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General equilibrium, electricity generation technologies and the cost of carbon abatement: A structural sensitivity analysis

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ABSTRACT

Electricity generation is a major contributor to carbon dioxide emissions, and abatement in this sector is a key determinant of economy-wide regulation costs. The complexity of an integrated representation of economic and electricity systems makes simplifying assumptions appealing, but there is no evidence in the literature on how important the pitfalls may be. The aim of this paper is to provide such evidence, drawing on numerical simulations from a suite of partial and general equilibrium models that share common technological features and are calibrated to the same benchmark data. We report two basic findings. First, general equilibrium intersectoral effects of an economy-wide carbon policy are large. It follows that assessing abatement potentials and price changes in the electricity sector with a partial equilibrium Marshallian demand can only provide a crude approximation of the complex demand-side interactions. Second, we provide evidence that widely used top-down representations of electricity technologies produce fuel substitution patterns that are inconsistent with bottom-up cost data. This supports the view that the parametrization of substitution possibilities with highly aggregated production functions is difficult to validate empirically. The overall picture that emerges is one of large quantitative and even qualitative differences, highlighting the role of key structural assumptions in the interpretation of climate policy projections.

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). On 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, the use of smooth functions is not well suited to capture the temporal and discrete nature of technology choice.[1]

The integration of bottom-up technology representation and economy-wide interactions into 'hybrid' models is the subject of a large literature. For example, reference is often made to 'soft-linked' models, where the combination of the two models either fail to achieve overall consistency (Drouet et al., 2005; Hofman and Jorgenson, 1976; Hogan and Weyant, 1982; Jacoby and Schäfer, 2006), or complement one type of model with a 'reduced-form' representation of the other, thereby lacking structural explicitness (Bosetti et al., 2006; Manne et al., 2006; Messner and Schrattenholzer, 2000; Strachan and Kannan, 2008). An alternative and more recent approach, referenced to as 'hard-linked', is to directly embed a set of discrete generation technologies into a top-down model (Böhringer,

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[1] In principle, production technologies can accommodate any microconsistent elasticity structure (Perroni and Rutherford, 1995), including time or regional differentiation. In practice however, data limitations make empirical validation of the parameters driving substitution possibilities difficult. In addition, we note that top-down representations of the electricity sector violate basic energy conservation principles away from the benchmark calibration point (see Sue Wing, 2008).

1998; Böhringer and Rutherford, 2008; Sue Wing, 2006). 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 Böhringer and Rutherford (2009) employs an iterative solution procedure to solve top-down and bottom-up model components consistently. This approach is essentially a soft-linked approach, but overcomes issues of dimensionality and consistency, and has been employed in the context of U.S. climate policy in Tuladhar et al. (2009).

Despite the large literature documenting efforts to reconcile top-down and bottom-up modeling paradigms, and a tendency towards ever more detailed models, there is no quantitative evidence on the pitfalls of different simplifying assumptions. The objective of this paper is to explore the implications of different structural assumptions concerning electricity supply and demand for the assessment of economy-wide carbon policies, thereby going beyond the usual parametric sensitivity analysis. 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 Böhringer 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, b). The electricity sector is represented by a multi-region model based 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] We assume imperfect factor mobility in the economy and fixed capacity of electricity generation technologies, so that the response to a policy shock is of short- to mid-term horizon.[3]

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. 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. We report evidence that such a modeling strategy is not sufficient to capture the underlying economy-wide changes, as represented in 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 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 by means of aggregate substitution elasticities. We implement two top-down technology specifications based on nested constant elasticity of substitution (CES) functions (Bovenberg and Goulder, 1996; Paltsev et al., 2009) which are widely adopted for ex-ante climate policy assessment. Our analysis suggests that these representations produce fuel substitution patterns that are inconsistent with bottom-up cost data, mainly because top-down representation of electricity markets implies 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). In our setup, structural assumptions about the technology representation translate into country-wide welfare costs that differ by as much as 60% for an emissions reduction target of 20%. We further observe large heterogeneity in regional discrepancies, mostly driven by the benchmark shares of carbon-intensive 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. While both approaches rely on the assumption of fully rational behavior, the structural setting makes empirical validation of the behavioral response in each modeling approach is difficult. Any analysis inevitably involves simplifications from a more complex reality, but we usually do not know how misleading assumptions might be when drawing policy conclusions from quantitative analysis. By providing evidence on the magnitude of structural assumptions, albeit in the context of models also using a set of restrictive assumptions, we believe that our investigation contributes to an improved understanding of the theoretical and methodological basis for carbon policy assessment with large-scale simulation models.

The remainder of this paper proceeds as follows. Section 2 provides an overview of the economy-wide model, describes the top-down and bottom-up representations of the electric power sector, and presents the integrated model. Section 3 investigates the importance of general equilibrium factors and the implications of top-down versus bottom-up technology representation for carbon policy assessment. Section 4 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 electricity generation. The final subsection describes the integrated framework.[4]

2.1. The MIT U.S. Regional Energy Policy model

The economy-wide model is based on a static version of the MIT U.S. Regional Energy Policy (USREP) 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 climate 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 the IMPLAN data set (Minnesota IMPLAN Group, 2008) with physical energy and price data from the State Energy Data System (EIA, 2009b). As a detailed description of the model is provided in Rausch et al. (2010a), including a full algebraic characterization of equilibrium conditions, we here only give a brief overview of key model features.

[2] Our database has a high resolution at the operator level, which allows us to incorporate realistic assumptions about the market structure in the electricity sector. To facilitate the comparison of top-down and bottom-up approaches, the present analysis maintains the usual assumption of marginal cost-pricing and perfect competition in the electricity sector. In a companion paper, we incorporate cost-of-service regulation at the operator level and non-competitive (Cournot) pricing behavior by large operators to investigate the role of non-competitive behavior for the design of climate policies.

[3] We refrain from using ad-hoc vintaging assumptions to restrict capital mobility in the economy-wide model, or specifying some capacity expansion elasticities in the electricity sector model, for example allowing expansion of renewable technologies under a carbon price. Our qualitative conclusions are not affected by these assumptions. Issues related to the structural representation of electricity demand and supply still apply in a dynamic setting, but forward-looking responses to carbon policy shocks is beyond the scope of our comparison exercise.

[4] All models are written in the GAMS software system and solved with the PATH solver (Dirkse and Ferris, 1995) for mixed complementarity problems (MCP).

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 transmission & distribution		

Notes: [a] Detailed regional grouping is provided in Fig. 1.

The structure of the model is summarized in Table 1. Much of the sectoral detail in the USREP model is focused on providing an 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. The model describes production and consumption sectors as nested CES production functions.

The regional structure of the model approximates the geographical structure of electricity markets by grouping states into ten regions. The resulting regional aggregation is shown in Fig. 1. This segmentation is mainly driven by available transmission capacity and by the evolving regulatory status of the electricity sector (see Joskow, 2005, for an overview).

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] Electricity cannot be traded across these three regions. Within each regional pool, electricity trade is modeled as an Armington (1969) good.[6]

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 that chooses a profit-maximizing level of output, subject to technological, institutional and resource constraints. In our setting, production technologies combine energy (E), capital (K), labor (L), and material inputs M_j from other sectors indexed by $j \in \{$*Agriculture*, *Services*, *Energy-intensive products*, *Other industries products*, *Transportation*$\}$. 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 Fig. 2 and Table 2, respectively.

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 and production from *Conventional Fossil*, *Nuclear*, and *Hydro* is resolved at the sub-sector level. Electricity produced from nuclear and hydro power relies on capital, labor, and sector-specific resource, and is assumed to be in fixed supply in order to be consistent with our bottom-up representation.[7]

For fossil-based electricity, we implement two different nesting structures widely adopted in the literature.[8] The nesting structure labeled (a) in Fig. 2 is in line with Rausch et al. (2010b), Paltsev et al. (2009) and Böhringer et al. (2010). The nesting structure labeled (b) is based on Bovenberg and Goulder, (1996), and has been used for policy analysis, e.g., in Goulder et al. (2010) and Sue Wing (2006). Elasticity values for each nesting structure are shown in Table 2.

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 is not represented separately but is instead treated via substitution between fuels. This implies limited substitution possibilities among fuels, thus representing their unique value for peak, intermediate, and base load.

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 trades off with an energy-materials composite whereas under the nesting structure (a) capital–labor can be substituted directly for composite energy. Another 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).

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). Table 3 lists the equilibrium values of the endogenous variables. Zero-profit conditions for fossil and non-fossil electricity generation determine the respective activity levels[9]:

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

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

where Π^{NF} and Π^{F} denote 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

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

[6] The Armington CES aggregator also entails small discrepancies in the physical accounting of electricity flows away from the benchmark. While this will typically have only minor implications for the interpretation of the results, this could motivate the representation of electricity trade in the bottom-up module.

[7] In line with our short- to mid-term time horizon, we hold production from nuclear and hydro sources constant so that generation from these energy sources does not expand in the presence of a carbon price.

[8] We refrain from imposing capacity bounds on the maximum output of fossil technologies, since these constraints would not be binding under a carbon policy.

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

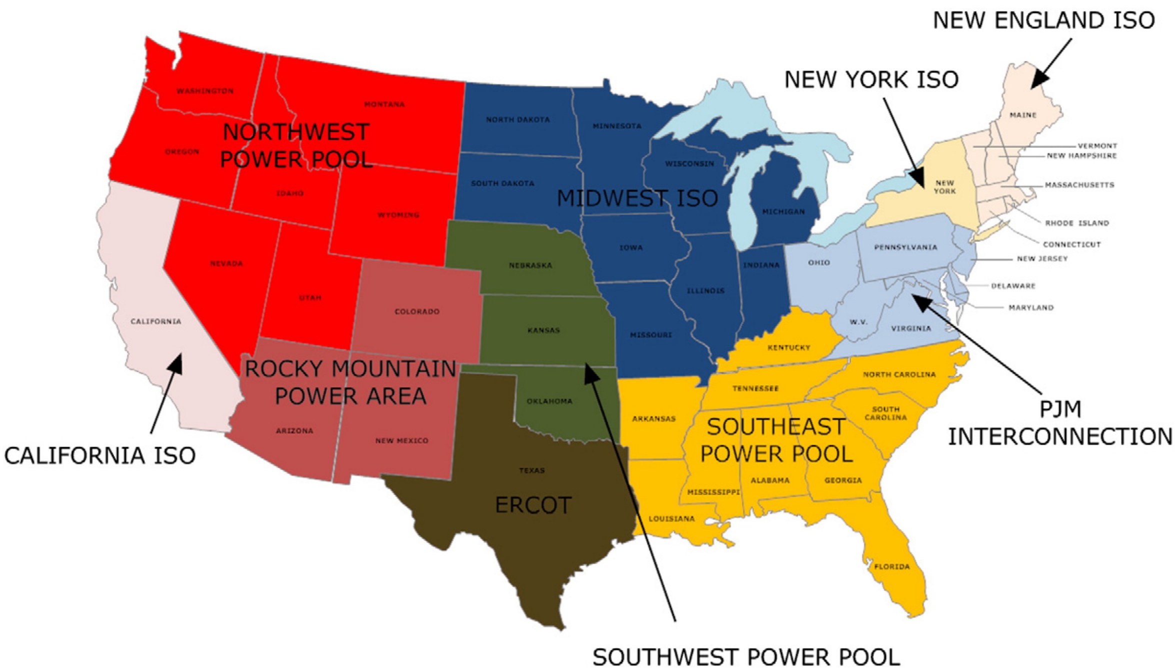

Fig. 1. Regions in the integrated economic-electricity model.

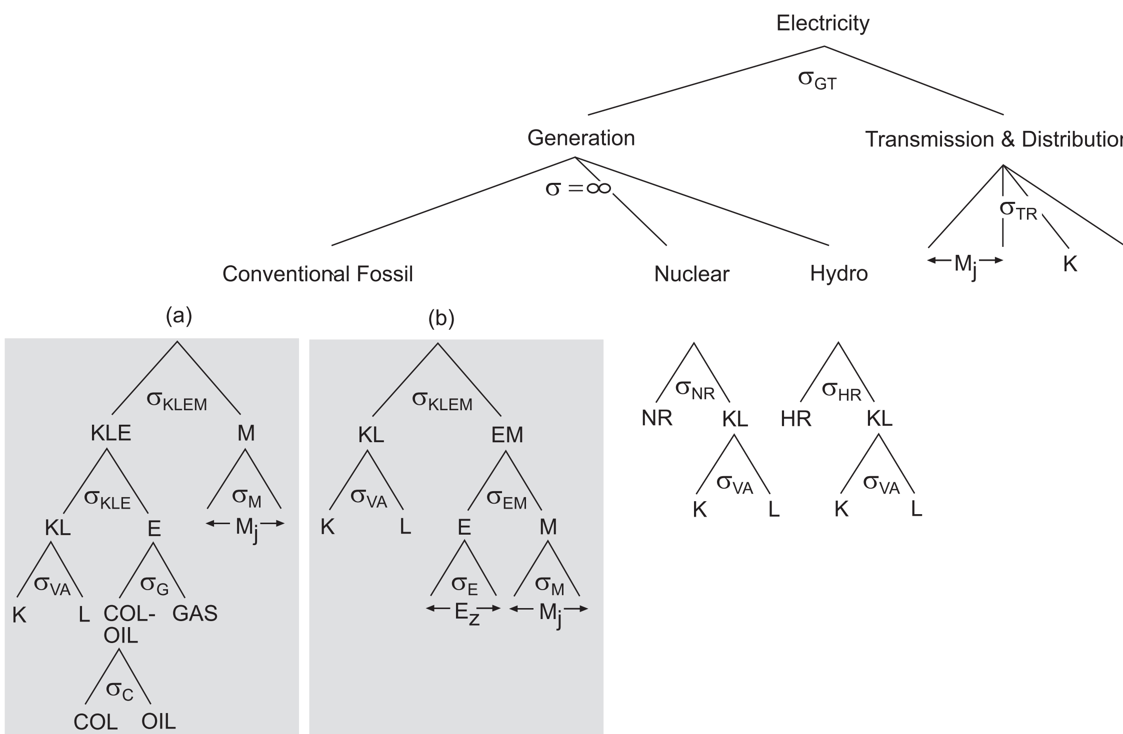

Fig. 2. Top-down production structure of electricity sector.

the dual cost minimization problem of individual producers. Given the CES nesting structure displayed in Fig. 2 these can be written as:

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

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:

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

Table 2
Elasticity parameters for the top-down representations of electricity sector.

		(a)	(b)
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

Notes: Values shown in columns (a) and (b) refer to elasticity parameters used in the nesting structures shown in Panel (a) and (b) in Table 2, and are taken from Paltsev et al. (2009) and Bovenberg and Goulder (1996), respectively.

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:

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

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:

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

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:

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

Table 3
Equilibrium variables related to electricity in the top-down representations.

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

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:

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

where a variable with a bar denotes its benchmark value.

The regional labor market is in equilibrium if:

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

and the market clearance condition for capital is:

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

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

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

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

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 denotes 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 representation of electricity generation exhibits two key differences as compared to the top-down approach. First, it uses a cost-based description of discrete generation technologies to determine the least-cost utilization that meets the demand. Second, the bottom-up approach features a finer time resolution, dividing the yearly demand into load blocks to capture observed fluctuations of the physical demand for electricity.[10]

Our bottom-up representation of the electricity sector is based on a high resolution dataset of more than 16,000 electricity generators that were active in 2006 (EIA Form EIA-860, EIA, 2007a). It contains information on the capacity, generation technology and energy sources. Generation technologies and fuels included in the model are listed in Table 4. Each generator is characterized by a constant marginal generation cost and maximum output in each time period.[11] The marginal cost of generators includes variable operation and maintenance (O&M) costs (EIA, 2009a) and fuel costs. Contingent on generator-specific technology reported in EIA Form EIA-860 (EIA,

[10] 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. 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.

[11] For technologies with relatively low generation costs, we impute capacity factors from data on observed output (EIA Form EIA-920, EIA, 2007b). Thus technologies such as nuclear, hydro, wind and solar are modeled 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 the bottom-up model.

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

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

2007a), generators can use up to three different fuels. The choice of fuel depends on the relative fuel costs, including state-level fuel prices for 2006 (EIA, 2009c) and carbon intensity (EIA, 2008). Fuel costs are also determined by the efficiency of the plant based on EIA Form EIA-920 (EIA, 2007b).

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

As in the top-down representation, we assume that generators in each region and time period are price-takers. The market value of electricity generated, or wholesale price (net of transmission and distribution costs), varies by region, season and load block according to the generation costs of the marginal producer.

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 use lower case variables to indicate the correspondence with variables in the top-down representation. Electricity output at each generator g and load block t exhibits complementarity slackness with the zero profit condition:

$$-\pi_t^{g,z} \geq 0 \perp \ ele_t^{g,z} \geq 0. \tag{10}$$

The unit profit function is given by:

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

where c^g denotes variable O&M costs of generation and γ^g is a measure of the fuel requirements per unit of output.

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

$$\sum_{g,z} ele_t^{g,z} = d_t^{ele} \perp p_t^{ws}. \tag{11}$$

All submarginal generators earn scarcity rents μ_t^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:

$$\kappa_t^g \geq \sum_z ele_t^{g,z} \perp \mu_t^g \geq 0 \tag{12}$$

where κ_t^g is the maximum output of generator g in a given time period.[12]

The bottom-up model finds the optimal utilization of available capacity in order to meet the electricity demand, and the benchmark output $\overline{ele}_t^{g,z}$ and price $\overline{p}_t^{ws}$ are determined by simultaneously solving Eqs. (10)–(12), given benchmark demand $\overline{d}_t^{ele}$ and fuel prices $\overline{p}^z$. The regional fuel mix predicted by the model ($\hat{s}^z$) is reported in Table 6 and closely matches observed values (s^z).[13]

The response of the model to a carbon policy is driven by three mechanisms.[14] First, fuel costs increase according to their carbon content. Second, we add structure on the electricity demand response. Since a wide majority of electricity consumers are charged a near constant annual retail price (despite substantial time variations on the wholesale market), we assume that the generation costs passed forward to the consumers are an output-weighted yearly average of the wholesale price in each load block t:

$$p^{ele} = \frac{1}{\sum_{g,z,t} ele_t^{g,z}} \sum_{g,z,t} p_t^{ws} ele_t^{g,z}. \tag{13}$$

The demand schedule features a constant price elasticity and is calibrated to the benchmark quantities ($\overline{p}^{ele}$, $\overline{d}^{ele}$):

$$d_t^{ele} = \overline{d}_t^{ele} \left(\frac{p^{ele}}{\overline{p}^{ele}} \right)^{\epsilon} \tag{14}$$

[12] The explicit representation of rents as the complementarity variable to the capacity constraint can be interpreted as profits earned by the submarginal generators. In the integrated model, these profits are incorporated in the income balance equation.

[13] As a formal goodness of fit measure, we compute the coefficient of determination $R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \overline{y})^2}$, where y_i is observed outcome, $\hat{y}_i$ is the prediction from the model, and $\overline{y}$ 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.

[14] As already mentioned, we do not model capacity expansion, and low cost carbon-free technologies that are typically used at capacity in the benchmark cannot expand. We therefore focus on changes in the relative prices of different fossil generation technologies, which are not operated at capacity both in the benchmark and in policy counterfactual.

Table 7
Regional price elasticities for fuel supply and electricity demand.

Region	Electricity demand elasticities		Fuel supply elasticities: simulated values [b]	
	Estimated [a]	Simulated [b]	Coal	Natural gas
	$(\hat{\epsilon}_r)$	$(\tilde{\epsilon}_r)$	$(1/\tilde{\eta}_r^{coal})$	$(1/\tilde{\eta}_r^{natural\ gas})$
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 values from the USREP model.

where $\epsilon<0$ is the regional price elasticity of demand. Values for elasticity parameters are shown in Table 7. Besides regional econometric estimates from Bernstein and Griffin (2005), we use elasticities simulated from the USREP model to provide a local approximation of the general equilibrium demand response.[15]

The third response occurs through changes on the markets for coal and natural gas.[16] Defining the demand for fuel z as:

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

we assume a set of constant elasticity supply schedules calibrated to the benchmark fuel price and demand:

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

where $\eta_r^z>0$ is the regional supply price elasticity for fuel z. The local price elasticities are simulated from the economy-wide model and reported in Table 7.[17] Overall, the change in the demand from regional electricity sectors has a relatively small impact on the market price for coal, and an even smaller impact on the natural gas market. This reflects the small market share of each region in the national markets for coal and natural gas.[18]

2.4. Formulation of the integrated model

The 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 electricity model with electricity demand and fuel supply functions locally calibrated with top-down quantities and prices. We use an iterative algorithm based on Böhringer and Rutherford (2009) to solve the two models consistently. The key insight from Böhringer and Rutherford (2009) is that a linear Marshallian demand can be used as a 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. In this setting, income effects from changes in the electricity sector are small and do not affect the location of the demand schedule. Moreover, our computational experience with this model suggests that including an approximation of how fuel prices respond to changes of production in the regional electricity sectors in the bottom-up module increases convergence speed. Intuitively, fuel price schedule in the bottom-up model approximates general equilibrium adjustments, so that technology choice in the bottom-up model moves quicker towards their equilibrium value. A more detailed description of the algorithm is provided in the working paper version of this article (Lanz and Rausch, 2011).[19]

We now provide an algebraic description of the integrated model. Let $n=1, \ldots, N$ denote an iteration index and consider first the economy-wide component. Since electricity supply is exogenous, the zero-profit conditions for the electricity generation activities and resource-specific market clearance are dropped (Eqs. (1), (2) and (8)). The least-cost input requirement determined by solving the bottom-up model in iteration (*n-1*) is used to parameterize the economy-wide model in (n), replacing Eqs. (3)–(7) with a set of modified market clearance conditions:

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

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

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

$$\sum_r K_r^{(n)} = \sum_r \left(D_r^{K(n)} + \sum_{g,z,t} \phi_g^K c^g ele_t^{g,z(n-1)}\right) \perp P^{K(n)} \tag{6'}$$

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

where ϕ's denote the benchmark value share of capital, labor, and materials of variable O&M costs.[20] In addition, we modify the income balance (Eq. (9)) to account for capacity rents $\mu_t^{g(n-1)}$:

$$\begin{aligned} M^{(n)} = {} & P^{K(n)}\overline{\mathrm{K}} + P^{L(n)}\overline{\mathrm{L}} + \sum_{g,z,t} ele_t^{g,z(n-1)} \Big(P^{\mathrm{ELE}(n)} p_t^{\mathrm{ws}(n-1)} \\ & - c^g P^{c(n)} - \bar{p}^z P^{z(n)} \gamma^g \Big) \end{aligned} \tag{9'}$$

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 $P^{c(n)} = \sum_j \phi^j P^{j(n)} + \phi^L P^{L(n)} + \phi^K P^{K(n)}$. Note that in this approach the electricity-sector output and inputs are valued at market

[15] Simulating demand elasticities involves exogenously increasing the electricity price in a region and solving the USREP model, repeating the procedure for each region sequentially. The change in electricity demanded in each region is the basis to measure regional elasticities, which by construction includes all categories of customers (residential, commercial and industrial).

[16] For all other fuels, the electricity sector is assumed to be a price-taker.

[17] We simulate the inverse of the supply elasticity by increasing the demand for fuels in each regional electricity sector and solving for the fuel price increase in the USREP model, repeating the procedure for each region in a sequential manner.

[18] We emphasize that the objective of simulating fuel supply elasticities is to approximate the response of the USREP model at the regional level. Thus these elasticities should not be compared to econometric estimates of supply price elasticities that measure an aggregate supply response to a change in fuel prices. Note also that USREP model only features one type of coal, so that the same elasticity applies to the different types of coal in the electricity sector model.

[19] Before applying the algorithm, it is necessary to calibrate the two models to a consistent benchmark. Initial agreement in the benchmark is achieved if 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. Violation of this initial condition means that any simulated policy would be confounded with adjustments due to initial data inconsistencies. See Appendix B in Lanz and Rausch (2011) for a description of the calibration procedure.

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

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 response from the top-down model (i.e. elasticities ϵ_r and η_r^z simulated from the economy-wide model). 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:

$$d_t^{\mathrm{ele}(n)} = \overline{d}_t^{\mathrm{ele}(n)}\left(1 + \epsilon\left[\frac{p^{\mathrm{ele}(n)}}{\overline{p}^{\mathrm{ele}(n)}} - 1\right]\right). \tag{14′}$$

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:

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

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

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

Finally, the variable cost index is updated according to:

$$p^{c(n)} = \sum_j \phi^j P^{j(n)} + \phi^L P^{L(n)} + \phi^K P^{K(n)}. \tag{17′}$$

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

$$c^g p^{c(n)} + p^{z(n)}\gamma^g + \mu_t^{g(n)} \geq p_t^{\mathrm{ws}(n)} \perp \mathrm{ele}_t^{g,z(n)} \geq 0. \tag{10′}$$

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):

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

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

where $\overline{d}_t^{\mathrm{ele}(0)}$ and $\overline{p}^{\mathrm{ele}(0)}$ denote the benchmark value of electricity demand and the consumer price, respectively.

We find that despite the complexity and dimensionality in both modules, the algorithm is robust and provides rapid convergence. Numerical evidence and a discussion related to convergence can be found in Lanz and Rausch (2011).

3. 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 model 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.

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.

Our counterfactual imposes a national tax on CO_2 emissions in all regions and sectors of the economy.[21] 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.[22]

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 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.[23] Carbon price of $25 and $100 bring about welfare losses of about 0.1% and 1.3%, respectively.

Fig. 3 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.[24] 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

[21] 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.

[22] 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.

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

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

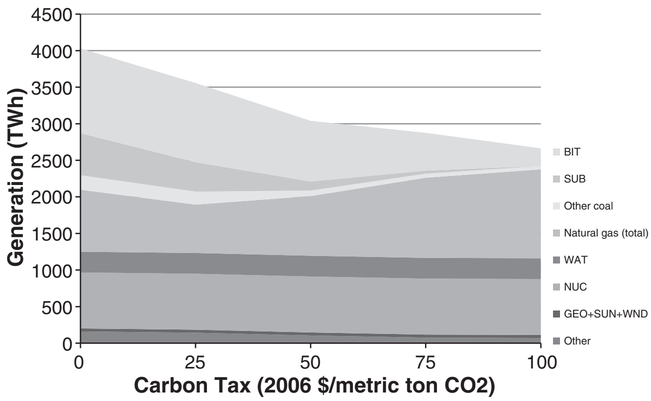

Fig. 3. Electricity generation by fuel from the integrated model for different carbon prices.

electricity consumption by about 10%, a $50 price yields a 20% reduction, while for a price of $100, demand declines by about 30%.

3.1. 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[25]:

- 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 ($\tilde{\eta}^z_{lr}$), 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 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 carbon-intensive activities induce a structural change in electricity demand, reflecting a shift in the demand rather than a movement along the demand schedule. The PE model with econometric estimates of price 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 regional electricity sectors on coal and natural gas prices when modeled independently.

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.[26] 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.

Table 9
Partial and general equilibrium changes in regional electricity prices and demands for a $50 carbon tax.

Region	Partial equilibrium (PE) electricity model			General equilibrium (GE) model
	(1)	(2)	(3)	(4)
	Estimated demand elasticities and no fuel price response[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 ($\eta^z_{lr}=\infty$). [b]PE model with simulated price elasticities for electricity demand ($\tilde{\epsilon}_r$) and exogenous fuel prices ($\eta^z_{lr}=\infty$). [c]Similiar to (b) but PE model here also includes constant-elasticity fuel supply schedules for coal and gas with simulated supply price elasticities ($\tilde{\eta}^z_{lr}$).

[25] The value of elasticities is reported in Table 7.

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

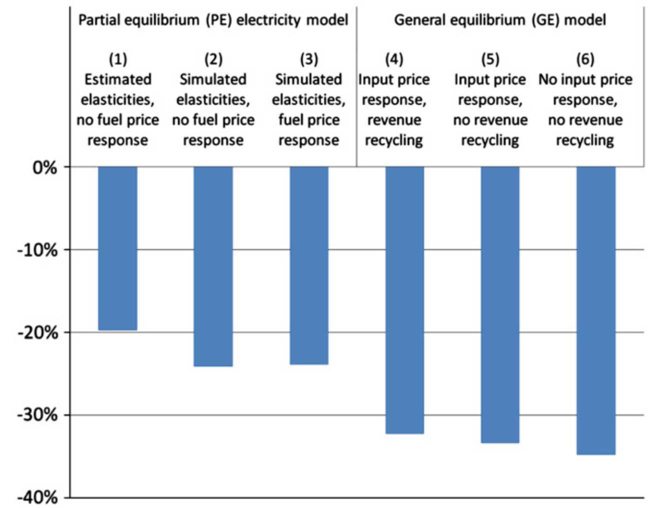

Fig. 4. Model comparison of U.S. CO_2 emission reductions from electricity generation for \$50 carbon tax (relative to BAU).

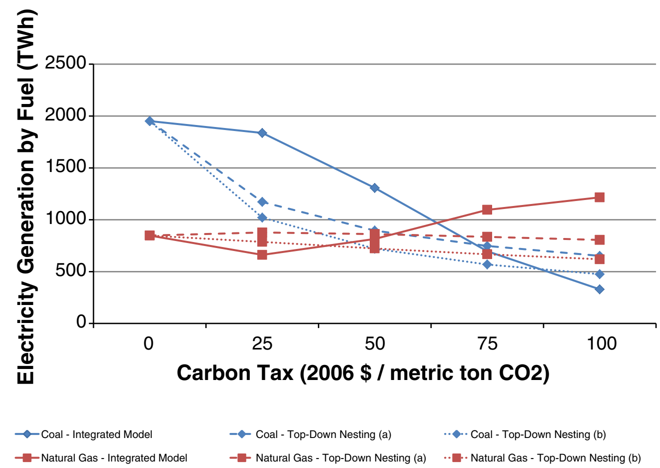

Fig. 5. Top-down vs. bottom-up comparison of U.S. electricity generation from coal and natural gas.

Fig. 4 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 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, emission reductions are slightly larger compared to (4) as reduced income lowers consumer demand and keeping input price constant implies higher generation costs. Overall, Fig. 4 suggests that economy-wide income and substitution effects on electricity demand are of first-order importance. Comparing the 'simple' PE model (1) with the full GE model (4), we find that emission reductions are 38% larger in the GE case. Evaluated at a carbon price of \$50 per metric ton, this is equivalent to \$17.7 billions worth of carbon revenue (or allowance value).

In summary then, the different parametrizations 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.

3.2. 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 model responses' can be attributed to the specific structural technology representation.

Fig. 5 shows U.S. electricity generation from coal and natural gas for different carbon prices.[27] For a carbon price of \$25, the integrated GE model suggests a modest 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 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. Indeed, as the carbon price increases, the bottom-up component of the integrated GE model suggests that coal-fired generation declines steadily and natural gas generation gradually expands. The 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.[28]

A key aspect of top-down models is that the nesting structure and elasticity parameters are typically identical across regions, whereas the response of the integrated model depends on the benchmark fuel costs and stock of available generation technologies.[29] Fig. 6 reports differences between models in terms of regional abatement for a \$50 carbon price, and suggests country-wide abatement in the integrated model is 23% and 31% lower than under the top-down representations (a) and (b), respectively. Interestingly, differences in emissions reductions are most striking in regions with a large share of coal-fired generation (SPP, PJM, SEAST, and MOUNT), for which the top-

[27] 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.

[28] 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.

[29] Of course, this is a modeling choice, and top-down models could be based on regionally differentiated data. To our knowledge however, this is typically not the case.

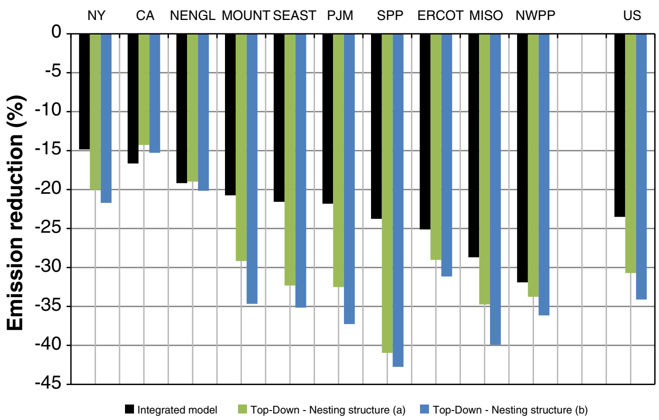

Fig. 6. Model comparison of regional CO_2 emission reductions for a $50 carbon tax (all sectors).

down models feature large emissions reductions.[30] 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 (the benchmark shares are kept constant).

Fig. 7 shows the 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, absolute welfare differences between bottom-up and top-down approaches are 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 and the top-down structure (b) are smaller, especially for emissions reductions above 30%.

Despite quantitative discrepancies, projections of carbon policies exhibit the same qualitative behavior especially when comparing nesting structure (a) with the integrated model. At the regional level however, we observe significant departures among these two modeling framework. We report results for three representative regions to illustrate the large heterogeneity across model outcomes even though the benchmark data is the same. 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.[31] 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 comparison of generation technology representation. First, the choice of bottom-up or top-down representations has a large effect on the projected 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 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. In any instances, the conceptual differences between the two model paradigms with respect to the transmission of the carbon price would be difficult to reconcile.

4. 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 projecting 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 observations, for two reasons. First, general equilibrium effects associated with carbon policies are complex and difficult to identify from historic data. Second, while nested CES function can accommodate any substitution patterns, the empirical validation of these structures to represent substitution among electricity generation technologies is difficult. In our framework, bottom-up and top-down models represent a structural representation of the electricity supply and demand respectively, and our comparison exercise generates quantitative insights on the implication of these assumptions for policy assessment.

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

[31] 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.

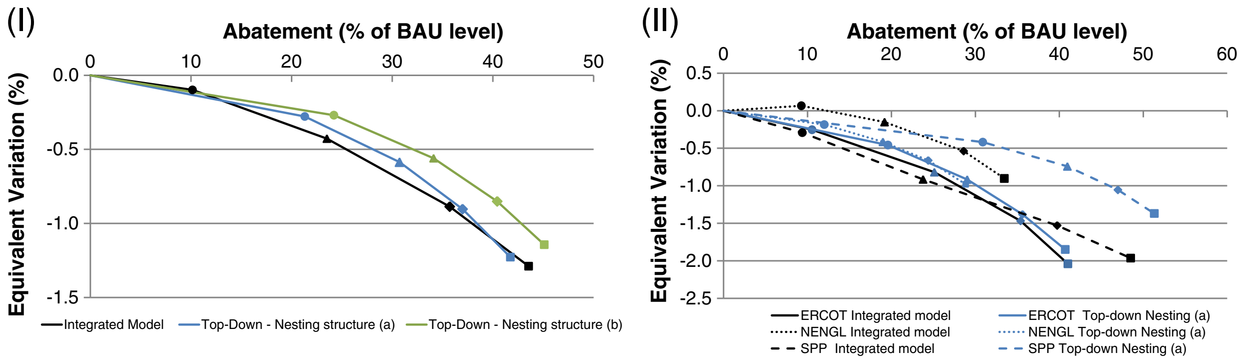

Fig. 7. Model comparison of welfare costs and emission reductions for U.S. (I) and selected regions (II).

As a final note, we emphasize that our quantitative results are model-specific and abstract from a number of features. First, we do not represent the dynamic response to a policy shock. Specifically, the response of the electricity sector is constrained by the existing generation capacity, and most of the actions take place in the substitution between coal and gas. While our analysis is informative in this respect, carbon-free technologies such as wind, solar, hydro and nuclear are used at their effective capacity in the benchmark, and thus cannot expand as they get more competitive under a carbon price. The expansion of renewable technologies under a carbon price is obviously an important research question, but in our view the structural assumption about electricity sector will be even more important in a capacity-expansion model. Thus we expect discrepancies between modeling frameworks to be even more important in a forward-looking framework. Second, our analysis abstracts from physical constraints on the transmission network which are likely to hamper the flexibility in the substitution among technologies and might increase the welfare costs of carbon policy. We note that such constraints will be difficult to represent accurately in a highly aggregated top-down representation of electric power technologies. Finally, while the assumption of marginal cost pricing makes the comparison across different modeling paradigms more transparent, carbon abatement policies is likely to be affected by the extent of state regulation and imperfect competition in the U.S. electricity markets. Quantifying the effects of market structure on the cost of carbon regulation is, however, beyond the scope of the present paper.

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