

Disaggregating Electricity Generation Technologies in CGE Models: A Revised Technology Bundle Approach with an Application to the U.S. Clean Power Plan[†]

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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. Clean 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. A model that does not consider the heterogeneity of generation technologies can possibly underestimate the size of the carbon price but overestimate the economic cost of mitigation.

Key Words: electricity, computable general equilibrium, environmental policy

[†] The analysis and conclusions expressed here are those of the authors and not necessarily those of the Commonwealth Scientific and Industrial Research Organisation (CSIRO) or the U.S. Energy Information Administration.

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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. It is projected to achieve a 30 percent cut from 2005 emissions by 2030, with an interim target of 25 percent on average between 2020 and 2029. While expectations for the plan are clear, the economic costs are not.

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, 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 focus on CGE models for several reasons. Importantly, this class of models has been widely used in analysing the economic impacts of energy and climate policies. CGE models are primarily used to evaluate a broad range of policies in terms of welfare. This is because the clear theoretical foundations of these models allow an interpretation of policy changes in terms of the consumers and firms in the model. These models can also track the flows of factors of production and goods in the economy in addition to their relative prices.

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 [1]. 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.

Our next step is to describe implementation of the technology bundle approach. We apply the theoretical structure to the GTAP 8 database [2], and show how its electricity sector can be disaggregated using data from either the U.S. Energy Information Administration (EIA) or the International Energy Agency (IEA). Furthermore, we outline a method for calibrating the inter-fuel elasticities of substitution in the technology bundle to existing empirical results in the literature.

Finally, we use two dynamic CGE models (CTEM and CTAP) to simulate the proposed U.S. Clean Power Plan. Both CTEM and CTAP are dynamic variants of the GTAP model [3], and each adopts its global trade and economic core from GTAP. The two models are identical except for the fact that CTEM features disaggregated modelling of the electricity sector through the technology bundle approach, while CTAP does not. 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. A model that does not consider the heterogeneity of generation technologies can possibly underestimate the size of the carbon price but overestimate the economic cost of mitigation.

Our paper adds to the literature in four ways. First, we present a revised technology bundle approach that unifies the structure of Sue Wing [4,5] and the original work of Pant [6], and carefully explains the mathematical properties and economic intuition. Second, we illustrate how the GTAP database can be disaggregated in order to create variants of the widely used GTAP model with our approach. Third, we establish the link between the mathematical structure and empirical estimates of inter-fuel elasticities, which provide a guideline for calibration of CGE models using the technology bundle approach. Finally, we apply the approach to study the U.S. Clean Power Plan, and highlight policy implications.

2 Approaches to Modelling the Electricity Sector

CGE models are a popular tool for analyzing both energy and environmental policies [7-12]. A CGE model reproduces the structure of the global economy and records the economic transactions among regional producers and households. The global economy is in “equilibrium” between the producers’ and consumers’ profit/utility maximizing behavior across all regions such that, through adjustment in prices, markets of commodities and factors all clear given the current constraints of capital endowment, labour supply, productivity level and policy [13].

Typically, the world economy is divided into a set of autonomous regions. Each region has a representative household, which (1) owns and supplies factor inputs of production, (2) owns the regional income and determines regional savings, and (3) consumes goods and services. In each region, local production is divided into multiple commodity sectors/industries. The regions interact with each other through trade and capital flows, and regional households consume both domestic and imported goods [3].

Within the CGE framework, all economic activities related to the life cycle of power generation are recorded. This includes investment, employment, the uptake of technologies and the use of fuels for production, the sale of electricity to end users, and the payment to households for investment and employment. Such a model is capable of tracking complex policy effects through different channels and in various causal directions.

However, CGE models are often referred to as “top-down” because of their high levels of aggregation [14, 15]. In particular, it is standard to represent the production of energy as based on a single technology. This technology allows for 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 [16]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 [4, 14]. 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 [4, 5] 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 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 [17-19]. In the more recent Phoenix model [20], Sue Wing and co-authors place generation into three nests: base load, intermediate load, and peak load. Coal power is included in the base load portfolio but still combined with natural gas, nuclear, hydro, and others through the CES function.

Sands [21], Schumacher and Sands [22], and Fujimori et al. [14] 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

¹ LCOE is often cited as a convenient summary measure of the overall competitiveness 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.

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 economics.

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 has been used in various versions of the GTEM model [6, 15], and the WIATEC model [23], among others. The technology bundle approach disaggregates the electricity sector between generation and non-generation activities, and combines the competing generation technologies through a CRESH function [1]. The approach follows from standard economic theory, and allows for different assumptions about substitutability between technologies. However, there has been little written about the approach's mathematical properties, or the link between its parameters and various econometric estimates of substitution between fuels and technologies in electricity generation. This paper aims to fill the gap in the literature.

3 A Revised Technology Bundle Approach

3.1 Overview

In this section, we apply the mathematical structure of Sue Wing [4, 5] for a revised look at the technology bundle approach [6]. Following Sue Wing [4, 5], we assume that electricity is a homogenous good produced by aggregating Generation (GEN) and O&M and Distribution (OMD), as shown in Figure 1.

Here, GEN is the key component of this set-up that allows for a bundle of heterogeneous and competing electricity generation technologies. OMD is a combination of TD and OH that represents all non-technology-specific activities such as construction and daily maintenance.³ OMD aggregates intermediate inputs that are used to produce electricity, but which are not specific to a particular generation technology. The complementarity of GEN and OMD reflects the fact that electricity generators are connected to end-users through electricity transmission grids.

[Figure 1 about here.]

² For this reason the Logit function is often used for estimating elasticities related to substitution between fuels. See for example [17-19].

³ These activities are combined due to a lack of data, but this simplification is an area for future research.

In order to construct the technology bundle, competing electricity technologies are combined through the CRESH function as in Pant [6]. The 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.⁴ The intermediate goods include fossil fuels (used by carbon-emitting technologies), refined uranium (nuclear), 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 [4, 5].

There are substantial conceptual and structural differences between the CRESH function used in the technology bundle approach and a standard nested CES function used in many other CGE models. For example, in the popular GTAP-E model [24], the nested CES function is used to model the energy use of a generic sector, which includes the electricity sector. Specifically, sectoral production is a Leontief function of the non-capital factor composite, the capital-energy composite, and intermediate inputs. The capital-energy composite is a CES function of capital and energy, which is in turn a CES function of electricity and a non-electric composite. The non-electric composite is a CES function of coal and a non-coal composite. And finally, the non-coal composite is a CES function of gas, crude oil and petroleum.

In the context of the electricity sector, the capital-energy substitution approximates the substitution between non-fossil fuel and fossil fuel technologies, while the substitution inside

⁴ Following Sue Wing [5], 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.

the non-electric composite approximates the substitution among the fossil technologies. A drawback of this nested CES approach is that it does not further distinguish the non-fossil fuel technologies (approximated by capital use), or the conventional and CCS fossil fuel technologies (approximated by fossil fuel use). Furthermore, the nested CES approach uses factor inputs such as capital and labor that are not disaggregated and coupled with the use of fuels to reflect the different cost structures of various generation technologies as illustrated in [16].

In comparison, the technology bundle approach uses the CRESH function to model the substitution between 13 technologies. Each technology differs in the use of fuels, as well as capital and labor intensities.

3.2 Mathematical Details

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

$$E = \text{Min}\{A_1 \cdot X, B_1 \cdot Y\} \quad (1).$$

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.

In reality, the advancement of smart grid and energy-saving transmission technologies can reduce power losses. This suggests some degree of substitution between GEN and OMD. However, because the room for substitution is limited and largely uncertain, we decided not to allow such substitution in this modeling exercise. Therefore, our simulation results should be taken as a conservative estimate for energy efficiency improvements.

Generation

As is shown on the right-hand side of Figure 1, the X units of electricity can be generated by a bundle of technologies (Q_i) through a CRESH production function.⁵ The production function is implicit, but satisfies:

⁵ The CRESH function is due to Hanoch [1] and its mathematical derivation is available from Dixon et al. [25, p. 64-76].

$$\sum_i (Q_i/X)^{d_i} \cdot D_i/d_i = \kappa \quad (2).$$

252 In this equation d_i is a parameter with a value less than 1 but not equal to zero, each D_i
 253 parameter associated with a particular technology is positive, and the D_i values and κ are
 254 normalized such that $\sum_i D_i = 1$. The set-up generalizes the CES production technology of
 255 Sue Wing [4, 5]; in the special case where when $d_i = d$ for all i , the CRESH function
 256 collapses to the CES function:

$$X = \frac{1}{d \cdot \kappa} \cdot \left[\sum_i (Q_i)^d \cdot D_i \right]^{\frac{1}{d}} \quad (3).$$

257 Given the amount of total generation (X) and production costs for each technology (P_i), the
 258 electricity producer chooses demand for each technology (Q_i) to minimize total cost $\sum_i Q_i \cdot$
 259 $P_i = C$, subject to equation (1). The linearized solution to this problem yields:⁶

$$q_i = q_X - a_i \cdot (p_i - p_X^*) \quad (4),$$

260 where $a_i = \frac{1}{1-d_i}$, $p_X^* = \sum_i a_i \cdot S_i \cdot p_i$, and $S_i = Q_i \cdot P_i / \sum_i Q_i \cdot P_i$ (the cost share of technology
 261 i). Here, p_i , q_i , and q_X are the percentage changes of P_i , Q_i , and X , respectively. Equation (4)
 262 shows that demand for each technology depends upon total demand for generation,
 263 production costs for each technology, and various parameters.

264

265 The a_i parameter in equation (4) is particularly important in this context because it
 266 summarizes substitution between technologies. This can be shown beginning with price

⁶ The first-order conditions from this problem require that:

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

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

$$p_i = \lambda + d_i \cdot (q_i - q_X) - q_i \quad (f2),$$

and

$$\sum_i (q_i - q_X) \cdot (Q_i/X)^{d_i} \cdot D_i = 0 \quad (f3).$$

Here, p_i , q_i , q_X and λ are the percentage changes of P_i , Q_i , X , and Λ , respectively. Substituting (f1) into (f3)
 yields:

$$\sum_i q_i \cdot S_i = q_X \quad (f4),$$

where $S_i = Q_i \cdot P_i / \sum_i Q_i \cdot P_i$ 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:

$$\lambda = \sum_i a_i \cdot S_i \cdot p_i + q_X \quad (f5).$$

Substituting equation (f5) into equation (f1) yields equation (4) above.

elasticities of demand for each technology and then linking them to different definitions for elasticities of substitution.

Hanoch [1, 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:

$$\varepsilon_{i,j} = \partial(\ln Q_i) / \partial(\ln P_j) = \frac{S_i a_i a_j}{\sum S_k a_k} \quad (5),$$

and

$$\varepsilon_{i,i} = \partial(\ln Q_i) / \partial(\ln P_i) = \frac{S_i a_i a_i}{\sum S_k a_k} - a_i \quad (6).$$

Equation (6) associates a particular definition for the elasticity of substitution between two technologies with the a_i parameters and technology cost shares (S_i). These can be linked to the Morishima elasticity of substitution ($M_{i,j}$), which summarizes the change in relative demands for two technologies given a change in their relative prices when one price is fixed [26, p. 93-97]:

$$M_{i,j} = \partial \left(\ln \frac{Q_i}{Q_j} \right) / \partial \left(\ln \frac{P_i}{P_j} \right) \Big|_{\text{fixing } P_j} = \varepsilon_{i,j} - \varepsilon_{i,i} \quad (7).$$

A variant of the Morishima elasticity of substitution is more commonly used. This shadow elasticity of substitution ($\delta_{i,j}$) is defined similarly, but holds consumption (C) fixed, and can also be tied back to the cost shares:

$$\delta_{i,j} = \partial \left(\ln \frac{Q_i}{Q_j} \right) / \partial \left(\ln \frac{P_i}{P_j} \right) \Big|_{\text{fixing } C} = \frac{S_i}{S_i + S_j} M_{i,j} + \frac{S_j}{S_i + S_j} M_{j,i} \quad (8).$$

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.⁷ 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.

⁷ 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.

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 (5) to (8)).

Conventional Thermal and CCS Technologies

As is shown at the bottom of Figure 1, the Q_i units of fossil fuel generation can be produced by the sub-technologies ($Q_{i,j}$) through a CES function:

$$Q_i = \left[\sum_j (Q_{i,j})^{\frac{1-\tau}{\tau}} \cdot D_{i,j} \right]^{\frac{\tau}{1-\tau}} \quad (9),$$

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:

$$q_{i,j} = q_i - \tau \cdot (p_{i,j} - p_i) \quad (10).$$

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).⁸ 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 (4) to ensure additivity in physical units:

$$q_i = q_X - a_i \cdot (p_i - p_X^*) + Adj \quad (11).$$

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

$$q_{i,j} = q_i - \tau \cdot (p_{i,j} - p_i) + Adj \quad (12).$$

⁸ Because the CES function is a special case of the CRESH function it is subject to the same problem.

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).⁹

Technology Production

For each specific technology or sub-technology, we assume that it is a fixed-coefficients production function of primary factor composite (F_i) and intermediate inputs (G_i):

$$Q_i = \text{Min}\{A_2 \cdot F_i, B_2 \cdot G_i\} \quad (13).$$

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 [4] and shown in Figure 2.

[Figure 2 about here.]

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

$$G_i = \left[\rho_{Dom} (G_i^{Dom})^{\frac{\sigma-1}{\sigma}} + \rho_{Imp} (G_i^{Imp})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \quad (14).$$

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 [27] for additional details. The imported good G_i^{Imp} is a CES composite of shipments from various sources $G_{r,i}^{Imp}$:

$$G_i^{Imp} = \left[\sum_r \rho_r (G_{r,i}^{Imp})^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \quad (15),$$

where ρ_r is budget share parameter, and η is the elasticity of substitution among imports from different sources. Given prices of the imported and domestic goods, the linear solutions to the producer's cost minimization are standard and they can be found in [27].

⁹ Introducing the adjustment factor does not change inter-technology substitution responses to price changes, because for two technologies we have:

$$q_i - q_j = -a_i \cdot (p_i - p_x^*) + a_j \cdot (p_j - p_x^*) \quad (f6),$$

which is free of the adjustment factor.

The OMD Sector

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

$$Y = \text{Min}\{B_3 \cdot G\} \quad (16).$$

Here, B_3 is a vector of scale factors 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 about here.]

4 Implementation of the Technology Bundles

In this section we describe implementation of the technology bundle approach outlined above. We begin by outlining construction of an Input/Output matrix for various electricity generation technologies, and then describe calibration of elasticities of substitution between the technologies. Our implementation uses the GTAP 8 database and other available data from the IEA and EIA.¹⁰

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 table¹¹ provides production data on more than 20 electricity technologies for over 100 regions. This balance table is available for purchase from the IEA website. EIA's International Energy Outlook¹² provides a cost-free alternative for liquids, gas, coal, nuclear, hydro, wind, solar, geothermal, and other

¹⁰ In this paper we use a regional aggregation that includes the U.S. (USA), Canada (CAN), Mexico (MEX), 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).

¹¹ Source: http://data.iea.org/ieastore/product.asp?dept_id=101&pf_id=205.

¹² Source: <http://www.eia.gov/forecasts/ieo/>.

renewables for 15 global regions.¹³ 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 3.2. In the 2007 world energy balance table there are no accounts for CCS sub-technologies, and a CGE model cannot predict CCS use if an initial value of 0 is used. Based on a recent report from the Global CCS Institute [28], we have assumed that the CCS sub-technologies are 0.004% of their conventional counterparts.¹⁴ For full detail, Table A1 in the 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 [16]. We use the U.S. values for the other regions in the model in lieu of better data.¹⁵ 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 appendix shows the cost structure of various technologies.

¹³ 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.

¹⁴ Global CCS Institute [27] 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.

¹⁵ 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.

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:

$$F_i^{GTAP} = F_{electricity}^{GTAP} \cdot \frac{Q_i \cdot C_i}{\sum_i Q_i \cdot C_i} \quad (17).$$

The fixed-factor energy resources used by carbon-free technologies are not available from the GTAP 8 database. Therefore, we follow Sue Wing [5] 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 based on the estimate of the Intergovernmental Panel on Climate Change [29] using data available up to 2005.¹⁶

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 exclusively by the OMD activity. 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

¹⁶ This cost estimate is not for the reference year (2007) of the GTAP 8 database, which means there could be some inconsistency. Unfortunately it is the best estimate we can obtain from the existing literature, and we believe this is an area for improvement in future research.

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 [17-19] for the U.S. electric power sector. Although these studies are about the price elasticity of fossil fuel demand in the U.S. power sector, they are still an appropriate target. Under the technology bundle approach, because we assume that fuels are Leontief inputs of each fossil technology, the demand for fossil fuels is proportional to the demand for fossil fuel generation technologies. Therefore the price elasticity of fossil fuel demand coincides with price elasticity of fossil fuel electricity demand. Calibration of elasticities related 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, we choose final parameter values of 0.6 for coal, 0.2 for oil, and 1 for gas.¹⁷

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.¹⁸ 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. “CA” is the elasticity as implied by our parameter settings; “DKT” is the estimate of [16] using the translog model; “DKL” is the estimate of [17] using the logit model; “KD” is the estimate of [18] using the translog model; and “EIA” is the estimate of [19] using the logit model. For example, the cross-price elasticity of coal demand with respect to the natural gas price in our calibration (CA: 0.19) implies that 1% increase in the price of gas power will lead to 0.19% increase in the demand for coal power.

¹⁷ A Python script is available upon request from the authors to implement this calibration.

¹⁸ These elasticity estimates are not for the reference year (2007) of the GTAP 8 database, which means there could be some inconsistency. Unfortunately it is the best estimate we can obtain from the existing literature, and we believe this is an area for improvement in future research.

This is higher than both the logit estimate of [19] (EIA: 0.17) and the translog estimate of [17] (DKT: 0.14), but lower than the logit estimate of [17] (DKL: 0.2) and that of [18] (KD: 0.28).

Overall, our choice of parameters leads to elasticities that are within the range found in empirical studies. The few exceptions are the oil-related own and cross price elasticities. The International Energy Agency [30, p. 186] has observed a continuously declining trend in the share of oil in global power generation over the last few decades. In most regions, oil only plays an auxiliary role as emergency backup for other generators or distributed applications in remote areas. As such, we have intentionally made oil demand inelastic to price changes for the power sector.

[Table 1 about here.]

Except for nuclear and hydro, the α_i values are set to 2.5 for carbon-free technologies. This leads to own price elasticities ($\varepsilon_{i,i}$) of renewable technologies ranging from 2.39 to 2.50 (see Table A3), consistent with the empirical finding of Johnson [31]¹⁹. The α_i value for nuclear is set to 0.5, resulting in an own price elasticity of 0.44. This relatively low value (compared to other clean technologies) reflects public safety concerns about nuclear power generation. Similarly, the α_i value for hydro is set to 1 (own price elasticity of 0.97), due to the resource and environmental constraints on hydro power.

Table A3 in the 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.

Although the technology bundle approach does not directly model base, intermediate, and peak generation, the values of the own price elasticities account for some differences between them. Lower values are associated with coal, nuclear, and hydro generation, technologies that are usually base load generators; higher values are associated with natural gas and other renewables that are usually peak load generators. We do, however, acknowledge the

¹⁹ The author finds the price elasticity of renewable electricity generation to be 2.67; the 95% confidence interval ranges from 1.74 to 3.60. The author states the estimate as the “supply elasticity” from the final consumer’s point of view, while in the paper we interpret it as the “demand elasticity” from the national power grid’s point of view.

importance of further integrating the technology bundle approach with base, intermediate, and peak segmentation in future research.

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 in the following section suggest that these parameter settings lead to rather conservative estimates of future CCS expansion. As a starting point, we apply the same parameter values for technologies and sub-technologies to all other regions. Because these regions have different shares of fossil fuels and renewables in their electricity portfolio, the inter-fuel elasticities will be significantly different from the U.S. according to equations (4) and (5).

5 Application to the U.S. Clean Power Plan

In this section we illustrate the technology bundle approach through model simulations. We consider the impacts of the Clean Power Plan 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 construct an economy-wide, multi-regional, dynamic recursive CGE model named CTEM. The CTEM model adopts the global trade and economic core from the widely-used GTAP CGE model [3], but features disaggregated modelling of the electricity sector through the technology bundle approach. Following the GTAP-E model [24], CTEM aggregates coal, petrol, gas and electricity into an energy composite for industrial use and private consumption, and the elasticity parameter for inter-fuel substitution is set to 0.5. Commodity-embedded flows of energies and greenhouse emissions (CO₂, N₂O, CH₄ and F-gases) are calculated based on CTEM's social accounting matrix (SAM). Accordingly, carbon prices are factored into the SAM using the formula of [6]. Investment takes place across regions through the following rule [15]:

$$Q_{inv_r} = \left(S_r / P_{inv_r} \right)^\theta \cdot e^{\tau \cdot (R_r - \bar{R})} \cdot \aleph^{\varphi_r} \quad (18).$$

Here Q_{inv_r} and P_{inv_r} are the quantity and price of regional investment; S_r is the gross regional saving; θ is a time-variant parameter that is negatively linked to the ratio of region's foreign debt DB_r to gross domestic product, $\theta = \vartheta \cdot e^{-\chi \left(\frac{DB_r}{GDP_r} \right)}$; R_r is the regional rate of return on capital, $\bar{R}$ is global average rate of return on capital; τ is global investment's responsiveness to capital differential; $\aleph$ is a global uniform adjustment factor that is endogenously determined to ensure the Walras' law:

$$\sum_r Q_{inv_r} \cdot P_{inv_r} = \sum_r S_r \quad (19),$$

and φ_r is each region's responsiveness to this adjustment. In the current version of CTEM, τ is set to 5, ϑ and χ are both set to 0.5, and φ_r is set to 1 for all regions, so that $\bar{R}$ converges to a long term steady rate of 4%. The capital stock K of region r changes over time according to the level of investment $I_r = Q_{inv_r} \cdot P_{inv_r}$ and the level of depreciation of existing capital δK , i.e.,

$$\dot{K}_r = I_r - \delta K_r \quad (20).$$

Following GTAP convention, we set the depreciate rate δ to 0.04 for all regions.

To demonstrate the benefits of our approach, we construct another model (CTAP) that is otherwise identical to CTEM, but 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.

[Figure 4 about here.]

CTAP assumes primary factors are 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 between

capital and energy is set to be 0.2. This is the same elasticity that McKibbin et al. [11] assume for the substitution between capital, labor, energy and materials in a study of U.S. power sector carbon mitigation. The comparisons between CTEM and CTAP 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, 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 two models are identical. Each model is built upon the GTAP 8 database, and both are simulated on a year-to-year basis from 2007 through 2030.

5.1 Baselines

The baselines of the two models are calibrated to reflect a ‘business-as-usual’ scenario with no carbon policies as per the reference case of EIA’s International Energy Outlook²⁰ (IEO 2013). Specifically, the population trajectories are taken from IEO 2013, and we iteratively derive the non-energy input-productivity shocks so that CTEM and CTAP’s GDP projections follow IEO 2013. Also, we iterate on gas, crude oil and coal productivities so that CTEM and CTAP energy production (in terms of annual % change) are the same as IEO 2013. We have assumed 8% heat rate improvement in power generation from now to 2030 as per EPA’s 2013 modelling assumption²¹, 2.5-3% annual transport fuel efficiency improvement according to the BP Energy Outlook 2035 [32], and 1% annual electricity efficiency improvement from EU history [33]. Both baselines include the proposed New Source Performance Standards (NSPS) that prohibit new coal power without CCS beyond 2020 (see Table A4 of the appendix).²²

CTEM and CTAP projections for regional energy consumption are broadly consistent with IEO 2013. Under our assumptions about energy production and consumption, CTEM and CTAP have projected similar trajectories of U.S. power sector emissions that peak and flatten around 2020 due to the implementation of NSPS.

²⁰ Source: <http://www.eia.gov/forecasts/ieo/>.

²¹ Source: <http://www.epa.gov/powersectormodeling/BaseCasev513.html> (Appendix HRI).

²² Source: <http://www.epa.gov/compliance/monitoring/programs/caa/newsources.html>.

5.2 Policy Scenario

We implement the Clean Power Plan 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 [Figure 5]. This approach follows McKibbin et al. [11], 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 appendix.

[Figure 5 about here.]

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 [34].

5.3 Results

Both CTAP and CTEM show declines in real Gross Domestic Product (GDP) as a result of the policy scenario (Table 2). CTEM estimates average annual losses of 14.5 billion (2007\$), while CTAP comes in at an average of 19.3 billion (2007\$) over this time period.

[Table 2 about here.]

The average annual reductions in GDP from the two models fall between estimates of the EPA and the U.S. Chamber of Commerce. EPA estimates that annual compliance costs for the Clean Power Plan will peak in 2030 at roughly 8.1 billion (2007\$).²³ 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

²³See 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>.

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\$).²⁴

The differences in simulated economic costs of the U.S. Clean Power Plan between the CTAP and CTEM models are related to assumptions about electricity generation. While CTEM allows the existence of carbon-free technologies, CTAP has only one single representative technology. To approximate the substitution between non-fossil fuel and fossil fuel technologies, some degree of substitution (with elasticity of 0.2) between factor inputs (mainly capital) and energy is allowed for this representative technology in CTAP. In comparison, there is assumed to be no substitution between factor inputs and fuels in the fossil fuel technologies of CTEM. As a result, for the same level of carbon mitigation from fossil fuels, CTEM will predict a higher carbon price due to the lack of substitutability between factor inputs and fuels.

However, being the average of all generation technologies, the representative technology in CTAP always requires at least a little of each input, including fossil fuels. In other words, power generation from this representative technology cannot decouple from fossil fuel consumption or carbon emissions. In contrast, power generation in CTEM is able to shift to carbon-free technologies and buffer the price impact on economic activity. As a result, although CTEM predicts a higher carbon price, the economic impact turns out to be smaller.

As Figure A2 of the appendix shows, despite a higher carbon price, CTEM's approach results in a lower price for electricity than CTAP, and therefore a smaller reduction in electricity consumption [Table 3]. The electricity price is lower in CTEM because coal and natural gas prices rise by less than in CTAP [shown in Figure A1 of the appendix]: the demand for these fuels is lower as they are replaced by cleaner technologies in generating electricity.

[Table 3 about here.]

Table 4 shows another benefit of the technology bundle approach in CTEM—it can distinguish changes from base in electricity generation by technology when simulating the Clean Power Plan. This feature is unavailable in CTAP.

²⁴ <https://www.uschamber.com/press-release/energy-institute-report-finds-potential-new-epa-carbon-regulations-will-damage-us>.

[Table 4 about here.]

As expected, coal-based generation shows large losses (-471 TWH or -22% from baseline in 2030) due to its high carbon intensity. Natural gas power also sees a substantial reduction (-122 TWH or -8% from baseline as of 2030), but less than coal. Although demand for natural gas in the U.S. power sector is almost two times more responsive to price changes as compared with coal, it still displaces coal for base load generation because it is much cleaner. Oil power does not lose much because of the minor role it plays in the U.S. electric sector.

Our simulation results also suggest that reductions in generation via fossil fuel technologies are partially replaced by generation through carbon-free ones. In particular, both nuclear and hydro power see reasonable increases from the baseline. Growth in nuclear generation peaks at 4% in 2030, within the range of a recent EIA estimate that uprates have the potential to increase U.S. nuclear capacity by 5-9% without major plant modifications.²⁵ As for hydro-power, CTEM predicts growth of 12% (49 TWH) by 2030. 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.²⁶ This can potentially generate 200 TWH of electricity per year, accommodating CTEM's predicted hydro growth after the U.S. Clean Power Plan.

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 1% of the reduction in the conventional thermal sub-technologies.

6 Conclusion

²⁵ Source: <http://www.eia.gov/todayinenergy/detail.cfm?id=7130>.

²⁶ Source: <http://www.eia.gov/todayinenergy/detail.cfm?id=17051>.

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 CGE models.

To demonstrate this approach, we simulate the proposed U.S. Clean Power Plan using different levels of disaggregation in the electricity sector and highlight the differences. By comparing two dynamic variants of the GTAP model, one with an electricity technology bundle and one without, we see how a disaggregated electricity sector can change results. The comparison indicates that a conventional CGE model that does not consider the heterogeneity of generation technologies can potentially underestimate the size of the carbon price but overestimate the economic cost of mitigation.

The size of such errors is highly uncertain, but is certainly present given the complexity of the electricity sector. We believe the best way to mitigate some of this uncertainty is to use a modelling approach that approximates reality as far as possible, and that also uses actual data in construction. The method outlined in this paper follows such a path.

Our paper can contribute to future research in the energy-carbon-environment nexus in several ways. First, the paper has provided an intuitive interpretation of the “technology bundle”, and described the mathematical structure of the CRESH function. This will continue to advance the theoretical understanding of electricity modelling in the CGE framework. Second, the paper has shown how the input and output structure of the electricity sector in the GTAP 8 database can be disaggregated using data from international agencies. This provides a recipe to create variants of the widely used GTAP model [3] that can account for the heterogeneity of electricity technologies. Finally, the paper has also established a link between parameters of the CRESH function and elasticity estimates. This offers a guideline for estimating and quantifying the degree of substitution between various electricity generating technologies in CGE models.

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

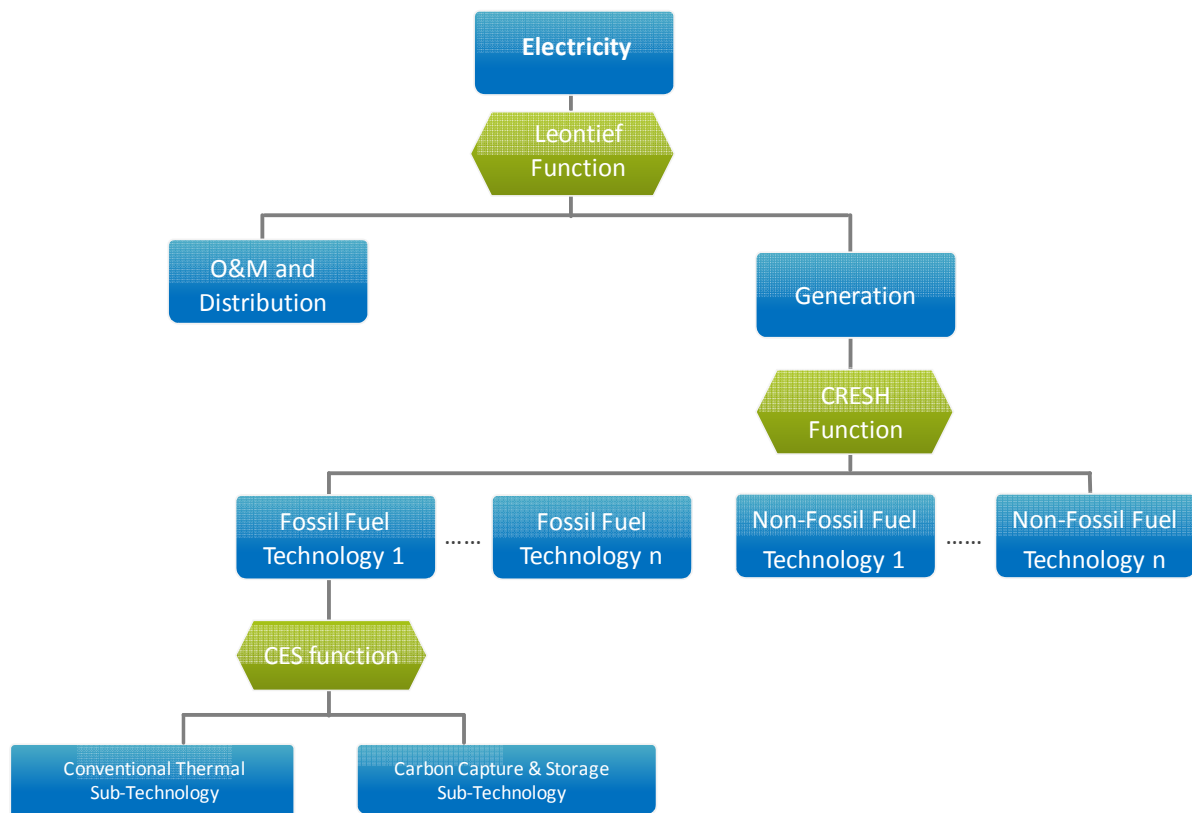


Figure 2: Production Structure of an Electricity Technology Within the Generation Activity

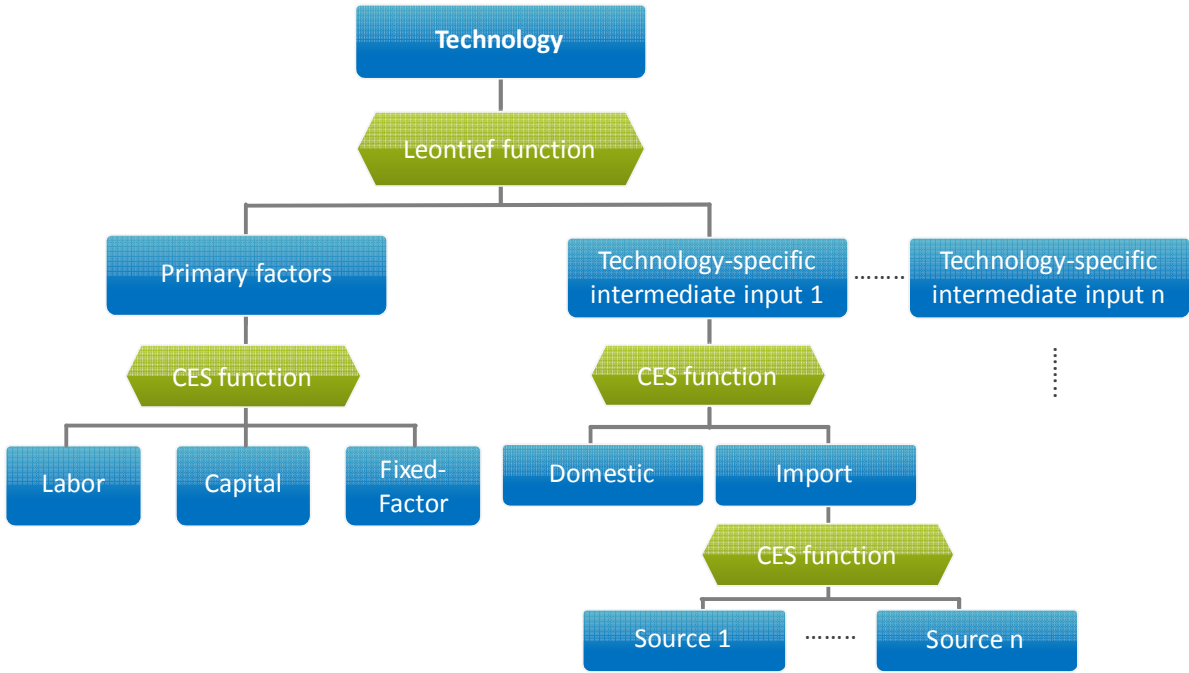


Figure 3: Production Structure of O&M and Distribution

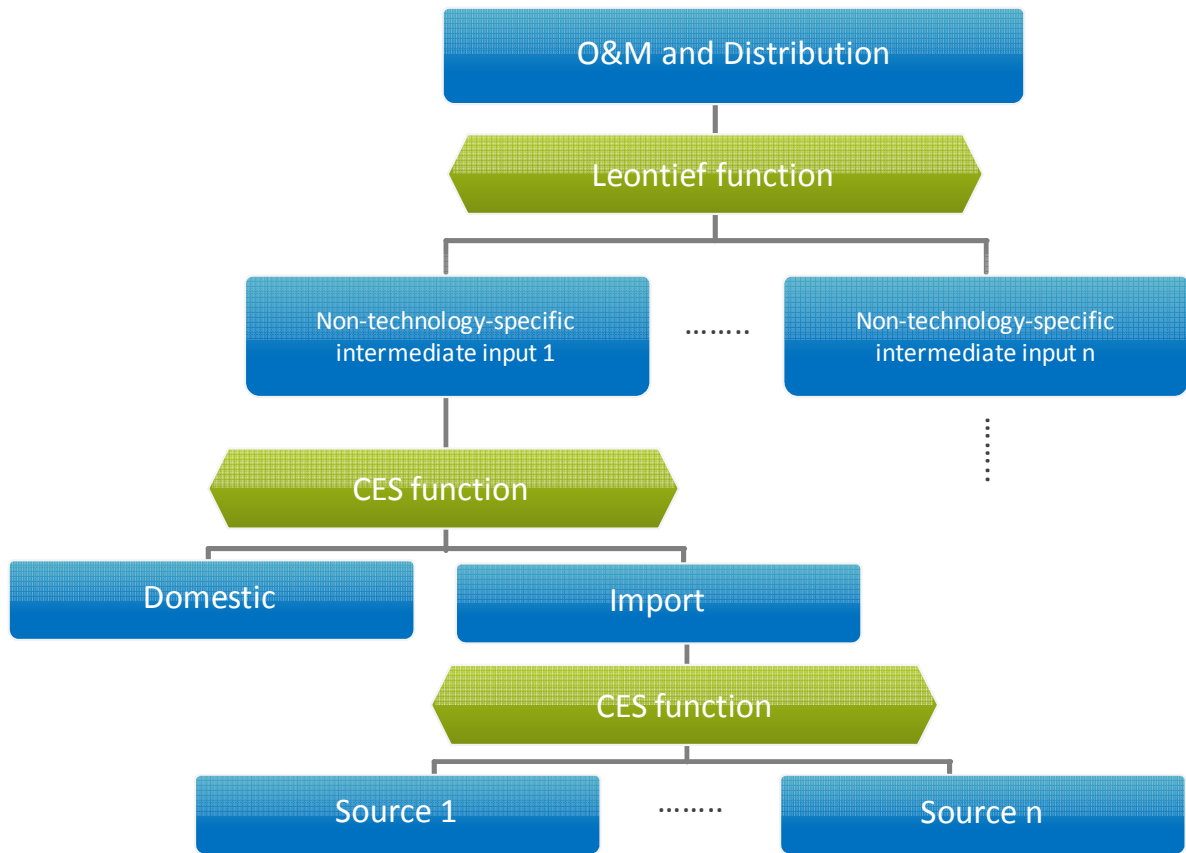


Figure 4: Production Structure of Electricity in CTAP

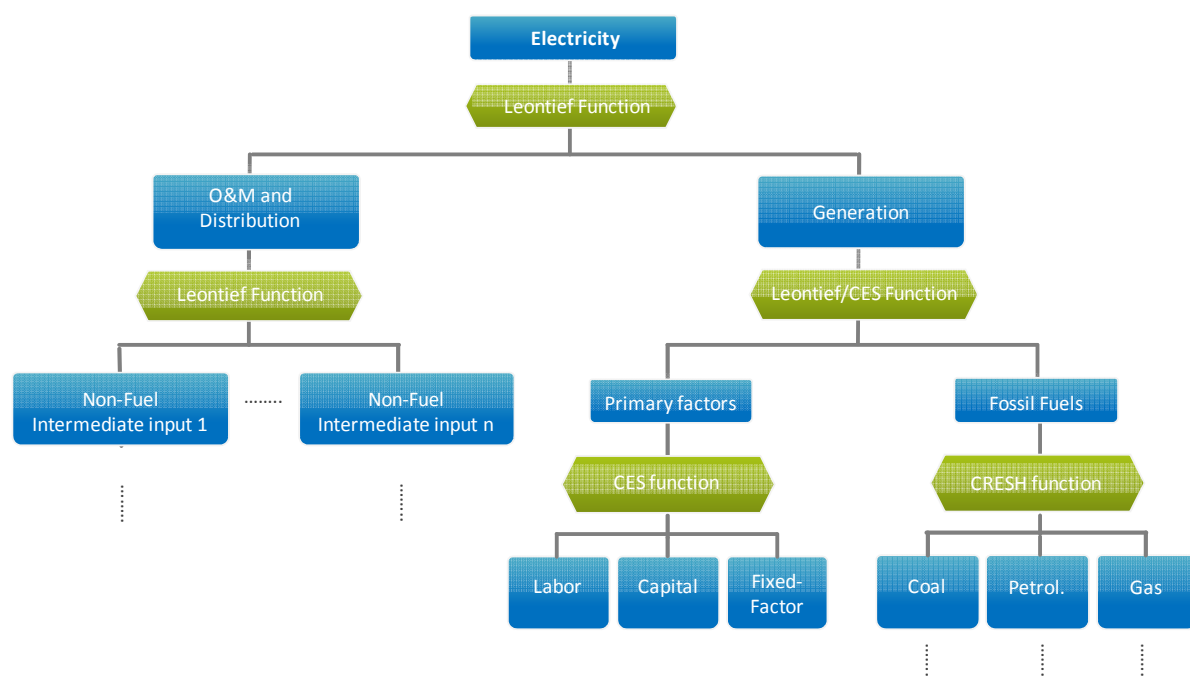
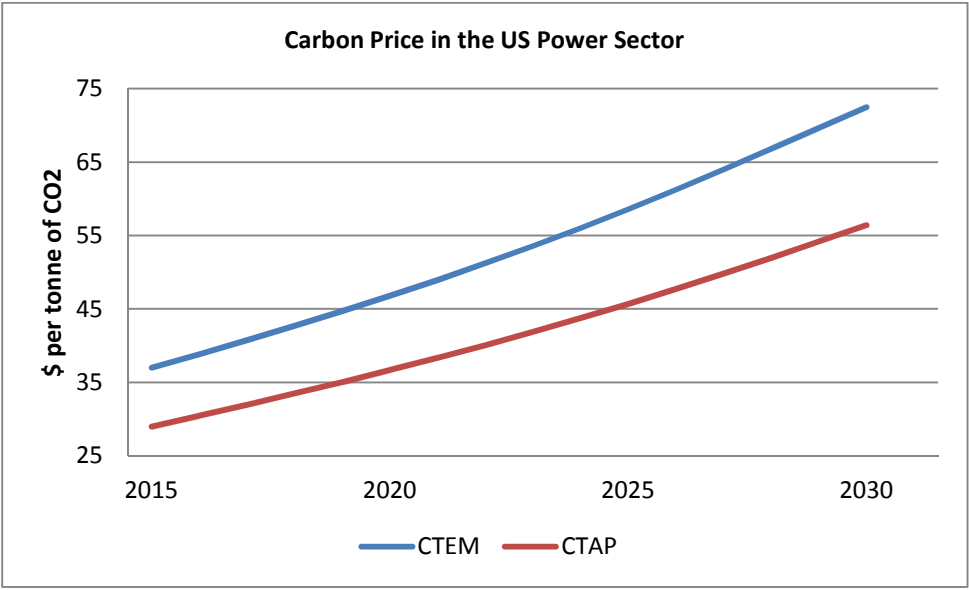


Figure 5: U.S. Carbon Price for the Electricity Sector



Source: Author calculations.

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	CA: -0.39 DKT: -0.16 DKL: -0.26 KD: -0.57 EIA: -0.11	CA: 0.015 DKT: 0.02 DKL: 0.06 KD: 0.29 EIA: -0.06	CA: 0.19 DKT: 0.14 DKL: 0.2 KD: 0.28 EIA: 0.17
Oil Demand	CA: 0.07 DKT: 0.74 DKL: 0.29 KD: 3.21, EIA: 1.89	CA: -0.19 DKT: -0.72 DKL: -1.04 KD: -3.05 EIA: -1.26	CA: 0.06 DKT: 0.02 DKL: 0.75 KD: -0.15 EIA: 0.82
Gas Demand	CA: 0.36 DKT: 0.28 DKL: 0.75 KD: 1.54 EIA: 0.14	CA: 0.03 DKT: 0.21 DKL: 0.25 KD: -0.08 EIA: 0.14	CA: -0.69 DKT: -0.49 DKL: -1.00 KD: -1.46 EIA: 0.29

Table 2: Deviation of Real U.S. GDP from the Baseline Under a Carbon Price

Deviation Billion 2007\$ (Deviation in %)	2015	2020	2025	2030	Average
CTEM	-3.4 (-0.02%)	-9.5 (-0.05%)	-18.8 (-0.09%)	-27.1 (-0.12%)	-14.5 (n.a.)
CTAP	-6.61 (-0.04%)	-12.0 (-0.07%)	-24.6 (-0.12%)	-35.4 (-0.15%)	-18.1 (n.a.)

Source: Author calculations.

Table 3: Deviation of U.S. Electricity Consumption from the Baseline Under a Carbon Price

Deviation in TWH (Deviation in %)	2015	2020	2025	2030
CTEM	-130 (-2.7%)	-137 (-2.7%)	-184 (-3.3%)	-225 (-3.8%)
CTAP	-129 (-2.7%)	-156 (-3.0%)	-216 (-3.8%)	-273 (-4.5%)

Source: Author calculations.

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	-229 (-11%)	-242 (-12%)	-372 (-18%)	-471 (-22%)
Oil	-2 (-2%)	-2 (-3%)	-4 (-4%)	-7 (-6%)
Gas	-79 (-7%)	-96 (-8%)	-99 (-7%)	-122 (-8%)
Nuclear	40 (4%)	37 (4%)	44 (4%)	43 (3%)
Hydro	28 (10%)	29 (9%)	40 (11%)	49 (12%)
Wind	22 (39%)	28 (38%)	44 (50%)	64 (59%)
Solar	1 (38%)	2 (37%)	3 (49%)	4 (57%)
Biomass	39 (46%)	48 (44%)	70 (58%)	94 (68%)
Waste	19 (46%)	24 (44%)	38 (59%)	54 (68%)
Other Ren.	1 (39%)	12 (38%)	18 (50%)	24 (58%)
Coal + CCS	0.4771 (355%)	0.6215 (392%)	1.1038 (679%)	1.7816 (1017%)
Oil + CCS	0.0014 (37%)	0.0016 (39%)	0.0019 (40%)	0.0025 (45%)
Gas + CCS	0.2216 (475%)	0.2737 (515%)	0.3822 (619%)	0.5436 (778%)
Total	-150 (-3%)	-161 (-3%)	-216 (-4%)	-266 (-5%)

Source: Author calculations.

Appendix: Figures and Charts

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

Technology	USA	CAN	MEX	SAM	EUR	CHN	REA	IND	ROA	FSU	OCN	MDE	AFR	Total
Coal	2146	105	33	33	1537	3355	642	527	152	503	202	91	265	9590
Oil	88	13	55	140	195	62	226	24	103	124	4	238	58	1328
Gas	1017	52	128	129	1451	58	438	93	320	1618	48	532	178	6063
Nuclear	836	95	11	20	1064	62	449	17	3	164	0	0	11	2731
Hydro	250	373	28	671	578	485	96	125	107	177	39	63	94	3086
Wind	35	3	0	1	106	6	3	12	0	0	4	1	1	171
Solar	2	0	0	0	4	0	2	0	0	0	0	0	0	8
Biomass	59	8	2	26	140	13	17	7	2	13	5	0	2	295
Waste	26	1	0	0	77	0	13	0	1	21	0	0	0	140
Other Renewables	18	0	8	4	19	0	5	0	17	97	4	0	1	172
Coal + CCS	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Oil + CCS	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Gas + CCS	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	4476	652	264	1023	5172	4041	1892	805	705	2716	306	925	610	23586

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.

824 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

825 Source: EIA (2013a).

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828 Table A3: U.S. Cross and Own Price Elasticities of Demand Between All Generation
829 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	-0.3865	0.0154	0.1865	0.0905	0.0197	0.0076	0.0005	0.0276	0.0323	0.0065
Oil Demand	0.0712	-0.1949	0.0622	0.0302	0.0066	0.0025	0.0002	0.0092	0.0108	0.0022
Gas Demand	0.3558	0.0257	-0.6892	0.1508	0.0329	0.0126	0.0008	0.0459	0.0539	0.0108
Nuclear Demand	0.1779	0.0129	0.1554	-0.4246	0.0164	0.0063	0.0004	0.0230	0.0269	0.0054
Hydro Demand	0.3558	0.0257	0.3108	0.1508	-0.9671	0.0126	0.0008	0.0459	0.0539	0.0108
Wind Demand	0.8895	0.0644	0.7770	0.3770	0.0821	-2.4685	0.0020	0.1149	0.1347	0.0269
Solar Demand	0.8895	0.0644	0.7770	0.3770	0.0821	0.0315	-2.4980	0.1149	0.1347	0.0269
Bio. Demand	0.8895	0.0644	0.7770	0.3770	0.0821	0.0315	0.0020	-2.3851	0.1347	0.0269
Waste Demand	0.8895	0.0644	0.7770	0.3770	0.0821	0.0315	0.0020	0.1149	-2.3653	0.0269
Other Ren. Demand	0.8895	0.0644	0.7770	0.3770	0.0821	0.0315	0.0020	0.1149	0.1347	-2.4731

830 Source: GTAP 8 database for 2007 and author calculations.

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

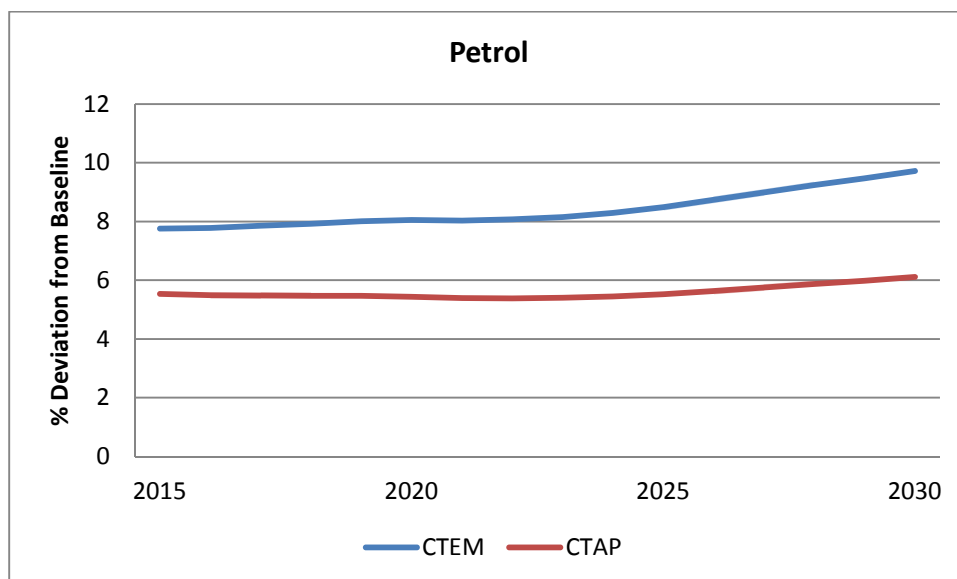
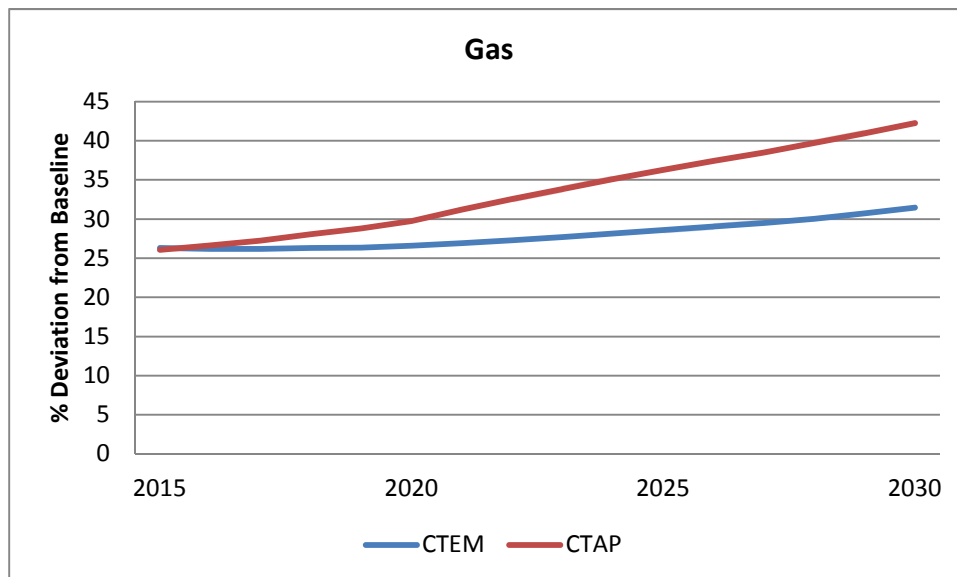
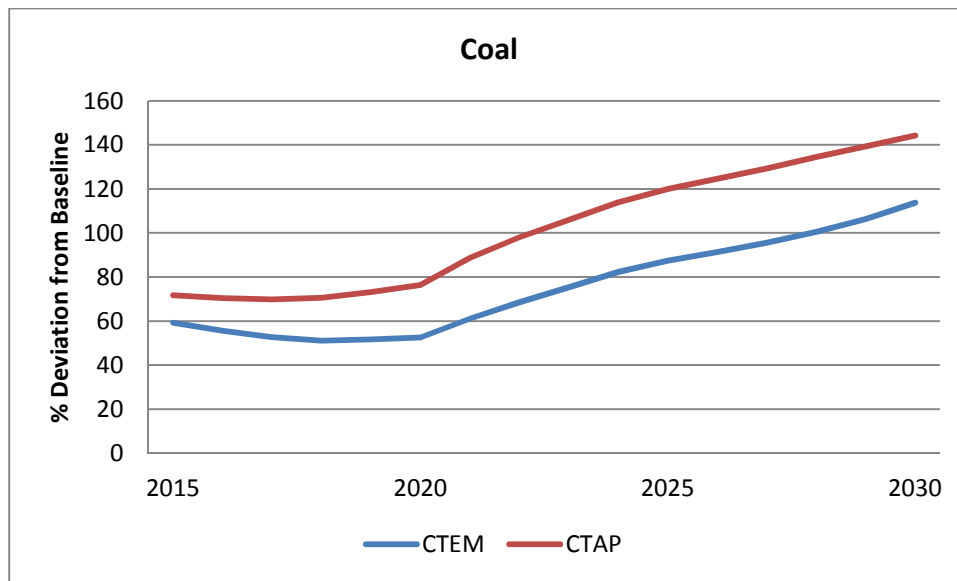
Scenarios	2015	2020	2025	2030
CTEM Baseline	2.27	2.30	2.28	2.27
CTEM Linear Path to Target (Annual)	2.23	2.05	1.87	1.69
CTEM Linear Path to Target (Cumulative)	2.23	12.85	22.56	31.37
CTEM Hotelling Rule (Annual)	2.03	2.05	1.93	1.84
CTEM Hotelling Rule (Cumulative)	2.03	12.20	22.07	31.45
CTAP Baseline	2.18	2.24	2.24	2.25
CTAP Linear Path to Target (Annual)	2.15	2.00	1.84	1.69
CTAP Linear Path to Target (Cumulative)	2.15	12.43	21.95	30.71
CTAP Hotelling Rule (Annual)	1.92	1.97	1.91	1.89
CTAP Hotelling Rule (Cumulative)	1.92	11.68	21.30	30.78

834 Source: Author calculations.

835 Note: These numbers are higher than the EIA statistics because the GTAP 8 database
836 combines electricity and heat into a single sector.

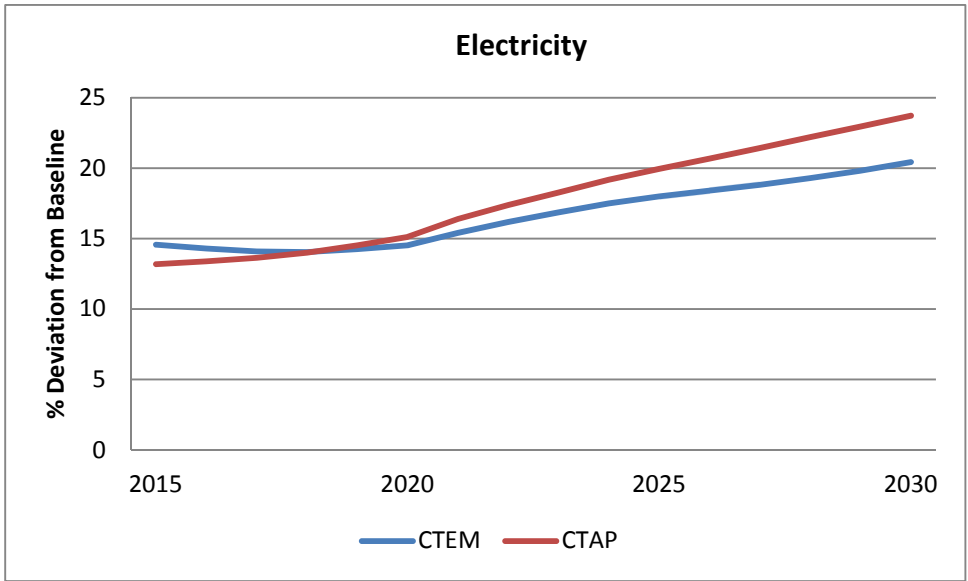
837

838 Figure A1: Deviation of U.S. Fossil Fuel Prices to Power Generation After Clean Power Plan



Source: Author calculations.

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



Source: Author calculations.