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Disaggregating Electricity Generation Technologies in CGE Models

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Disaggregating Electricity Generation Technologies in CGE Models*

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Abstract

We illustrate the importance of disaggregating electricity generation when considering responses to environmental policies. We begin by reviewing various approaches to electric sector modelling in Computable General Equilibrium (CGE) models, and then clarify and expand upon the structure and calibration of the "technology bundle" approach. We also simulate the proposed U.S. Clear Power Plan and show how a disaggregate electricity sector can change results. Our simulations indicate that both the ability to switch between generation technologies and the manner of aggregation in electricity production are important for quantifying the economic costs of the plan.

* The analysis and conclusions expressed here are those of the authors and not necessarily those of the U.S. Energy Information Administration or the CSIRO.

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1 Introduction

The U.S. Environmental Protection Agency's (EPA's) June 2014 proposed Clean Power Rule requires substantial reductions in carbon dioxide emissions from the power sector by 2030. What will be the economic costs? Any model-based assessment of this policy requires making assumptions about how electricity is and will be produced in the United States. Such generation technologies differ across many dimensions, including their costs, resource requirements, emissions, and flexibility. These differences can be important when considering responses of the overall economy to environmental policies. However, many models used to analyze the impact of various environmental policies are too aggregated to account for differences in electricity generation technologies, possibly biasing their results.

This paper clarifies, expands, and illustrates the "technology bundle" approach to disaggregated modelling of the electricity sector in Computable General Equilibrium (CGE) models. We also demonstrate how to calibrate important parameter values and apply the method using the GTAP 8 database and model, supplemented with data from national and international agencies. Throughout, we focus on benefits of the technology bundle approach as applied to the electricity sector in CGE models: the ability to account for important heterogeneity in power generation technologies and reliance on data that is widely available and utilized.

We begin by reviewing approaches to modelling the electricity sector in CGE models and then provide a description and outline of the technology bundle approach. Within this description we explain the structure of the CRESH (Constant Ratios of Elasticities of Substitution, Homothetic) function, which allows for differing levels of substitution between electricity generation technologies (Hanoch, 1971). Our explanation of the CRESH function also establishes the link between its parameters and various econometric estimates of substitution between fuels and technologies in electricity generation. There has been little written about quantifying the degree of substitution between the various electricity generating technologies in CGE models.

Our next step is to describe implementation of the technology bundle approach. We show how the structure of its electricity sector can be disaggregated in various ways using data that are available from either the U.S. Energy Information Administration (EIA) or the International Energy Agency (IEA). This structure is then applied to variants of the widely-used GTAP model (see Hertel, 1997) in combination with other data from the GTAP 8 database (see Narayanan et al., 2011).

Finally, we simulate the proposed U.S. Clear Power Plan and show how a disaggregated electricity sector can change results. Our simulations indicate that both the ability to switch between generation technologies and the manner of aggregation in electricity production are important for quantifying the economic costs of the plan.

2 Approaches to Modelling the Electricity Sector

CGE models are a popular tool for analyzing both energy and environmental policies. They are often referred to as "top-down" because of their high levels of aggregation. In particular, it is standard to represent the production of energy as based on a single technology. This technology allows for imperfect substitution between labor, capital, intermediate inputs, and natural resources. Such technological generality is problematic when considering energy policies, as specific aspects of energy production technologies have important differences. These differences can have important implications for energy prices and economy-wide output.

Electricity is a notable example because of its importance for the analysis of environmental policies. There are large differences in terms of the cost and emissions profiles of electricity generation technologies. For example, the levelized cost of electricity (LCOE) for a conventional coal power plant is much lower than that of a comparable solar one (EIA, 2014).[1] But electricity generated through solar power is emissions-free. Because of these differences, there will be variations within the electricity sector in response to environmental policies such as a carbon tax.

Assuming there is only one technology in electricity production does not account for this heterogeneity, and can bias the results (see for example Sue Wing, 2006 and Fujimori et al., 2014). Given that the electricity sector accounts for over 30% of global greenhouse gas (GHG) emissions, the inability to support disaggregated energy analysis is a short-coming for standard CGE models and limits their ability to assess the impacts of different environmental policies.

There have been several notable attempts to incorporate additional technological detail in the electricity sector within a CGE framework. Sue Wing (2006, 2008) proposes a structure and numerical algorithm to disaggregate electricity production into three parts: generation (GEN), transmission and distribution (TB), and overhead (OH). Each of the three activities is modelled as a production function that combines inputs of primary factors, fuels, and other intermediate inputs. The GEN activity distinguishes between multiple technologies that are imperfect substitutes. However, this approach uses a constant elasticity of substitution (CES) production function that assumes the degree of substitution between any two competing technologies is the same. This is inconsistent with the evidence in Dahl and Ko (1998), Ko and Dahl (2001), and EIA (2012).

Sands (2004), Schumacher and Sands (2006), and Fujimori et al. (2014) move away from the production function approach and incorporate different functions to determine the share of electricity production from a particular generation technology. Such Logit functions are commonly used in “bottom-up” energy models and allow for different degrees of substitution between electricity generation technologies.[2] The difficulty with using this approach in CGE models is that Logit functions are difficult to relate to the models’ underlying economic.

The technology bundle approach outlined and expanded upon in this paper was one of the first attempts to disaggregate the electricity sector in a CGE model. It was first used in ORANI (see Adams et al., 1991) and then modified and used again in GTEM (see Pant, 2007). The technology bundle approach disaggregates the electricity sector between generation and non-generation activities. Importantly, it both allows for different

[1] LCOE is often cited as a convenient summary measure of the overall competiveness of different generating technologies. It represents the per-kilowatt-hour cost (in real dollars) of building and operating a generating plant over an assumed financial life and duty cycle. Key inputs to calculating LCOE include capital costs, fuel costs, fixed and variable operations and maintenance (O&M) costs, financing costs, and an assumed utilization rate for each plant type.

[2] For this reason the Logit function is often used for estimating elasticities related to substitution between fuels. See for example Dahl and Ko (1998), Ko and Dahl (2001), and EIA (2012).

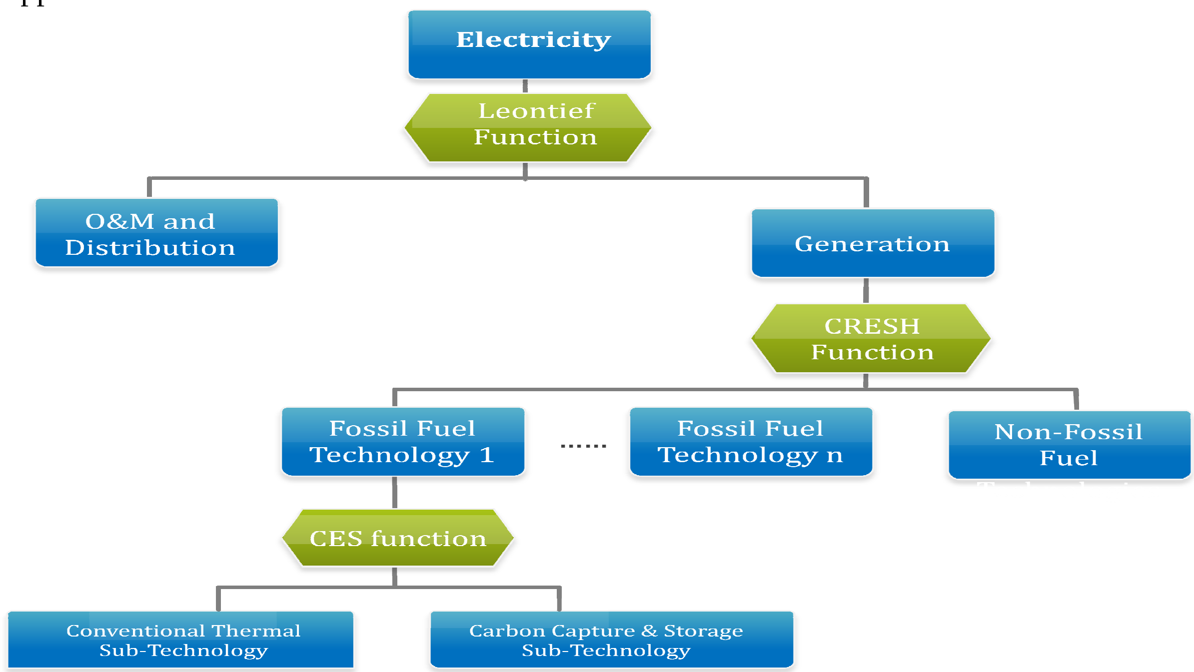
assumptions about substitutability between competing generation technologies, and follows from standard economic theory.

3 The Technology Bundle Approach

3.1 Overview

Under the technology bundle approach, electricity is a homogenous good produced by aggregating Generation (GEN) and O&M and Distribution (OMD), as shown in Figure 1. The GEN activity is the key component of this set-up that allows for a bundle of heterogeneous and competing electricity generation technologies. The role of the OMD is to aggregate other general goods that are important in electricity production, but not specific to generation technologies.

Figure 1: Aggregated Structure of the Electricity Sector Using a Technology Bundle Approach



In order to construct the technology bundle, competing electricity technologies are combined through the CRESH function. Use of the CRESH function allows for differing levels of substitution between each of the generation technologies. All of the technologies are comprised of primary factor inputs and intermediate inputs specific to that particular technology.   Fossil fuel technologies allow for the possibility of carbon capture and storage (CCS) sub-technologies, in combination with conventional thermal sub-technologies.

Primary factor inputs include labor and capital, which are used by all technologies, as well as "fixed-factor" energy resources used only by carbon-free technologies.[3] The intermediate goods include fossil fuels (used by carbon-emitting technologies), refined uranium (nuclear),

[3] Following Sue Wing (2008), these fixed-factor energy resources are understood as the land area with incident insolation, atmospheric boundary-layer follow in the case of solar and wind, topographically-determined hydrostatic potential in the case of hydroelectricity, or geologically-determined hot dry rock in the case of geothermal energy.

or agricultural feedstock (biomass). Intermediate goods are the output of other sectors of the economy, and may be produced domestically or imported, but are specific to each technology. As an example, consider a U.S. natural gas technology. This combines domestic labor and capital (the primary factors) with natural gas that is either domestically produced or imported from Canada (the intermediate good). We show below that the GEN activity is a generalization of Sue Wing (2006, 2008).

The OMD activity aggregates intermediate inputs that are used to produce electricity, but which are not specific to a particular generation technology. It is a combination of the TD and OH activities of Sue Wing (2006, 2008). The OMD activity reflects the fact that power plants require non-technology-specific activities, such as construction and daily maintenance, and that they are connected to end-users through electricity transmission grids.

3.2 Mathematical Details

At the top level electricity production (E) is a Leontief function of the GEN activity (X) and OMD activity (Y):

$$E = Min\{A_1 \cdot X, B_1 \cdot Y\}.$$

Here, A_1 and B_1 are scale factors representing the efficiency of each activity, and Min is the minimum operator. This operator indicates that the two activities are non-substitutable, so that the outputs of GEN and OMD are combined in fixed proportions.

Generation

The generation activity combines different technologies through a CRESH function, as shown on the right-hand side of Figure 1.[4] For X units of generation, the demand for each technology (Q_i) satisfies:

$$\textstyle\sum_i (Q_i/X)^{d_i} \cdot D_i/d_i = \kappa \qquad (1).$$

In this equation d_i is a parameter with a value less than 1 but not equal to zero, each D_i parameter associated with a particular technology is positive, and the D_i values and κ are normalized such that $\sum_i D_i = 1$. The set-up generalizes the CES framework of Sue Wing (2006, 2008); in the special case where when $d_i = d$ for all i, the CRESH function collapses to the CES function:

$$\frac{1}{d \cdot \kappa} \cdot [\textstyle\sum_i (Q_i)^d \cdot D_i]^{\frac{1}{d}} = X \qquad (2).$$

Given total demand for generation (X) and production costs for each technology (P_i), the electricity producer chooses demand for each technology (Q_i) to minimize total cost $\sum_i Q_i \cdot P_i = C$, subject to equation (1). The linearized solution to this problem yields:[5]

[4] The CRESH function is due to Hanoch (1971) and its mathematical derivation is available from Dixon et al. (1997), p. 64-76.

[5] The first-order conditions from this problem require that:

$$P_i + \Lambda \cdot (Q_i/X)^{d_i} \cdot D_i/Q_i = 0 \qquad \text{(f1)},$$

where Λ is the Lagrange multiplier. Log-linearizing equations (1) and (f1) gives:

$$p_i = \lambda + d_i \cdot (q_i - q_X) - q_i \qquad \text{(f2)},$$

$q_i = q_X - a_i \cdot (p_i - p_X^*)$ (3),

where $\mathrm{a_i} = \frac{1}{1-\mathrm{d_i}}$, $p_X^* = \sum_{\mathrm{i}} \mathrm{a_i} \cdot \mathrm{S_i} \cdot \mathrm{p_i}$, and $\mathrm{S}_i = Q_i \cdot P_i / \sum_i Q_i \cdot P_i$ (the cost share of technology *i*). Here, p_i, q_i, and $\mathrm{q_X}$ are the percentage changes of P_i, Q_i, and X, respectively. Equation (3) shows that demand for each technology depends upon total demand for generation, production costs for each technology, and various parameters.

The $\mathrm{a_i}$ parameter in equation (3) is particularly important in this context because it summarizes substitution between technologies. This can be shown beginning with price elasticities of demand for each technology and then linking them to different definitions for elasticities of substitution.

Hanoch (1971, p. 697-699) defines expressions for the cross ($\varepsilon_{i,j}$) and own ($\varepsilon_{i,i}$) price elasticities of demand for each technology under the CRESH demand function as:

$$\varepsilon_{i,j} = \partial(ln\, Q_i)/\partial\left(ln\, P_j\right) = \frac{S_i a_i a_j}{\sum S_k a_k} \quad (4),$$

and

$$\varepsilon_{i,i} = \partial(ln\, Q_i)/\partial(ln\, P_i) = \frac{S_i a_i a_i}{\sum S_k a_k} - a_i \quad (5).$$

These can be linked to the Morishima elasticity of substitution ($\mathrm{M_{i,j}}$), which summarizes the change in relative demands for two technologies given a change in their relative prices when one price is fixed (Chambers, p. 93-97, 1988):

$$\mathrm{M_{i,j}} = \partial\left(ln\frac{Q_i}{Q_j}\right)\Big/\partial\left(ln\frac{P_i}{P_j}\right)\bigg|_{fixing\ P_j} = \varepsilon_{i,\mathrm{j}} - \varepsilon_{\mathrm{i,i}} \quad (6),$$

Equation (6) associates a particular definition for the elasticity of substitution between two technologies with the $\mathrm{a_i}$ parameters and technology cost shares (S_i). A variant of the Morishima elasticity of substitution is more commonly used. This shadow elasticity of substitution ($\delta_{\mathrm{i,j}}$) is defined similarly, but holds consumption (C) fixed, and can also be tied back to the cost shares:

$$\delta_{i,j} = \partial\left(ln\frac{Q_i}{Q_j}\right)\Big/\partial\left(ln\frac{P_i}{P_j}\right)\bigg|_{fixing\ C} = \frac{S_i}{S_i+S_j}M_{i,j} + \frac{S_j}{S_i+S_j}M_{j,i} \quad (7).$$

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and
$\sum_i (q_i - q_X) \cdot (Q_i/X)^{d_i} \cdot D_i = 0$ (f3).
Here, p_i, q_i, $\mathrm{q_X}$ and λ are the percentage changes of P_i, Q_i, X, and Λ, respectively. Substituting (f1) into (f3) yields:
$\sum_i q_i \cdot S_i = q_X$ (f4),
where $\mathrm{S}_i = Q_i \cdot P_i / \sum_i Q_i \cdot P_i$ is the cost share of technology *i*. Multiplying (f1) by $\frac{S_i}{d_i - 1}$, summing over all *i* , and using equation (f4) gives:
$\lambda = \sum_{\mathrm{i}} \mathrm{a_i} \cdot \mathrm{S_i} \cdot \mathrm{p_i} + q_X$ (f5),
Substituting equation (f5) into equation (f1) yields equation (3) above.

Irrespective of the definition, the key points are that the parameters of the CRESH function are directly linked to substitutability between technologies, and that because the parameters differ between technologies, so can the elasticities of substitution.[6] The fact that the CRESH framework allows heterogeneity in substitution between technologies is consistent with econometric studies of such elasticities, and one of the benefits of using the technology bundle approach.

A concern with the CRESH approach is that for a given number of technologies there are the same numbers of parameters available to calibrate elasticities. However, the number of elasticities exceeds the number of technologies because there are own-price elasticities as well as cross-price elasticities that must be calibrated (see equations (4) to (7)).

Conventional Thermal and CCS Technologies

A fossil fuel technology combines conventional thermal and CCS sub-technologies through a CES function, as shown at the bottom of Figure 1. For Q_i units of generation, the demand for each sub-technology ($Q_{i,j}$) satisfies:

$$\left[\sum_i \left(Q_{i,j}\right)^{\frac{1-\tau}{\tau}} \cdot D_{i,j}\right]^{\frac{\tau}{1-\tau}} = Q_i \qquad (8)$$

where τ is the shadow elasticity of substitution, and each $D_{i,j}$ is a positive parameter. Given total demand for a fossil fuel technology (Q_i) and production costs for each sub-technology ($P_{i,j}$), the electricity producer chooses demand for each sub-technology ($Q_{i,j}$) to minimize total cost $\sum_j Q_{i,j} \cdot P_{i,j} = C_i$, subject to equation (8). The linearized solution to this problem yields:

$$q_{i,j} = q_i - \tau \cdot \left(p_{i,j} - p_i\right) \qquad (9).$$

Additivity of Technologies and Sub-Technologies

The electricity produced by differing technologies is a homogenous good. This leads to another drawback when using CRESH or CES functions: changes in electricity output depend upon changes in production from each technology that are weighted by cost shares (see equation f4 above).[7] This leaves the possibility that output from each technology as measured in physical units may not equal total electricity output. The problem is aggravated by CES aggregation of the fossil sub-technologies.

We add a uniform adjustment factor (Adj) to all non-fossil technologies in equation (3) to ensure additivity in physical units:

$$q_i = q_X - a_i \cdot (p_i - p_X^*) + Adj.$$

The adjustment factor is also added to all fossil sub-technologies in equation (9):

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[6] In the CES case when $d_i = d$ for all i, this implies that $a_i = a$; the expressions above simplify so that $\varepsilon_{i,i} = (s_i - 1) \cdot a_i$, $\varepsilon_{i,j} = S_j a = \varepsilon_{k,j}$ for any $i \neq k$, and $M_{i,j} = \delta_{i,j} = a$ for any i, j. That is, the degree of substitution between any two competing technologies is assumed to be the same.

[7] Because the CES function is a special case of the CRESH function it is subject to the same problem.

$q_{i,j} = q_i - \tau \cdot (p_{i,j} - p_i) + Adj.$

This adjustment factor is endogenously calculated to ensure the additivity of all non-fossil technologies and fossil sub-technologies into a single industrial output (X).[8]

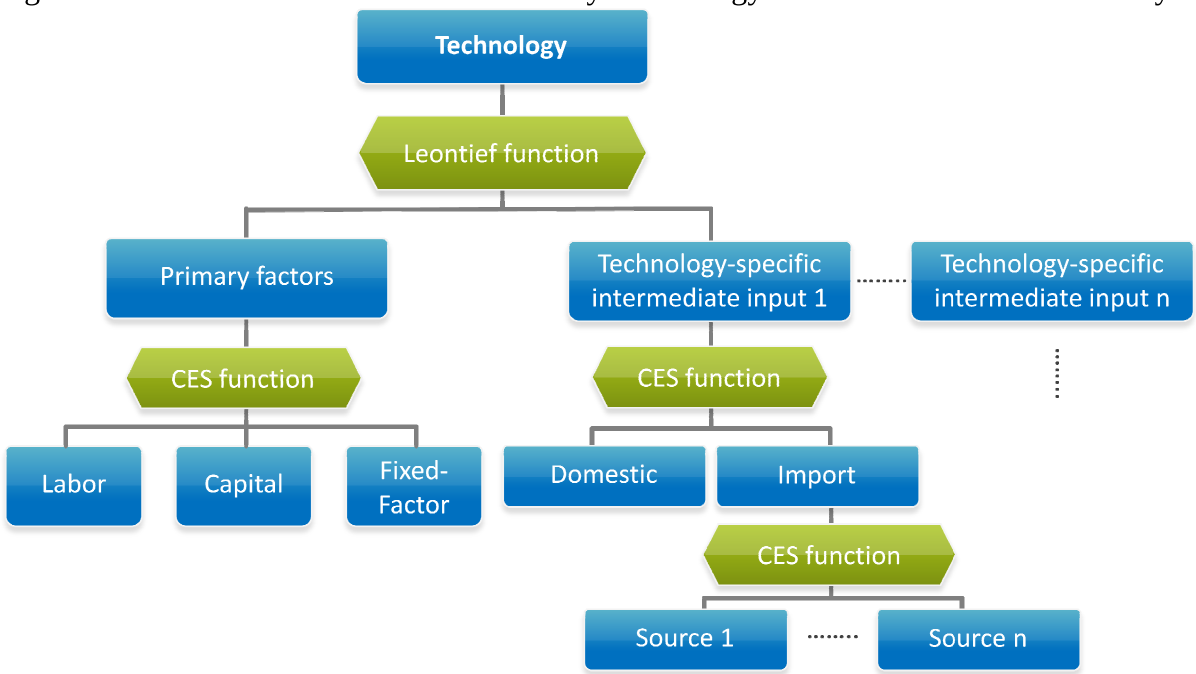
Technology Production

Below the generation activity and within each specific technology or sub-technology, we assume a fixed-coefficients production function of primary factor composite (F) and intermediate inputs (G):

$Q_i = Min\{A_2 \cdot F, B_2 \cdot G\}.$

In this equation A_2 and B_2 are scale factors representing the efficiency of each activity, and Min is the minimum operator. The factor composite is an aggregate of labor, capital, and the fixed-factor energy resources (if applicable). This is consistent with the set-up in Sue Wing (2006) and shown in Figure 2.

Figure 2: Production Structure of an Electricity Technology Within the Generation Activity



Each of the intermediate inputs is an aggregate of imported and domestic goods. The aggregation is represented by a CES function, which allows imperfect substitution between imported and domestic goods, G_i^{Imp} and G_i^{Dom}:

[8] Introducing the adjustment factor does not change inter-technology substitution responses to price changes, because for two technologies we have:
$q_i - q_j = -\mathrm{a_i} \cdot (\mathrm{p_i} - p_X^*) + \mathrm{a_j} \cdot (\mathrm{p_j} - p_X^*)$ (f6),
which is free of the adjustment factor.

$$G_i = \left[\rho_{Dom}\left(G_i^{Dom}\right)^{\frac{\sigma-1}{\sigma}} + \rho_{Imp}\left(G_i^{Imp}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}.$$

Here, σ is commonly known as the Armington elasticity of substitution between imported and domestic goods, and ρ_{Dom} and ρ_{Imp} are budget share parameters. See Burfisher (p. 75, 2011) for additional details. The imported good G_i^{Imp} is a CES composite of shipments from various sources $G_{r,i}^{Imp}$:

$$G_i^{Imp} = \left[\sum_r \rho_r \left(G_{r,i}^{Imp}\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}.$$

where ρ_r is budget share parameter, and η is the elasticity of substitution among imports from different sources.

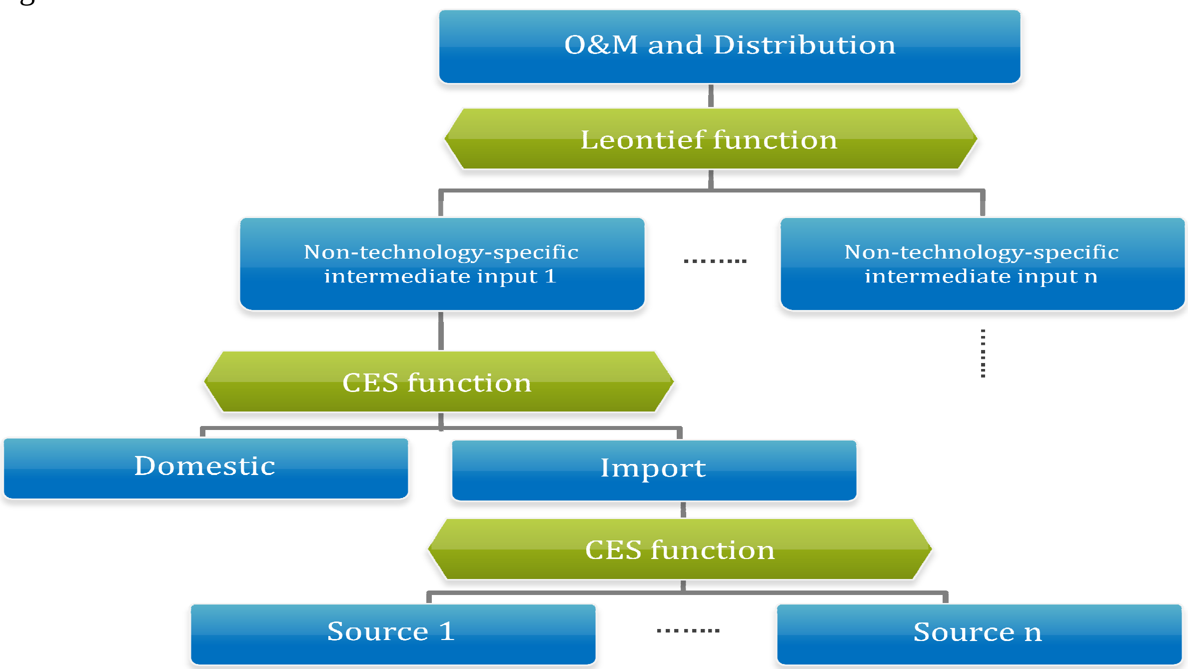
The OMD Sector

The OMD activity, shown in Figure 3, is a Leontief function of non-technology-specific intermediate inputs:

$$Y = Min\{B_3 \cdot G\}.$$

B_3 is a scale factor representing the efficiency of each intermediate input and Min is the minimum operator. As before, the intermediate inputs are aggregates of domestic and imported goods.

Figure 3: Production Structure of O&M and Distribution



4 Implementation of the Technology Bundles

In this section we describe implementation of the technology bundle approach outlined above. We begin by considering the appropriate levels of detail for power generation technologies and then describe calibration of elasticities of substitution. Our implementation uses the GTAP 8 database and other available data from the IEA and EIA.[9]

4.1 Allocating the Output, Inputs and Emissions of Electricity into Technologies

The first practical challenge in implementing the technology bundle approach is allocating the output, inputs, and emissions of the electricity sector into technologies in a manner consistent with a CGE model's social accounting matrix. Choosing the appropriate level of output and input detail for power generation technologies in each region of the model is particularly challenging.

In terms of output, the IEA world energy balance table provides production data on more than 20 electricity technologies for over 100 regions (International Energy Agency, 2007). This balance table is available for purchase from the IEA website. EIA's International Energy Outlook (2013) provides a cost-free alternative for liquids, gas, coal, nuclear, hydro, wind, solar, geothermal, and other renewables for 15 global regions.[10] Either of these sources can be used in disaggregating regional electricity outputs. Because the GTAP 8 database lumps both electricity and heat into a single sector, we have chosen to use the IEA world energy balance table which accounts for both electricity and heat.

For ease of implementation, we group into 10 technologies: coal, oil, gas, nuclear, hydro, wind, solar, biomass, waste, and other renewable. The fossil technologies (coal, oil and gas) are further divided into conventional coal, oil and gas, and their counterparts with carbon capture and storage (CCS). This structure follows Figure 1 and is outlined in sub-section 2.2. In the 2007 world energy balance table there are no accounts for CCS sub-technologies, hence we have assumed that the CCS sub-technologies are 0.004% of their conventional counterparts.[11] For full detail, Table A1 in the online appendix shows world electricity and heat generation in terawatt-hours (TWH) for 2007 by the 10 technologies we have chosen in each region.

The challenge on the input side is deciding the appropriate weights for each factor of production and technology-specific intermediate input. In terms of the capital and labor split for each technology, EIA provides estimates of overnight capital and O&M (variable and fixed) costs for various electricity generating technologies in the United States (EIA, 2013a).

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[9] We use a regional aggregation that includes the U.S. (USA), rest of North America (RNA), South America (SAM), Europe (EUR), China (CHN), rest of East Asia (REA), India (IND), rest of Asia (ROA), former Soviet Union (FSU), Oceania (OCN), middle-East (MDE), and Africa (AFR).

[10] Another alternative is at: http://www.eia.gov/cfapps/ipdbproject/iedindex3.cfm?tid=2&pid=alltypes&aid=12&cid=regions&syid=2007&eyid=2007&unit=BKWH. However, this has only one account for conventional thermal, which lumps coal, oil and gas together.

[11] Global CCS Institute (2013) suggests that around 20 large-scale integrated projects (LSIP) in power generation are being planned across the world. It is estimated these facilities will capture more than 0.5 million tonnes of CO2 each year, around 0.004% of 2007 global CO2 emissions from the power sector. This suggests that CCS technologies will be of a similar share in total fossil fuel generation. Because these projects are not yet in operation, we hold CCS constant in the model simulations until the carbon price is sufficiently high.

We use the U.S. values for the other regions in the model in lieu of better data.[12] To reconcile our electricity technologies with EIA's specification we assume that oil power generation is better represented by conventional gas/oil combined cycle technology, and gas-fired technologies by advanced gas/oil combined cycle technology. Table A2 in the online appendix shows the cost structure of various technologies.

We interpret overnight capital as the "capital" in the GTAP 8 database, and assume that variable and fixed O&M costs consist entirely of labor, which makes up the "labor" in the GTAP 8 database. Using these cost estimates (C_i) as auxiliary weights, we disaggregate GTAP capital and labor inputs ($F_{electricity}^{GTAP}$) by the following formula:

$$F_i^{GTAP} = F_{electricity}^{GTAP} \cdot \frac{Q_i \cdot C_i}{\sum_i Q_i \cdot C_i}.$$

The fixed-factor energy resources used by carbon-free technologies are not available from the GTAP 8 database. Therefore, we follow Sue Wing (2008) and assume these resources compose 20% of capital input and are split from the capital account in constructing the database. The capital and resource outputs in the GTAP 8 database are also modified to maintain consistency.

For the technology-specific intermediate inputs, non-ferrous metal and mineral products are associated with nuclear, agricultural goods are assigned to biomass, and all fuels are allocated to coal, gas and oil accordingly. The emissions are allocated in the same manner as the fuels. To distinguish conventional thermal and CCS fossil fuels sub-technologies we assume CCS sub-technologies use 20% more fuels and emit 90% less GHG gases for the same amount of generation. This is consistent with the estimate of IPCC (2005).

All other intermediate inputs are allocated to the OMD activity. It should be noted that we have split intermediate inputs into those that are technology-specific, and those that are used by the OMD activity, exclusively. This enables us to simplify the process of disaggregating the GTAP inputs into electricity.

4.2 Calibration of Electricity Generation Elasticities of Substitution

Once the appropriate level of detail in technology inputs and outputs is chosen, estimates of substitutability between technologies can be specified. Given the cost share (S_i) of each technology, the cross ($\varepsilon_{i,j}$) and own ($\varepsilon_{i,i}$) price elasticities of demand are functions of the a_i values according to equations (4) and (5). As was discussed in sub-section 2.2, the CRESH function does not allow for exact calibration of all own and cross-price elasticities of demand together. Specifically, there are 10 a_i values that can be set (one each for coal, oil, gas, nuclear, hydro, wind, solar, biomass, waste, and other renewables), but there are a total of 100 own and cross-price elasticities. Because they have been extensively studied in the literature, we focus on substitution between fossil-based technologies.

Our ultimate goal in calibration is to reflect findings in Dahl and Ko (1998), Ko and Dahl (2001), and EIA (2012) for the U.S. electric power sector. Calibration of elasticities related

[12] To extend our simplified approach we can use supplementary information (if available) to infer the cost-of-generation for other non-U.S. regions from the OpenEI Database (http://en.openei.org/apps/TCDB/). This is an open-source database that compiles historical cost-of-generation, projections, and distributions of the estimates for each technology. Data is collected from the EIA, IPCC, and other sources.

to coal and gas are prioritized, because oil only accounts for a minor share of U.S. power generation. Taking account of the fact that the CRESH function requires all a_i values to be positive, in all regions we choose final parameter values of 0.6 for coal, 0.5 for oil, and 1.75 for gas.[13]

Table 1 shows the U.S. cross ($\varepsilon_{i,j}$) and own ($\varepsilon_{i,i}$) price elasticities of demand as implied by our parameter settings and the GTAP 8 database for 2007, and compares them with estimates from the literature. The rows in the table are technology demands and the columns are technology prices; diagonal cells represent own-price elasticities, and the remainder are cross-price elasticities. For instance, the intersection of the "Coal Demand" row and "Gas Price" column is the cross elasticity of coal power demand with respect to the gas power price.

There are five estimates in each cell. "AC" is the elasticity as implied by our parameter settings; "DKT" is the estimate of Dahl and Ko (1998) using the translog model; "DKL" is the estimate of Dahl and Ko (1998) using the logit model; "KD" is the estimate of Ko and Dahl (2001) using the translog model; and "EIA" is the estimate of EIA (2012) using the logit model. For example, the cross-price elasticity of coal demand with respect to the natural gas price in our calibration (AC: 0.22) implies that 1% increase in the price of gas power will lead to 0.22% increase in the demand for coal power. This is higher than both the EIA estimate (EIA: 0.17) and those of Dahl and Ko (DKT: 0.14, DKL: 0.2), but lower than Ko and Dahl's (KD: 0.28). Overall, our choice of parameters leads to elasticities that are within the range found in empirical studies.

Table 1: U.S. Cross and Own Price Elasticities of Demand
Between Coal, Oil, and Gas Generation Technologies

Elasticity ε	**Coal Price**	**Oil Price**	**Gas Price**
Coal Demand	AC: -0.46 DKT: -0.16 DKL: -0.26 KD: -0.57 EIA: -0.11	AC: 0.03 DKT: 0.02 DKL: 0.06 KD: 0.29 EIA: -0.06	AC: 0.22 DKT: 0.14 DKL: 0.2 KD: 0.28 EIA: 0.17
Oil Demand	AC: 0.12 DKT: 0.74 DKL: 0.29 KD: 3.21, EIA: 1.89	AC: -0.48 DKT: -0.72 DKL: -1.04 KD: -3.05 EIA: -1.26	AC: 0.18 DKT: 0.02 DKL: 0.75 KD: -0.15 EIA: 0.82
Gas Demand	AC: 0.42 DKT: 0.28 DKL: 0.75 KD: 1.54 EIA: 0.14	AC: 0.08 DKT: 0.21 DKL: 0.25 KD: -0.08 EIA: 0.14	AC: -1.12 DKT: -0.49 DKL: -1.0 KD: -1.46 EIA: 0.29

Except for nuclear, the a_i values are set to 2.7 for carbon-free technologies. This leads to own price elasticities ($\varepsilon_{i,i}$) of renewable technologies around 2.6, consistent with Johnson

[13] For numerical stability of the model, these parameters also need to be significantly greater than zero. The drawback of this approach is that we are assuming all regions have the same a_i values as the U.S., but it is a useful starting point. A Python script is available upon request from the authors to implement this calibration..

(2014).[14] The a_i value for nuclear is set to 1, resulting in an own price elasticity of 0.8. This relatively low value reflects public safety concerns about nuclear power generation.

Table A3 in the online appendix summarizes the U.S. cross and own price elasticities of demand between all generation technologies as implied by our parameter settings and the GTAP 8 database for 2007. The table shows that substitutions to carbon-free technologies can be sizable when the costs of fossil fuels increase.

As for the substitution between conventional and CCS fossil fuels, the elasticities of substitution in the CES functions (τ) are set to 5 for coal and oil, and 10 for gas. These are ad hoc settings chosen because sufficient data is unavailable, and we leave this for future research. Our simulation results suggest that these parameter settings lead to rather conservative estimates of future CCS expansion.

5 Application and Discussion

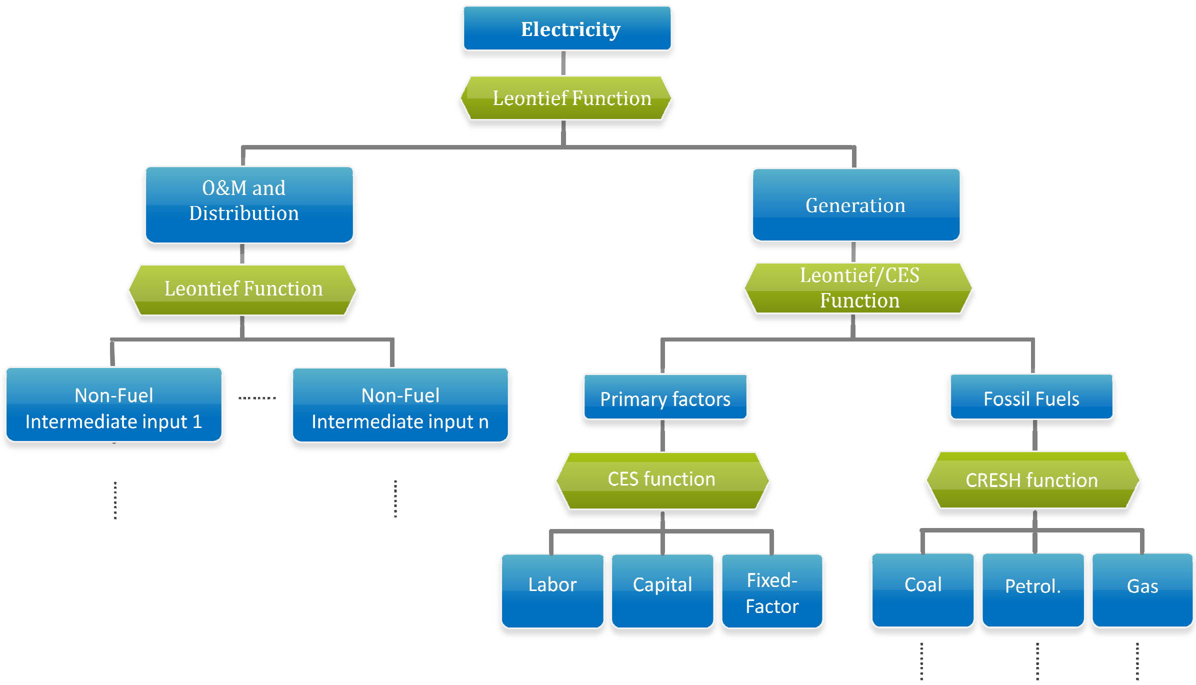
In this section we illustrate the technology bundle approach through model simulations. We consider the impacts of the Clear Power Plan Rule that was released by the U.S. Environmental Protection Agency (EPA) in June 2014. By 2030 the proposed rule requires the U.S. power sector to reduce carbon dioxide emissions by 30% on 2005 levels.

We use the CSIRO Trade and Energy Model (CTEM), an economy wide, multi-regional dynamic recursive CGE mode with origins in the widely-used GTAP CGE model (Hertel, 1997). CTEM features disaggregated modelling of the electricity sector through the technology bundle approach (see Cai et al., 2014). For comparison, we construct another model (CTAP) that is otherwise identical to CTEM, but which does not use an electricity technology bundle. Figures 1 and 4 show the production structures of electricity in both models.

CTEM's technology bundle approach allows substitution between fossil generation technologies and renewable alternatives. A carbon price causes a wedge between fossil generation and renewable generation prices, stimulating the uptake of clean energies. In contrast, CTAP does not have a technology bundle, but allows for substitution between a primary factor composite (labor, capital, and fixed- factor energy resources) and a fuel composite (coal, petroleum, and gas). This fuel composite is a CRESH function of fossil fuels, which allows for substitution among fossil fuel generation technologies as in CTEM.

[14] Johnson (2014) finds the price elasticity of renewable electricity capacity to be 2.67; the 95% confidence interval ranges from 1.74 to 3.60.

Figure 4: Production Structure of Electricity in CTAP



We use two versions of the CTAP model. The first, CTAP-0, assumes that primary factors are complementary to fossil fuels in electricity generation (through the Leontief function). CTAP-0 represents an extreme case of CTEM where fossil fuel technologies are not substitutable by carbon-free alternatives. Comparisons between CTAP-0 and CTEM allow an assessment of the importance that the potential for switching has for model results.

The second version, CTAP-0.2, assumes primary factors are imperfect substitutes to fossil fuels in electricity generation (through a CES function). This model specification mimics the uptake of clean energies through substitution from fossil fuels to capital and fixed-factor energy resources, as in CTEM. But it considers electricity production via a single technology. The elasticity of substitution is set to be 0.2. This is the same elasticity that McKibbin et al. (2014) assume for the substitution between capital, labor, energy and materials in a study of the U.S. power sector carbon mitigation. The comparisons between CTAP-0.2 and CTEM allow us to investigate the impacts of modelling electricity production technologies as homogenous.

To minimize differences between models we use the same parameters for the CES aggregate of primary factors in electricity generation. For the CRESH aggregate of fuels in CTAP-0 and CTAP-0.2, we use the same α_i values for coal, petroleum, and natural gas as those for coal, oil and gas technologies in CTEM. All other parameters of the three models are identical. Each model is built upon the GTAP 8 database, and all are simulated on a year-to-year basis from 2007 through 2030.

5.1 Baselines

The baselines of the three models are calibrated to reflect a 'business-as-usual' scenario with no carbon policies. The population estimate is taken from the medium variant of the United

Nations' World Population Prospects.[15] We also follow Hertel et al. (2008) to set the inter-factor elasticities of substitution such that the long-term supply elasticities of coal, oil and gas are consistent with the estimates of Beckman et al. (2011) and EIA (2013b). The GDP trajectories are based on the recent IMF World Economic Outlook (up to 2017) and our assumptions about future economic growth. Over the period from 2010 to 2030, the average annual GDP growth rates are 2.2% for the U.S., 1.7% for the E.U., 6.3% for China, 5.9% for India, and 3.0% for the world.

The baseline calibration is implemented in two stages. The first stage derives the path of economy-wide input-augmenting productivities in each model which yield the baseline GDP estimates. These input-augmenting productivity shocks are applied uniformly to all sectors in each region. In the context of energy inputs such as coal, oil, gas and electricity, the input-augment productivity shocks are commonly understood as autonomous energy efficiency improvements (AEEI). To match the historical trend (Riahi et al., 2011, Figure 11), an extra 0.25% input-augmenting productivity shock is added to all energy used in production, making the global average of AEEI roughly 1% per year for the three models.

Given assumptions for population and economic growth, the second stage is to specify long-term average growth rates for each region's energy production and consumption. We match these growth rates to EIA's International Energy Outlook (2013). This is implemented in all models by varying productivity on fossil fuel production and preferences in energy consumption, respectively.

5.2 Policy Scenario

We implement the Clear Power Plan Rule in each model by solving for a carbon price path such that the power sector achieves the same cumulative emissions by 2030 as if there were a linear decline in emissions. This approach follows McKibbin et al. (2014), and ensures the total amount of emissions reductions from 2015 to 2030 are the same in each model while still meeting the specified target of a 30% reduction on 2005 levels. The different pathways of power sector emissions in the United States are shown in Table A4 of the online appendix.

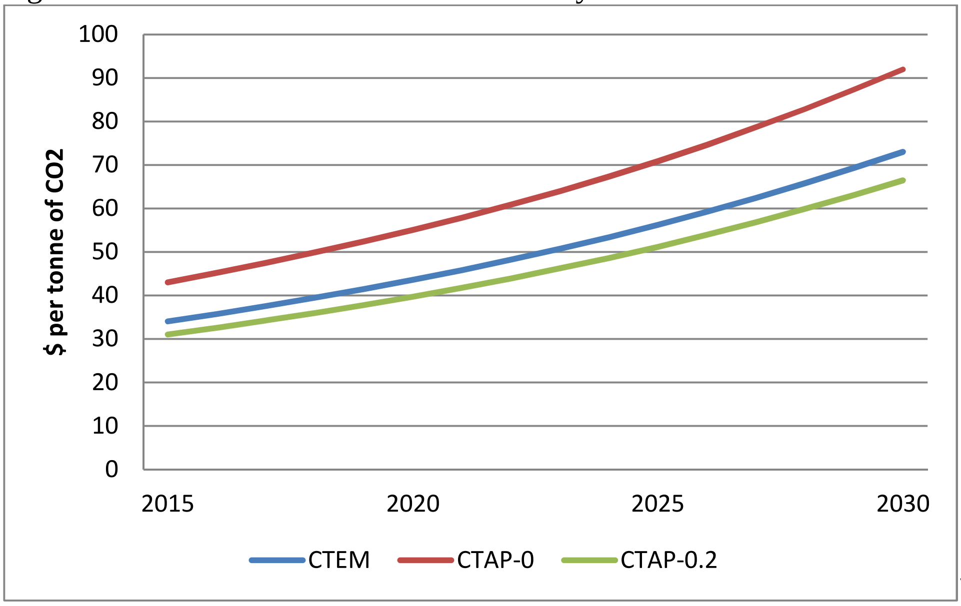
The carbon price can be interpreted either as a carbon tax or the market price of an emissions permit in the U.S. power sector. The carbon price will increase by 4%, roughly the value of the nominal interest rate each year. This so-called "Hotelling Rule" mimics the expected behavior of an efficient market that allows for the banking and borrowing of emissions rights, which minimizes the business cost of mitigation (McKibbin et al., 2009).

5.3 Overview of Results

Carbon prices associated with the declining emissions profiles in each model are displayed in Figure 5. In 2015 the starting price is $31 in CTAP-0.2, $34 in CTEM, and $43 in CTAP-0. These are all higher than the estimate of McKibbin et al. (2014), who simulate a 42% reduction on 2005 levels by 2030, with prices that start at $23 in 2012 and reach $26 in 2015.

[15] See http://esa.un.org/wpp/.

Figure 5: U.S. Carbon Price for the Electricity Sector



Source: Author calculations.

The imposition of a carbon price raises the cost of fossil feed-stocks to power generation [shown in Figure A1 of the online appendix]. Because coal is the cheapest and most polluting of the fuels considered, it has the largest increase in feedstock prices across models. As of 2030, there is a nearly 200% increase in CTAP coal prices, and the cost of coal rises by more than 150% in both CTEM and CTAP-0.2. The prices of both natural gas and oil rise as well in all three models.

The carbon price is passed on to consumers and firms through higher electricity prices (Figure A2, online appendix). CTAP-0 results suggest that the U.S. electricity price rises by about 45% through 2030, whereas CTEM and CTAP-0.2 project an increase around 30%, although CTAP-0.2 is slightly higher than CTEM. Greater reductions in electricity consumption are observed in the CTAP-0 as a result (Table 2).

Table 2: Deviation of U.S. Electricity Consumption from the Baseline Under a Carbon Price

Deviation in TWH **(Deviation in %)**	**2015**	**2020**	**2025**	**2030**
CTEM	-273 (-5%)	-334 (-6%)	-414 (-7%)	-528 (-8%)
CTAP-0	-330 (-6%)	-413 (-7%)	-517 (-9%)	-662 (-10%)
CTAP-0.2	-261 (-5%)	-330 (-6%)	-418 (-7%)	-541 (-8%)

Source: Author calculations.

Higher electricity prices raise the cost of production and consumption. This will spread to all economic sectors and reduce national output. At the aggregate level, all three models see a decline in Gross Domestic Product (GDP) (Table 3). CTAP-0 projects real GDP (2007$) losses in excess of 31 billion each year on average from 2015 through 2030, CTAP-0.2 estimates average annual losses of 23 billion (2007$), while CTEM comes in at an average of 12.5 billion (2007$) over this time period.

Table 3: Deviation of Real U.S. GDP from the Baseline Under a Carbon Price

Deviation Billion 2007$ (Deviation in %)	**2015**	**2020**	**2025**	**2030**	**Average**
CTEM	-4.0 (-0.03%)	-9.8 (-0.05%)	-15.1 (-0.08%)	-20.92 (-0.10%)	-12.5 (n.a.)
CTAP-0	-17.0 (-0.11%)	-26.1 (-0.15%)	-35.5 (-0.18%)	-48.1 (-0.22%)	-31.3 (n.a.)
CTAP-0.2	-12.6 (-0.08%)	-19.2 (-0.11%)	-26.4 (-0.13%)	-36.0 (-0.16%)	-23.3 (n.a.)

Source: Author calculations.

The average annual reductions in GDP from the three models all fall within the range found by the EPA and the U.S. Chamber of Commerce. EPA estimates that annual compliance costs for the Clear Power Rule will peak in 2030 at roughly 8.1 billion (2007$).[16] A rough back-of-the-envelope calculation suggests the annual average costs are around 6.5 billion (2007$). The U.S. Chamber of Commerce (2014) investigate the economic consequences of reducing U.S. power sector CO2 emissions 40% below 2005 levels by 2030. They find the annual average cost of mitigation to be about 43 billion (2007$).[17]

5.4 Discussion of Modelling Differences

The level of the electricity sector carbon price throughout the simulations is greater in CTAP-0 than either CTAP-0.2 or CTEM. One reason is that CTAP-0 has a higher trajectory of baseline emissions than the other models. More importantly, fossil fuels are considered a supplement to primary factors in CTAP-0. That is, the model does not allow substitution from electricity produced by fossil technologies to electricity produced by carbon-free alternatives. These carbon-free alternatives are directly modelled in CTEM, and approximated by substitution to primary factors in CTAP-0.2. Thus, power generation cannot be decoupled from emissions, and the only way to meet the mitigation target is by reducing electricity consumption (induced by a higher carbon price).

This is in contrast to both CTEM and CTAP-0.2, where power generation can use a non-emitting renewable (CTEM) or substitute to primary factors (CTAP-0.2), leading to a lower carbon price. The remaining differences between CTEM\CTAP-0.2 and CTAP-0 reflect these variations in carbon prices.

The CTAP-0.2 and CTEM estimates for carbon prices themselves are -higher than that of McKibbin et al. (2014) which achieved a tighter reduction target of 42% reduction on 2005 levels. This is because McKibbin et al. (2014) assume an earlier introduction of the carbon price (2012). Furthermore, the G-Cubed model used by McKibbin et al. (2014) assumes forward-looking expectations (see McKibbin and Wilcoxen, 1999). This means future rises in carbon prices impact current energy consumption, enhancing mitigation effects.

The differences in outcomes between CTAP-0.2 and CTEM, however, reflect the assumption about homogenous or heterogeneous technologies in electricity generation. The way that CTAP-0.2 treats electricity production via a single technology averages the cost

[16]See State Compliance under Option 1 of Table ES-4 on page ES-8 at: http://www2.epa.gov/sites/production/files/2014-06/documents/20140602ria-clean-power-plan.pdf.
[17] https://www.uschamber.com/press-release/energy-institute-report-finds-potential-new-epa-carbon-regulations-will-damage-us.

characteristics of different technologies. With this "averaged" technology, the fuel intensities of fossil technologies are diluted, while the substitutions between primary factors and fuels are exaggerated. This will raise the impacts of carbon prices on carbon mitigation, thus leading to lower carbon prices for the same mitigation target. Furthermore, the carbon-free technologies are "forced" to require some fossil fuel input and to share the burden of carbon price. This will raise the impacts of carbon prices on the electricity price and consumption, leading to higher economic costs of mitigation.

In contrast, CTEM treats electricity production via a bundle of heterogeneous technologies. All fossil fuels are accrued to a single technology, and no substitution between primary factors and fuel is allowed. Therefore, higher carbon prices are required to achieve the same mitigation target. However, the electricity producer can avoid the burden of carbon prices by substituting to carbon-free technologies. This will reduce the impacts of carbon prices on electricity prices and consumption, leading to lower economic costs of mitigation.

Another benefit of the technology bundle approach is shown in Table 4, which displays the changes from base in electricity production by technology in applying the Clean Power Rule. Models that do not distinguish between generation technologies are unable to account for changes in electricity production in terms of underlying changes in those technologies.

Table 4: Deviation of U.S. Electricity Generation from the Baseline in CTEM Under a Carbon Price

Deviation in TWH (Deviation in %)	**2015**	**2020**	**2025**	**2030**
Coal	-438 (-19%)	-524 (-21%)	-643 (-25%)	-802 (-29%)
Oil	-1 (-1%)	-2 (-2%)	-2 (-3%)	-3 (-3%)
Gas	-142 (-13%)	-198 (-17%)	-271 (-21%)	-378 (-27%)
Nuclear	119 (12%)	146 (13%)	182 (15%)	233 (18%)
Hydro	139 (35%)	184 (41%)	248 (51%)	333 (65%)
Wind	7 (38%)	8 (45%)	11 (55%)	14 (70%)
Solar	0.3 (35%)	0.4 (41%)	0.5 (51%)	0.7 (65%)
Biomass	21 (40%)	25 (47%)	31 (57%)	38 (73%)
Waste	15 (43%)	17 (50%)	20 (62%)	24 (79%)
Other Ren.	7 (42%)	9 (50%)	10 (61%)	12 (78%)
Coal + CCS	0.0000 (0%)	0.0408 (47%)	0.1082 (124%)	0.2264 (260%)
Oil + CCS	0.0000 (0%)	0.0002 (7%)	0.0006 (16%)	0.0011 (32%)
Gas + CCS	0.0000 (0%)	0.0190 (49%)	0.0549 (142%)	0.1406 (363%)
Total	-273 (-5%)	-334 (-6%)	-414 (-7%)	-528 (-8%)

Source: Author calculations.

As expected, coal-based generation shows large losses, but so does natural gas. Specifically, coal power sees the largest absolute reduction (-802 TWH), followed by gas power (-378 TWH). However, in percentage terms, the reduction in gas power (-27%) is almost the same as that in coal (-29%), even though the coal price increase in CTEM is more than double that of natural gas. The reason is that the own price elasticity of demand for gas power (-1.12) is two and half times higher than that of demand for coal power (-0.46), consistent with empirical estimates.

Our simulation results suggest that the reduction of electricity generation via fossil fuel technologies will be partially made up by generation through carbon-free technologies. In particular, both nuclear and hydro power see reasonable increases from the baseline.

In terms of nuclear, uprates have the potential to increase U.S. nuclear capacity by as much as 20% without building new reactors according to EIA.[18] Nuclear growth in the simulations peaks at 18% in 2030.[19] As for hydro-power, a recent study conducted by Oak Ridge National Laboratory (ORNL) for the U.S. Department of Energy found that 61 gigawatts (GW) of hydroelectric power potential exists in the U.S.[20] This can potentially generate 200 TWH of electricity per year, assuming the current capacity factor of 40%. Raising assumptions about the capacity factor to 75% can raise potential generation to the 333 TWH shown in the simulations in 2030.

Biomass and waste power also see an increase, as do wind, solar, and other renewables. Although small when measured in TWH, the expansions of these technologies are large in terms of percentage changes, primarily because they start from a low base. However, they appear quite plausible when compared to the growth of clean energy in Australia over the last decade (Clean Energy Council, 2012).

The growth rates of CCS technologies are minor, accounting for less than 0.1% of the reduction in the conventional thermal sub-technologies. Such a pace of switching is rather conservative.

6 Conclusion

The manner in which electricity generation is modelled can lead to different quantitative estimates of the costs and benefits of environmental policies. This paper clarifies, expands, and illustrates the "technology bundle" approach to disaggregated modelling of the electricity sector in Computable General Equilibrium (CGE) models.

We provide an intuitive interpretation of the "technology bundle", describe the mathematical structure of the CRESH function, and establish a link between parameters of the CRESH function and elasticity estimates. We also show how the input and output structure of the electricity sector in the GTAP 8 database can be disaggregated using data from international agencies. Finally, we simulate the proposed U.S. Clean Power Rule under using different levels of disaggregation in the electricity sector and highlight the differences.

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[18] Source: http://www.eia.gov/todayinenergy/detail.cfm?id=7130

[19] Additionally, U.S. nuclear plants are running at a capacity factor of 90% on average, thus improvements in capacity factor can also contribute to the growth of nuclear power: http://www.eia.gov/electricity/monthly/epm_table_grapher.cfm?t=epmt_6_07_b.

[20] Source: http://www.eia.gov/todayinenergy/detail.cfm?id=17051

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Appendix: Online Figures and Charts

Table A1: World Electricity and Heat Generation (terawatt-hours) in 2007 by Technology and Region

Technology	USA	RNA	SAM	EUR	CHN	REA	IND	ROA	FSU	OCN	MDE	AFR	Total
Coal	2176.5	150.3	112.7	1226.2	3373.9	659.7	570.0	153.6	826.0	185.5	143.4	295.9	9873.7
Oil	87.6	66.2	97.2	201.8	93.5	239.5	35.3	94.1	173.9	2.5	213.7	56.7	1362.1
Gas	968.8	182.3	142.3	1124.5	51.0	406.7	69.6	282.9	1905.9	39.8	411.8	140.4	5726.0
Nuclear	838.9	110.8	66.1	1073.7	67.8	438.3	20.9	63.3	300.8	32.9	90.9	40.5	3144.9
Hydro	298.7	387.9	571.8	503.7	408.4	115.6	95.0	81.3	260.0	39.0	53.3	67.5	2882.1
Wind	14.3	1.0	1.5	57.6	1.7	1.4	5.0	2.2	1.6	1.0	0.7	1.1	89.2
Solar	0.6	0.0	0.1	0.9	0.1	0.0	0.0	0.1	0.3	0.0	0.1	0.5	2.6
Biomass	43.6	11.1	19.4	89.1	7.2	11.5	2.1	6.7	18.5	1.4	5.1	2.6	218.2
Waste	31.2	0.8	5.7	77.9	26.4	13.7	5.3	3.9	27.0	0.8	3.8	3.1	199.6
Other Renewables	15.5	7.0	4.4	15.6	10.5	5.2	2.1	16.4	2.5	3.1	1.6	1.9	85.9
Coal + CCS	0.2	0.0	0.0	0.1	0.3	0.1	0.1	0.0	0.1	0.0	0.0	0.0	1.0
Oil + CCS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
Gas + CCS	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.6
Total	4476.0	917.5	1021.0	4371.3	4040.9	1891.8	805.3	704.6	3516.8	305.9	924.5	610.3	23586.0

Source: IEA World Energy Balance Table (2007) and author calculations.
Note: For each region, the numbers are scaled such that the sum of all technologies coincides with total electricity output in the GTAP 8 database.

Table A2: U.S. Cost Characteristics of Electricity Generating Technologies

Technology	EIA Specification	Overnight Capital Cost ($/kW)	Fixed O&M Cost ($/kW-yr)	Variable O&M Cost ($/MWh)
Coal	Scrubbed Coal New	$2,925	$31	$4
Oil	Conv. Gas/Oil Comb Cycle	$915	$13	$4
Gas	Advanced Gas/Oil CC	$1,021	$15	$3
Nuclear	Adv Nuclear	$5,501	$93	$2
Hydro	Conventional Hydroelectric	$2,435	$15	$3
Wind	Onshore Wind	$2,213	$40	$0
Solar	Photovoltaic	$3,564	$25	$0
Biomass	Biomass CC	$4,114	$106	$5
Waste	Municipal Solid Waste	$8,312	$393	$9
Other Renewables	Geothermal	$2,494	$113	$0
Coal CCS	Dual Unit Advanced PC with CCS	$6,567	$73	$8
Oil CCS	Advanced CC with CCS	$2,084	$32	$7
Gas CCS	Advanced CC with CCS	$2,084	$32	$7

Source: EIA (2013a).

Table A3: U.S. Cross and Own Price Elasticities of Demand Between All Generation Technologies

Elasticity ε	Coal Price	Oil Price	Gas Price	Nuclear Price	Hydro Price	Wind Price	Solar Price	Bio. Price	Waste Price	Other Ren. Price
Coal Demand	-0.46	0.03	0.22	0.12	0.04	0.002	0.0001	0.01	0.03	0.004
Oil Demand	0.12	-0.48	0.18	0.10	0.04	0.002	0.0001	0.01	0.02	0.003
Gas Demand	0.42	0.08	-1.12	0.35	0.12	0.01	0.0004	0.04	0.08	0.01
Nuclear Demand	0.24	0.04	0.36	-0.80	0.07	0.004	0.0002	0.02	0.05	0.01
Hydro Demand	0.65	0.12	0.98	0.55	-2.51	0.01	0.0006	0.07	0.13	0.02
Wind Demand	0.65	0.12	0.98	0.55	0.19	-2.69	0.0006	0.07	0.13	0.02
Solar Demand	0.65	0.12	0.98	0.55	0.19	0.01	-2.70	0.07	0.13	0.02
Bio. Demand	0.65	0.12	0.98	0.55	0.19	0.01	0.001	-2.63	0.13	0.02
Waste Demand	0.65	0.12	0.98	0.55	0.19	0.01	0.001	0.07	-2.57	0.02
Other Ren. Demand	0.65	0.12	0.98	0.55	0.19	0.01	0.001	0.07	0.13	-2.68

Source: GTAP 8 database for 2007 and author calculations.

Table A4: Path of U.S. Power Sector Carbon Dioxide Emissions (1000 Million Tonnes of CO2) Before and After Clean Power Rule

Scenarios	2015	2020	2025	2030
CTEM_Baseline	2.91	3.01	3.13	3.29
CTEM_Linear (Annual Target)	2.84	2.54	2.25	1.95
CTEM_Linear (Cumulative)	2.84	16.14	27.97	38.32
CTEM_Policy (Annual)	2.40	2.401	2.38	2.37
CTEM_Policy (Cumulative)	2.40	14.39	26.33	38.21
CTAP-0_Baseline	3.10	3.25	3.41	3.59
CTAP-0_Linear (Annual Target)	3.00	2.65	2.30	1.95
CTAP-0_Linear (Cumulative)	3.00	16.93	29.12	39.57
CTAP-0_Policy (Annual)	2.38	2.45	2.49	2.50
CTAP-0_Policy (Cumulative)	2.38	14.52	26.91	39.39
CTAP-0.2_Baseline	3.09	3.25	3.40	3.59
CTAP-0.2_Linear (Annual Target)	2.99	2.65	2.30	1.95
CTAP-0.2_Linear (Cumulative)	2.99	16.92	29.11	39.56
CTAP-0.2_Policy (Annual)	2.39	2.45	2.48	2.48
CTAP-0.2_Policy (Cumulative)	2.39	14.54	26.88	39.28

Source: Author calculations.

Note: These numbers are higher than the EIA statistics because the GTAP 8 database lumps both electricity and heat into a single sector. Also the CTEM CO_2 emissions database has been scaled up by a factor of 1.155 to match the 2007 emissions of RCP8.5 (Riahi et al., 2011).

Figure A1: Deviation of U.S. Fossil Feedstocks to Power Generation from Baseline Under a Carbon Price

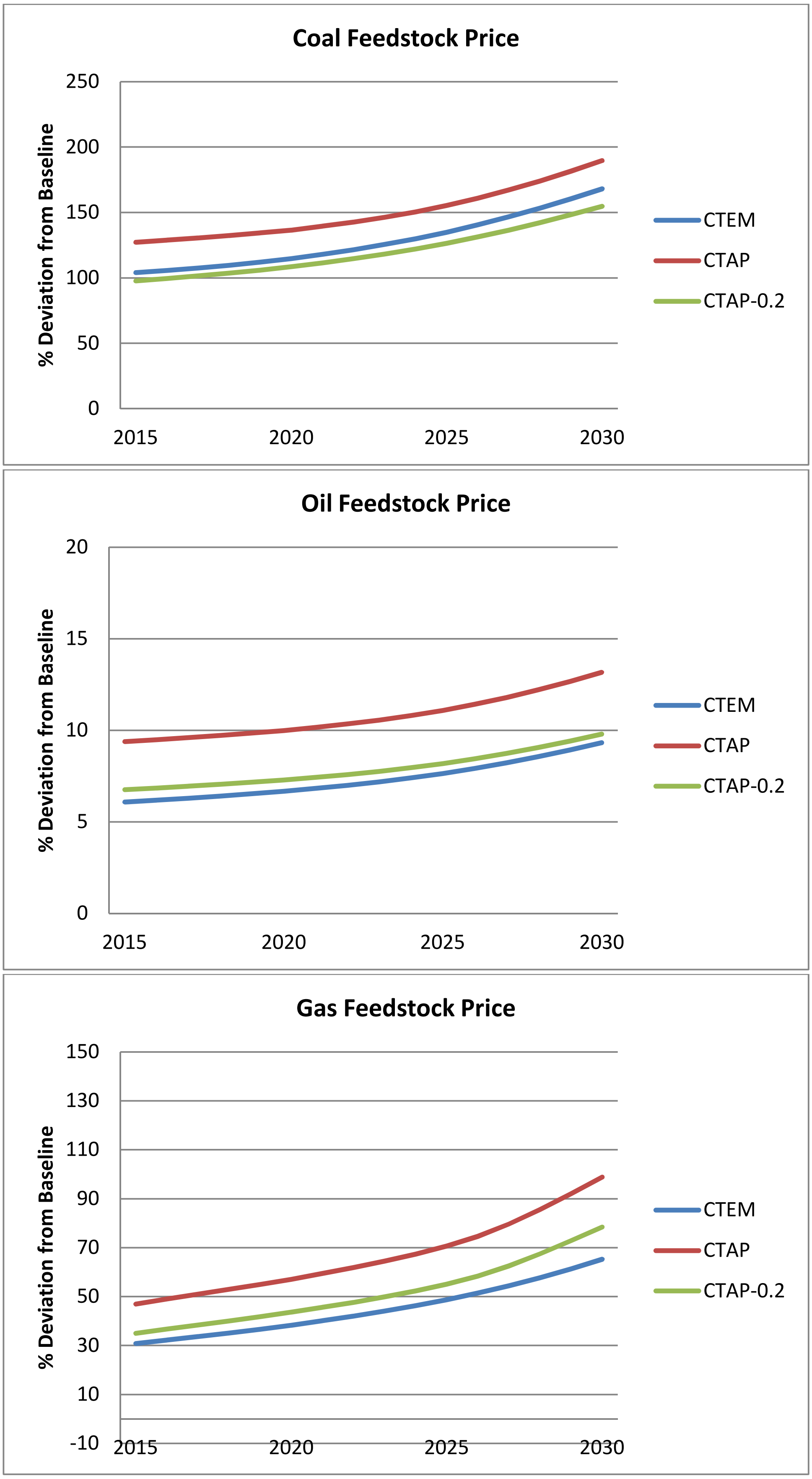

Figure A2: Deviation of U.S. Electricity Price from the Baseline Under a Carbon Price