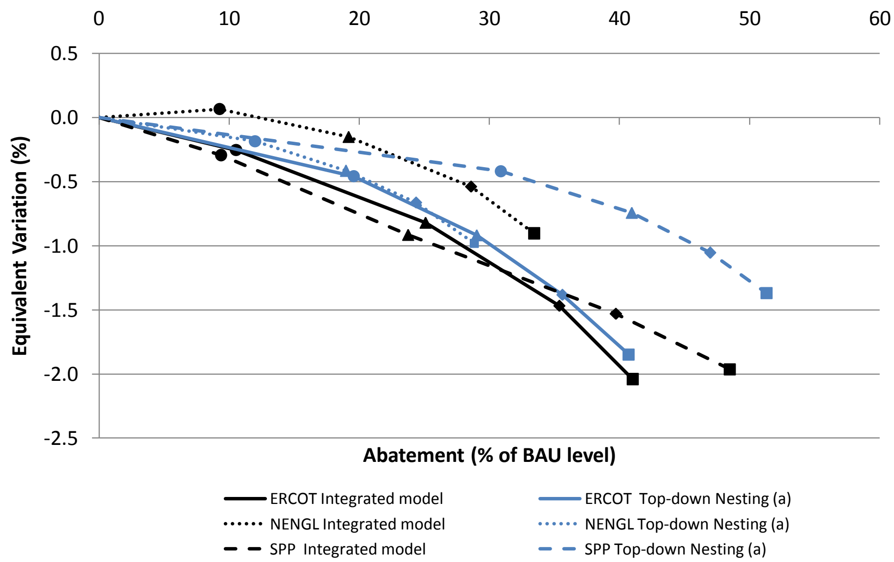

Figure 11. Model Comparison of Welfare Costs and Emissions Reductions for Selected Regions.

aggregated substitution elasticities is a challenging task. Moreover, this would require structural accordance of the bottom-up and top-down models in terms of key model dimensions such as, for example, regional configuration and input structure. Finally, conceptual differences between the two model paradigms with respect to the transmission of the carbon price would be difficult to reconcile.

5. CONCLUDING REMARKS

Large-scale numerical models have become a popular and widespread tool to assess the economic implications of climate and energy policies. While the virtue of top-down models is their representation of general equilibrium effects, a major source of critiques is their reliance on smooth aggregate production functions to describe the technology choice in the electric power sector. In contrast, bottom-up models have a rich technological underpinning but typically do not account for general equilibrium effects. By developing an integrated benchmark model that embeds a bottom-up technology representation of the electricity sector within a multi-sector general equilibrium framework, we generate numerical evidence on (1) the importance of general equilibrium effects for partial equilibrium bottom-up models of the electricity sector, and (2) the implications of top-down versus bottom-up representations of electric generation technologies for assessing the cost and environmental effects of CO_2 control policies.

In the context of U.S. climate policy, our numerical analysis suggests that the general equilibrium effects and the mode of representation of electricity technologies are of crucial importance for estimating electricity prices and demand, carbon abatement potentials, and welfare costs. Moreover, the elasticity parameters needed for a reduced-form model response are difficult to estimate from empirical data, for two reasons. First, general equilibrium effects associated with carbon policies are complex and difficult to identify from historic data. Second, the discrete and temporal nature of electricity generation is difficult to represent by means of aggregate substitution possibilities among various electric power technologies. Our analysis therefore suggests that integrating a bottom-up electricity sector model into a general equilibrium framework provides an attractive structural alternative for ex-ante policy modeling.

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APPENDIX A: Integrated Electricity Regions

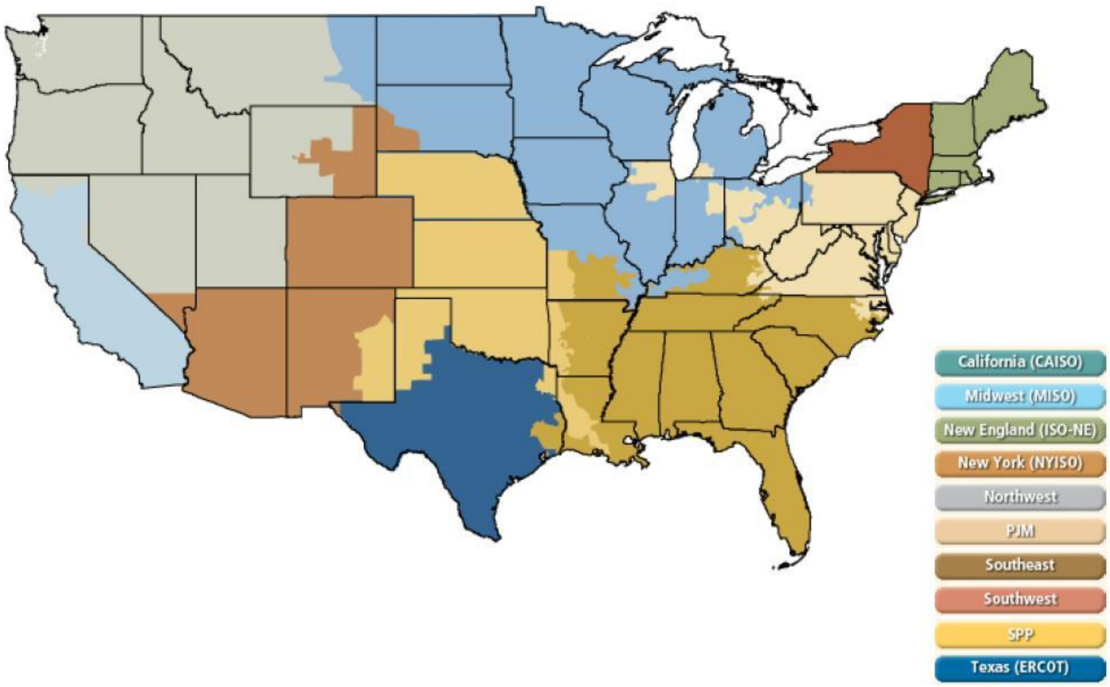

Figure A1. Overview of U.S. Electric Power Markets (Source: Federal Energy Regulatory Commission, 2010)

APPENDIX B: Data Reconciliation and Model Calibration

This appendix outlines our approach to calibrate both components of the integrated model to a common benchmark that is based on historical data for the year 2006 and that satisfies general equilibrium conditions. The involved steps are as follows:

1. *Benchmarking of bottom-up electricity sector model.*

   The initial step involves benchmarking the bottom-up model to observed physical electricity demand by region. Let $\bar{Q}_r^{\text{ELE}}$ denote benchmark demand by region (in MwH) that is consistent with the augmented Social Accounting Matrix (SAM) data underlying the USREP model.[24] Solving a version of the bottom-up model that comprises equations (10) through (12) (hence dropping equations (13) through (16) to suppress demand and fuel supply responses), and that parameterizes electricity demand in equation (14) according to $d_{r,t}^{\text{ele}} = \bar{Q}_r^{\text{ELE}} \frac{\bar{y}_{r,t}}{\sum_{t'} \bar{y}_{r,t'}}$ (hence effectively sharing

[24] Economic data in the form of a Social Accounting Matrix is typically in units of dollars. The USREP model is based on augmented SAM data that merges together economic data from IMPLAN and physical energy data from EIA's State Energy Data System.

out aggregate demand based on observed reference output $\bar{y}_{r,t}$), yields a vector of cost-minimizing outputs and inputs that is consistent with meeting observed demand, given generation costs and capacity constraints.

2. *Benchmarking of top-down general equilibrium model.*

   (a) Reconciliating bottom-up generation costs and top-down demand. Let G_r denote total generation costs that are defined as an output-weighted average of generation costs as defined in equation (13), i.e. $G_r = \sum_t p_r^{\text{ele}} d_{r,t}^{\text{ele}}$. The discrepancy between bottom-up generation costs and top-down user costs of electricity is reconciled by imputing transmission and distribution costs ($\overline{\text{TD}}_r$) in each region as: $\overline{\text{TD}}_r = \bar{D}_r^{\text{ELE}} - \bar{G}_r$. We further assume that T&D costs are denominated in terms of capital, labor, and materials, and apply residual cost shares from IMPLAN data to determine individual cost components.

   (b) Mapping bottom-up electricity inputs to commodity accounts in SAM. Having reconciled electricity output in physical and value terms, the remaining steps involve integrating cost-minimizing input demands into the SAM data such that general equilibrium conditions are satisfied, i.e. the resulting SAM data is *micro-consistent* and can be used to calibrate the CGE model. First, we need to determine how various electricity sector inputs costs are mapped to commodity accounts in the SAM data. More specifically, we assume that variable O&M costs are composed of capital, labor, and materials costs, where cost shares are based on IMPLAN data for the electricity sector. Due to lack of more disaggregated data, we assumed that cost shares are uniform across generators in a given region. Disaggregated fuel categories from the bottom-up model are mapped to the CGE commodity structure as shown in Table 4. We map fuels and other goods demands derived from electricity production in the bottom-up model to import (intra-national and foreign) and domestic demand in the SAM data according to benchmark IMPLAN shares, and adjust trade flows to ensure that domestic trade is balanced. This preserves the value share of imported inputs into the electricity sector. Note that we do not have to adjust electricity trade in the macroeconomic data, as in the first step the bottom-up model has been benchmarked to observed electricity demand, and thus implicitly to trade flows. The price of fuels that do not have direct counterparts in the top-down model are assumed to be exogenous, and remain constant under policy simulations.

   (c) Accounting for capacity rents. Technology-specific rents arise from the limited capacity for each generator, and make up the difference between the market price and the unit generation costs of sub-marginal generators. These rents are accounted for in the economy-wide framework by increasing the capital earnings of households in proportion to their benchmark capital earnings.

   (d) Balancing of Social Accounting Matrix data. Having established a mapping between electricity inputs and commodities in the SAM data, and given that domestic

trade is balanced, we finally re-balance the SAM data, one region at a time, holding trade flows and all electricity variables fixed at their benchmark values. More specifically, we adjust the value of domestic output, value-added and intermediate inputs, private demand, and factor income. We use least-square optimization methods to obtain a balanced SAM matrix for each region that is benchmarked to the no-policy solution of the bottom-up electricity sector model, consistent with observed trade flows from IMPLAN data, and that satisfies general equilibrium constraints. Note that the adjustments necessary to produce a balanced SAM are minor as the size of the electricity sector (in value terms) compared to the rest of the economy is small, i.e. less than 4.3% of total income in each region. Based on balanced SAM data, the calibration of production and consumption technologies using base year data on prices and quantities is a standard exercise (e.g., Robinson, 1991 or Rutherford, 1999), and hence needs no further discussion.

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