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Decreasing substitutability between clean and dirty energy

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Abstract

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Keywords

Elasticity of substitution, climate change, energy, electricity, production function

JEL Classification

O33, Q40, Q41, Q42

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Decreasing substitutability between clean and dirty energy

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A review of the literature indicates a decreasing long-run elasticity of substitution between clean and dirty inputs as the share of clean inputs rises. In the power sector, which is the largest contributor to greenhouse gas emissions, integrating intermittent clean energy supply becomes increasingly difficult as the clean share rises. This paper describes a simple structural model of electricity generation which: demonstrates how the elasticity falls as the clean share rises; can replicate the range of results from the electricity literature; considers the effects of storage; and facilitates estimation of a suitable production function. A bimodal production function with two elasticity regimes - an elasticity above 8 up to a 50 to 70 per cent clean share and an elasticity below 3 beyond this share – can replicate results well from the structural model. (JEL O33, Q40, Q41, Q42)

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The treatment of energy varies between structural macroeconomic models. Some recent literature includes a simple representation of energy through an isoelastic function of clean and dirty inputs.[1] Such an approach assumes a constant elasticity of substitution between clean and dirty inputs across a broad range of clean input shares. Other models include greater sectoral detail, implying a changing effective elasticity between clean and dirty aggregates.[2]

This paper focusses on how the elasticity between clean and dirty inputs may vary with different clean energy shares, with a focus on the electricity sector, and how this variation can be incorporated into macroeconomic models. Empirical estimates of the elasticity of substitution between clean and dirty energy include: an elasticity of 2 for electricity and 3 for nonenergy industries (Papageorgiou, Saam, & Schulte, 2017); 1.6 between fossil-fuel and renewable energy (Lanzi & Sue Wing, 2011); 1 or less for the interfuel substitution between coal, oil and electricity in industries other than electricity generation (Stern, 2012); and around 0.5 for the electricity sector (Pelli, 2012). In contrast, the elasticity of substitution between clean and dirty inputs used in integrated assessment and macroeconomic models are sometimes much higher and generally lie between 10 and 1.[3] An argument for using an elasticity as high as 10 is the perceived high substitutability between clean and dirty inputs in electricity generation and between fuel and electricity inputs in vehicles (Greaker & Heggedal, 2012).

But how appropriate is an isoelastic function between clean and dirty inputs, and is a high elasticity of around 10 reasonable? Unfortunately, few economies have high shares of clean energy that can help determine how the elasticity between clean and dirty inputs might change as the share of clean energy rises. Regions that do have high clean shares generally take advantage of endowments that may not be transferable to other countries, such as hydro resources. Thus, a lack of data points

[1] For example, Acemoglu, Aghion, Bursztyn, and Hemous (2012).

[2] For example, Golosov, Hassler, Krusell, and Tsyvinski (2014) differentiate between fuel inputs coal, gas/oil and renewables.

[3] For example see Lanzi and Sue Wing (2011) and Acemoglu et al. (2012).

makes estimating an elasticity for high clean shares a challenge. Therefore this paper builds a structural model of electricity using the well-defined nature of supply substitution in this market, which is then used to calibrate and test various production functions.

Two types of literature are surveyed for substitutability estimates at different clean shares: an empirical macro study; and structural electricity papers which rely on empirically-based regional models of electricity. Both approaches are conjectural, as they consider anticipated behaviour under high clean shares, but provide the best available guidance for such shares. Results from structural electricity models are used by both private and public sector agents and regulators, reflecting the complex but precisely defined nature of the electricity market including supply substitution. The electricity sector is a large source of emissions and energy use and offers the greatest opportunity for substitution between dirty and clean energy. Both types of literature identify a common trend: a decreasing elasticity between clean and dirty inputs as the share of clean energy rises.

To understand why a decreasing elasticity may apply, at least in the electricity sector, I briefly describe the characteristics of an electricity market. Electricity is not easily storable and demand varies hour by hour and day by day, resulting in a load duration curve (LDC) which reflects this variation in aggregate demand. The variation increases the total costs of supply, and the optimal supply consists of a mix of technologies with different fixed and variable cost ratios. New investment in clean generation is dominated by the variable renewable energy (VRE) sources wind and solar that increase the variation in demand that must be met by dispatchable generation: one part of the integration costs associated with VRE. At low clean shares the cost is relatively low, implying a high elasticity between clean and dirty generation. As the clean share increases, the utilisation rates of dispatchable generation decrease and curtailment of intermittent generation occurs, further increasing costs, so the elasticity falls.

After discussing evidence of a decreasing elasticity as the clean share rises in the literature, this paper describes a simple structural electricity model, building on Wiskich (2014), that replicates this key feature. Deriving and calibrating a parsimonious model using a stylised structural model has the advantage that changes in elasticity can be identified clearly, which can assist with empirical estimation. I discuss the impact of storage, or demand management, which the electricity literature highlights as an important determinant of substitutability between clean and dirty inputs as it counteracts some effects of intermittency. Of course, electricity generation differs vastly between regions and over time. For example, the availability of wind and solar resources, and the correlation of these sources with peak demand, varies between regions. Thus, I consider a variety of parameter choices.

Due to the lack of data for high clean shares, the performance of potential production functions incorporating clean and dirty inputs are measured against results from this structural model. This method also allows comparison of results assuming different parameter settings. Three production functions with a decreasing elasticity of substitution, as well as an isoelastic function, are tested to see how well they perform in replicating results from this structural model. Four parameter settings in the structural model are used for these tests, corresponding to low and high storage prices and guaranteed VRE supply percentages.[4]

Previous studies that use a production function with a changing elasticity of substitution generally have a parameterised continuous path of variation in the elasticity. I discuss two such approaches: one that uses the Variable Elasticity of Substitution (VES) function, introduced by Sato and Hoffman (1968) and Revankar (1971); and another that uses a couple of isoelastic nests with different elasticities, combining in a Leontief function. Motivated by inspection of the model output, I

[4] For VRE capacity W, a guaranteed supply per centage of m means that the minimum supply of VRE is mW.

include a third production function that allows for a step-change in the elasticity of substitution as the share of clean inputs increases. A similar production function is described in Antony (2009) and builds on Jones (2003). An isoelastic function is also applied for comparison.

All three functions can better replicate results from my structural model than an isoelastic function. My preferred approach is the bimodal one: as well as doing a good job of emulating the results from the structural energy model, a step change is simple to implement and to conceptualise and is therefore suitable to a range of macroeconomic models. The bimodal approach provides a parsimonious alternative to the inclusion of a detailed bottom-up model, or a constant elasticity of substitution (CES) nesting structure. [5]

Estimation of the bimodal function suggests an elasticity of over 8 up to a switch point of around 50 to 70 per cent clean share, with an elasticity between 1 and 3 beyond this share. While this high elasticity partially supports the use of such an elasticity in previous modelling,[6] the implication of a switch to a much lower elasticity is an interesting research question. Using a stylised way of modelling storage, I explain the implications for the bimodal production function. The key finding is that storage can be modelled via an increase in the switch point, extending the highly elastic part of the production function to cover a greater share of clean inputs, as well as an increase in the share parameter.

This paper contributes to the literature on energy elasticities by drawing out the implication of a decreasing elasticity between clean and dirty inputs from an empirical macro study and regional models of electricity. The structural electricity model developed in this paper is transparent and generates results broadly consistent with the electricity literature. The use of a bimodal isoelastic production

[5] See Ueckerdt et al. (2015) for a discussion of the various methods of incorporating variable generation into long-term energy-economy models.

[6] Such as AABH and Greaker and Heggedal (2012).

function, or indeed the VES and dual isoelastic nest production functions, in an energy context is novel. Estimation of the elasticity of substitution between clean and dirty inputs from a range of outputs from a structural model is also novel and worthy of further investigation using empirically-based structural energy models. The bimodal nature of the production function enables consideration of a key impact of storage or demand responsiveness; an increase in the switch point share. By capturing an important characteristic of energy supply in a simple way, this paper can promote additional insights from the use of macroeconomic models in climate change and energy analysis.

While this paper discusses reasons why a decreasing long-run elasticity of substitution applies, a limitation is that capital life is not considered. Although it is normal to omit capital adjustment considerations when focussing on long-run effects, the capital stock in the energy sector is long-lived. Existing capital stocks would tend to increase substitutability over time as the capital stock adjusts. Mattauch, Creutzig, and Edenhofer (2015) investigate an increasing elasticity of substitution as a proxy for the temporal consideration of a gradual increase in energy infrastructure. In contrast, the decreasing substitutability in the production functions in this paper is linked with the share of clean energy and reflects long-run considerations of supply and demand.

Section 1 infers elasticities from the literature sources described previously. Section 2 describes a simple structural model which, in section 3, is used to estimate different production functions and examine dependence on storage. Section 4 concludes.

I. Inferred elasticities from the literature

Two types of literature are examined in this section. The first uses a recently published paper that derives a distribution of productivity gaps between clean and dirty technologies by using patent and industry sector data. I have been unable to find other comparable literature that can complement these results. The second considers results from empirically-based regional structural electricity models that are able to extrapolate system costs at high clean energy shares. Both methods have limited application to deriving a macro elasticity of substitution for various reasons, most obviously as they each focus on (separate) parts of the energy system. The goal of this section is simply to identify a common theme to changes in elasticity as the clean share increases, and present a range of estimates.

Industry sector data

Acemoglu, Akcigit, Hanley, and Kerr (2016), hereafter AAHK, derive a distribution of productivity gaps between clean and dirty technologies, shown in Figure 1. For each SIC3 industry, AAHK sum patents made by clean and dirty firms during the period 1975-2004, and use this data to derive the initial distributions of an endogenous growth model in which clean and dirty technologies compete in production. A negative productivity gap indicates that clean energy leads dirty energy, which occurs in 9 per cent of cases according to the data. I approximate the data by fitting the distribution

$$density = \frac{a}{(1 + |gap - 1|)^b} \qquad (1)$$

where a and b are chosen so that the sum of densities in the interval [0,60] equals the sum of densities in the data, and the square of errors in the same interval is minimised. Results are $a = 0.3085$ and $b = 1.42$ and the fitted line matches the data well as Figure 1 shows.[7]

[7] The fitted line is only shown for positive values, which are relevant in determining substitution as clean prices fall relative to dirty prices.

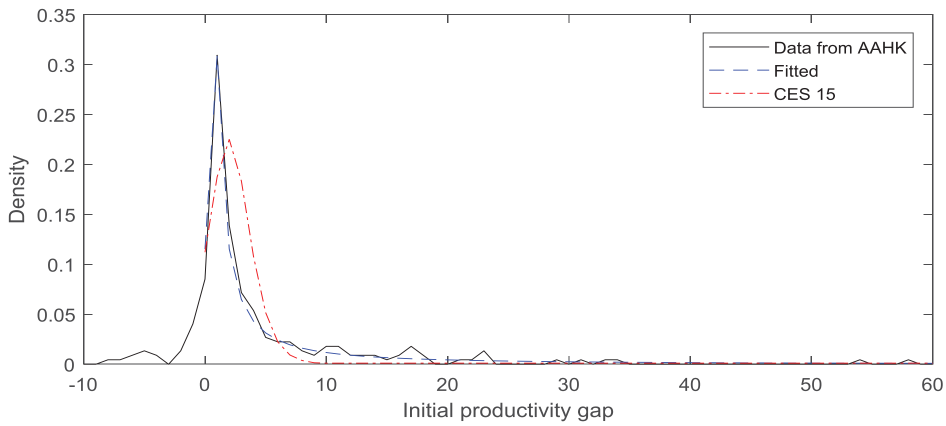

FIGURE 1: DENSITY OF FIRMS BY INITIAL PRODUCTIVITY GAPS

To infer an elasticity from the distribution, I use the most straightforward method possible and assume that productivity changes uniformly across industries. Thus, if the productivity of clean energy increases by 10 per cent, this increase occurs across all industries so that the distribution shown in Figure 1 retains the same shape and shifts to the left. I use a standard assumption that each industry uses whichever technology (clean or dirty) has greater productivity. If the clean price falls by the same extent as the productivity increase, the elasticity can be inferred. Using the fitted data, the amount of clean energy is the integral of the density function to the left of the origin. For a ratio of clean to dirty energy $\frac{Y_c}{Y_d}$, which begins at 0.1, the elasticity is given by

$$(2) \qquad elasticity \approx \frac{\Delta \ln\left(\frac{Y_c}{Y_d}\right)}{\ln(\lambda)},$$

where λ is the innovation step size as estimated by AAHK to be 1.063. Thus, if clean productivity increases by one step, the profile shown in Figure 1 shifts to the left by one unit, raising the clean share, and the price of clean technology decreases by 6 per cent relative to dirty technology. While this method abstracts from the approach used by AAHK, which includes more complex dynamics of innovation, it provides an indication of the profile of elasticity as the share of clean inputs increases. Using this method, Figure 1 also shows the implied profile if the elasticity is a constant, with a value 15 chosen so that the starting density is similar to the data. Comparison between this isoelastic profile and the data implies the inferred elasticity is higher than 15 for a low clean share and then falls as the share increases. The elasticity profile calculated from (2), shown in Figure 2, verifies this decrease.

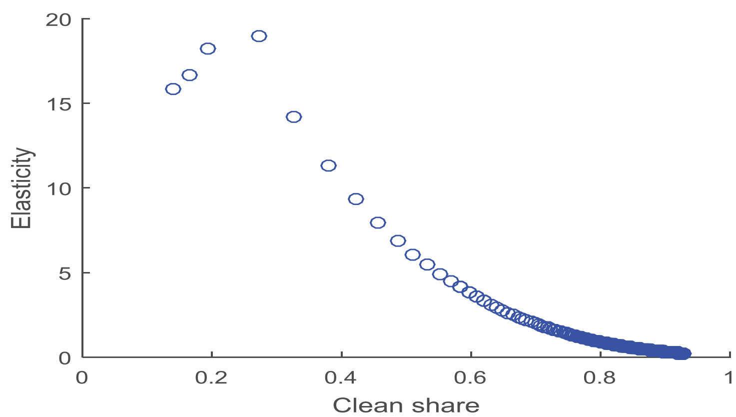

FIGURE 2: INFERRED ELASTICITY VERSUS SHARE OF CLEAN ENERGY

1.2 Results from regional electricity models

A number of papers use structural electricity models, typically calibrated to a region, to discuss the costs of integrating VRE (clean) inputs into the residual (dirty) system. Such costs vary with the share of VRE and can be used to infer an indicative elasticity of substitution. As a function of the clean to dirty ratio w, integration costs (Δ_{vre}) can be added to the levelised cost of electricity (LCOE) to create a metric called the system LCOE of VRE ($sLCOE_{vre}$):

$$sLCOE_{vre}(w) := LCOE_{vre}(w) + \Delta_{vre}(w). \tag{3}$$

An optimal quantity of VRE generation occurs when the system LCOE of VRE equals the LCOE of the conventional (non-VRE) system:

$$sLCOE_{vre}(w^*) = LCOE_{conv}. \tag{4}$$

Ueckerdt, Hirth, Luderer, and Edenhofer (2013), hereafter UHLE, outline this approach and define total integration costs (C_{int}) as the extra cost in the residual system imposed by VRE. However, this definition excludes curtailment costs[8], defined as excess VRE generation that is wasted times the price $LCOE_{vre}$. To understand this exclusion, note that if a unit of VRE is added and (in the extreme case) all of its output is curtailed, the residual system is unaffected**.** Like UHLE and other papers, I wish to include the costs of curtailment as an integration cost, and therefore I add curtailment costs (C_{curt}) to the definition of integration costs, and marginal integration costs (Δ_{vre}), as follows:

$$C_{int}(w) = C_{resid}(w) - \frac{E_{resid}(w)}{E_{tot}} C_{conv} + C_{curt}(w, LCOE_{vre}) \tag{4}$$

$$\text{and } \Delta_{vre} := \frac{\partial C_{int}}{\partial E_{vre}}.$$

Thus, integration costs are the extra costs of the residual system over a conventional one, plus curtailment costs. Curtailment costs vary not only with the

[8] Although curtailment costs are excluded in the definition in UHLE's methodology section, they are included as an integration cost in their results.

VRE share, but also with the price of VRE. This complicates the conceptual framework, as ideally we would be able to define integration costs relative to the price of a conventional system and independently of the VRE price. Total costs (C_{tot}) are the sum of non-curtailed VRE costs (C_{vre}), curtailment costs and residual costs, and using (4) can be written as the sum of VRE costs, integration costs and conventional system costs:

$$C_{tot} = C_{vre} + C_{int} + \frac{E_{resid}}{E_{tot}} C_{conv}. \tag{5}$$

Optimality implies that the quantity of VRE generation minimises total costs:

$$\frac{\partial C_{vre}}{\partial E_{vre}} + \frac{\partial C_{int}}{\partial E_{vre}} + \frac{\partial}{\partial E_{vre}}\left(\frac{E_{resid}}{E_{tot}} C_{conv}\right) = 0. \tag{6}$$

As $E_{resid} = E_{tot} - E_{vre}$, we have $\frac{\partial E_{resid}}{\partial E_{vre}} = -1$ and marginal integration costs are the difference between the average price of a conventional system minus the price of VRE, consistent with (3):

$$\Delta_{vre}(w^*) = LCOE_{conv} - LCOE_{vre}(w^*) \tag{7}$$

$$\text{where } LCOE_{vre} := \frac{\partial C_{vre}}{\partial E_{vre}} \text{ and } LCOE_{conv} := \frac{C_{conv}}{E_{tot}}.$$

For a positive price $LCOE_{vre} > 0$, (7) indicates that the integration cost is bounded above by the conventional price under optimal conditions when no climate externality is considered. However, the cost as defined in (4) is not bounded from above under suboptimal conditions, such as setting a predetermined VRE share, which is the method used in the literature discussed below.

As the price of clean energy changes with respect to dirty (conventional) energy, the degree to which clean inputs change depends on how integration costs vary with the clean input share. Consider a fixed price for dirty and a shift in clean price Δp, induced by technological change or policy such as a renewable subsidy. For (3) to hold, the clean share adjusts by Δw until the change in integration cost ($\Delta\Delta_{vre}$) balances Δp, assuming that changing the clean share does not in itself influence the price of clean energy supply.[9] As integration costs are a function of the price of VRE at high clean shares, due to curtailment, an inferred elasticity only applies for this price and thus should only be taken as indicative. Given a profile of integration costs with the share of VRE, this indicative elasticity can be inferred using

$$\text{(8)} \qquad \text{elasticity} \approx \frac{\ln\left(1 + \frac{\Delta w}{w}\right)}{\ln\left(1 + \frac{\Delta p}{p}\right)}.$$

Hirth, Ueckerdt, and Edenhofer (2015), hereafter HUE, report wind profile costs, which they find is the dominant component of integration costs. Profile costs relate to the impact of timing of generation on the market value and reflect the opportunity costs of matching VRE generation and load profiles through storage. HUE survey 30 publications and their long-term estimate of how profiles costs[10] increase with the clean share is shown in the first panel of Figure 3. The data is limited to wind generation shares up to 40 per cent and, as they show the line of best fit, is naturally linear. Other studies can complement and extend this data as they consider higher VRE shares and other renewable technologies.

[9] I therefore ignore the fact that $LCOE_{vre}(w)$ will likely be a decreasing function of w, as the most productive VRE sites are used first, which would mean that the inferred elasticity is an overestimate.

[10] Profile costs are shown as a ratio of the average electricity price of 70 €/MWh used by HUE.

UHLE report profile costs for wind and solar technologies. They also find that profile costs make up the bulk of integration costs, particularly for high clean shares. As optimal policy could include both technologies, I construct a combined "profile" cost: I take the solar profile costs from UHLE and add the extra cost of solar as a ratio of wind LCOE, which shifts the line up by just over 0.2.[11] UHLE present a clear profile of costs up to a 40 per cent wind share and 25 per cent solar share. To extend the range of profile costs further, I extrapolate the wind profile cost up to a 50 per cent share. By assuming profile costs are independent of each other and using the AEO solar/wind cost ratio, a combined "profile" cost of both wind and solar can be derived.[12] Costs are shown in the second panel of Figure 3**.**

Elliston, Riesz, and MacGill (2016), hereafter ERM, report average energy cost profiles for different shares of renewable energy up until a 100 per cent share, for a low and high gas price. After inputting average prices from the ERM paper, I adjust data points to ensure that the slope of the average price is non-decreasing with the clean share. This adjustment ensures that the calculated marginal cost (discussed below) is non-decreasing with the share of clean energy, so that the share increases as the renewable price falls and the inferred elasticity is positive. The resulting average costs for both gas price scenarios, after smoothing, are shown in the third panel of Figure 3**.**

[11] UHLE report that solar system LCOE costs start for zero penetration at double the cost of wind. Capital costs have changed significantly in recent years and costs are projected to continue to decline. Projected capacity-weighted system LCOE costs for new generation resources entering service in 2022 are 48 $/MWh and 59.1 $/MWh for wind (onshore) and solar respectively (Annual Energy Outlook 2018). These costs imply solar LCOE costs 23 per cent higher than wind.

[12] The combined costs have been smoothed.

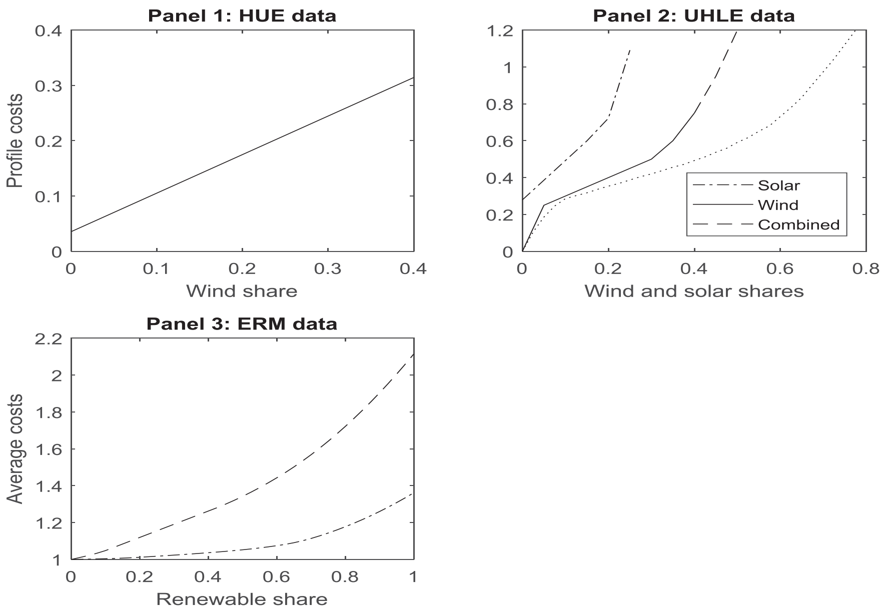

FIGURE 3: COST ESTIMATES FROM THE LITERATURE

Notes: All costs are in units of the average cost of the conventional system ($LCOE_{conv}$).

The HUE and UHLE data discussed above are marginal integration costs, while the reported ERM data are average costs. The average costs are based on constant prices, and the increase in the average price with renewable share may be due to both a higher LCOE price for clean energy over dirty energy, and to integration costs: $\frac{\partial C_{tot}}{\partial E_{vre}} = LCOE_{vre} - LCOE_{conv} + \Delta_{vre}$. Thus, if integration costs are zero, the slope of the average cost simply reflects a higher price of clean energy. I assume integration costs are close to zero when the clean share is zero and hence approximate the difference in LCOE prices ($LCOE_{vre} - LCOE_{conv}$) by the slope of the average price at zero clean share.

All integration costs are combined in the first panel of Figure 4. While there is a significant range of estimates, the gradients tend to increase at high (above 50 per cent) clean energy shares, where this data exists. Elasticity estimates are shown in the second panel of Figure 4, based on (8). Although there is a considerable variation between papers, elasticities tend to decrease as the clean share increases.

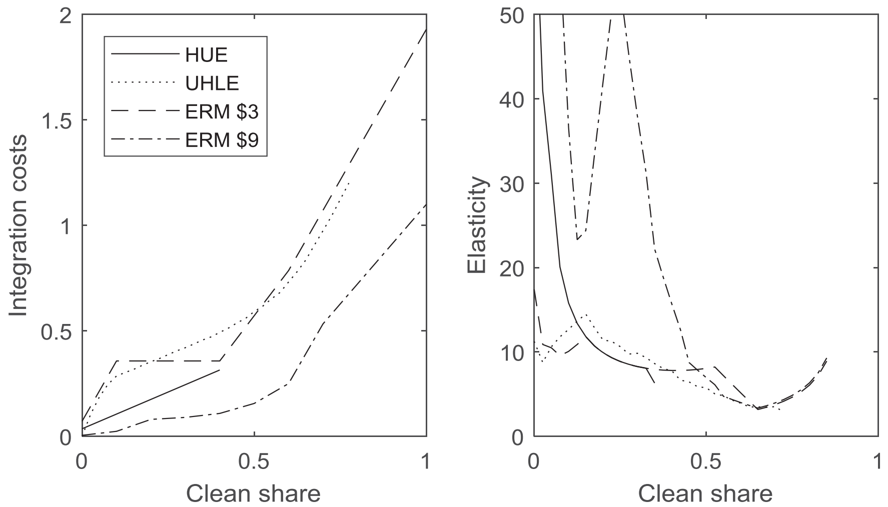

FIGURE 4: COMBINED INTEGRATION COST ESTIMATES AND INFERRED ELASTICITIES

Notes: Integration costs are in units of the average cost of the conventional system ($LCOE_{conv}$).

A key reason for the decreasing elasticity is the increasing rate of curtailment with the share of VRE. Curtailment can be reduced using storage technology, demand-side measures and integration between regions with different temporal VRE characteristics. The studies above include assumptions of storage options that help balance supply and demand. For example, ERM find that pumped storage hydro and concentrating solar thermal help reduce costs at high clean shares. Therefore, consideration of storage at high clean shares is important for any structural model.

II. A simple structural electricity model

This section develops a structural model to enable estimation of an appropriate production function between clean and dirty energy inputs. The model also describes how this function changes with the price or availability of storage.

Structural Model

The market is structured to minimise the total cost of meeting demand. Two high-level types of generation exist: dirty which is dispatchable; and clean which is intermittent or variable, as in wind or solar which generate according to weather conditions.

Dirty dispatchable generation—A stylised linear load duration demand curve (LDC) reflects how total system demand varies with time: $\mathrm{LDC(x)} = 2 - \mathrm{x},\ 0 \leq \mathrm{x} \leq 1$. Production consists of three types of dirty dispatchable generation - base, intermediate and peak - as used in Wiskich (2014) and Ueckerdt et al. (2015). Each technology is characterised by a fixed and variable cost. Given fixed costs $F_B > F_I > F_P$ and variable costs $V_B < V_I < V_P$, the cost of production given capacity factor X is the sum of fixed costs and variable cost: $F + XV$. I assume that 'peak and intermediate', and 'intermediate and base' total generation costs are the same at capacity factors X_1 and X_2 respectively:

$$(9) \qquad \begin{aligned} F_P + X_1 V_P &= F_I + X_1 V_I \quad \text{(Peak to Intermediate)} \\ F_B + X_2 V_B &= F_I + X_2 V_I \quad \text{(Intermediate to Base).} \end{aligned}$$

The generation of each type is shown in the shaded areas in Figure 5. Peak capacity is only used a small proportion of the time; when the capacity factor is low and the fixed cost dominates the total cost. Intermediate capacity is used around half of the time on average and base capacity is used almost all the time. Total fixed costs are $X_1F_P + (X_2 - X_1)F_I + (2 - X_2)F_1$ and total variable costs are $\frac{{X_1}^2}{2}V_P + \left(\frac{(X_2-X_1)^2}{2} + (X_2 - X_1)X_1\right)V_I + \left(1 + (1 - X_2)X_2 + \frac{(1-X_2)^2}{2}\right)V_B$.

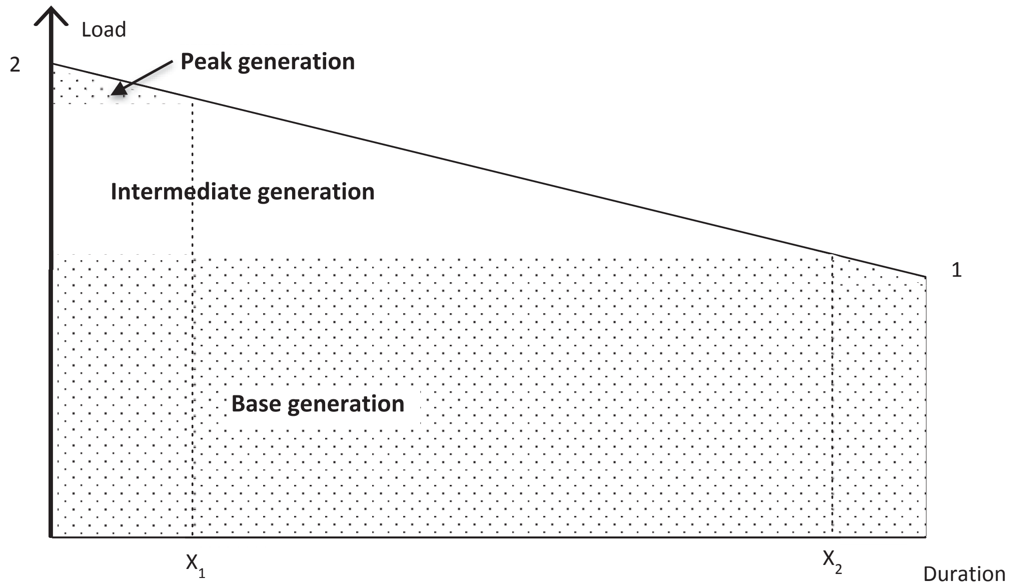

FIGURE 5: LOAD DURATION ASSUMPTION WITH BASE, INTERMEDIATE AND PEAK GENERATION

Clean variable generation—Intermittency of clean generation lowers and changes the shape of the residual LDC (RLDC) faced by dispatchable generation, as shown in Figure 6. The derivation of (5) is broadly based on International Energy Agency (2012) and generalises an approach that I have previously used (Wiskich, 2014). The key assumption is a uniform distribution of variable generation with a minimum supply proportion of m, as explained in (10) below. Ueckerdt et al. (2015) also use a RLDC approach but assume the quadrilateral shape shrinks and distorts in such a way to match the variable generation supply and demand data.

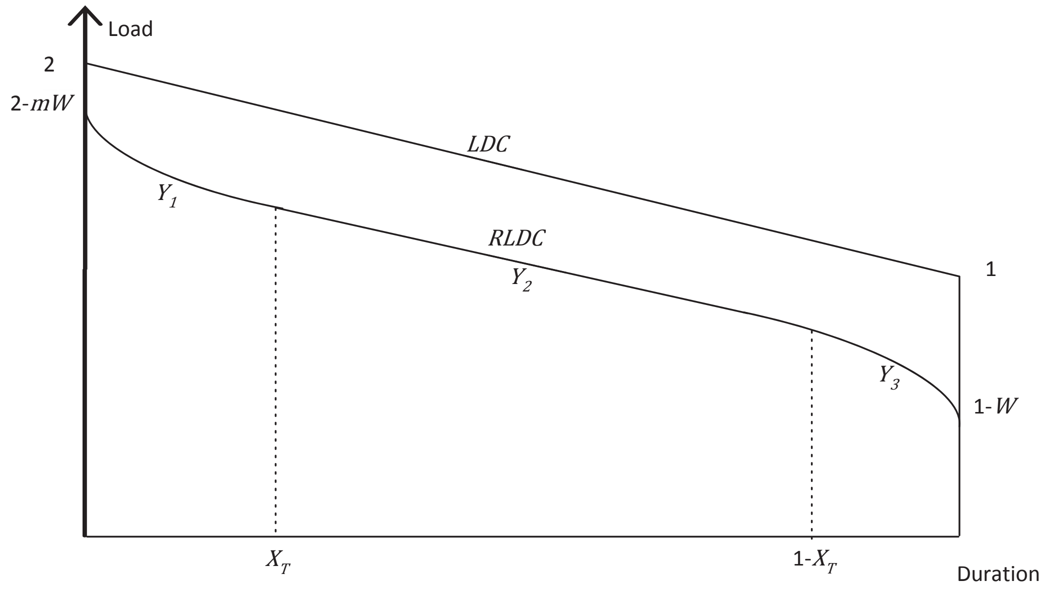

FIGURE 6: RESIDUAL LOAD DURATION CURVE

The key effects of intermittent generation include; reduced utilisation of base and peak generation, and increased/decreased capacity of peak/base generation. The RLDC (10) describes the effect of intermittent generation which varies uniformly between mW $(0 \leq m \leq 1)$ and W. Let $W' := (1-m)W$, then we have

$$(10)\ \ RLDC = \max(0, Y) \ \text{ where } Y = \begin{cases} Y_1 & x < X_T \\ Y_2 & X_T < x < 1 - X_T \\ Y_3 & x > 1 - X_T \end{cases}$$

$$Y_1 = 2 - mW - \sqrt{2W'x}$$

$$Y_2 = \begin{cases} 2 - mW - \dfrac{W'}{2} - x & W' < 1 \\ 1.5 - mW - W'x & W' > 1 \end{cases} \qquad \text{and } X_T = \begin{cases} \dfrac{W'}{2} & W' < 1 \\ \dfrac{1}{2W'} & W' > 1. \end{cases}$$

$$Y_3 = 1 - W + \sqrt{2W'(1-x)}$$

Consider the case where $m = 1$ so clean generation consistently generates W units of electricity. Thus $X_T = 0$ and the RLDC is simply the LDC straight line lowered by W. Variability of generation between mW and W implies different functions Y_1 and Y_3 for the peak load and minimum load areas of the curve, with $Y_1(0) = 2 - mW$ corresponding to $LDC(0) = 2$ lowered by the minimum intermittent generation mW and $Y_3(1) = 1 - W$ corresponding to $LDC(1) = 1$ lowered by the maximum intermittent generation W. The quadratic forms of Y_1 and Y_3 follow from the assumption of a uniform distribution between mW and W which is uncorrelated with aggregate demand. That is, intermittent supply can be considered as a random number between mW and W for every point in time. When clean energy is high enough such that $W > 1$, curtailment occurs as $Y_3(1) < 0$. In other words, when maximum intermittent generation occurs at minimum demand, excess supply occurs and the excess is assumed to be wasted.

Electricity model simulations and estimated parameters

Generation shares of technologies which could be considered as base, intermediate and peak vary between regions. These shares can also vary within regions over time as prices change: a lower gas price might expand the generation share of intermediate, for example. Rather than model one particular region or set of fuel prices, it is useful to present results for a range of different configurations. Therefore, this paper considers multiple values $X_1 \in \{0.05, 0.1, 0.15\}$ and $X_2 \in \{0.75, 0.85, 0.95\}$ which, in the absence of intermittent generation, correspond to peak generation shares of 0.08 per cent, 0.3 per cent and 0.8 per cent and base generation shares of 70 per cent, 76 per cent and 81 per cent. X_1 and X_2 are derived in two ways: the first by altering fixed costs and the second by altering variable costs, leading to 18 simulations as listed in Table 1. Simulation 5a is referred to as the central scenario for demonstration purposes below.

TABLE 1: ELECTRICITY MODEL SIMULATION PARAMETER ASSUMPTIONS

	X_1, X_2,	V_B, V_I, V_P	F_B, F_I, F_P
1a	0.05,0.75	0.5,1.17,6.17	1,0.5,0.25
2a	0.05,0.85	0.5,1.09,6.09	1,0.5,0.25
3a	0.05,0.95	0.5,1.03,6.03	1,0.5,0.25
4a	0.1,0.75	0.5,1.17,3.67	1,0.5,0.25
5a	0.1,0.85	0.5,1.09,3.59	1,0.5,0.25
6a	0.1,0.95	0.5,1.03,3.53	1,0.5,0.25
7a	0.15,0.75	0.5,1.17,2.84	1,0.5,0.25
8a	0.15,0.85	0.5,1.09,2.76	1,0.5,0.25
9a	0.15,0.95	0.5,1.03,2.7	1,0.5,0.25
1b	0.05,0.75	0.5,1.09,3.59	1,0.56,0.44
2b	0.05,0.85	0.5,1.09,3.59	1,0.5,0.38
3b	0.05,0.95	0.5,1.09,3.59	1,0.44,0.32
4b	0.1,0.75	0.5,1.09,3.59	1,0.56,0.31
5b	0.1,0.85	0.5,1.09,3.59	1,0.5,0.25
6b	0.1,0.95	0.5,1.09,3.59	1,0.44,0.19
7b	0.15,0.75	0.5,1.09,3.59	1,0.56,0.19
8b	0.15,0.85	0.5,1.09,3.59	1,0.5,0.13
9b	0.15,0.95	0.5,1.09,3.59	1,0.44,0.07

For high VRE shares, residual costs tend to be dominated by fixed capacity costs. As the maximum load is $Y_1(0) = 2 - mW$, each additional unit of W lowers the maximum load by mW and so residual capacity is reduced by m. Thus, integration costs at high VRE shares are highly sensitive to m. A small value of m close to zero would be consistent with the RLDC profile in UHLE, but values in excess of 0.2 might be appropriate for some regions based on Ueckerdt et al. (2017). Thus, I show results for both $m = 0$ and $m = 0.3$. While no amount of intermittent generation can obviate residual generation when m is zero, for $m = 0.3$ no residual generation is required if $\mathrm{W} > \frac{2}{m} = 6.67$.[13]

Consider LCOEs[14] for coal, combined cycle gas turbines and renewables of \$70, \$55 and \$50/MWh (IEA 2015). Thus, a reasonable cost estimate for dirty (fossil fuel) is \$60/MWh, implying a clean to dirty LCOE price ratio of $\frac{\mathrm{P_c}}{\mathrm{P_d}} = \frac{50}{60} = 0.83$. I

13 This result is in the absence of storage (introduced below) which can reduce the amount of VRE required to obviate residual generation substantially.

14 Without carbon costs.

show clean generation shares for a wide range of price ratios from one to 0.3 in Figure 7, for all 18 simulations. In dollar terms with a fixed dirty cost of \$60/MWh, the clean price range is \$60/MWh to \$18/MWh, or with a fixed clean price of \$50/MWh, the range of dirty prices (which could reflect a carbon price) are \$50/MWh to \$167/MWh. I assume for the moment that no storage is used. Varying fixed costs (simulations 1b-9b) results in a wider spread than varying variable costs (simulations 1a-9a), but the general profile of results are similar.

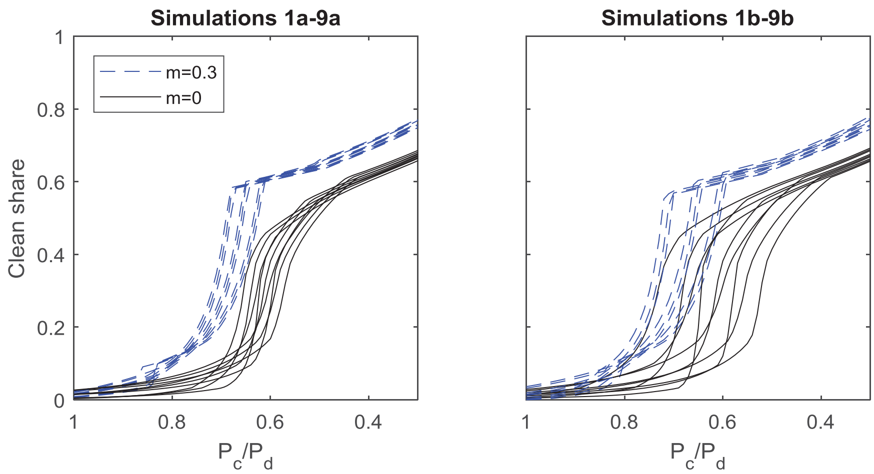

FIGURE 7: SIMULATION RESULTS FOR RATES OF CLEAN SHARES AS THE PRICE OF CLEAN INPUTS DECREASE, WITHOUT STORAGE

As the share of VRE increases, the model considers the reduced utilisation of thermal plant capital as well as curtailment, both components of the profile cost. As discussed in the previous section, profile costs are the most important integration cost of variable generation. Figure 7 suggests a production function between clean and dirty energy with two elasticities: a high one up to a certain VRE share depending on the value of m, and a lower elasticity above this share when curtailment begins to dominate.

Marginal integration costs are derived based on integration costs calculated in (4) and are shown in the first two panels of Figure 8, along with the upper and lower bounds from the literature taken from panel 1 of Figure 4. As discussed above, integration costs are a function of the clean price due to curtailment. Consistent with the literature discussed in the previous section, the integration costs are calculated based on a fixed clean price for comparison. I show results for a high and a low clean to dirty price ratio of 1 and 0.3, corresponding to the bounds of the simulations. Rather than inferring the elasticity from integration costs as described in the previous section, I directly use the change in the clean to dirty price ratio used in the simulations. A profile of high elasticities for low clean shares and low elasticities for high clean shares is shown in panel C.

Figure 8 demonstrates that the structural model can replicate a decreasing elasticity as inferred from the literature, as well as reflecting the range of costs for different clean shares. Integration costs at high clean shares are highly dependent on the clean price and become very high for both $m = 0$ and $m = 0.3$ with the high clean price. However, the model thus far does not account for storage or demand management, which is included in the literature discussed in section 1 and can lower marginal costs at high clean shares.

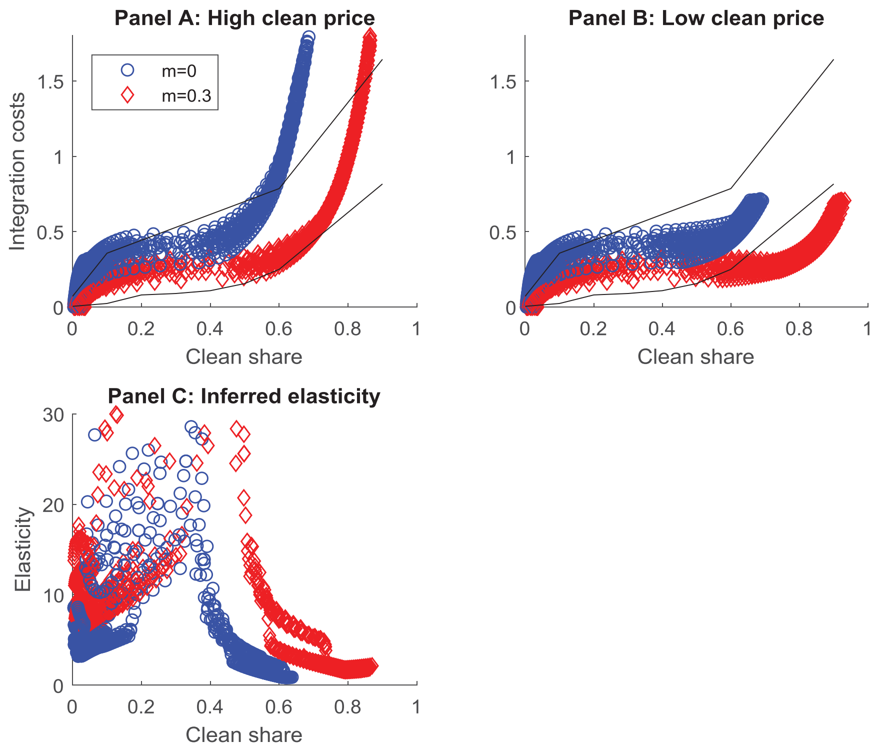

FIGURE 8: INTEGRATION COSTS AND INFERRED ELASTICITY FOR ALL SIMULATIONS WITHOUT STORAGE

Notes: Integration costs are in units of the average cost of the conventional system ($LCOE_{conv}$), and are calculated based on a fixed clean to dirty price ratio: 1 for Panel A and 0.3 for Panel B.

Storage

It is convenient to use a stylised[15] approach to modelling storage by flattening the ends of the RLDC as shown in Figure 9. Storage capacity, represented by area S, generates S units of power at peak times and requires S units of charging at times of lowest demand, thereby reducing and increasing the RLDC at these times. As

[15] Future projections for storage technology options include pumped Hydro storage, concentrating solar power and electric vehicles and batteries. These storage options have different cost and performance characteristics which are not considered in this paper.

the areas at each end are equal, there is no loss of charge assumed. The cost of storage is proportional to capacity.

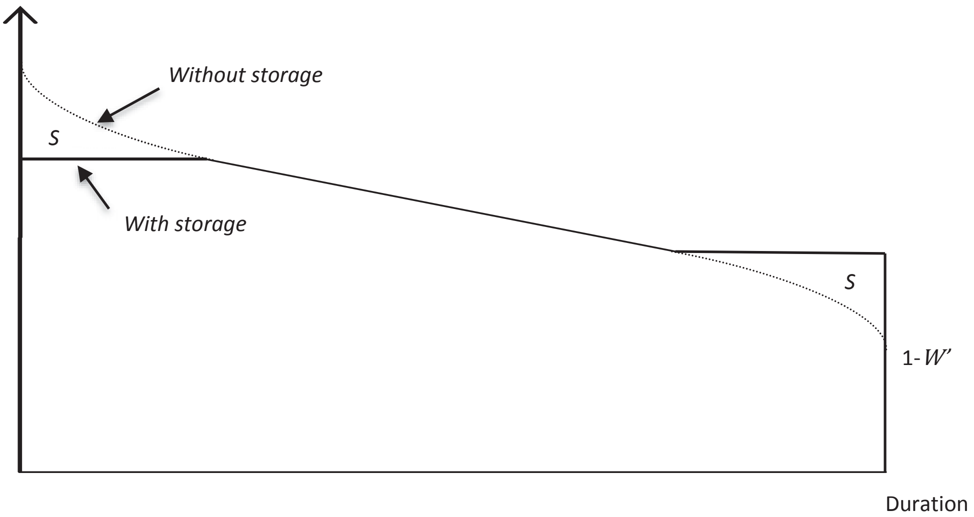

FIGURE 9: ASSUMPTION OF THE EFFECT OF STORAGE ON THE RLDC

An estimate of the cost of Lithium-Ion storage is \$268/MWh,[16] which may decline to around \$100/MWh by 2040 according to the World Energy Outlook 2017. Consider two storage prices in the model: an infinite price so there is no storage, and a price that is double the dirty price ($\mathrm{P}_s = 2\mathrm{P}_d$). Given a dirty price of \$60/MWh, this latter price corresponds to a storage price of \$120/MWh. This approach, while simplistic, allows investigation of the potential impact of storage on the substitutability between clean and dirty energy. Note that the amounts of storage, clean and dirty energy are all jointly optimised to minimise total costs. Figure 10 shows results when $m \in \{0, 0.3\}$ and $\mathrm{P}_S \in \{\infty, 2\mathrm{P}_d\}$. The availability of storage (at a fixed price) lowers integration costs and boosts the clean share for a given VRE price.

[16] https://www.lazard.com/perspective/levelized-cost-of-storage-2017

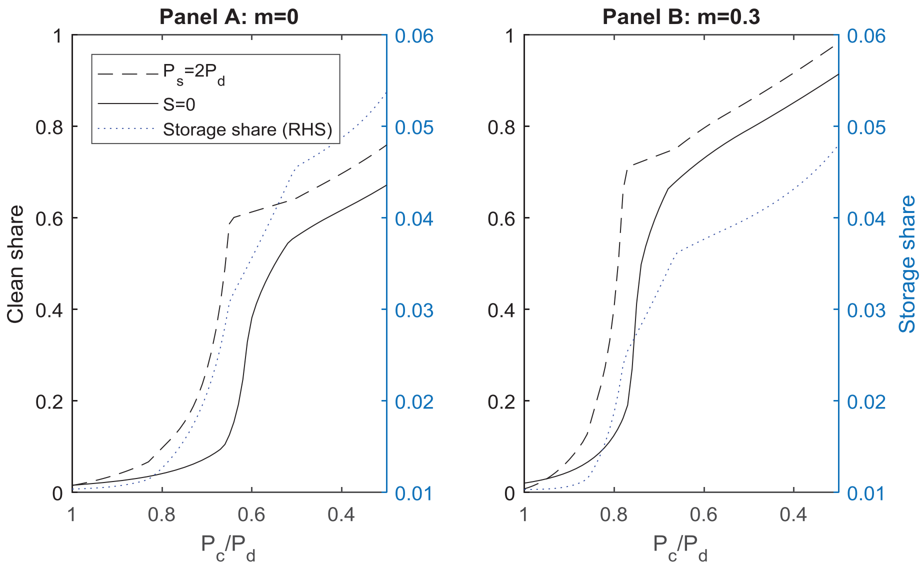

FIGURE 10: CLEAN AND STORAGE SHARES AS THE VRE PRICE DECREASES IN THE CENTRAL SCENARIO, FOR $m \in \{0,0.3\}$ AND $P_S \in \{\infty, 2P_d\}$.

Figure 10 also shows the storage shares when $P_S = 2P_d$.[17] As storage capacity increases with the clean share, there is a clear complementarity between storage and clean energy. So far I have presented results where the price of storage is fixed and the amount of storage is optimised to minimise total costs of generation. In Appendix A, I consider different fixed amounts of storage which are available at no cost, providing an understanding of the direct effect of storage on the production function. The uptake of electric vehicles, which may become a significant source of storage, will have other economic drivers, so it is useful to consider such an approach in this context. The effect of fixed amounts of storage is similar to the effect shown in the second panel of Figure 10.

[17] The share is the ratio of storage with total electricity demand, S/1.5.

While the described electricity model is transparent, it is still too complex for a macroeconomic model. A simpler representation, such as a modification of the CES workhorse of many economic models, would be more applicable, and the next section discusses some options.

III. Estimating production functions with a variable elasticity

This section describes three potential methods of incorporating a decreasing elasticity of substitution between clean and dirty energy. The first uses a "bimodal" production function with two isoelastic regimes depending on the clean share. The second uses the Variable Elasticity of Substitution (VES) function, introduced by Sato and Hoffman (1968) and Revankar (1971). The third uses a couple of isoelastic nests with different elasticities, combining in a Leontief function. Results are shown in Table 2 along with results using an isoelastic function where two parameters are estimated; the elasticity and a share parameter which is generally set by the initial equilibrium in an application. The goodness of fit is shown as R-squared.

Estimation is based on results from the structural electricity model, minimising the square of errors in the share of clean energy in total energy production across all 18 simulations weighted equally. I investigate four scenarios with different combinations of storage prices, $\mathrm{P}_S \in \{\infty, 2\mathrm{P}_d\}$, and minimum levels of VRE supply, $m \in \{0,0.3\}$.

Bimodal production function

The functional form for the bimodal elasticity of substitution production function is straightforward and similar to the form suggested by Antony (2009). For a clean to dirty input ratio w and switch point $\overline{w}$ where the elasticity changes from σ_1 to σ_2, the output to dirty input ratio y is given by:

$$(11) \qquad y = A\left(\beta w^{1-1/\sigma} + 1\right)^{\frac{\sigma}{\sigma-1}}$$

$$\text{where } \sigma, A, \beta = \begin{cases} \sigma_1, 1, \alpha & \mathit{if}\ w < \overline{w} \\ \sigma_2, \left(\overline{w}^{\frac{\sigma_1-1}{\sigma_1}} + 1\right)^{\frac{\sigma_1}{\sigma_1-1} - \frac{\sigma_2}{\sigma_2-1}}, \alpha\overline{w}^{\frac{1}{\sigma_2}-\frac{1}{\sigma_1}} & \mathit{if}\ w > \overline{w}. \end{cases}$$

Output and its derivative are continuous at the switch point. The second derivative is not continuous but is negative at all points, ensuring concavity and uniqueness. Figure 11 shows clean shares for the central scenario and the estimated bimodal function as the clean input price decreases.[18] The switch point where the elasticity changes corresponds to the discontinuity in slope. A bimodal function appears to be a very good approximation in all cases, confirmed by a high R-squared in Table 2.

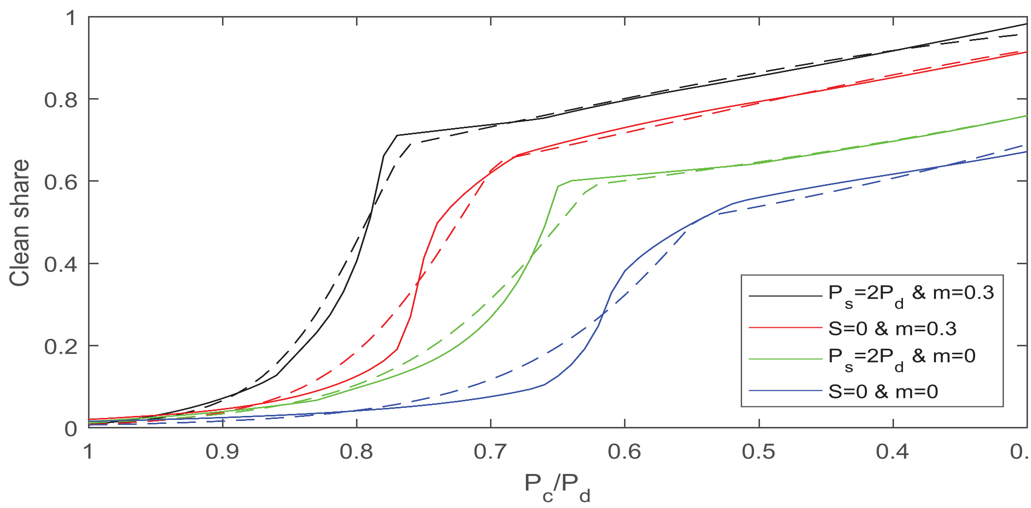

FIGURE 11: COMPARISON OF THE ESTIMATED BIMODAL FUNCTION (DASHED LINES) WITH STRUCTURAL MODEL RESULTS FOR THE CENTRAL SCENARIO

[18] Note that the function is estimated across all 18 simulations weighted equally, not just the central simulation.

Four parameters are estimated: elasticities σ_1 and σ_2, the switch point $\overline{w}$ and the share parameter α. In a modelling exercise, assumptions of initial equilibrium generation shares would set the α term, given values for the other parameters, similar to estimating an isoelastic function. All scenarios have a high elasticity over 8 for low clean shares. The availability of cheap storage increases the switch point and share parameter, while a minimum level of VRE supply increases all parameters.

Variable Elasticity of Substitution

The VES specification follows Karagiannis, Palivos, and Papageorgiou (2005). For clean (C) and dirty (D) inputs, the output to clean input ratio (y) is given by:

$$y \equiv \frac{Y}{C} = Ad^{a}(1 + bad)^{1-a} \tag{12}$$

where $d \equiv \frac{D}{C}, A > 0, 0 < a \leq 1, b > -1$ and $\frac{1}{d} \geq -b$.

This function is the most parsimonious of the three variable elasticity approaches, with only two parameters estimated: a and b. The elasticity of substitution is given by $\sigma(d) = 1 + bd$ and the clean share is $s_c = \frac{1-a}{1+bad}$. For a dirty price of one and clean price p, we have $d = \frac{pa}{1-a-abp}$. As the elasticity should decrease as the clean share rises (as d increases), the estimated parameter $b > 0$ and hence $d > 0$ if $p < \frac{1-a}{ab}$. Therefore for higher clean prices than this ratio, the clean share is set to zero. The VES function fits the data well when $m = 0.3$, but less so when $m = 0$ where the share plateaus at a lower value, as the first panel of Figure 12 shows. The R-squared is lower than the bimodal case in every simulation. The variation of the elasticity with the clean share is shown in the second panel of Figure 12.

The VES specification implies the elasticity approaches infinity as the clean share approaches zero. This behaviour may not present a challenge for previous applications to capital-labour substitutability where shares are roughly balanced, but may be difficult to implement for clean-dirty substitutability at low clean shares. Although the variation in elasticity with the clean share may be a challenge for estimation and conceptualisation, compared with the bimodal approach, the linear form of the elasticity with respect to the dirty to clean ratio is straightforward. This function may therefore be a good candidate to model clean and dirty substitutability, particularly if parsimony and a continuous profile of elasticity are desirable.

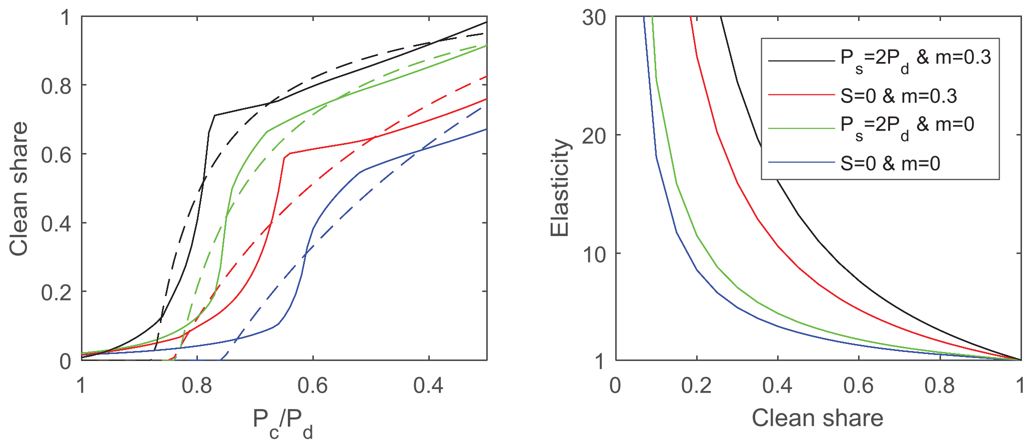

FIGURE 12: COMPARISON OF THE ESTIMATED VES FUNCTION (DASHED LINES) WITH STRUCTURAL MODEL RESULTS FOR THE CENTRAL SCENARIO, AND ELASTICITIES OF THE VES FUNCTION

Dual isoelastic nest

Conceptually, a dual isoelastic nest is similar to the bimodal production function. Outputs from two isoelastic production functions, each with clean and dirty inputs, combine as inputs in a Leontief (fixed input ratios) production function. Total clean/dirty energy inputs are the sum of these inputs across both isoelastic nests. The first nest has a high elasticity and drives a high elasticity for the aggregate production function for low clean shares. The second nest has a lower elasticity and drives dynamics at high clean shares. When estimated, the Leontief share between the nests acts like the switch point in the bimodal production function.

I estimate five parameters using this method: two elasticities and two weights for each nest, and the Leontief share. Unlike the bimodal case, the calibration of weights is indeterminate given an initial equilibrium condition as there are two of them. The R-squared is comparable to the bimodal case.

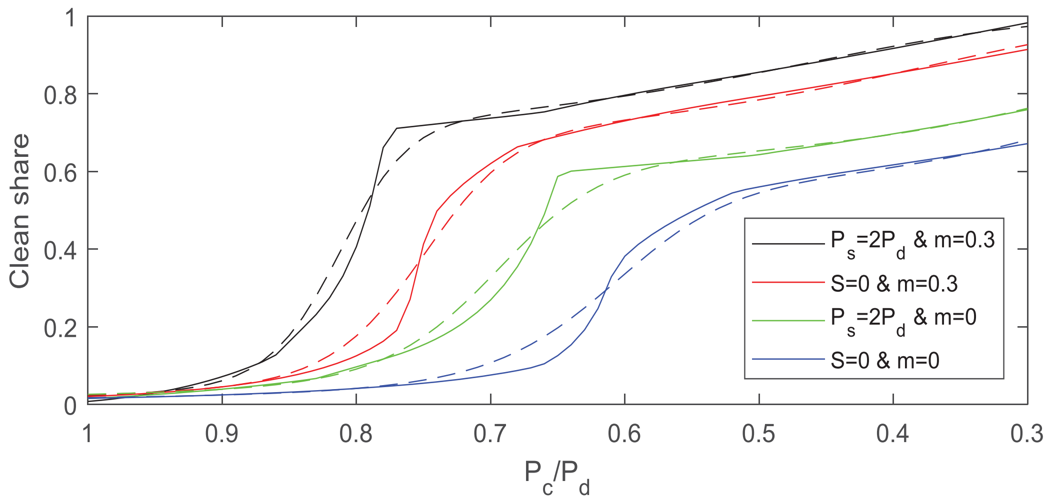

FIGURE 13: COMPARISON OF THE ESTIMATED DUAL ISOELASTIC NEST FUNCTION (DASHED LINES) WITH STRUCTURAL MODEL RESULTS FOR THE CENTRAL SCENARIO

This method has the most estimated parameters and the indeterminacy in calibrating shares seems problematic. In addition, the use of two nests is contrived as the aggregate elasticity is a combination of elasticities in each nest and input shares, making conceptualisation of the model difficult. The strength of this approach is that isoelastic nests are a common, straightforward method of incorporating different technologies and/or fuels.

TABLE 2: ESTIMATED BIMODAL PRODUCTION FUNCTION PARAMETERS

	Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4
	Ps	∞	$2P_d$	∞	$2P_d$
	m	0	0	0.3	0.3
Bimodal	σ_1	8.3	10.2	14.9	20.9
	σ_2	1.3	1.1	2.1	2.5
	$\bar{w}$ (% $share$)	1.0 (51)	1.4 (59)	1.9 (65)	2.2 (69)
	α	0.55	0.65	0.72	0.79
VES	a	0.20	0.18	0.11	0.14
	b	1.9	2.6	6.4	10.0
Dual isoelastic nest	σ_1	14.1	17.5	22.5	31.4
	σ_2	2.7	2.6	3.8	4.6
	share	0.38	0.47	0.57	0.63
	a1	0.62	0.71	0.76	0.82
	a2	0.27	0.32	0.48	0.55
Isoelastic	σ	3.8	4.0	7.1	9.8
	α	0.46	0.56	0.68	0.76
R-squared					
Bimodal		94.2	97.3	96.8	98.2
VES		92.5	94.4	95.9	97.0
Dual isoelastic nest		94.4	97.2	96.9	98.2
Isoelastic		85.6	84.4	89.7	90.4

III. Conclusion and discussion

Two types of literature are discussed in the context of a variable elasticity of substitution between clean and dirty energy inputs. The first, a single recently published paper, derives a distribution of productivity gaps between clean and dirty technologies by using patent and industry sector data. The second considers results from empirically-based regional structural electricity models that can extrapolate system costs at high clean energy shares. While both methods have limitations in inferring a macro elasticity of substitution, they both indicate a decreasing elasticity as the clean share increases.

Key reasons for a declining elasticity have been outlined in the context of the electricity sector, aided by a simple structural model. This structural model replicates a decreasing elasticity, reflects the range of integration costs reported in the electricity literature, and can incorporate the effects of storage. Three methods of incorporating the decreasing elasticity in a macroeconomic model are discussed: a “bimodal” production function with two elasticities; a variable elasticity of substitution (VES) function; and a couple of isoelastic nests with different elasticities, combining in a Leontief function. All methods can fit output from the simple structural model better than an isoelastic function. The bimodal function is a good candidate as the three key parameters - low and high share elasticities and the switch point where the elasticity changes – all have a clear conceptual interpretation. Existing models with an isoelastic function could also be easily modified to incorporate the bimodal characteristic.

The good performance of the bimodal approach is in large part due to the nature of curtailment of intermittent supply. A high elasticity of above 8 is appropriate up until a switch point of around 50 to 70 per cent clean penetration, after which a much lower elasticity between 1 and 3 is appropriate. As electricity is just one component of energy and thus, lower elasticities are probably appropriate for models that combine electricity and non-electricity into a single aggregate. Similarly, the switch point of between 50 and 70 per cent suggested by the model could be reduced when all energy types are aggregated. However, the model does not distinguish between carbon intensities of peak, intermediate and base generation. Coal typically fits into the base generation category which is displaced first by VRE. This effect would imply a higher switch share in terms of emissions. Overall, a high elasticity 3 or above and a low elasticity of below 3 seems reasonable at a macro level, with a switch point of roughly 50 per cent. Storage can be modelled by increasing the switch point and share parameter as the storage price declines or storage capacity increases.

Several research directions appear fruitful. Apart from the effect of a changing elasticity on energy projections and the cost of abatement, a decreasing elasticity may have interesting implications for optimal policy. In a related paper I examine some potential implications in a climate model with endogenous technical change (Wiskich, 2019). The interaction between a bimodal function and uncertainty in environmental damages, including tipping points, may be important, and the switch point and long-run elasticity themselves could be modelled under uncertainty. Elasticity and other parameter estimates, or the structure of the production function, could be refined using more detailed energy models. A more complex sectoral analysis would help highlight different effects on coal and gas, for instance, which have different emission intensities.

Appendix A – Fixed storage capacity

I show simulated results where storage is fixed from zero up to 3% of total generation. As is clear from Figure 14, the main effect of adding storage is to increase the switch point where the high elasticity reduces. A similar effect would apply for regions with a pre-existing Hydro capacity, particularly if pumped storage is available.

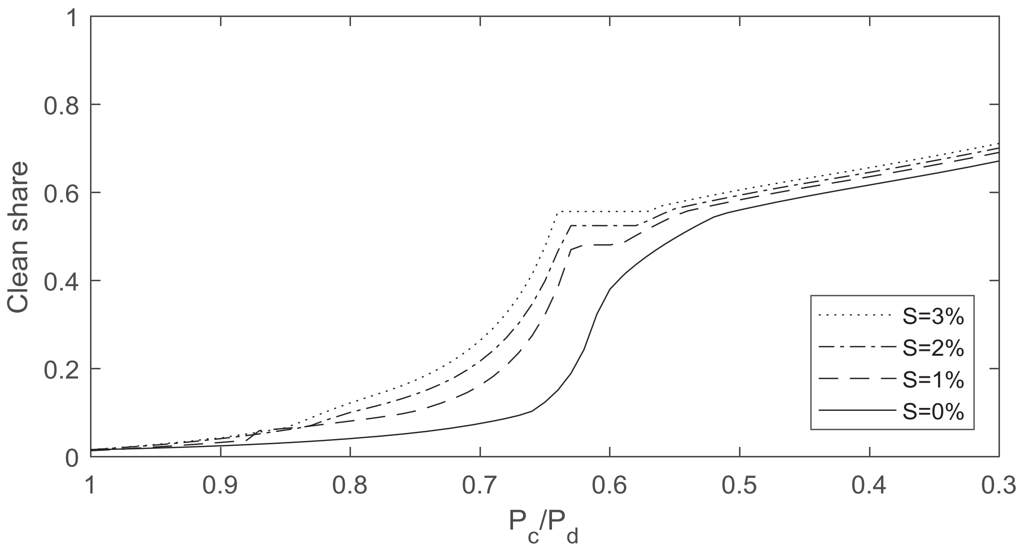

Figure 14: Simulated results for different fixed storage capacities in the central scenario with $m = 0$

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