Disaggregating the electricity sector in a CGE model to allow competition theory to explain the introduction of new technologies to the sector[1]

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Abstract

The electricity sector in most CGE models is highly aggregate which makes it unsuitable for use in the analysis of the impacts of climate change or energy policies on the sector. A conventional approach is to disaggregate this sector into different technologies and then recombine the outputs (or costs) into that of a single sector using an aggregate production function (such as CRESH) or market share function (such as LOGIT). Such an approach is useful but not entirely transparent because it does not explain completely why the outputs of different technologies are only 'imperfectly substitutable' while electricity is a homogeneous commodity. In this paper we propose a different approach where the 'imperfect substitutability' of different electricity outputs is explained not in terms of the nature of output and distribution activities but in terms of the different types of *capacities* used in the generation of electricity. These capacities have different economic and technological characteristics which differentiate themselves from one another and these characteristics also make each type of capacity suitable for the supply of electricity to different types of *demand* (or electricity 'loads'). The 'imperfect substitutability' between different electricity generation technologies, therefore, is derived from the imperfect substitutability between these different generation capacities rather than between their outputs. We illustrate the applicability of the new approach with some empirical examples taken from the case of the Japanese electricity sector. (230 words).

Keywords: Electricity generation, demand loads, technology competition, CGE modeling.

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1. Introduction

Following the accidents at the Fukushima nuclear power plants in Japan in 2011, there was a shift towards the use of non-nuclear energy in electricity generation which includes both fossil fuels (natural gas, coal, and oil) as well as renewable (hydro, wind, solar, geothermal) energy. This shift can have significant impacts on the environment (in terms of CO_2 emissions) as well as on the welfare of consumers (in terms of higher electricity prices). To understand these impacts, it is important that the scope and mechanism of substitution between different types of electricity generation technologies be properly understood. Up to now, models which are used for the study of this type of substitution are often 'bottom-up' partial equilibrium models which assume that outputs from these technologies are perfectly substitutable, but given the different capacities of these technologies in the short run and their different marginal running costs, their utilizations will depend on a 'merit order' (i.e. lowest marginal running cost capacities will be utilized first, then the next more expensive ones, until the most expensive (marginal) capacity is utilized to meet with a certain level of (total) demand. Such a 'partial equilibrium' approach may describe well the competition between different technologies in the short run but often leaves the levels of capacities for the long run unexplained. A 'top-down' general equilibrium model, on the other hand, may be able to explain the long run demand for capacities in terms, not only of short run marginal running costs, but also of long run marginal capital (i.e. capacity) costs. However, such a model is often highly aggregate, assuming only a single electricity sector with little description of the technologies involved. When the model is disaggregated into various 'sub-sectors' each to represent a different technology, a different issue arises and that is: how to re-aggregate the outputs of different technologies to add up to the total output of the single electricity sector. If the outputs of these technologies are assumed to be perfectly substitutable (which is reasonable since electricity is a homogenous commodity) then the outputs of these technologies can be simply added up to a total output. But perfect substitution poses a different challenge: 'corner' solution and how to overcome this. A bottom-up linear programming approach handles this issue by the assumption of fixed capacities for different types of technologies, and hence no single technology can cope with the total demand for electricity output, but fixed capacities (and the associated mathematical problem of mixed complementarities) are not easily handled within the neoclassical framework of a top-down CGE model, therefore a 'conventional' approach is to assume that electricity outputs from different technologies are only *imperfectly* substitutable so that they can be considered as though intermediate *inputs* into a neoclassical production function (such as CRESH) or as imperfect choices in a probabilistic market share function (such as LOGIT)[2] and then let these functions the selection of outputs from different sources (i.e. technologies). But the assumption of imperfect substitution (or imperfect choices) is artificial, and not well explained, when considered in the context of empirical evidences (since electricity is a fairly homogenous product and their production cost structures are fairly deterministic). For example, attempts at explaining the imperfect substitutability of the outputs in terms of the different transmission and distribution costs, or different 'availability factors' and/or supply characteristics ('intermittency, etc.) of the supplied outputs cannot be sustained. Firstly, transmission and distribution activities should be considered as part of the secondary (or 'margin') activities rather than the primary (generation or production) activities.[3] Transmission and distribution costs will often affect the final consumer's or purchaser's price but not producer's price. Secondly, if different technologies have different 'availability factors' and/or 'intermittency' characteristics, then this must be taken into consideration but as part of the determination of the *quantities* of their outputs rather than their 'qualities'. Confounding these issues can lead to artificiality and inaccuracies. For example, suppose that wind (or solar) electricity is available only for certain time periods. This may or may not affect the 'quality' (i.e. 'value') of supply, and even if it does, the effect may not always be in the same direction. Thus, if supply is available only during *peak* hours, then the effect would be different than if it is available only during *off-peak* periods. The values of the outputs in these cases are influenced, not by their supply 'qualities' but rather by the levels of *demand* during these different periods.

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[2] In the case of CRESH, this is the so-called 'technology bundle' approach first used in the MEGABARE model (ABARE (1996)) and subsequently also adopted in many other models (see Cai and Arora (2015) for a good review of this approach). In the case of LOGIT, this function strictly is not a 'production function but rather a 'market share' function, i.e. outputs are still assumed to be perfectly substitutable, but the costs of production are not directly 'substitutable' or comparable because they are 'probabilistic'. Clarke and Edmonds (1993) for example assumed that the costs of (steel) production are probabilistic due to the problem of 'geographical heterogeneity'. Probabilistic discrete choice function (such as LOGIT) is often used in the context of discrete *individual* choice, where the 'attributes' of the individual *consumers* are unobservable, and hence their utilities are assumed to be probabilistically distributed. In the case of technological choice, the interpretation must be different: here it is the 'unobserved attributes' or characteristics of the *supply* cost functions that makes the choices between these alternative supply sources 'imperfect'.

[3] In fact, most models, including our approach, will treat these activities as separate rather than as a single activity.

Because of this *conceptual*[4] difficulty associated with the assumption of imperfect substitutability between electricity outputs, in this paper, we retain the conventional assumption (in a 'bottom-up' linear programming approach) that electricity outputs from different technologies are perfectly substitutable. However, we recognize the 'imperfect substitutability' between the *technologies* that produce these outputs, and this imperfect substitutability arises not from the 'qualities' of their outputs but rather from the different *engineering* as well as *economic* characteristics of the *capacities* which are used to produce these outputs. It can be said that *ex-post* electricity outputs are perfectly substitutable once produced, but *ex-ante* (i.e. in consideration of the types of technologies (or types of capacities) used to produce them; the choices between these capacities are only 'imperfectly substitutable'. Furthermore, the choices between the different types of capacities are also conditional on the particular types of electricity *demand* (i.e. electric 'loads') which are to be satisfied, and these types of demand loads are also *imperfectly* substitutable. In short, while electricity outputs are highly substitutable, their means of production are only imperfectly substitutable.

The plan of the paper is as follows. Section 2 presents a theoretical analysis of the electricity sector with different features of demand and supply in electricity generation as well as different structures of the electricity supply market taken into account. Section 3 then applies this analysis to an empirical study of the Japanese electricity market to see how the imposition of various climate change and/or energy policies in Japan can impact on the electricity sector, especially after the Fukushima nuclear incidences. Section 4 concludes the paper and gives some suggestions for future extensions.

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[4] There is another more *practical* issue and that is the problem of non-addability of all the quantities of electricity outputs from different technologies into that of the sector as a whole when using an aggregate production function such as CRESH or CES (or in the case of a LOGIT market share function, non-addability of all the technology costs into the total cost of the sector as a whole because of the probabilistic nature of the cost functions). This 'adding up' problem, however, is a relatively minor issue because it can always be resolved either by an 'adjustment' factor, or by the use of a so-called 'volume preserving' production function such as ACES (see Dixon and Rimmer (2003)) This type of function has been used in the context of land-use and labour market specification (see Giesecke *et al.* (2013), Dixon and Rimmer (2003, 2006)). The problem, however, is more conceptual than practical because there is a significant difference between the assumption of 'imperfect substitutability' between *land* or *labour* inputs (which are seen to be heterogeneous commodities) and the assumption of 'imperfect substitutability' between electricity outputs (which are seen to be more homogeneous).

2. Theoretical analysis of the electricity supply sector

Electricity has some special characteristics which makes a study of the electricity market rather different from a study of other markets. Firstly, electricity is a non-storable commodity[5] therefore this imposes a special restriction on production activity: *output* at any time cannot exceed *capacity* of production. Secondly, electricity demand is highly variable in the short run (daily) as well as in the medium or long run (seasonally or yearly). This means the issue of *capacity planning* to meet with different types of demand (referred to as 'loads') must often be considered as joint decision with the issue of *output allocation*. Traditionally in the literature, these joint issues of capacity and output decisions are often discussed under the heading of 'peak load' pricing and investment rules where, firstly, total electricity demand is divided into different types of loads which together will make up a so-called 'load duration curve' (see Figure 1). From this load duration curve, demand at different periods of time can then be identified as consisting of many kinds of loads each to be looked after by different types of capacities.[6] These capacities are then considered as suitably constructed from different types of technologies, each with a different set of engineering as well as economic characteristics. For example, base load capacities (typically constructed from coal or nuclear technologies) would have high per unit capital costs but low running costs. In contrast peak load capacities (normally constructed from oil or gas technologies) would have low per unit capital costs but high running costs. Intermediate between these two types are 'intermediate load capacities' using technologies such as hydroelectric or geothermal. A theoretical concept which has been used to capture the engineering and economic characteristics of these different types of capacities is the so-called 'load factor'. Engineers define the load factor (of a machine, plant, or system) as the ratio of the average power to the maximum power during a certain period of time. This factor compares the average rate of output to the maximum rate and it can be used to indicate the extent of the 'reserve power' still held by a machinery while running. Such reserve power can then be used to indicate the extent of 'reliability' or 'certainty-of-supply' which can be expected from the

[5] Even if storable, the cost of storing electricity is large hence it is impractical (and expensive) to consider storing electricity as a means to circumvent the production-capacity constraint. In this respect, electricity is similar to other services (including for example transport as a service) even though electricity is a commodity rather than a service.

[6] Although different types of capacities are often associated with different types of demand e.g. (peak capacity for peak demand, base capacity for base demand, etc.) the correspondence between capacity type and demand type is not one-on-one. Thus, for example, gas-type capacity can be used to satisfy both peak demand as well as base demand, wind powered electricity or solar-powered electricity can be used to satisfy either base load or peak load, but depending on the timing of their output availability in particular regions.

machine. Seen from an economic point of view, however, the concept of load factor can be used to indicate the level of economic *efficiency* or *productivity* being associated with a particular type of capacity. Therefore, this concept can be used as a parameter or variable in the problem of production optimization (in the short run) or capacity planning (in the long run).[7]

Let K_i, i={1,2,3} stand for the base load, intermediate load and peak load capacities respectively, and let Q_i, i={1,2,3} be the total outputs generated by these capacities during the total time period T of the load duration curve. The 'load factors' for these capacities can then be defined as $\phi_i=Q_i/[K_iT]$. For example, if K_i is in megawatts (MW), T is in hours (h) then the *maximum* output that can be produced from capacity K_i in T hours is $[K_iT]$ in megawatt-hours (MWh). If the *actual* output produced from such capacity (measured by the area of the load duration curve covered by capacity K_i) is only $Q_i < K_iT$ then the load factor is $\phi_i=Q_i/[K_iT] <1$. It can be seen from Figure 1 that the load factor for a base load capacity is usually large relative to that of an intermediate or peak load capacity.

Let r_i be the marginal running costs associated with capacity K_i and c_i be the marginal capital *rental* cost of this capacity.[8] The total marginal cost of producing a unit of output from capacity K_i over the production time period T is therefore given by $[r_i+c_i/(\phi_iT)]$ where the first part r_i is

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[7] Load factor is not the same thing as 'capacity factor' which is purely an engineering factor and which defines the ratio of average unrestricted output of a machine relative to the maximum ('rated') output. Capacity factor is a 'supply' characteristic of a machine not dependent on demand, while load factor is *both* a supply characteristic and also an indicator of demand level. A capacity factor can be less than 100% if the machine needs regular shut down for maintenance and/or repair, or if (in the case of hydroelectric, wind, or solar powered generation plants) the 'inputs' required for the operation of the machine is not available at all times. In this latter case, the concept of an 'availability factor' can be used in place of 'capacity factor'. Both of these concepts, however, relate only to the supply side. On the demand side, a similar concept of 'demand factor' has also been used to describe the ratio of the average power *demanded* by a system of consumer-operated machineries relative to the maximum power which can demanded if *all* machineries are turned on together at the same time and at full capacity. Capacity factor and demand factor are only 'partial equilibrium' concepts, relating either to the supply, or to the demand side, but 'load factor' is a genuine 'general equilibrium' concept relating both to the supply side (engineering characteristics) as well as demand side (load characteristics). Thus, this is perhaps the reason why Watkins (1915) exclaimed: "We owe the term [load factor] to the electrical engineers. But it is not impossible that economists will prove the better interpreters of an idea that relates so definitely to economic technology".

[8] If both r_i and c_i are constants then they can also be referred to as the *average* or per unit running and capital costs respectively. Constant r_i implies there is no diminishing returns in the short run, while constant c_i implies there is 'constant returns to scale' (CRTS) in the long run. In practice, r_i can consist of things like materials, fuels, and labour costs associated with the production of a marginal unit of output while c_i can be measured by the so-called 'levelised capital cost' which is the 'rental' cost of a unit of capital of type i (to be distinguished from the capital price or per unit construction costs of capital).

also referred to as the 'short run' marginal cost (SRMC)[9] and the second part ($c_i/(\phi_i T)$ is referred to as the 'effective' marginal capital cost (MCC).[10] The sum of these two cost components then defines the 'long run' marginal cost (LRMC) and this is the cost to be considered in the long run optimization of capacity. The LRMC is therefore seen to be dependent on the load factor ϕ_i while the SRMC is not.

[9] Since in the short run, capacity is assumed to be fixed, its costs do not enter into the marginal (i.e. variable) cost calculation.

[10] Note that r_i will be measured in (\$/kWh) while c_i is in (\$/kW), therefore (c_i/T) is in (\$/kWh) and ϕ_i is a dimensionless ratio used to convert the *actual installed* capacity cost c_i into *effective* (i.e. *utilized*) capacity cost.

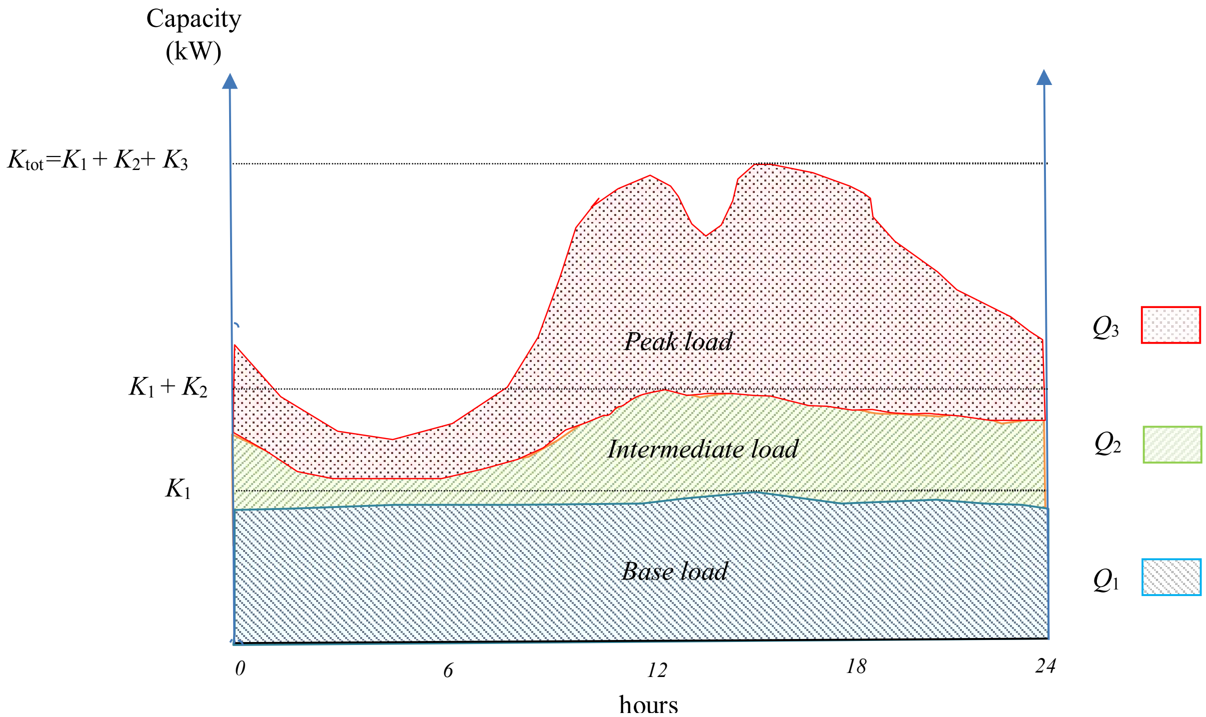

Figure 1
A typical load duration curve for an electricity market

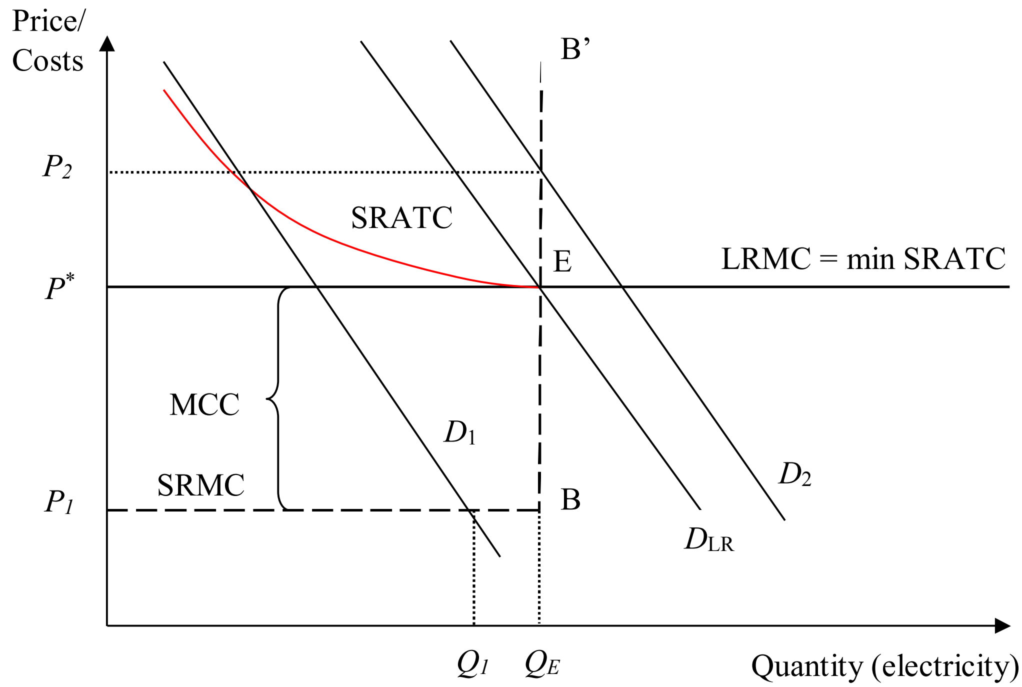

Figure 2
Cost curves for a technology with constant returns to scale in the long-run and capital is divisible (i.e. continuously variable).

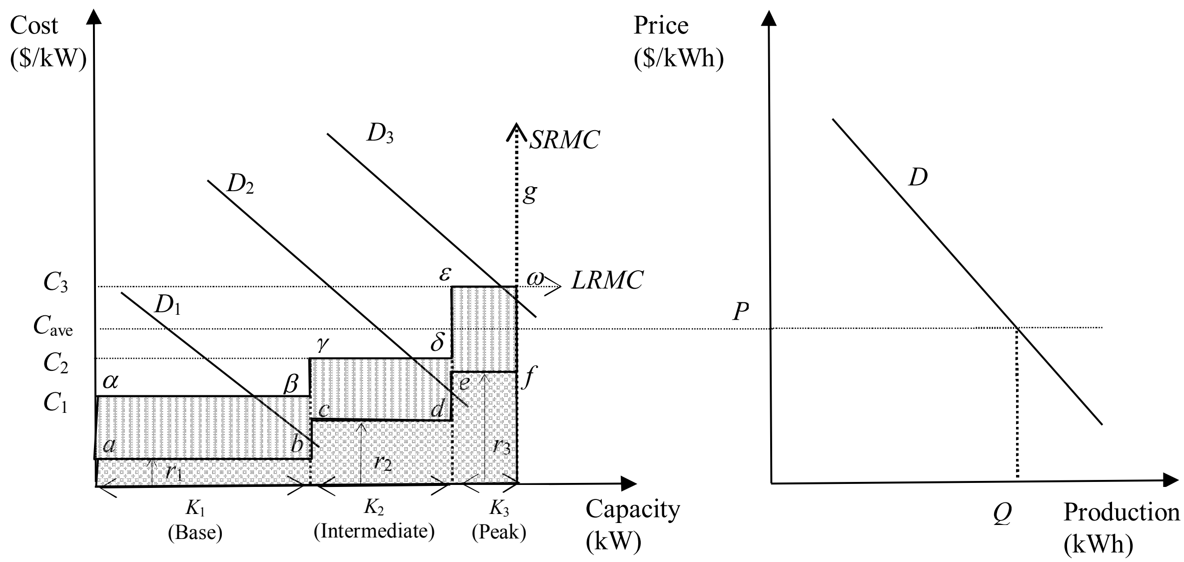

Figure 3
Capacity utilization and production level in the electricity generation market

2.1 Constant returns to scale in production and perfect competition in the market

Now consider the case of an electricity supply technology with constant returns to scale (CRTS) operating in a perfectly competitive (PC) market. CRTS implies the long run marginal cost (LRMC) of production is constant (while short run marginal cost can be increasing with production level due to diminishing returns in the short run).[11] For simplicity, assume that the SRMC is a constant hence average variable cost (AVC) will also be a constant. Short run average total cost (SRATC) therefore will be a decreasing function of production with the minimum being at the point of maximum capacity utilization where LRMC = SRMC + MCC (see Figure 2). If demand in the short run falls short of the maximum capacity utilization level (e.g. D_1 in Figure 2) then to ensure that capacity is utilized to the full extent possible, price may need to fall below the level of LRMC to reach the level of SRMC (e.g. P_1 in Figure 2). On the other hand, if demand far exceeds capacity in the short run then the price level may need to rise above the LRMC (e.g. to P_2 in Figure 2) to ration demand to existing capacity. Only when demand is equal exactly to long run equilibrium level (assumed to be D_{LR} in Figure 2) that the competitive pricing rule P = LRMC will result in both full cost recovery for the supplier and also market equilibrium.

Now, assume that total electricity demand *on average* is represented by a demand curve such as D on the right hand diagram of Figure 3. Since actual demand is highly fluctuating and is assumed to consist of different types or 'loads', the (instantaneous) level of demand can be assumed to be represented by different demand curves such as D_1 (when only the 'base' load is present), D_2 (when both the 'base' and 'intermediate' loads are present), or D_3 (when the 'peak' load is also present). These are represented in the left diagram of Figure 3 with *demand* (i.e. output units in kWh) being converted into *capacity* unit (kW). To cater for the different types (and therefore levels) of demand, supply capacities are also categorized into different types: 'base', 'intermediate', and 'peak' capacities.[12] If these capacities are now 'ordered' along the

[11] LRMC is defined as the minimum of all SRATC (short run average total cost) as the level of 'scale' or capacity is continuously varied. SRATC is the sum of average fixed cost (AFC) and average variable cost (AVC).

[12] In practice, there is also a special type of capacity called "always turned on" which applies to the case of some renewable energy technologies (such as solar, wind, etc.). These capacities are "always turned on' because the outputs from these capacities are not subject to the supplier's decision but are conditional on the natural environment (availability of sunlight, wind, etc.), therefore they must be left 'turned on' (except when under repair or

horizontal axis according to their levels of increasing LRMC costs, then the overall LRMC curve can be said to represent the 'supply curve' (of capacity) for the electricity market.[13] Capacity planning therefore implies the following optimisation problem:

$$\underset{K_i}{\text{Minimise}}\ C_{tot} = \sum_i [r_i Q_i + c_i K_i] = \sum_i [r_i \phi_i T + c_i] K_i \tag{1}$$

$$\text{s.t.}\ \sum_i K_i \geq K_{tot} \tag{2}$$

where C_{tot} is the total production cost over the production time period T and K_{tot} is the (minimum) total capacity required to satisfy demand at all times for the period T; K_i, $i=\{1,2,3\}$ are the 'optimal' levels of capacities for different types. The first order condition for optimality gives:[14]

$$\partial C_{tot} / \partial K_i = [r_i \phi_i T + c_i] = \lambda; \quad i = 1,2,3. \tag{3}$$

where λ is the Lagrange multiplier associated with the total capacity constraint (2). Equation (3) can be interpreted as the requirement that at optimality the LRMC of supply (for a unit of capacity) must be equal to the 'shadow value' of capacity, i.e. λ, for any type of capacity. To determine the value of λ, multiply both sides of equation (3) with K_i and sum up over all i's, we have:

$$V_{tot} + F_{tot} = \lambda K_{tot} = C_{tot} \tag{4}$$

with:

$$\begin{aligned} V_{tot} &= \sum_i (r_i Q_i) \\ F_{tot} &= \sum_i (c_i K_i) \end{aligned} \tag{5}$$

maintenance). The concept of 'load factor' in this case is replaced by the concept of 'availability factor', i.e. the percentage of the total time when output is available from this type of capacity.

[13] For simplicity, it is assumed in Figure 3 that each capacity of a particular type (e.g. base capacity) has a single and constant LRMC curve but in practice, each LRMC curve can be upward-sloping and also consisting of different types dependent on the particular type of technology used. Hence instead of a simple step function as shown in Figure 3, the actual LRMC can be of multi steps or smoothly upward sloping. This, however, will not change the main arguments of the analysis.

[14] Strictly speaking, the values of ϕ_i's can be seen to be related to the choices of K_i's for any given load duration curve, therefore, although the optimization problem of (1)-(2) is formulated in terms of the values of K_i's, the optimal results can be formulated in terms of the values of ϕ_i's rather than K_i's.

The values of V_{tot} and F_{tot} can be referred to as the total variable (i.e. running) and total fixed (i.e. capital) costs respectively and equation (4) says that with optimal capacities K_i's being chosen, the shadow value of capacity will be given simply by the total effective utilization cost per unit of capacity, i.e. (C_{tot}/K_{tot}). From the values of r_i, c_i, and λ, equations (3) can be used to determine the optimal values of the load factors ϕ_i's (and hence the optimal values of K_i's) as follows. First, assume that one of the load factors can be chosen as a 'reference' parameter, ϕ_R (for example, choose the load factor for the base capacity as a 'reference' parameter, i.e. ϕ_1=ϕ_R). Other load factors can then be determined relative to this reference parameter using equation (3):

$$\begin{aligned} \phi_i / \phi_R &= (r_R / r_i)[(c_R - c_i)/(\phi_R r_R T) + 1] \\ &= (r_R / r_i)[(c_R - c_i)(K_R /(r_R Q_R)) + 1] \quad i \neq R. \end{aligned} \tag{6}$$

From equation (6) the (optimal) levels of the load factors can be determined *relative* to an assumed load factor of a 'reference' capacity, i.e. ϕ_R . The find the *absolute* levels of all the optimal load factors, it is necessary to refer to the actual level of the load duration curve. Thus, for example, assuming that $\phi_R^{(0)}$ is the initial value of the load factor assumed for the reference capacity. From equation (6), the (relative) optimal load factors for all other capacities can be estimated. Refer to these as $\phi_i^{(0)}$ and calculate the total outputs produced from all capacities, as $\sum_i Q_i^{(0)} = \sum_i (\phi_i^{(0)} K_i\, T)$. Clearly, it is unlikely that this total will happen to be equal to the *actual* level $\sum_i Q_i$ as derived from the load duration curve, therefore we write: $\sum_i Q_i = \alpha \sum_i (\phi_i^{(0)} K_i\, T)$ where $\alpha \neq 1$. We then iterate the next level of the reference load factor as $\phi_R^{(1)} = \alpha \phi_R^{(0)}$ and re-estimate all the non-reference load factors using (6) again. Repeat this process until the value of α gets close to 1.[15]

With equation (6), it can be seen that if $r_i \cong 0$ then the optimal load factor for capacity *i* should be considered as 'infinite'. This can correspond to the case of some renewable electricity technologies such as wind or solar electricity where running cost is practically zero because there

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[15] We carry out this iteration in one of our experiments (see section 3 below) and the value of α is seen to converge fairly quickly, from .858 to .972 in just two iterations, and then .994 and .999 if the iterations continue. Furthermore, it was also observed that the final absolute values of the optimal load factors are not dependent on the initial choice of a 'reference' load factor. In our experiment, we can choose either coal or oil technologies as a 'reference' case without changing the final results.

is no fuel cost. In practice, however, 'infinite' load factor implies capacity should 'always be left on'[16] which means it is excluded from the optimization problem of equation (1). Therefore, equation (6) in fact applies only to those capacities which have $r_i>0$. In these cases, if we compare two different types of capacities with $r_i>r_R$ but $c_i<c_R$ (for example, comparing oil-based and gas-based electricity to coal based electricity), equation (6) will say that $\phi_i<\phi_R$ and this makes sense. On the other hand, if $r_i<r_R$ and $c_i<c_R$ (for example, the case of biomass or waste-based electricity as compared to coal based electricity), equation (6) will say $\phi_i>\phi_R$ which is also reasonable. Finally, for the intermediate case of $r_i<r_R$ but $c_i>c_R$ (for example, the case of nuclear electricity versus coal-based electricity), equation (6) cannot say definitely whether $\phi_i>\phi_R$ or $\phi_i<\phi_R$ and this depends on the relative magnitudes of c_i and c_R. This is also reasonable. Therefore, all of this can show that equation (6) is indeed a reasonable criterion for guiding the decisions on *outputs* of different technologies to meet with electricity demand in the short run (given fixed capacities). Alternatively, it can also be used in the long run to *plan for capacities* as shown below.

In the short run when capacities (K_i's) are fixed, output allocation will be guided mainly by the relative values of the short run marginal costs (r_i's). If some of these costs are changed (for example, following the imposition of a climate change policy which puts a tax on the emissions of CO_2 in some technologies), the optimal load factors for these technologies will also change. The change in the optimal load factors can be used to guide production changes in the short run when capacities are fixed. This can be explained as follows.

Let K={i} be the set of technologies (also used to denote the set of capacity), and let D={j} denote the set of demand categories.[17] Let A={A_{ij}} be a matrix which describes the proportion of total *capacity* which is of type i and used to cater for demand of type j. We can also define a corresponding matrix B={$\phi_i A_{ij} / \sum_i \sum_j \phi_i A_{ij}$}={$B_{ij}$} which will represent the proportion of total

[16] See footnote 13. In fact, with renewable electricity, the 'load factor' is not a relevant parameter and therefore, it is replaced by the so-called 'availability factor' which is an exogenous parameter rather than one being determined endogenously by optimization

[17] Up to now, it has been assumed that different capacity types are used to cater for different demand categories ('loads' type). However, the match between capacity types and demand loads is not one-to-one, hence the different sets K and D.

output or production which is from capacity i and used to cater for demand of type j. We then have:

$$S_j^D = (\sum_i \phi_i A_{ij}) / \sum_i \sum_j \phi_i A_{ij} = \sum_i B_{ij} = B_j \tag{7a}$$

$$S_i^S = (\sum_j \phi_i A_{ij}) / \sum_i \sum_j \phi_i A_{ij} = \sum_j B_{ij} = B_i \tag{7b}$$

$$\sum_i S_i^S = \sum_j S_j^D = \sum_i \sum_j A_{ij} = \sum_i \sum_j B_{ij} = 1 \tag{7c}$$

where $S_i^S = (Q_i^S / Q^S)$ is the proportion of total output (supply) coming from technology (capacity) of type i, and $S_j^D = (Q_j^D / Q^D)$ is the proportion of total demand belonging to category j. These proportions are given by the column sum and row sum respectively of the B matrix as seen from equations (7a) and (7b). For equilibrium between supply and demand, we also have: $Q^D = Q^S = Q$.

Let $q^S = d\ln Q^S$ be the log-change in total supply and $q_i^S = d\ln Q_i^S$ be the log-change in supply from capacity of type i. We have:

$$\begin{aligned} q^S &= d\ln Q^S = d\ln(\sum_i Q_i^S) \\ &= \sum_i S_i^S d\ln Q_i^S = \sum_i S_i^S q_i^S \\ &= \sum_i \sum_j B_{ij} q_i^S \end{aligned} \tag{8}$$

Similarly, let $q_j^D = d\ln Q_j^D$ be the log-change in demand of category j, and $q^D = d\ln Q^D$ be the log-change in total demand.[18] We have:

[18] Q^D is the total area under the load duration curve, and Q_j^D is the component area covered only by the specific demand load of type j (see Figure 1).

$$
\begin{aligned}
q^D &= d\ln Q^D = d\ln(\sum_j Q_j^D) \\
&= \sum_j S_j^D d\ln Q_j^D = \sum_j S_j^D q_j^D \qquad (9)\\
&= \sum_i \sum_j B_{ij} q_j^D
\end{aligned}
$$

In the short run when capacity is fixed, we simply have: $q_i^S = d\ln Q_i^S = d\ln \phi_i$.

2.1.1 Static short run production analysis.

If we now assume that in the short run, not only are capacities being fixed, i.e. $q_i^S = d\ln Q_i^S = d\ln \phi_i$, but there are no relative supply-price (or cost) movements between the different technologies. This means production decisions can be based simply on a *static* picture of the relative cost differences between different technologies which in turn resulted in the *relative* optimal load factors of the different capacities as given by equation (6), then we can assume that $q_i^S = d\ln \phi_i = \gamma + d\ln \phi_i^*$ where γ is a constant to be determined by the equilibrium condition between total supply and total demand in the short run.[19] Now we can now set the market equilibrium as $q^S = q^D = q$, and from equations (8) and (9), we have:

$$
\sum_j \sum_i B_{ij} q_j^D = \sum_i \sum_j B_{ij} q_i^S
$$

or

$$
\sum_j S_j^D q_j^D = \sum_i S_i^S q_i^S = \gamma + \sum_i S_i^S d\ln \phi_i^* \qquad (10)
$$

Equation (10) can then be used to estimate the equilibrium value for γ which is then used to determine the optimal supply from various capacities as given by the relationship $q_i^S = d\ln \phi_i = \gamma + d\ln \phi_i^*$.

[19] We also note from equation (6) that optimal load factor is a *relative* concept, i.e. its absolute level cannot be determined without reference to a specific equilibrium condition between total supply capacities and total demand for all of their outputs. Therefore the constant γ can be interpreted as a necessary parameter for this equilibrium condition, rather than as an arbitrary factor to relate the *actual* load factor level ϕ_i to its optimal value ϕ_i^*.

Consider, for example, a simple situation where demand from various categories change by the same proportion[20] (which is also equal to the proportionate change in total demand), i.e. $q_j^D = q^D; \forall j$. In this case equation (10) can be re-written as:

$$\gamma = q^D - \sum_i S_i^S d \ln \phi_i^* \tag{11}$$

i.e. the value of γ is given simply by the difference between the log-change in total demand q^D and the quantity share-weighted log changes in optimal load factors.

2.1.2 Dynamic short run production analysis.

Optimal load factors take into account the *static* (but optimal) supply *constraints* with respect to production activities in the short run, but it does not take into account the full *dynamic* picture of production variation over time when the supply-price or cost levels of various technologies can change (even if the relative optimal load factors do not change). This means the equilibrium 'constant' γ in equation (11) needs to be interpreted as a static equilibrium condition for total supply/demand rather than as a behavioral parameter to be used for setting the supply levels of various technologies over time. To avoid using this static parameter in such a dynamic situation, we can revise the condition $q_i^S = d \ln \phi_i = \gamma + d \ln \phi_i^*$ as follows. Firstly, we can let $q_i^S = d \ln \phi_i \leq d \ln \phi_i^*$ when $\phi_i \leq \phi_i^*$ and $d \ln \phi_i^* > 0$. On the other hand, if $\phi_i > \phi_i^*$ and $d \ln \phi_i^* < 0$ then we set $q_i^S = d \ln \phi_i = d \ln \phi_i^*$. The first condition implies ϕ_i^* continues to act as though a constraint to production level even if this constraint is not binding. The second condition represents the situation when the optimal load factor constraint actually becomes binding. The use of ϕ_i^* therefore is being restricted to being just a constraint (actual[21] as well as optimal) to production activities, but not being used to set production levels.

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[20] i.e. the 'shape' of the load duration curve remains the same even if the absolute level of the curve has shifted. In this case, it can be assumed that the 'structure' of underlying demand loads (i.e. shapes of *individual* load curves) have remained the same, and this means the quantity shares of all the loads stay the same, not only for the overall time period, but also for specific individual time-periods.

[21] In estimating the values of ϕ_i^* according to equation (6), the actual (i.e. physical) limits to these optimal values are implicitly incorporated because the absolute level of ϕ_i^* is determined only in relation to a particular

To set the actual levels of production, we can rely on standard microeconomic theory of production in the short run, i.e. using the short run marginal cost curve of each technology as a 'supply' curve, and from this, estimate a short run 'price elasticity of supply' for each technology (E_i^S). With this elasticity parameter, and with ϕ_i^* acting as a constraint, we can now set production levels as follows:

$$q_i^S = d\ln\phi_i^* \leq d\ln\phi_i = E_i^S d\ln P_i^S \quad \text{if } \phi_i > \phi_i^* \tag{12a}$$

$$q_i^S = d\ln\phi_i = E_i^S d\ln P_i^S \leq d\ln\phi_i^* \quad \text{if } \phi_i \leq \phi_i^* \tag{12b}$$

From equation (12a), it can be seen that if E_i^S is very large (supply curve is almost horizontal[22]) then ϕ_i^* will always act as a *binding* constraint[23]. On the other hand (equation (12b)), if E_i^S is very small, almost zero (supply curve is almost vertical[24]) then we end up with ϕ_i^* still acting as a constraint, but almost always *non*-binding.

2.1.3 Long run capacity planning

For the long run, when capacities can be changed, the planning for different capacities can proceed as follows. Firstly, we note that optimal load factors can change in the long run not only due to expected changes in *running* costs in the future but also to changes in marginal *capital* costs (see equation (6)). Secondly, demand levels in the future are also expected to change. Therefore, capacity changes in the future can be given by the following relation:

$$\begin{aligned} d\ln K_i &= d\ln Q_i^S - d\ln\phi_i^* = q_i^S - d\ln\phi_i^* \\ &= (1/S_i^S)[q^S - \sum_j \sum_{k\neq i} B_{kj} q_j^D] - d\ln\phi_i^* \end{aligned} \tag{13}$$

---

equilibrium condition, therefore implicitly ϕ_i^* is optimal but also within the boundary of 'actual' (i.e. technologically *feasible*) values.

[22] For example, unlimited wind or solar powered electricity at zero production cost because these resources – if available – are 'free'. Also, if coal-based electricity is available, and coal is very cheap, its supply curve can also be considered as though horizontal.

[23] This case is equivalent to the 'static' pricing condition considered in the previous section.

[24] Which may represent a situation of physical resource constraint, such as wind or solar electricity production being bounded by actual the actual wind or solar condition of a particular region rather than being constrained by economic cost of production.

In the simple case when it is assumed $q_j^D = q^D = q^S = q; \forall j,$ equation (12) can reduce to:

$$\begin{aligned} d \ln K_i &= (1/S_i^S)[q^S - \sum_{k \neq i} S_k^S q^D] - d \ln \phi_i^* \\ &= q - d \ln \phi_i^* \end{aligned} \tag{14}$$

Equation (13) can be used to determine the level of planning for capacity of various technologies, depending on the changes in the level of their optimal load factors in the long run, as well as on the predicted changes in the level of demand for electricity of various categories. This equation gives more details as to the ('bottom-up') factors that can affect investment in a particular type of technology/capacity as compared to a the more 'general' approach of a conventional top-down model. In the latter case, the concern is often focused only on a 'rate of return' to capital investment – usually applicable to the whole electricity sector rather than to any particular technology, and no details are mentioned of the technological factors (such as load factor optimization and constraints) or economic factors (such as demand variation and changes between different categories, i.e. the level and shape of the load duration curve). The new approach presented here thus can be regarded as an improvement, not only over the conventional 'top-down' approaches, but also over a standard bottom-up model where capacities are often assumed as fixed or given exogenously rather than being considered as factors which can be endogenous determined within the model.

2.2 Imperfect Competition

So far, it has been assumed that the marginal capacity costs (c_i) are constant for all capacity types, implying that all technologies are subject to constant returns to scale (CRTS) and furthermore capacity level K_i can be continuously varied ('infinitely divisible') so that it can correspond exactly to the optimal level as indicated by the intersection between the long run demand curve and LRMC curve (see Figure 2). In practice, however, some technologies may exhibit a certain degree of scale economies due to a number of factors. For example, these technologies may require large up front capital investments which cannot be divided into smaller (optimal) amount (problem of so-called capital indivisibility or 'lumpiness').[25] In such a case, the

[25] The 'lumpiness' of capital or capacity can arise from factors other than technological. For example, coal-fired power stations may need to be located nearer to the source of coal supply (mines or ports) to minimize transport costs. Nuclear powered stations may need to be located nearer to the source of water supply (for cooling purposes).

actual *installed* capacity would tend to be larger[26] than the optimal level and this means the average long run total cost (ATC) will tend to be a decreasing function of production level rather than being a constant (at the minimum ATC level). In this case the LRMC (minimum long run ATC) will stay below the actual level of ATC and therefore competitive pricing rule (price = LRMC) cannot apply because such a pricing rule will result in producers running at a loss. Scale economies, on the other hand, imply some degree of 'natural monopoly' or market power (Baumol, 1977). This means instead of the competitive pricing rule, producers can mark-up the supply price over LRMC and control the level of production accordingly. The extent of this price mark-up will depend on the strength of the market power that each supplier possesses. Thus, for example, in a model which assumes one or two 'dominant' suppliers among a group of 'fringe competitors'[27], the dominant suppliers are those who possess some degree of market power such that they together can act as though Cournot oligopolists restricting supply to raise the price above the LRMC level to maximize their profits. The Cournot oligopolists (as a group) will face with a demand curve which is 'residual' from the total market demand curve after subtracting the competitive supply curves (i.e. LRMC curves) of all the 'fringe competitors', i.e. we have:

$$Q_{tot} = \sum_{i \in L} Q_i + \sum_{j \in F} Q_j = Q_L + Q_F \qquad (15)$$

where Q_{tot} is the total level of demand for the market, Q_i and Q_j are the outputs of individual i and j respectively in the L- and F-groups (L stands for '*L*eaders' and F stands for '*F*ringe'). Assuming that fringe competitors behave as perfect competitors, i.e. their output and capacity decisions will continue to be determined by the optimal relation: $q_i^S = d \ln \phi_i = d \ln \phi_i^*$ as described in the previous section,[28] this then leaves only the decisions of members of the L-group to be considered in this section. Since total Q_L is 'given' (as the 'residual' demand from Q_{tot} after

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Both are also to be located further away from residential areas to conform to environmental regulations. This results in geographical concentration and hence in capital 'lumpiness' of these power plants.

[26] It can also be smaller, but for reason of security of supply (to avoid the problem of black out or brown out when demand temporarily exceeds normal total supply) it is more likely to be larger.

[27] This is the so-called 'dominant versus fringe competitors' model of electricity supply, often adopted in most 'bottom-up' approaches, see for example, Cardell, Hitt, and Hogan (1997), Bonacina and Gulli (2007), Wolak (2007).

[28] In this case, there is no need for the adjustment constant γ for the F-group because the supply by the L-group will act as a 'residual' which ensures total supply and demand are in equilibrium, because $\sum_{i \in L} S_i^S q_i^S = q^S - \sum_{j \in F} S_j^S q_j^S = q^D - \sum_{j \in F} S_j^S d \ln \phi_j^*$ where S_i^S and S_j^S are relative shares within the L-group and F-group respectively, i.e. $S_i^S = Q_i^S \sum_{k \in L} Q_k^S$, and $S_j^S = Q_j^S \sum_{k \in F} Q_k^S$.

taking away the total output Q_F of the F-group), the only issue is how the Cournot oligopolists will share this total among themselves. Cournot oligopolists are known to maximize their own profits according to the following model:

$$Max_{Q_i} \pi_i (Q_i, \overline{Q}_i) = P_L(Q_i + \overline{Q}_i).Q_i - C_i(Q_i) \tag{16}$$

Here, $\pi_i(Q_i, \overline{Q}_i)$ is the profit function of the ith-member in the L-group, taking the level of production of all other members in this group, i.e. $\overline{Q}_i = (Q_L - Q_i)$, as given; $P_L(Q_i + \overline{Q}_i)$ is the inverse of the residual demand function, and $C_i(.)$ is the total cost function for the i-producer. Assuming that both $P_L(.)$ and $C_i(.)$ are differentiable, then the first-order condition for optimality is given by:

$$P_L + (\partial P_L / \partial Q_i).Q_i - dC_i / dQ_i = 0 \tag{17}$$

The first two terms on the left-hand side of the equation represent the marginal revenue from an additional unit of output, while the third term represents the marginal cost (MC_i) of that output.[29] Given that each Cournot oligopolist takes the total outputs of all other members are given, this implies dQ_i=dQ_L, or $(\partial P_L / \partial Q_i) = (dP_L / dQ_L)$. Equation (16) can then be written in an alternative form:

$$\begin{aligned}(P_L - MC_i)/P_L &= -(Q_i / Q_L)(dP_L / dQ_L)(Q_L / P_L) \\ &= (S_i^S / \mathrm{E}_L^D)\end{aligned} \tag{18}$$

Equation (18) says that a Cournot oligopolist's price mark-up over its MC is proportional to its market[30] share within the group (i.e. $S_i^S = Q_i^S / Q_L^S$) and inversely related to the price elasticity of the residual demand curve (i.e. E_L^D). If MC is to change, for example following the imposition of some climate change or energy policies in the electricity sector, then the level of equilibrium supply price for the L-group as a whole will also change. This determines not only the supply price for the L-group but also for the F-group (since they are price-takers or price-followers), i.e.

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[29] Note that in contrast to the optimization problem (1) which is concerned with *capacity* planning (in the long run), optimization problem (16) is concerned only with profit maximisation in the short run, i.e. conditional on the given levels of capacities. Therefore, the value of $dC_i/dQ_i = MC_i$ in equation (17) is to be interpreted as equal to the value of the short run (i.e. running) cost r_i.

[30] Note that this 'market share' is defined in terms of quantity rather than cost- or value share. See also footnotes 16 and 18 above.

for the market as a whole. From equation (18), let λ_i be the ratio (or power of change) of the *MC* for the *i*-supplier, i.e. $\lambda_i MC_i$ is the 'new' marginal cost level compared to the 'old' level MC_i. If similarly λP_L is defined as the 'new' equilibrium price for the *L*-group as a whole compared to the 'old' equilibrium price P_L, then a relationship between λ and the λ_i's can be determined as follows. Let S_i and S_i^* be the 'old' and the 'new' shares for supplier *i* respectively following changes to the equilibrium price. From equation (18) we can write:[31]

$$\mathrm{E}_L^D (P_L - MC_i) / P_L = S_i \tag{19a}$$

$$\mathrm{E}_L^D (\lambda P_L - \lambda_i MC_i) / (\lambda P_L) = S_i^* \tag{19b}$$

Summing over all *i*'s in equation (19a) and (19b) and noting that $\sum_{i\in L} S_i = \sum_{i\in L} S_i^* = 1$, we have

$$\sum_{i\in L} [(\lambda P_L - \lambda_i MC_i) / \lambda P_L] = \sum_{i\in L} [(P_L - MC_i) / P_L] \tag{20}$$

or:

$$\lambda = \left(\sum_{i\in L} \lambda_i MC_i \right) / \left(\sum_{i\in L} MC_i \right) \tag{21}$$

Equation (21) says that λ is simply the marginal-cost-weighted average of all the λ_i's. Equation (21) can then be used to determine the new equilibrium price (for the *L*- group and the market as a whole), and given this equilibrium price, the outputs for members of the *L*- group can be determined accordingly. For example, equation (19a) can be used to 'calibrate' the value of the elasticity E_L^D assuming an initial equilibrium price for the oligopolists (which is also the initial equilibrium price for the market). Given this elasticity value, equation (19b) then can be used to determine the new share S_i^* for the *i*th-member of the *L*-group.

As an alternative to equation (21), we can also sum up equation (18) over the *L*-group to give:

---

[31] Assuming that the price elasticity of demand for the residual demand curve E_L^D is an 'arc-elasticity', i.e. measured as an average over the two price situations.

$$[P_L - (\sum_{i \in L} MC_i)/n]/P_L = (1/\mathrm{E}_L^D)] \tag{22a}$$

or:

$$P_L = (\sum_{i \in L} MC_i)/[n - (1/\mathrm{E}_L^D)] \tag{22b}$$

where n is the number of members in the L-group. Equation (22) is equivalent to saying that the oligopolists as a whole acts as though as a monopolist, with price markup over the (average) marginal cost given by the inverse of the price elasticity of the (residual) demand curve. Equation (22b) can therefore be used to determine the ('new') equilibrium price P_L for the monopolist (and the market as a whole) following some policy 'shocks' to the marginal costs. Once this new equilibrium price is determined, the relative market shares between the oligopolists can then be determined via equation (18) or (19a)-(19b) as before. The relative market shares must of course be conditional on the feasibility of production levels given the (short run) fixed capacities of all the oligopolists. Therefore, we can impose the 'feasibility' constraints on these shares as follows:

$$\begin{aligned} d\ln S_i^S &= d\ln Q_i^S - d\ln Q_L^S \\ &\leq d\ln\phi_i^* - [d\ln Q^S - \sum_{j \in F} S_j^S d\ln Q_j^S] \end{aligned} \tag{23}$$

The first term on the right hand side of equation (23) indicates the constraint that – given fixed capacity, production changes cannot exceed the change in (optimal) load factor. The terms within the square brackets on the right hand side of equation (23) stands for the change in 'residual' demand (i.e. total 'residual supply' from of the L-group), taking into account changes in total supply ($d\ln Q^S$) and changes in supply of the F-group.

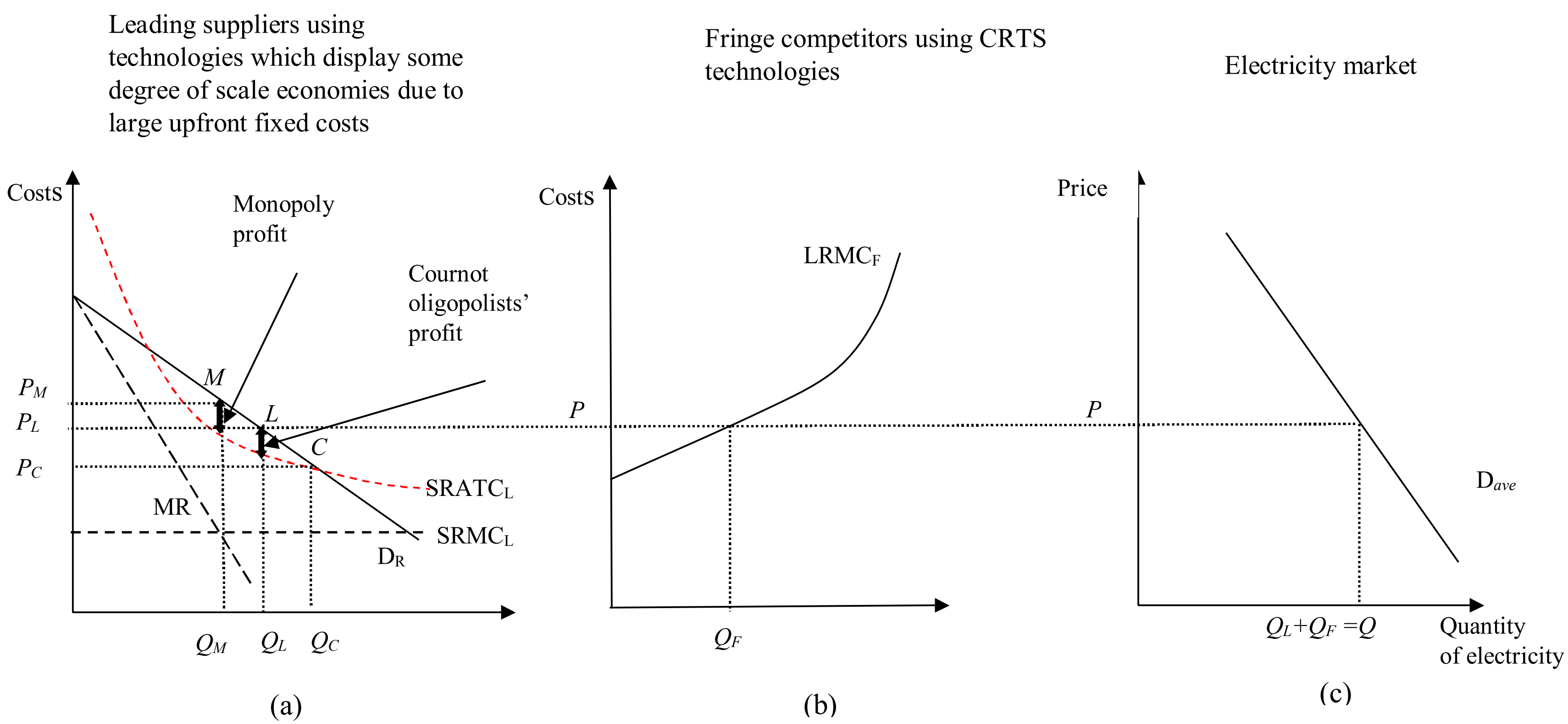

Figure 4
Strategic behaviour between (a) Cournot oligopolists price leaders (*L*) using technologies which have scale *e*conomies, and (b) perfectly competitive fringe suppliers (*F*) who use technologies which have no scale economies, in (c) the electricity market (graphs are not to scale).

3. Application to the case of Japan

Electricity in Japan is produced from coal, oil, gas, nuclear energy and hydro power with some small proportions from renewable energy sources. To decompose the electricity sector in the GTAP v9 data base[32] (Aguiar *et al.*, 2016) into these different technologies, we use a methodology which can be described as follows. First we define the set of electricity generation technologies as consisting of those using coal, oil, gas, nuclear energy, hydro power, onshore wind, solar energy, biomass, waste, and other renewable energy (mainly geothermal). To facilitate a study into future usage of carbon capture and storage (CCS) technologies, we also add coal CCS, oil CCS, and gas CCS to the set of technologies by taking away 1% of the shares from coal, oil, and gas respectively and giving these to the CCS counterpart.[33] Next, to distribute the values of the inputs into the electricity sector in the GTAP data base to these technologies, we make the following assumptions.

a. *Generation activities*: generation activities are technology specific, therefore the distribution of fuels, capital, labour and non-fuel materials inputs into these technologies must vary according to the different cost structures of these technologies:

i. *Fuel inputs*: All coal inputs into the electricity sector are assumed to go into the coal and coal-CCS technologies in proportion to their outputs[34]; similarly for gas as fuels into gas and gas-CCS technologies, and oil (and p_c) as fuels into oil and oil-CCS technologies. For nuclear technology, in principle, uranium should be considered as the main source of fuel into this technology. However, in practice, since there is no explicit 'uranium' commodity in the GTAP data base, a 'proxy' fuel must be found such that this can adequately represent the extent of fuel inputs into (and therefore, running costs of) this technology. First, we look at commodity 'omn' (other mining and minerals nec commodities) which is supposed to include 'uranium' within it, but in the GTAP data base, 'omn' makes up only a negligible value compared to the value of nuclear

[32] We use GTAP v9 database but choose the base year as 2007 rather than 2011. This is because 2011 is the year of the Fukushima accidents and we want to use the model to test the impacts of the Fukushima accidents, hence 2011 cannot be chosen as the base year.
[33] This small proportion will not affect greatly the accuracy of the initial data base but will allow the simulation of the growth of CCS technologies to be carried out because growth cannot occur on a zero initial basis.
[34] We assume that CCS technologies use 20% more fuels than non-CCS counterpart However, the emissions levels from CCS technologies are assumed to be 1/10 of the emissions from non-CCS counterparts, i.e. 9/10 of the emissions are 'captured and stored', see IPCC (2005).

electricity output. Therefore, this cannot be a main fuel source for nuclear electricity. Next, we look at the 'p_c' commodity (which is described as including also the 'processing of nuclear fuel'). However, since almost all of the p_c commodity input into the electricity sector has been allocated to the oil and oil-CCS technologies (to make up the required 'fuel-to-output' ratios for these technologies), there is little left to be considered as significant input into other technologies. Therefore, we finally look at *electricity* as a potential candidate. Electricity input makes up about 10% of the value of total electricity output which is a significant figure that cannot be attributed simply to 'own consumption' or considered as part of the 'transmission and distribution losses'. The only feasible alternative explanation for this level of electricity input is that it must have been used as part of the total fuels input into the production of nuclear electricity, e.g. used in the processing of uranium. We therefore allocate a significant part of this total electricity input into the electricity sector as fuels to the nuclear technology, to make up to a level of about 21% of the total value of the nuclear electricity technology output.[35] The rest of the electricity input is then distributed to all other technologies (including 'non-generation' activities) in accordance with the values of their outputs. Finally, for the rest of other technologies, we make the following assumptions: (1) for Biomass technology, we assume that all 'agricultural and forestry commodity inputs' into the electricity sector can be regarded as 'fuels' for the Biomass technology; (2) for electricity produced from 'waste' (ElyWas), since 'waste' is in principle 'a commodity of no value', there is no explicit representation of the value of waste in the data base; however, 'waste' can be considered as part of the 'margin' commodity in the 'trade and transport' of commodities from producers to consumers, therefore, we assign a small proportion of this margin commodity to the 'fuels input' into the ElyWas technology to make up to a level of 10% of the total value of this technology output.

ii. *Capital inputs*: we use the EIA (2013) and IEA/NEA/OECD (2010) information on 'overnight capital cost' ($/kW) – see Table 1, and also information on installed capacities (Million kW) for electricity generation by various technologies in Japan[36] to estimate the values of the capital *stock* ($US million) in these technologies. The 'capital'

[35] 21% is the empirically accepted value of fuel-to-output ratio in the nuclear electricity technology for Japan in 2007.

[36] http://www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm?tid=2&pid=2&aid=7.

endowment input in the GTAP database, however, refers to the value of capital *services* rather than capital stock. However, if we assume that the values of capital services are also in proportion to the values of the capital stocks, then we can use the latter to distribute the former. For the total value of capital services associated with the generation of electricity (as versus in non-generation activities), we assume a proportion of 67.7% (i.e. 32.3% is the total value of capital services are assumed to be associated with non-generation activities).

iii. *Labour inputs*: the EIA (2013) information on fixed ($/kW-yr) and variable ($/MWh) O&M (operation and maintenance) costs – see Table 1, together with the information on production outputs (billion kWh) of various technologies can be used to estimate the total value of O&M costs for each technology. Assuming that these costs would consist mainly of labour (and some material costs), the relative proportions of these costs for different technologies therefore can then be used to distribute the total value of labour endowment in the generation of electricity. Again, as in the case of capital services, we assume 67.7% of the total value of all labour inputs into the electricity sector is associated with generation activities (leaving 32.3% to be allocated to the non-generation activities).

iv. Intermediate material inputs: non-fuel material inputs into the electricity sector can be allocated to generation and non-generation activities as follows. Firstly, as in the case of capital and labour inputs, we assume 32.3% of all non-fuel material inputs into the electricity sector are allocated to non-generation activities.[37] The rest is then allocated to the generation technologies in such a way that the total supply prices of all technologies are in accordance with some empirically estimated relative supply price.

b. *Non-generation activities*: As already mentioned above, 32.3% of the total value of capital, labour, and some non-fuel material inputs into the electricity sector output in Japan in 2007 are assumed to belong to non-generation activities. This makes up about 20.8% of the total value of the total electricity sector output (see Table 2).

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[37] Except for 'agricultural sector' commodity inputs which have already been allocated to biomass technology, 'minerals' which are allocated to nuclear technology, part of the margin commodities which are allocated to the electricity-from-waste technology.

Table 1: Cost Characteristics of Electricity Generating Technologies in the US and Japan

Code	Technology Description	EIA Specification	Overnight Capital Cost ($/kW)	Fixed O&M Cost ($/kW-yr)	Variable O&M Cost ($/MWh)
ElyCoa	Coal	Scrubbed Coal New	2,719	31	4
ElyOil	Oil	Conv. Gas/Oil Comb Cycle	915	13	4
ElyGas	Gas	Advanced Gas/Oil CC	1,549	15	3
ElyNu	Nuclear	Advanced Nuclear	5,501	93	2
ElyHyd	Hydro	Conventional Hydroelectric	2,936	15	3
ElyWon	Wind	Onshore Wind	2,213	40	0
ElySol	Solar	Photovoltaic	3,564	25	0
ElyBio	Biomass	Biomass CC	4,114	106	5
ElyWas	Waste	Municipal Solid Waste	8,312	393	9
ElyOth	Other Renewables	Geothermal	2,494	113	0
CoaCCS	Coal CCS	Dual Unit Advanced PC with CCS	6,567	73	8
OilCCS	Oil CCS	Advanced CC with CCS	2,084	32	7
GasCCS	Gas CCS	Advanced CC with CCS	2,084	32	7

Source: Figures for Japan are from IEA/NEA/OECD (2010) Table 3.1 and for the US are from EIA (2013), Cai and Arora (2015).

Table 2: Output and cost components of the generating and non-generating activities in the electricity sector in Japan in 2007

Technology	Output share	Output (Billion kWh)	Capacity (Million kW)	Capital ($ mill.)	Labour ($ mill.)	Natural Resource ($ mill.)	Fuels ($ mill.)	Non-fuels ($ mill.)	Supply price ($/kWh)
ElyCoa	0.252	259.7	43.9	4310.1	3183.8	0	6904.5	7076.9	0.083
ElyOil	0.130	134.0	78.6	2599.0	1641.6	0	26514.1	3650.8	0.257
ElyGas	0.273	281.3	54.5	3050.5	2586.0	0	15636.9	7666.6	0.103
ElyNu	0.256	263.8	47.5	9436.2	1624.3	0	4601.6	7189.2	0.087
ElyHyd	0.076	78.3	47.3	4015.4	719.9	1004	161.5	2134.3	0.103
ElyWON	0.0009	0.9	1.5	97.7	0.012	24	1.8	24.0	0.168
ElySol	0.0007	0.7	1.9	197.7	0.005	49	1.4	18.4	0.394
ElyBio	0.0055	5.6	2.1	316.1	86.4	0	13.4	153.5	0.101
ElyWas	0.0020	2.1	0.8	237.4	58.0	0	63.3	57.1	0.199
ElyOth	0.0010	1.0	0.5	38.4	0.040	10	2.1	27.9	0.076
CoaCCS	0.0010	1.0	0.2	41.7	25.3	0	32.5	28.1	0.124
OilCCS	0.0010	1.0	1.2	92.7	22.1	0	244.3	28.1	0.376
GasCCS	0.0010	1.0	0.2	18.5	22.1	0	68.3	28.1	0.133
Non-GEN(*)				8252.2	4756.5		754.4	13339.5	0.030
Total	1.000	1030.5	280.3	32703.5	14726.1	1087.3	55000.1	41422.3	0.144

(*): non-generation (transmission and distribution) activities.

From the output, capacity, and cost information in Table 2, we can calculate the actual load factor (ALF) for different technologies in Japan in 2007 and compare these with the theoretically 'optimal' values (OLF) which are estimated using equation (6). These values are shown in Table 3. It can be seen from this Table that the actual load factors for fossil fuel technologies (ElyCoa, ElyOil, ElyGas) are generally higher than their theoretical optimal values, whereas the opposite is true for nuclear, hydro and other renewable technologies.. This implies that fossil fuel technologies are being 'over utilized' inefficiently and the opposite is true for non-fossil fuel technologies. This information is useful because it indicates that (in the short run) there are rooms for reducing the use of fossil fuel technologies and increasing the use of non-fossil fuel technologies and this will in fact improve on the efficient utilization of existing capacities.

Table 3: Actual and Optimal Load Factors for Different Generating Technologies in Japan in 2007

Technology	Actual load factor (ALF)	Optimal load factor (OLF)	Availability factor (AF)	Actual LF/ Optimal LF (ALF/OLF)	Optimal LF/ Avail. Factor (OLF/AF)
ElyCoa	0.676	0.560	0.9	1.21	0.62
ElyOil	0.195	0.156	0.9	1.25	0.17
ElyGas	0.589	0.402	0.9	1.47	0.45
ElyNu	0.634	0.727	0.9	0.87	0.81
ElyHyd	0.189	0.450	0.45	0.42	1.00
ElyWon	0.066	0.250	0.25	0.26	1.00
ElySol	0.040	0.120	0.12	0.34	1.00
ElyBio	0.302	0.700	0.7	0.43	1.00
ElyWas	0.302	0.434	0.7	0.70	0.62
ElyOth	0.219	0.700	0.7	0.31	1.00
CoaCCS	0.669	0.444	0.9	1.51	0.49
OilCCS	0.096	0.129	0.9	0.74	0.14
GasCCS	0.478	0.322	0.9	1.49	0.36

Having decomposed the electricity sector data for Japan into various technologies, the next step is to implement the theoretical structure of this sector (as explained in section 2) into a CGE model[38] and use this for various simulation experiments. The implementation consists of creating three options: (1) all technologies in the electricity sector are assumed to be subject to constant returns to scale and all suppliers are perfect competitors (see section 2.1), this option is referred to as the 'perfectly competitive' (PC) scenario; (2) some technologies[39] in the electricity sector are assumed to be market 'leaders', i.e. possessing some degree of market power due to the inherent 'scale economies' in their cost structures, and if these market leaders are assumed to act as though Cournot oligopolists (as described in section 2.2) then this option is referred to as the 'imperfectly competitive' (IC) scenario; (3) finally, to facilitate a comparison with a 'conventional' approach where the so-called 'technology bundle' approach (using a CRESH production function) is used, we also implement this approach in the model, and refer to this option as the 'CRESH' approach.[40] With a CRESH approach, there is the issue of value-preserving (i.e. sum of all the values of technology 'inputs' should equal the value of total electricity output) or 'volume (or quantity)-preserving' (i.e. sum of all the *quantities* of technology 'inputs' should equal the total quantity of electricity output), therefore, we distinguish between these two cases by referring to them respectively as CRESHV (value-preserving) and CRESHQ (quantity-preserving) cases. Furthermore, a CRESH approach does not pay attention to the issue of capacity (i.e. 'optimal' load factor) constraint. Therefore, to facilitate a comparison with our approach, this restriction is also implemented as an option (L).[41]

Experiment 1: Japan's heavy reliance on non-nuclear technologies following the Fukushima accidents

After the accidents at the Fukushima nuclear power plants in Japan in March 2011, electricity generation in Japan had to rely mainly on natural gas, coal, and petroleum products with some

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[38] We use the GTAP-E model (Burniaux and Truong, 2002) as a basic platform to implement this structure and the modified model is then referred to as GTAP-ETD for "GTAP-E model with electricity 'Technology Decomposition'

[39] The model is flexible with respect to this choice because in practice, different market situations in different countries or regions may have different sets of technologies which can play the role of 'dominant' suppliers. For the case of Japan, we assume that (after the Fukushima accidents) only coal, gas technologies can play this role.

[40] Details of this approach are given in the Appendix.

[41] This means 'CRESHQ' implies a standard CRESH approach with quantity-preserving restriction but no load-factor restriction. This means the load factor can exceed 1, which is infeasible. In our approach, we impose the restriction that load factor cannot exceed the 'optimal' value implied by equation (6). Therefore, only CRESHQL would be comparable with our approach.

small contribution from hydro and other renewable technologies to replace nuclear electricity capacity which was damaged in this accident (see Figure 5). To test the realism of our model in describing the Japanese electricity sector, we use the model to simulate a scenario of 'Fukushima accidents'. To simulate this scenario, we shock the level of electricity generation *capacity* as well as *output* of nuclear technology by about -93% (this represents a fall in nuclear electricity output from a level of around 263.8 billion kWh in 2007 to a level of about 17.5 billion kWh in 2012 after the accident). We also shock the *total* level of electricity generation in Japan by about -8.7% (representing a fall in total electricity production from 1030.5 billion kWh in 2007 to 940.8 billion kWh in 2012). Note that in our model, we make a distinction between supply structure (composition of different types of capacities) and demand structure (composition of different types of demand), therefore an assumption must be made about the relationship between the two (i.e. structure of the A matrix as described in section 2.1).[42] This is described in Table 4. We then let the model work out the various shares of all the technologies in the electricity market as well as estimating the possible increase in electricity price following these changes in supply capacity and outputs. The results are shown in Figures 6 and 7.

In Figure 6, it can be seen that following the Fukushima accident, coal oil and gas (and also renewable) energy were used to replace nuclear energy in the generation of electricity and therefore the market shares for these technologies expanded. With a conventional CRESH approach, it seems all technologies (including hydro) will share in this expansion. However, with our new approach, it seems gas technology will enjoy the greatest expansion then followed by coal and oil. Hydro electricity does not expand as much as predicted by the CRESH approach. When we compare these model predictions with the actual data in 2013, it is clear that our model predictions are much closer to the actual result of 2013. Comparing the results of the PC and IC assumptions, it seems they are fairly close, although the outputs (and hence market shares) for gas and coal technologies (assumed to be 'dominant' players) are slightly less for the IC case as compared to the PC case. This is to be expected because suppliers with some market power would tend to restrict production output to raise the price level. This is confirmed in Figure 7 where the price increase for the IC case is slightly higher than that for the PC case (12.58% as compared to (12.55%) although this difference is almost negligible (partly because this is the

[42] The A matrix is given exogenously (and can be shocked) but the B matrix is endogenously determined because it depends on the optimal values of the load factors.

short run). The price increase for the case of CRESH approach seems to be the highest at 12.65% but only for the case of 'quantity-preserving' restriction (CRESHQ), otherwise, price increase would be smaller at (11%) if this restriction is not imposed (CRESHV). All the price increases by all approaches as predicted by the model do fall within the range of the actual price increases in 2012 when household experienced a price increase of 8% and industrial customers, 15%. These actual price increases continued to magnify through to 2013, when their values are nearly double of those in 2012. All this seem to indicate that our model predictions are very much 'short run' predictions, and this is also to be expected.[43]

[43] The 'closure' for our Fukushima experiment is a 'short run' one with all factor endowments assumed to remain unchanged and the only 'shocks' to the economy are those relating to capacity and total output of the electricity sector.

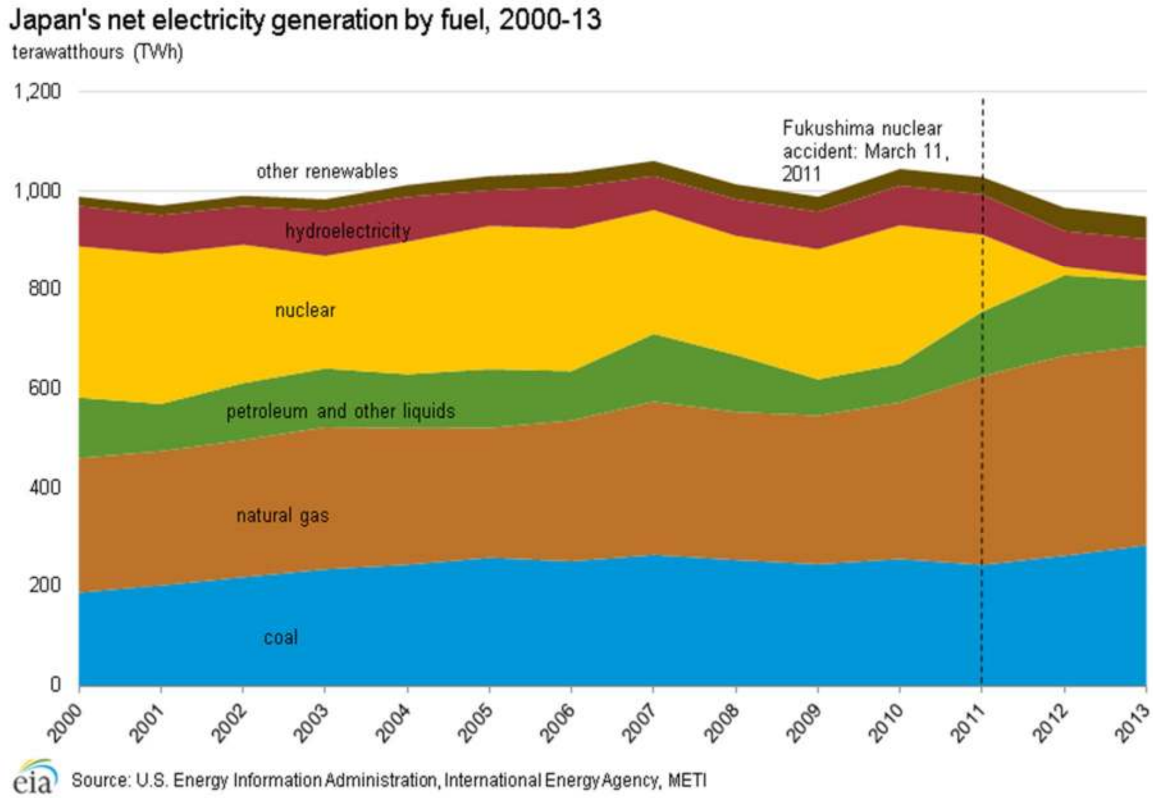

Figure 5
Japan's net electricity output by different technologies before and after the Fukushima accident in 2011

Table 4: Shares of supply and demand categories in the electricity generation market for Japan in 2007

Technology (supply options)	Shares of demand categories supplied by each supply option category			
	Peak	Intermediate	Base	Total
ElyCoa	0	0	0.157	0.157
ElyOil	0.28	0	0	0.28
ElyGas	0	0.194	0	0.194
ElyNu	0	0	0.169	0.169
ElyHyd	0	0	0.169	0.169
ElyWon	0.002	0.001	0.002	0.005
ElySol	0.005	0.002	0	0.007
ElyBio	0	0	0.008	0.008
ElyWas	0	0	0.003	0.003
ElyOth	0	0	0.002	0.002
CoaCCS	0	0	0.001	0.001
OilCCS	0.004	0	0	0.004
GasCCS	0	0.001	0	0.001
Total	0.292	0.199	0.51	1

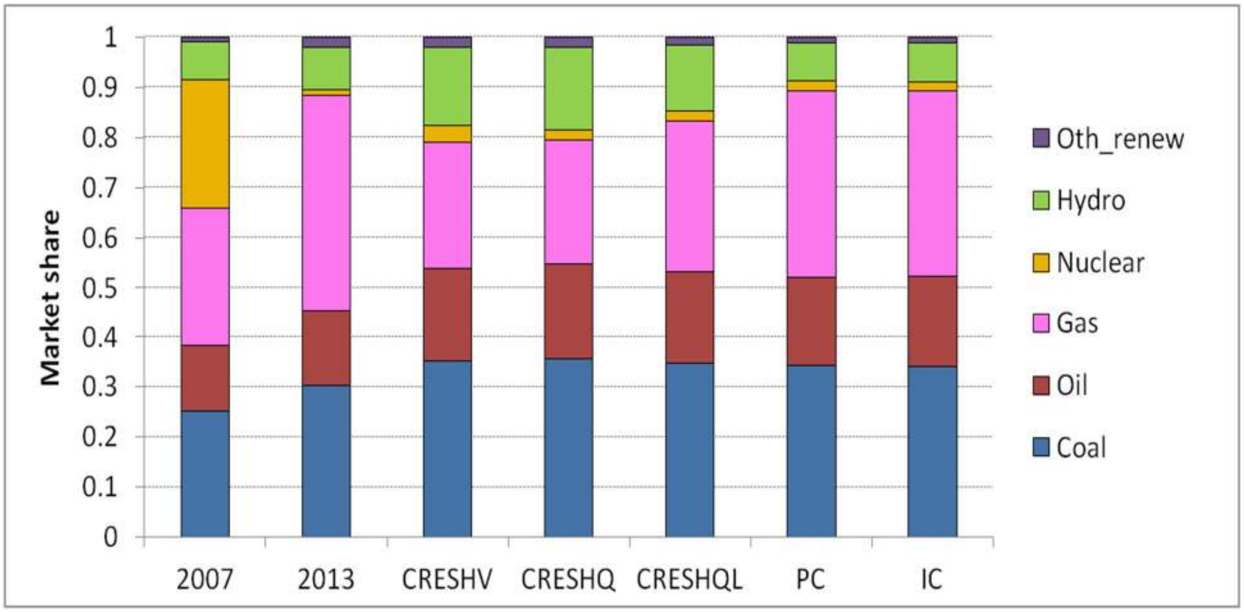

Figure 6

Impacts of the Fukushima accidents: actual and predicted market shares for different electricity generating technologies in Japan before and after the accidents: (1) 2007 and 2013: actual shares, (2) CRESH: model predictions using the 'technology bundle' value-preserving (V), or quantity-preserving (Q) constraints imposed, and/or also load factor (L) restriction; (3) PC: model prediction using the new approach with the 'perfectly competitive' market assumption; (4) IC: model prediction using the new approach with the 'imperfectly competitive' market assumption (with coal, gas, and nuclear technologies assumed to be 'dominant' players).

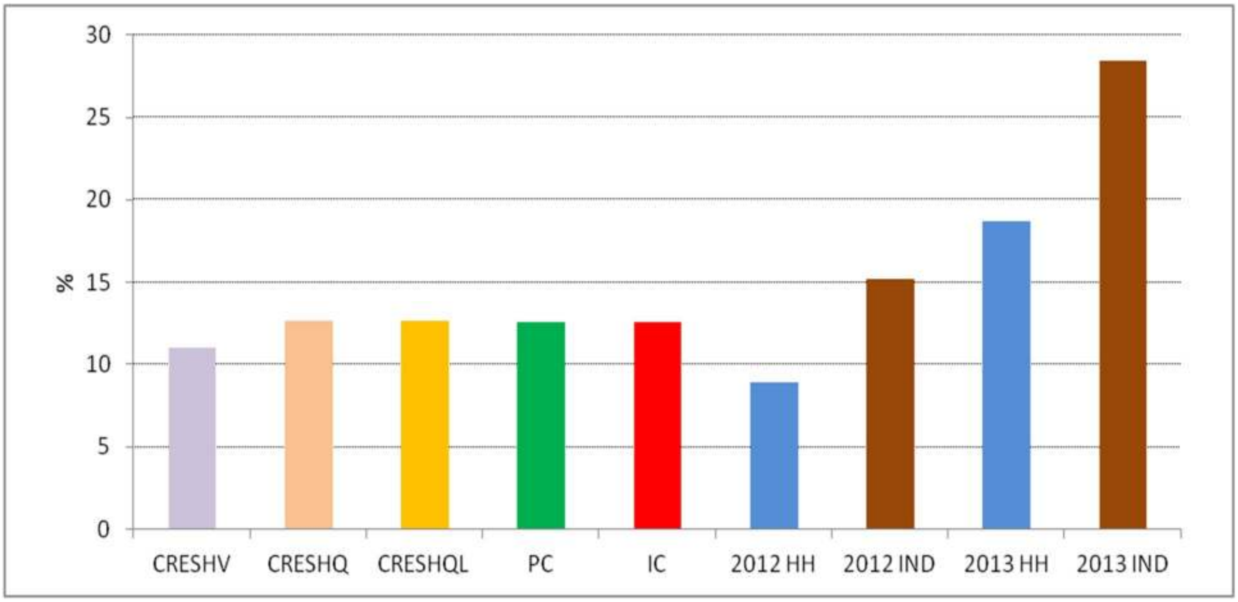

Figure 7

Impacts of the Fukushima accidents: actual and predicted electricity price increases following the Fukushima accident: (1) 2012 and 2013: actual percentage price increases in 2012 and 2013 respectively for household (HH) and industrial (IND) customers, (2) CRESH: model predictions using the 'technology bundle' approach with value-preserving (V), or quantity-preserving (Q) constraints imposed, and/or also load factor (L) restriction; (3) PC: model prediction using the new approach with the 'perfectly competitive' market assumption; and (4) IC: model prediction using the new approach with the 'imperfectly competitive' market assumption (with coal, gas, and nuclear technologies assumed as 'dominant' players).

Experiment 2: Japan's Post-Kyoto commitments with and without an accompanying energy targeting policy

Japan's obligation under the Kyoto Protocol involves a cut back on CO_2 emission levels by about 31.8% (if measured from the 2007 emissions level). 'Post Kyoto', however, the target as aimed by the Government of Japan[44] is to reduce CO_2 emissions by about 26% (measured from the 2013 level) and this is to be achieved by the year 2030. The government can impose this CO_2 emissions target on the economy with or without an accompanying energy policy. It is expected that without an accompanying energy policy, the increase in market shares of non-fossil fuel based technologies will not be as great as to be able to replace for the reduction in the market share of nuclear based electricity. Therefore, the government also imposed some targets for energy shares for the year 2030.[45] These consist of : 20-24% share for renewable electricity (of which 1.0-1.1% is for geothermal, 3.7-4.6% is for Biomass, 1.7% is for wind energy 7% is for solar, and 8.6-9.2% is for hydro electricity); coal oil and gas shares will be 26%, 3% and 27% respectively, and finally, nuclear electricity will also be targeted to reach 20-22% by 2030.

We can use our model to estimate what would be the economic cost (in terms of a carbon tax or emission price to be put on CO_2 emissions level in Japan[46] to achieve the climate change policy target, but also to estimate the impacts of the energy targeting policy on the climate policy. To do this, we first bring the data up-to-date to 2013 by shocking the levels of electricity generated by different technologies to the actual levels of 2013 and also shock the capacity level of nuclear electricity to the actual level in 2013 after the Fukushima accidents.[47] Next, as estimated by the government, electricity generation (and consumption) would be increased by about 1.45% over the period 2013-2030, so this would be used as an exogenous shock for electricity generation in the model to reflect the 'reference' situation. The 'Post-Kyoto' climate policy scenario (CP) is then defined as the situation when the total level of CO_2 emissions in 2030 would be reduced by

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[44] See http://www.mofa.go.jp/press/release/press4e_000811.html.

[45] See http://www.meti.go.jp/press/2015/07/20150716004/20150716004_2.pdf.

[46] Emission levels and prices refer to all sectors of the Japanese economy and not just the electricity sector. In this paper, we assume that there is a domestic emission trading scheme imposed on the Japanese economy, therefore the emission price would be uniform across all sectors, but the cut back on emissions would be different across different sectors.

[47] This would be similar to the 'Fukushima' experiment except that here the market shares of different technologies would be exogenously shocked to bring them to the actual 2013 levels (whereas in the Fukushima experiment these market shares are endogenously determined and only the total level of production was exogenously shocked).

26% below the 2013 level (but keeping the total amount of electricity generation and consumption in the economy at the same as in the 'reference' case). A CO_2 tax can be imposed which would be regarded as the 'price' for achieving this total emission reduction. Figures 8-16 report on the results of our model simulations.

Firstly, from Figure 8, it can be seen that our model's prediction of what would happen to the market shares of different technologies when a climate change policy is imposed would depend on the types of approaches used. If a conventional technology bundle approach is used, the results seem to indicate that depending on whether a value-preserving (V) or a quantity-preserving (Q) option is chosen, the picture can be significantly different over the long run.[48] A quantity-preserving option may allow for the market shares of all technologies to vary more 'freely' than if a value-preserving option was chosen. Neither of these options, however, can guarantee that the variations in market shares (i.e. in production volumes) are always consistent with existing or future capacity constraints. Therefore, to guarantee this consistency, a 'double' restriction may be imposed, and that is, not only that quantities add up (or are 'preserved') but also the variations in production volumes are consistent with variations in capacities. This is implied in the 'QL' option, i.e. *Q*uantity-preserving with *L*oad factor constraint restriction imposed. When this 'double restrictions' are imposed, interestingly, the results then come back being closer to the original 'value-preserving' option results. Furthermore, these results are also closer to the results of the new approach, in the sense that (i) expansion in nuclear technology is seen to be very limited, (ii) hydro and other renewable technologies can expand, but not to the same extent as gas and oil technologies – contrary to a common expectation that non-fossil fuel technologies would tend to do better than fossil fuel technologies under the imposition of a climate change policy. Finally, the CRESH approach would tend to predict that coal technology would be reduced significantly, but our new approach seem to maintain that this is not necessarily the case. Coal may suffer, but at the expansion of gas, rather than oil, hydro, or renewable. The extent of gas expansion would differ under the PC and IC assumptions, with the combined market shares of gas and coal *increased* under the IC case (as expected, because both are assumed to be 'suppliers with market powers') but coal cannot compete against gas, even if both are assumed to be 'oligopolists'. Comparing the results of all approaches with the 'energy targets' for 2030, it is clear that these targets are not achievable, unless some conscious

[48] That is, comparing the results of Figure 8 with those of Figure 7 which corresponds to a 'short run' experiment.

'restrictions' or 'regulations' are imposed by the government in addition to climate change policy. For example, it is clear that the nuclear energy target is far from being achievable without any efforts at restoring the *capacities* of this technology to the pre-Fukushima level. Similarly with renewable technologies: although under the CRESH approach, hydro and renewable technologies can do well (CRESHQ) but this is under the implicit assumption that (generating) capacities can always and easily *follow* production levels. Without *explicitly* allowing for this important issue of capacity expansion, all of the approaches (including CRESHQL) would seem to indicate that a reliance on just (short run) production costs alone will not be able to achieve any target (whether for nuclear, or for hydro and renewable).[49] Therefore, the issue of energy targeting' must be considered in the context of an issue of *capacity* expansion and investment rather than being regarded only as a matter of short run production (i.e. 'running') costs alone.

Figures 9-12 show what the (implicit)[50] capacities of various technologies would look like, if the technologies are to compete under the impact of a climate change policy without any additional 'energy targeting' policies imposed. Under a 'traditional' CRESHV approach (Figure 9), only capacities for fossil fuel technologies seem to expand, but if a quantity-preserving restriction is imposed (CRESHQ), capacities for hydro and other renewable technologies would also increase (Figure 10). The picture is different with respect to the new approach: only the capacity for coal technologies would expand under the PC assumption (Figure 11), and only with the IC assumption that capacity for gas technology will also expand. At first sight, the results seem to be counter-intuitive because production levels of coal technology has decreased rather than increased (Figure 8). But on closer examination, the results can be explained by the fact that the *load factor* for coal technology has always been 'low to medium' pre-Fukushima accidents (it was around 0.68 in 2007 with 'optimal level' being estimated to be around 0.56 – see Table 3). Since the Fukushima accidents, however, its load factor has increased significantly, to around 0.8 in 2013, perhaps as a way of replacing lost electricity production levels from nuclear technology by electricity production from coal. Therefore, with the imposition of climate change policy

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[49] Note that CRESH relies on price (or cost of production) to allocate outputs between technologies, and these costs are primarily *short run marginal* cost, because the cost of capital ('fixed costs') is considered only in the context of investment, i.e. *capacity* expansion. Similarly, our approach looks at the issue of 'optimal' load factors, but in the short run, only differences between *running costs* of different technologies determine the relative levels of load factors. Only for consideration of investment that marginal capital (or capacity costs are taken into account.

[50] A CRESH approach does not explicitly consider the issue of 'capacity' (or 'load factor') therefore, for comparison with the new approach, we assume that changes in load factor and changes in demand (i.e. production) levels *imply* certain changes in capacity level.

which makes the *running costs* of coal technology increase quite significantly relative to other technologies, the 'optimal' level of the load factor for coal technology will be *decreasing* rather than increasing relative to other technologies. Therefore, despite production level being decreased relative to other technologies, capacities would expand to allow for load factor of coal technology to recover to its pre-Fukushima levels (i.e. around 2/3 the value in 2013) *if there was no climate* policy, and in fact because of climate policy the 'optimal' level of this load factor has even decreased further, therefore, capacity must expand relative to other technologies.

Figures 13-15 show what the capacities for various technologies would look like if an energy targeting policy is imposed, in addition to the climate change policy. To be consistent with the energy (electricity *production*) targets (as seen in Figure 8) not only will production levels from nuclear and other renewable technologies need to increase to increase their market shares, but also their generation capacities. Because renewable technologies such as wind, solar, and even hydro electricity, typically have very low load factors as compared to those of fossil fuel technologies (see Table 3), their capacities need to increase even more than their production levels if they are to replace the outputs of fossil fuels, hence the sharp rise in capacities of these renewable technologies.

Finally, Figure 16 shows the 'cost' of implementing the Post-Kyoto climate change policy in Japan, with and without an accompanying energy-targeting policy according to the different approaches. It seems that the predictions by the CRESH approach would vary greatly depending on the particular restriction (V or Q) imposed in the approach, with the Q-restriction resulting in much higher value predictions than are the V-option results. Using the new approach suggested in this paper, however, the model predictions would tend to fall roughly half-way between the two levels predicted by the CRESH approach. All these predictions, however, would come closer together if the assumption of an energy target policy is also imposed. This is because with a fixed set of energy targets (i.e. a fixed set of market shares for all the technologies) the cost of eventually achieving these targets are almost determinable, and hence there is little room for variations between the different approaches.

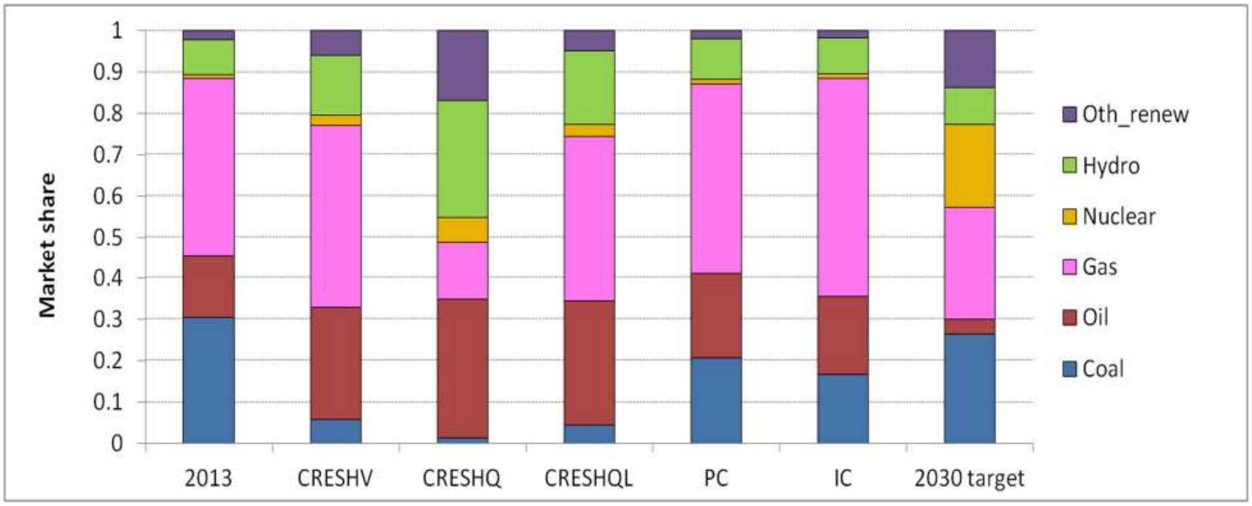

Figure 8

Effects of climate change policy without an accompanying energy target policy: (1) 2013: actual market shares in 2013; (2) CRESH: predicted market shares for different electricity generating technologies in Japan in 2030 under the impact of climate change policy without an accompanying energy targeting policy using the CRESH (technology bundle) approach with value-preserving (V), or quantity-preserving (Q) and load factor (L) restrictions imposed; (3) PC, IC: similarly, but using the new approach with the assumption of 'perfect competition' and 'imperfect competition' in the electricity market respectively; (4) 2030-target: market shares in 2030 if an accompanying energy targeting policy is also imposed.

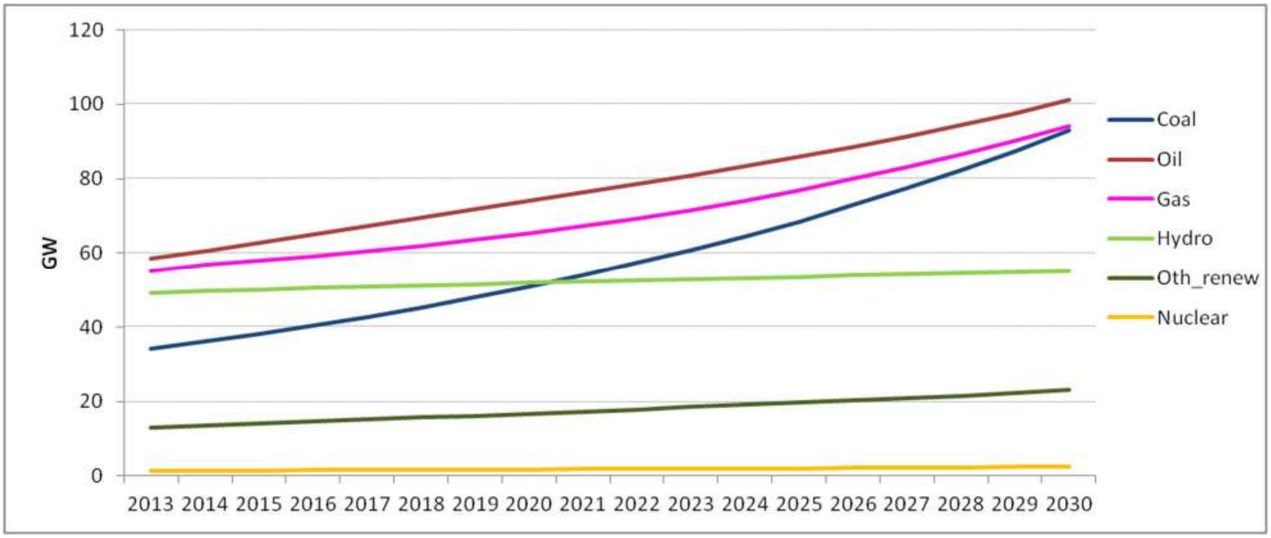

Figure 9

Capacity expansion under the impact of climate change policy (without energy targeting) according to a 'technology bundle' (CRESH) approach with 'value-preserving' (V) restriction imposed.

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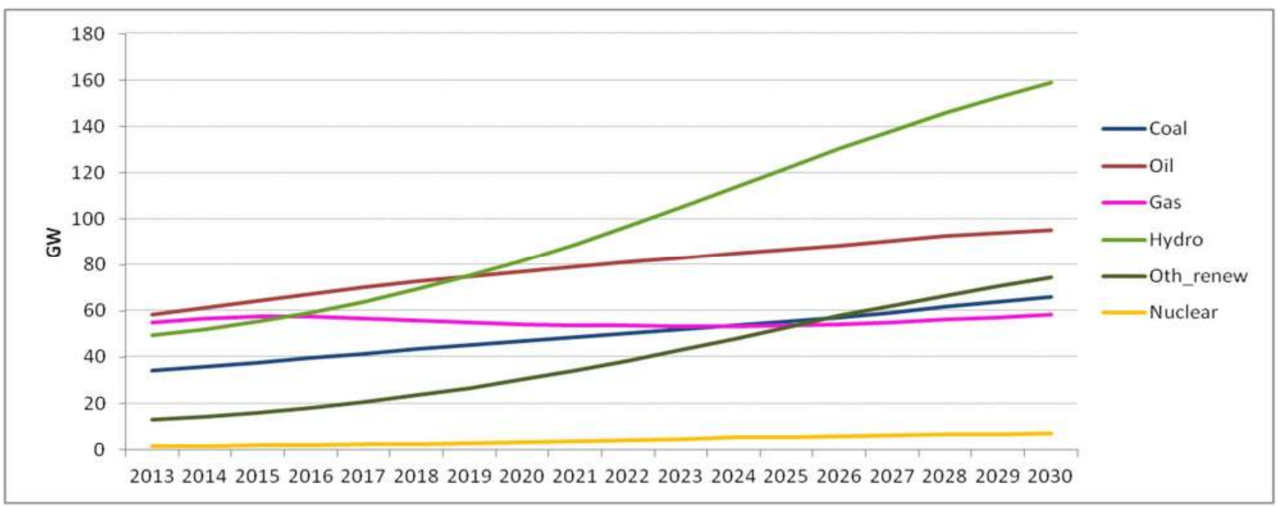

Figure 10

Capacity expansion under the impact of climate change policy (without energy targeting) according to a 'technology bundle' (CRESH) approach with 'quantity-preserving' (Q) restriction imposed.

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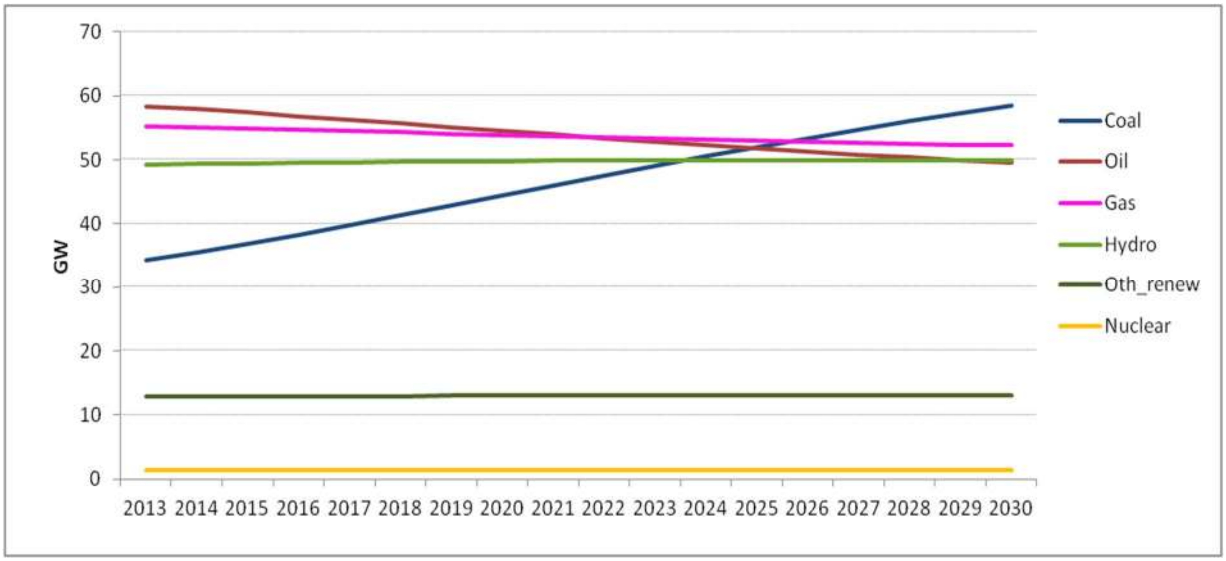

Figure 11

Capacity expansion under the impact of climate change policy (without energy targeting) consistent with the new approach under the assumption of perfect competition (PC).

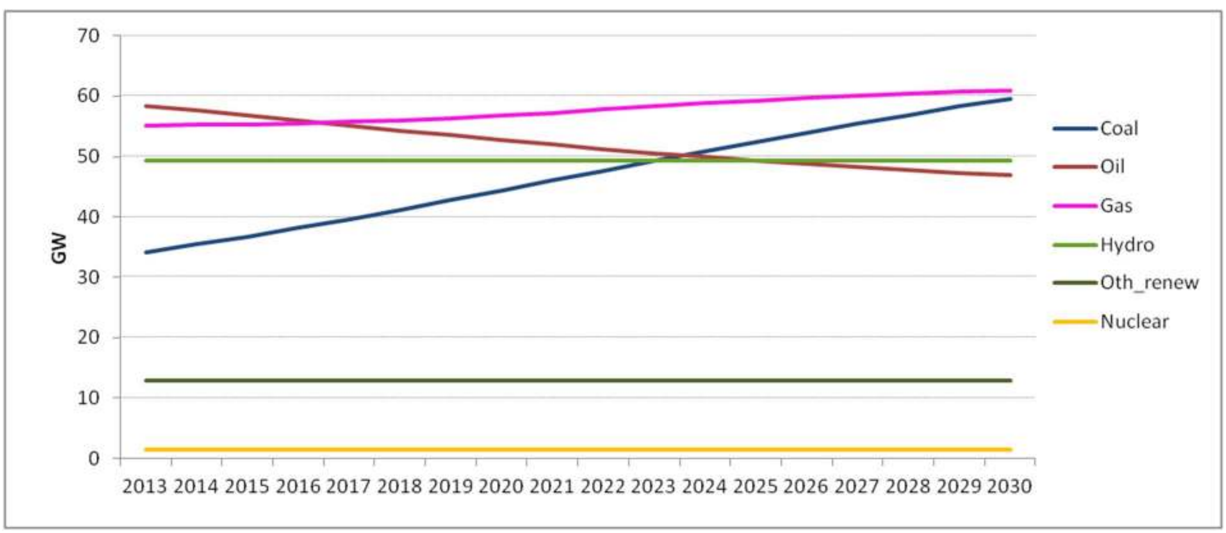

Figure 12

Capacity expansion under the impact of climate change policy (without energy targeting) consistent with the new approach under the assumption of imperfect competition (IC).

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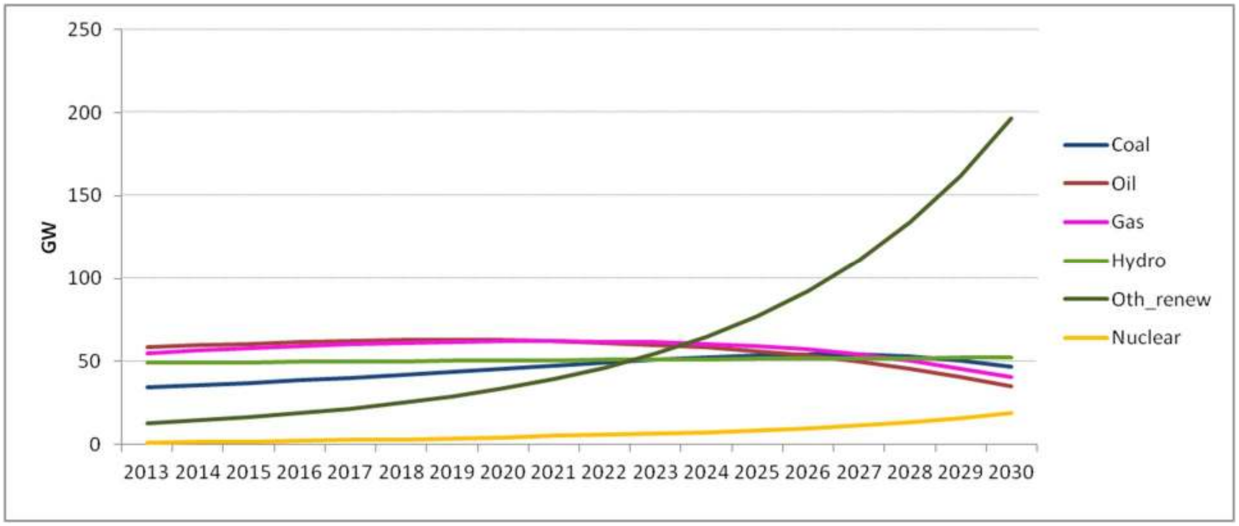

Figure 13

Capacity expansion under the impact of climate change policy *with* energy targeting according to a ‘technology bundle’ approach with ‘quantity-preserving’ (CRESHQ) restriction imposed

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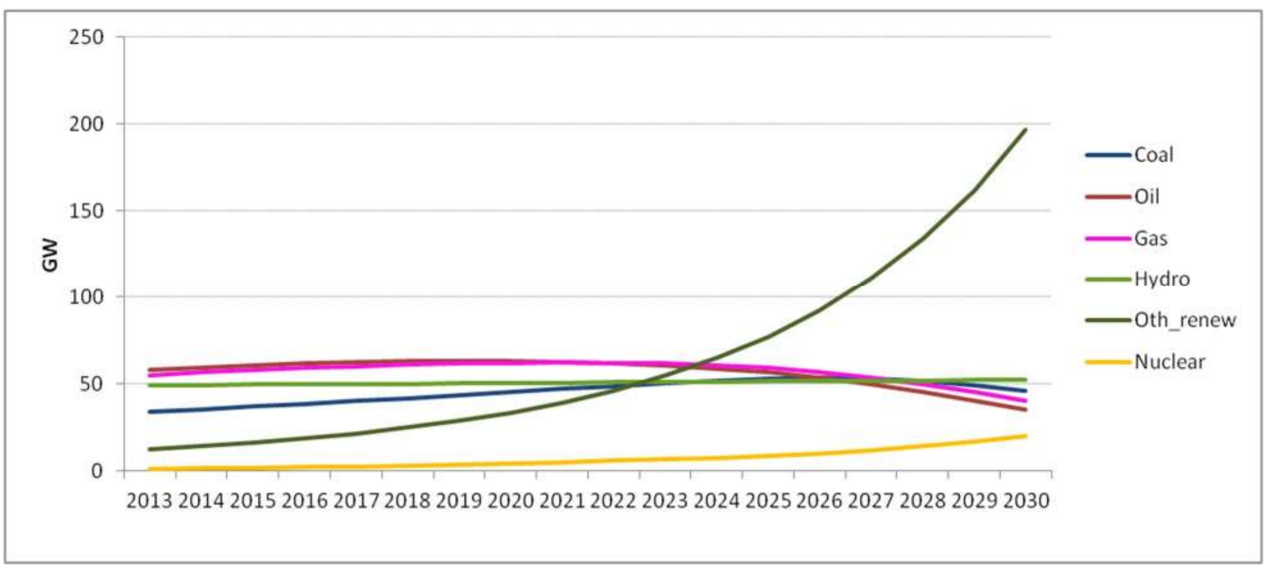

Figure 14

Capacity expansion under the impact of climate change policy *with* energy targeting consistent with the new approach under the assumption of perfect competition (PC).

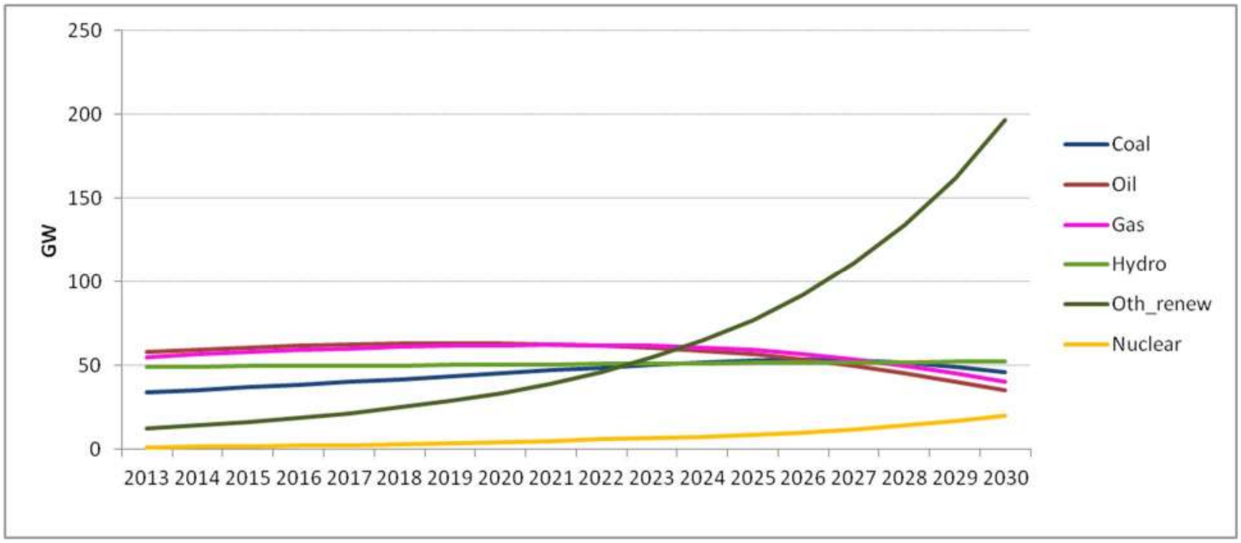

Figure 15

Capacity expansion under the impact of climate change policy *with* energy targeting consistent with the new approach under the assumption of imperfect competition (IC).

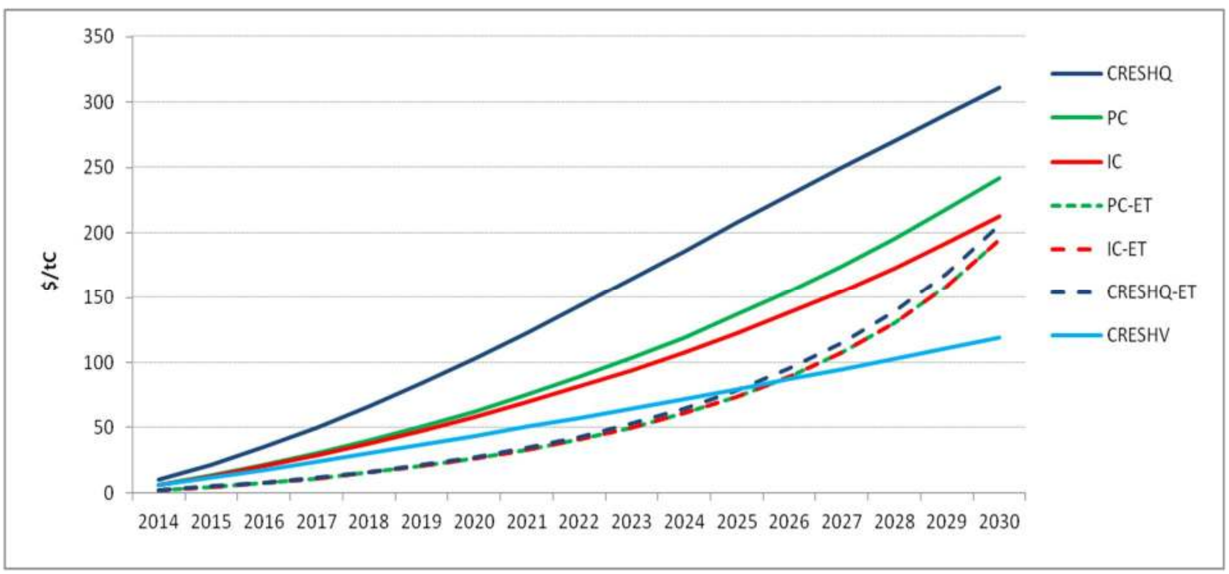

Figure 16

Effects of climate change policy without an accompanying energy target policy: Cumulative carbon tax level to achieve the Post-Kyoto CO_2 emission reduction target in Japan according to the different approaches.

Conclusion

In this paper we have shown a new way for disaggregating the electricity sector in a CGE model to take account of different technologies used in the sector and for explaining how outputs from these technologies can 'compete' to provide total supply for the sector as a whole. The approach adopted here provides an alternative way to explain how *technologies* compete. This competition depends not only on *technological factors* (such as availability and load factors of different generating capacities) but also *economic* factors (such as scale economies and lumpiness of capital, relativities between long run capital (or capacity) costs and short term marginal running costs). Up to now, a 'conventional' approach in a top-down model is to use an 'aggregate production function' (such as CRESH) or possibly a 'probabilistic market share function' (such as LOGIT) to explain how this competition occurs by treating the outputs from different technologies as though imperfect substitutes. Such an explanation lacks the realism of an actual electricity market because it ignores crucial characteristics, not only of the *supply* side (such as capacity and load factor constraints) but also of the demand side (such as variation in the different categories of demand which makes up a total 'load duration curve' in the electricity market). A 'bottom-up' model for the sector can take into account certain features of the supply side such as capacity constraints, or of the demand side, such as different types of load, but instead of explaining how competition can result in different levels of these supply capacities themselves, it often assumes that these levels are given exogenously of the model. The new approach adopted in this paper is an advancement over this approach because it seeks to 'endogenise', not only the decision on production levels (in the short run), but also of the capacity planning in the long run. It uses the framework of a top-down CGE model where both types of these decisions can be taken into account in a consistent and interrelated fashion, but also introducing into such framework the factors that are up to now considered only in partial equilibrium bottom-models, namely technological factors.

Using the theoretical framework as explained above, the paper then showed how such a framework can be implemented in a practical CGE model to be used to analyse the impacts of climate change and energy polices on the electricity sector, using the case of the Japanese electricity sector as an example.

Appendix

Technology bundle approach: To compare the new approach adopted in this paper with a 'standard' approach used in many CGE models which is called the 'technology bundle' approach, this approach is also implemented in our model (as a third option alongside with the PC and IC options described in the paper). Under this approach, all outputs from different technologies are assumed to be imperfectly substitutable and therefore can be treated as though 'inputs' into a CRESH production function. This function 'produces' the final output for the electricity sector. A CRESH production function (Hanoch, 1971) can be described as:

$$q_i = \bar{q} - \sigma_i [p_i - \sum_j W_j^* p_j] \qquad \text{(A.1)}$$

where (q_i) is the percentage change in quantity of technology i and (p_i) is the percentage change in its price; (W_i^*) is the modified *value*[51] share of input i which is related to the ordinary value share ($W_i = P_i Q_i / \sum_j P_j Q_j$) via the relationship: ($W_i^* = \sigma_i W_i / \sum_j \sigma_j W_j$) (see Dixon *et al.* (1982), p. 86 for more details); (σ_i) are the CRESH elasticities of substitution. These substitution elasticities can be shown to be related to the own- and cross-price elasticities of demand for the outputs from technologies if we derive these elasticities from equation (A.2) [52]

$$\varepsilon_{ii} = (q_i / p_i)\big|_{p_j = 0, j \neq i} = -\sigma_i (1 - W_i^*) < 0 \qquad \text{(A.2)}$$

$$\varepsilon_{ij} = (q_i / p_j)\big|_{p_k = 0, k \neq j} = \sigma_i W_j^* > 0 \qquad \text{(A.3)}$$

For n CRESH parameters to be calibrated, there are only [(n^2/2)-(n/2)-1] independent observation points[53] in equations (A.2)-(A.3) which can be used. Therefore, if n>2, there would be more observation points than there are parameters to be calibrated and the system of equations in (A.2)-(A.3) is therefore 'over-identified'. If n=2, however, the system is exactly identified. This means we can use equations (A.2)-(A.3) to identify the CRESH parameters for any selected

[51] To be distinguished from the *quantity* share used in equation (17) of section 2.2 to describe Cournot competition between members of the *L*-group.

[52] Note that $W_i^* < 1$ and $\sum_i W_i^* = 1$ this means that since $\sigma_i \geq 0$ for $\forall i$ therefore $\varepsilon_{ii} < 0$ and $\varepsilon_{ij} \geq 0$ for $\forall i, j$.

[53] Since the (n^2) values of the own and cross-price elasticities in equations (A.2)-(A.3) are subject to (one) homogeneity constraint and [n(n-1)/2] symmetry constraints there are only n^2-[n(n-1)/2]-1= [(n^2/2)-(n/2)-1] degrees of freedom or observational points left for use in the calibration of the n CRESH parameters.

pair of technologies if the values of their own and cross price elasticities of demand are known. For fossil fuel based technologies, first, we define three ‘composite’ technologies as CES combinations of CCS and non-CCS technologies: Coatec=CES(ElyCoa, CoaCCS), Oiltec= CES(ElyOil, OilCCS), and Gactec=CES(ElyGas, GasCCS).[54] Next, we assume that the own- and cross-price elasticities of demand for these composite technologies are known and are as given in Table A.1, From this information, we then estimate the CRESH parameters for different pairwise combinations of these technologies. It can be seen from Table A1 that the estimated CRESH parameter for each individual technology is fairly independent of the pairwise combinations of technologies being chosen, hence we can take the ‘average’ of these estimations as the final values of the CRESH parameters for each technology.

For non-fossil based technologies, we do not have information on their empirical price elasticities of demand but we have some information on their price elasticities of *supply*. For example, an empirical study by Johnson (2011) for the case of the US found that price elasticities of supply for renewable electricity technologies to be about 2.7. For hydro-electricity it can be assumed that price elasticity of supply for this technology is about 0.5, reflecting the fact that the growth of this technology is subject to severe resource constraint, especially in the case of Japan. For nuclear technology, price elasticity of supply can be set to a zero or very low value if government policy is to restrict the return (and growth) of nuclear electricity in Japan, otherwise, it can be set to a high value such as 2. In other words, price elasticities of supply for different technologies can be estimated empirically, or assumed to be restricted to a certain range of values to reflect either policy or resource constraints. These elasticities are given in Table A.2. From the price elasticities of supply, we can assume that the CRESH elasticities of substitution (for non-fossil fuel technologies) are also close to these price elasticities of supply. This can be explained as follows. From equation (A.1), we can re-write this equation as:

$$q_i = \overline{q} + \sigma_i[\overline{p} - p_i] \qquad \text{(A.4)}$$

[54] The values of these CES elasticities for combining the CCS and non-CCS technologies are assumed to be 5, 5, and 10 respectively for Coatec, Oiltec, and Gastec, following from Arora and Cai (2015) who also use similar composite technologies.

where the term $\sum_j W_j^* p_j]$ is now replaced by a single variable $\bar{p}$ which reflects the *general* shift in the supply curve of all technologies in the electricity market.[55] The gap $[\bar{p} - p_i]$ therefore must represent a *movement* along a technology-specific supply curve *i* such that this can induce a change in the supply from this technology by an amount of $\sigma_i[\bar{p} - p_i]$. The CRESH parameter σ_i is seen to act as a price elasticity of *supply* for technology *i.* Therefore the former can be assumed to be close to the value of the latter (in cases where cross-price effects are assumed to be relatively small). As a result, for the case of non-fossil fuel based technologies, it can be assumed that CRESH elasticities of substitution are simply be given by the price elasticity of supply.[56]

[55] This can be due, for example, to a change in factor price inputs which affects all technologies equally.

[56] Conversely, for the case of fossil fuel based technologies, the price elasticities of supply assumed for these technologies must also be consistent with the CRESH elasticities of substitution, therefore they are assumed as given in Table A.2).

Table A.1: Price elasticity of demand for fossil fuel based technologies and their corresponding CRESH elasticities of substitution

Technology	Own- and cross-price elasticities of demand(*) (ε_{ii} , ε_{ij})			Estimated CRESH parameter based on pair-wise consideration of the price elasticities of *demand* (σ_i)			Average CRESH parameter using pairwise estimations based on price elasticities of *demand* (σ_i)	CRESH parameter based on price elasticity of *supply* (σ_i)
Coatec	-.46	.03	.22	.603		.604	.60	
Oiltec	.12	-.48	.18	.505	.503		.50	
Gastec	.42	.08	-1.12		1.744	1.761	1.75	
ElyNu								0 – 2 (#)
ElyHyd								.5
ElyWon								2.7
ElySol								2.7
ElyBio								2.7
ElyWas								2.7
ElyOth								2.7

(*) Based on Arora and Cai (2015) Table 1; (#) reflecting different policy options.

Table A.2: Price elasticity of supply for different electricity generation technologies

Technology	Price elasticity of supply
ElyCoa	.6
ElyOil	.5
ElyGas	1.75
ElyNu	0 - 2
ElyHyd	.5
ElyWon	2.7
ElySol	2.7
ElyBio	2.7
ElyWas	2.7
ElyOth	2.7
CoaCCS	.6
OilCCS	.5
GasCCS	1.75

For renewable technologies, the values are based on an empirical study by Johnson (2011); for fossil fuel technologies, the values are assumed to be equal to the CRESH parameters (Table A.1); for the rest of the technologies, the values are assumed to reflect either resource and/or policy constraints.

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