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CAMA Working Paper 27/2023
June 2023

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Abstract

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JEL Classification

O33, Q41, Q42, Q54, Q58

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ISSN 2206-0332

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Perfect so far? Substitutability between wind & solar and dirty electricity generation

By ANTHONY WISKICH*

Wind and solar are driving the clean transition in electricity: this paper uses panel data to investigate how these technologies substitute with dirty (fossil fuel) electricity generation. Production functions with a constant and a variable elasticity of substitution are estimated. Results suggest a higher elasticity of substitution than previous estimates, aligning with long-run analysis from electricity dispatch models and assumptions often made in economic models. Little evidence is found of the elasticity decreasing so far. However, the uptake of wind and solar decreases the utilisation rates of dirty capital. (JEL O33, Q41, Q42, Q54, Q58)

Keywords: Elasticity of substitution; climate change; energy; electricity; production function.

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Responding to climate change involves transitioning the global economy from dirty to clean energy. The substitutability between these inputs is an important factor in determining optimal policy and the cost of this transition. Transformation of the electricity generation sector is crucial as it is a major source of greenhouse gas emissions, and electrification allows other sectors, such as transport, to transition away from fossil fuels. Wind and solar (W&S) generation is predicted to drive the clean transformation of the electricity sector globally, making up most of the clean generation in 2050 in the IEA's net zero pathway.[1] This paper examines how these technologies have substituted with fossil-fuel generation so far.

At a high level, one can conceptualise a W&S aggregate displacing a fossil fuel aggregate consisting mostly of coal and natural gas. While in one sense, electricity is identical no matter the generation source, the intermittent nature of W&S and other factors imply imperfect substitutability between these generation types. In economic models, a constant elasticity of substitution (CES) function between such aggregates is a parsimonious way to reflect imperfect substitutability, parameterised by a share parameter and the elasticity of substitution.[2]

There is a disconnect between empirical estimates of the elasticity of substitution between clean and dirty inputs and the elasticity adopted in many economic models used to study climate mitigation. Such models often have a long-term focus and adopt a high elasticity greater than 2 for clean and dirty energy substitution.[3] For example, Acemoglu, Aghion, Bursztyn, and Hemous (2012) adopt elasticities of 3 and 10, pointing out that electricity is the same no matter the generation source. A high elasticity is supported by detailed electricity dispatch (supply) models, which indicate almost perfect long-run substitutability for moderate (under 50% or so) W&S shares (Stöckl & Zerrahn, 2023; Wiskich, 2019).

But the limited empirical estimates do not support such high elasticities: 1.6 between fossil fuel and renewable energy (Lanzi & Sue Wing, 2011); and for electricity around 0.5 (Pelli, 2012) and 2 (Papageorgiou, Saam, & Schulte, 2017).

[1] https://www.iea.org/reports/net-zero-by-2050

[2] Rather than use a stylised production function of clean and dirty inputs, some models explicitly consider intermittency such as Ambec and Crampes (2012) and Ambec and Crampes (2019).

[3] In principle, a long-run value below 1 in a CES function implies nonsensical results for electricity: aggregate output becomes zero without clean generation, no matter how much dirty generation exists; and the expenditure share on clean energy falls as the clean share rises.

However, through replication, I find the result in Papageorgiou et al. (2017) relies on an inconsistency between their regressions and their paper, so the gap between the elasticity used in economic models and empirical estimates persists.[4]

My empirical approach uses a nonlinear, direct estimation of production functions of two inputs - clean (W&S) and dirty (fossil fuel) aggregates – to generate electricity. Panel data comes from the International Energy Agency and Global Energy Monitor. I exclude hydro and nuclear in the main specification, which dominate over W&S, as I expect this approach will provide a better indication of substitutability under a clean transition. Unlike the estimation of a first-order condition equation, this supply-side approach does not consider prices, avoiding some difficulties in untangling the effects of regional policies that may induce W&S investment through price or quantity mechanisms. It is also well suited to capture reductions in the utilization rates (the proportion of time that a generator produces electricity, also known as capacity factors) of fossil generation due to the introduction of intermittent generation (Ueckerdt, Hirth, Luderer, & Edenhofer, 2013). An initial investigation of the data confirms that dirty utilization rates have fallen markedly with W&S uptake.

Reduced utilization of incumbent generation is the largest integration cost of intermittency, defined as the marginal long-run cost (per unit of output) borne by an electricity supply system from an additional unit of intermittent generation. These integration costs are close to zero when no W&S is present and increase as the W&S share rises (Hirth, Ueckerdt, & Edenhofer, 2015; Ueckerdt et al., 2013), implying a decreasing elasticity of substitution with the W&S share (Stöckl & Zerrahn, 2023; Wiskich, 2019).[5] Due to this fundamental asymmetry, I estimate

[4] I discuss some limitations of Papageorgiou et al. (2017) in Section 5.

[5] A decreasing elasticity is found at least for W&S shares below 50%. The conversion of integration costs to an elasticity of substitution is discussed in Wiskich (2019). Aleti and Hochman (2020) also find a decreasing elasticity from a model that considers consumer preferences.

variable elasticity of substitution (VES) functions in addition to CES functions. The VES form I use has an infinite elasticity at zero W&S share, which declines as the share rises.

Results for the standard CES function suggest an infinite, or high, elasticity of substitution. But the substitution, while close to "perfect", is "less-than-complete": one unit of W&S electricity substitutes for 0.57 units of generation-normalised dirty capacity in the main specification.[6] Results using the VES function are consistent, showing little evidence of the elasticity declining.

Perfect substitutability applied in an economic model means once the W&S price (relative to dirty) falls below a certain point, it is optimal to use W&S entirely in the long run once capital can adjust. However, caution should apply if extrapolating results to very high W&S shares, which are absent in the data I analyse: hence substitution appears "perfect so far". Further, in section 5, I explain that while previous estimation based on first-order conditions tends to understate the elasticity, the production function method I use probably overstates it, partly due to sluggish capital adjustment. Estimation challenges will likely diminish as the decarbonisation of the electricity sector unfolds and more data points become available. This paper provides a basis for further analysis and for using a high long-run elasticity of substitution in economic models.

1. An initial investigation

To help understand the results in Section 4 and to motivate the estimation of a VES function, this section considers the effect that W&S uptake has on dirty utilization rates. Figure 1 suggests the utilisation of a measure of dirty capital

[6] Dirty capacity is normalised so that it corresponds to generation in an initial period with little W&S, that is when the utilisation rates of dirty capacity have not yet been materially reduced by intermittent technologies.

(*Dutil*) has fallen as the W&S share of electricity generation (*W&Sshr*) has risen.[7] Dispatch models that analyse long-run optimal supply also predict this outcome, indicating the result is not just due to sluggish capital adjustment (Ueckerdt et al., 2013). Consider a regression that includes time and country fixed effects (a_i and b_t) and the growth in electricity production (gY_{it}), which may affect utilisation rates, as follows:

$$(1.1) \qquad Dutil_{it} = W\&Sshr_{it} + gY_{it} + a_i + b_t + \varepsilon_{it}.$$

A strongly significant, negative effect of *W&Sshr* on dirty utilisation is found, with coefficient -1.105 with robust standard error 0.349.[8] What type of production function would be consistent with this characteristic of declining dirty utilisation? Consider a CES production function that combines a clean generation input (C_t, GWh) with dirty capacity input (D_t, GW) to generate electricity (Y_t, GWh):[9]

$$(1.2) \qquad Y_t = A\left(\omega {C_t}^{\psi} + (1-\omega){D_t}^{\psi}\right)^{1/\psi}.$$

The elasticity of substitution is $\sigma = 1/(1-\psi)$ and define the dirty utilisation as $U_t = (Y_t - C_t)/D_t$. It is straightforward to show that dirty utilisation will decrease initially (when W&S input is zero) if $\omega < 0.5$ and $\psi = 1$ or if $\psi > 1$.[10] The latter case is not generally classed as CES, as the production possibilities

[7] Definitions of *Dutil* and *W&Sshr* are underneath Figure 1.

[8] This finding is robust to compositional effects, such as the inclusion of growth in gas capacity and the initial coal share.

[9] Clean capacity could also be used instead of generation, if a fixed capacity factor for this technology was assumed (this would just change ω and A), but using clean generation is simpler.

[10] Set $D = 1$ and $Y|_{C=0} = 1$ without loss of generality. $U = Y - C$ so $dU/dC|_{C=0} = \omega C^{\psi-1}/(1-\omega) - 1 = \begin{cases} \omega/(1-\omega) - 1 \text{ if } \psi = 1 \\ -1 \text{ if } \psi > 1 \\ \infty \text{ if } \psi < 1 \end{cases}$

frontier becomes convex to the origin.[11] So the only standard CES class of functions with initially decreasing dirty utilisation have perfect substitutability and vary only by the share parameter ω. Figure 2 shows some examples of CES functions.

Now consider a VES function – the specification is close to Karagiannis, Palivos, and Papageorgiou (2005). For clean ($\mathrm{C_t}$) and dirty ($\mathrm{D_t}$) inputs as before and parameters α and β, electricity output ($\mathrm{Y_t}$) is given by:

(1.3) $$Y_t = A{D_t}^{\alpha}(C_t + \beta\alpha D_t)^{1-\alpha} \text{ where } 0 < \alpha \leq 1 \text{ and } \beta > 0.$$

The elasticity of substitution is given by $\sigma_t = 1 + \beta\, D_t/C_t$, so the elasticity approaches infinity as the clean share approaches zero, $1+\beta$ when clean and dirty inputs are equal and 1 when dirty inputs are zero. The function is asymmetric, and optimal clean inputs are zero unless the price of clean relative to dirty is below a threshold. Now the condition for dirty utilisation to decrease initially is $(1-\alpha)/(\alpha\beta) < 1$, which can occur given any permitted value of α or β with the freedom to choose the other.[12] Thus, a VES function may better capture this data characteristic, and Figure 2 shows some examples.

[11] Convexity implies that, like the perfect substitution case, there is a relative price where the optimal solution jumps from one corner to the other (i.e. from all dirty to all clean inputs). Unlike perfect substitution where any share is optimal if prices are equal, output is maximised at the corners so an internal solution is never optimal – it is always optimal to either go dirty or clean, never a combination.

[12] Set $D = 1$ and $Y|_{C=0} = 1$ without loss of generality. $U = Y - C$ so $dU/dC|_{C=0} = (1-\alpha)/(\alpha\beta) - 1$.

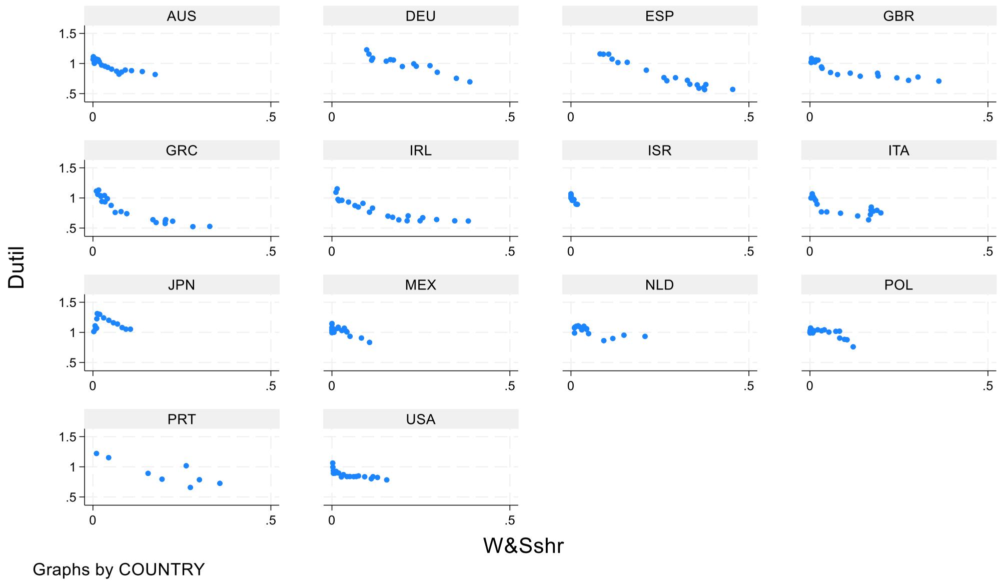

FIGURE 1: W&S SHARE AND DIRTY CAPITAL UTILISATION

W&Sshr is the share of W&S in combined W&S and dirty generation. Dirty capital utilisation (*Dutil*) is generation per GW of all fossil fuel generation, normalised to 1 based on 1995-1999 data. The data source and inclusion criteria are described in Section 3.

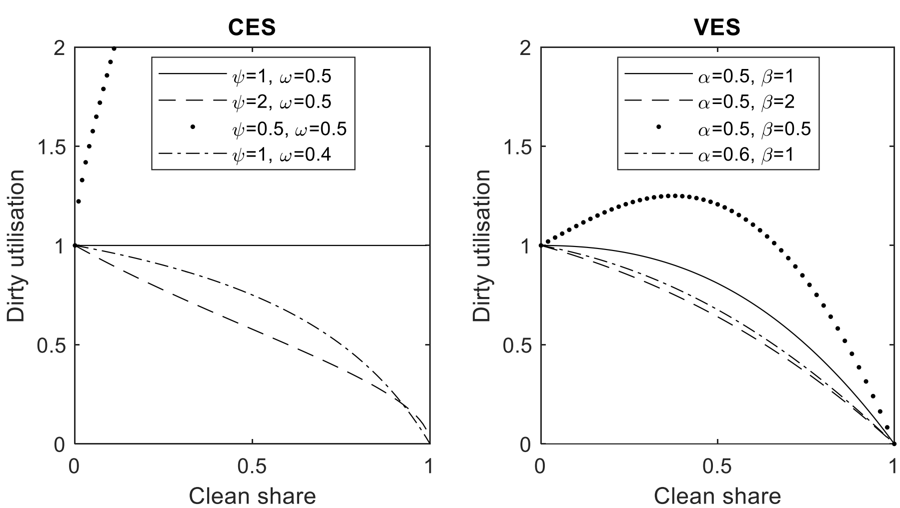

FIGURE 2: DIRTY UTILISATION FOR SOME CES AND VES FUNCTIONS

2. Production function estimation approach

The estimation is based on aggregate CES and VES production functions for electricity, combining an input measure for W&S and a measure representing dirty inputs.

CES Specification

For substitution parameter ψ and share parameter $0 \leq \omega \leq 1$, country *i*, year *t*, output Y_{it}, W&S input C_{it} and dirty input D_{it}, the CES specification is:

$$(2.1) \qquad lnY_{it} = a_i + b_t + \frac{1}{\psi} ln\left(\omega {C_{it}}^{\psi} + (1-\omega){D_{it}}^{\psi}\right) + \varepsilon_{it}.$$

The elasticity of substitution relates to the curvature of the isoquant of the two inputs (C_{it} and D_{it}) and is derived as $\sigma = 1/(1-\psi)$. The dependent variable of electricity output (Y_{it}) is measured as generation in GWh. This measure is simple but excludes reliability, the electricity grid, demand management costs and different regional economic values of generation. The dirty input is measured by generation capacity (GW). I normalise this measure based on an initial period, so the value represents the amount of generation in each region that would be generated from the dirty capacity without effects from W&S.[13] Electricity generation assets are long-lived and take years to build, so there is little risk of endogeneity between these regressors and the error term. As dirty generation is typically dispatchable, there probably is a strong correlation between fuel inputs and the error term as dispatchable dirty generation is worked harder (greater fuel

[13] That is, without material effects (such as reduced utilisation) from the presence of W&S generation. This normalisation puts clean and dirty inputs into common units (generation) – see León-Ledesma, McAdam, and Willman (2010) for a discussion of the importance of normalisation.

input) under a demand shock. For this reason and simplicity, fuel is excluded from the specification.

The country dummies a_i take care of different time-independent factors between regions. The time dummies b_t capture global demand or supply shocks, such as to fuel prices, that affect electricity output across all regions. The main specification and 7 "robustness" specifications are listed in Table 1, reflecting different choices in approach.

A first choice is what data points to include. As described above, a key reason for imperfect long-run substitutability between W&S and dirty energy is a reduction in dirty capital utilisation rates, resulting from the link between intermittency and inelastic demand. Two key factors reduce the effect of this link: the presence of dispatchable clean generation, particularly hydro, and the presence of electricity trade. I limit their effect by removing data points where the share of hydro or trade (half the sum of imports and exports over production) is above a certain value. Thus, I focus on substitutability in systems where integration is relatively hard. Further, other generation technologies, such as nuclear, may bias results. To limit this potential effect, I also exclude data points with a high nuclear share (using a more lenient cutoff). Finally, after the previous exclusions, I remove regions with either less than 5 data points or less than 5 dirty generators to avoid the effect of capital lumpiness. The robustness specifications *Lenient* and *Strict* consider different data cutoffs.

The clean input measure (C_{it}) in the main specification is the combined generation from W&S technologies (GWh). Using generation rather than capacity may avoid bias from input-augmenting technical change due to relative changes in clean and dirty utilization rates, such as from W&S technology improvements. As W&S generation depends on the weather and typically cannot respond to demand like dispatchable generation, endogeneity through simultaneity should not be a problem. Further, given inelastic demand for electricity, variation in annual generation per unit of W&S capacity will be counterbalanced by a change in dirty dispatchable output, assuming no trade, which should limit correlation with the error term. A potential concern with using generation instead of capacity is it may not capture the effects of curtailment at high W&S shares – however, such effects should be minor as the W&S share is less than 50% in the data. Further, using generation does not allow for different quality of sites within a region which may be an important source of variation in the aggregate production function. For example, as W&S shares increase, the remaining potential areas may be less productive as the best sites are exploited first. Thus, the robustness specification *W&Scap* combines W&S capacity (GW) as the clean input instead.

The dirty input measure in the main specification combines the generation capacity of different fuel-based technologies (predominantly coal, gas and oil). While simple, this approach does not reflect the economic cost of different technologies per GW. Coal requires higher utilisation rates and is less flexible than gas, so W&S affect these technologies differently. The *DirtyCost* robustness specification considers the higher cost per GW of coal, reducing the data points available.[14]

As clean inputs approach zero in the CES function, the marginal gain in output per marginal increase in clean input approaches 0 if $\psi > 1$, ω if $\psi = 1$ and ∞ if $\psi < 1$. Such divergent behaviour, combined with the indeterminacy of ψ when clean inputs are zero, could make estimation of the elasticity imprecise and unstable, compounding the difficulties of using nonlinear estimation. The robustness specification *MinW&S* removes data points with a W&S share below a threshold.

[14] Labour costs are excluded due to a relative lack of data, but are a minor part of generation costs.

A challenge with focusing on W&S is how to treat other clean generation technologies: hydro, nuclear and (to a lesser extent) geothermal and tidal.[15] The main specification excludes these sources from all variables, allowing identification of the substitutability between W&S and dirty energy but potentially resulting in bias. As nuclear may perform a similar "baseload" role to coal in generation, robustness specification *Nuclear* includes it both in the "dirty" measure and its generation in the LHS dependent variable.[16]

Finally, the robustness specification *CapDelay* considers the effect of the delayed adjustment in dirty capital from increases in clean generation. As electricity capital is long-lived and has high fixed costs, the adjustment to long-run equilibrium may take years: dirty capital will persist, provided it remains profitable operationally. Sluggish capital adjustment likely biases the long-run estimate of ψ upwards (discussed further in section 5). To verify, the dirty input measure $\widehat{D}_{it}$ assumes capital adjustment from a change in clean inputs takes δ periods, so long-run dirty capital levels at time t are set according to clean inputs at time $\tau = t - \delta$. Then dirty inputs are adjusted by the multiple of the increase in clean input over that period, times the ratio of the marginal gains in output from each input.[17]

$$(2.2) \qquad \widehat{D}_{it} = D_{it} - \frac{\partial Y_{it}/\partial C_{it}}{\partial Y_{it}/\partial D_{it}}(C_{it} - C_{i\tau}) = D_{it} - \frac{\omega}{1-\omega}\left(\frac{C_{it}}{D_{it}}\right)^{\psi-1}(C_{it} - C_{i\tau}).$$

VES specification

For clean (C_{it}) and dirty (D_{it}) inputs and parameters $0 < \alpha \leq 1$ and $\beta > 0$, electricity output (Y_{it}) is given by:

15 As described above, data points with high hydro and nuclear shares are excluded, but generation from these sources remains and still needs to be considered.

16 Nuclear generation typically has a very high utilization rate due to high fixed costs and low variable costs, similar to coal generation historically.

17 W&S inputs increase almost monotonically in the data, so the adjustment decreases dirty inputs.

$$(2.3) \qquad lnY_{it} = a_i + b_t + \alpha ln(D_{it}) + (1-\alpha) ln(C_{it} + \alpha\beta D_{it}) + \varepsilon_{it}.$$

The elasticity of substitution is given by $\sigma_{it} = 1 + \beta\, D_{it}/C_{it}$. The same robustness specifications described above are applied, with the dirty capital adjustment equation for the *CapDelay* robustness specification as follows:

$$(2.4) \qquad \widehat{D}_{it} = D_{it} - \frac{\partial Y_{it}/\partial C_{it}}{\partial Y_{it}/\partial D_{it}}(C_{it} - C_{i\tau}) = D_{it} - \frac{1-\alpha}{\alpha\left(\frac{C_{it}}{D_{it}}\right) + \alpha\beta}(C_{it} - C_{i\tau}).$$

TABLE 1 —ESTIMATION SPECIFICATIONS

Name	Clean input (C)	Dirty input (D)	Notes
Main	GWh	GW	
W&Scap	GW	GW	W&S capital input
DirtyCost	GWh	Capital Cost	Uplift factor for coal GW
MinW&S	GWh	GW	Exclude very low W&S shares
Nuclear	GWh	GW	Include nuclear in dirty aggregate
CapDelay	GWh	GW	Delay in dirty capital adjustment
Lenient	GWh	GW	Less data excluded
Strict	GWh	GW	More data excluded

Capacities (GW) and capital costs are normalised at the country level to match electricity output.

3. Data

Data on generation and capacity is primarily from the International Energy Agency (IEA) Electricity Information Statistics. As the uptake of W&S has predominantly occurred this century, I consider the years from 2000 to the most recent year of 2020. Dirty capacity is normalised based on average generation from 1995 to 1999 when W&S shares were low.[18] In the *DirtyCost* robustness specification, I use data from Global Coal Plant Tracker as the IEA data has some gaps in the capital stock

[18] If this data does not exist, I use the earliest 5 periods in the data for each region.

breakdown for different technologies.[19] Coal capacity is valued at 3 times the cost of all other dirty capacities (mostly gas generation), roughly consistent with the relative overnight costs of ultra-supercritical coal and combined cycle gas generation listed in the EIA Annual Energy Outlook (AEO) 2021. In the *W&Scap* robustness specification, W&S capacity is normalised at the region level to reflect average generation for all periods. Table 2 lists the assumptions for data construction. The number of dirty plants comes from the World Resources Institute.[20]

TABLE 2 —DATA CONSTRUCTION DETAILS

	Name	*Main*	*Lenient*	*Strict*
Criteria for inclusion	Trade share	0.2	0.3	0.1
	Hydro share of production	0.2	0.3	0.1
	Nuclear share of production	0.25	0.35	0.15
	Minimum number of dirty plants	5		
DirtyCost	Coal economic cost uplift factor (per GW)	3		
MinW&S	Minimum W&S share	1%		
CapDelay	Delay in dirty capital adjustment (δ)	5 years		

4. Results

I use difference regressions in all specifications due to serial correlation in the residuals from levels regressions and evidence of unit roots (discussed further in Appendix A). Table 3 shows the CES results. Ensuring consistency with a standard CES function ($\psi \leq 1$) leads to perfect substitution (estimate $\hat{\psi} \rightarrow 1$) in the main specification. This result is common across most sensitivities except *Nuclear* and *CapDelay*, where the estimated elasticity is still high (5.7 and 2.3). Without restricting ψ leads to estimations $\hat{\psi} > 1$ (except for *Nuclear* and *CapDelay*), as foreshadowed in Section 1 (results in Appendix A). Estimates of the share

[19] Global Energy Monitor, January 2021
https://globalenergymonitor.org/projects/global-coal-plant-tracker/summary-data/

[20] http://resourcewatch.org/

parameter ω are close to 0.5, as expected for a high degree of substitutability (due to normalization). For the main specification, $\hat{\omega}$ is 0.365, which implies that one unit of W&S electricity substitutes for $\omega/(1-\omega) = 0.57$ units of generation-normalised dirty capital.

TABLE 3 —NONLINEAR CES ESTIMATIONS

	Main	**W&Scap**	**DirtyCost**	**MinW&S**	**Nuclear**	**CapDelay**	**Lenient**	**Strict**
$\boldsymbol{\psi < 1}$	1.000	1.000	1.000	1.000	0.826	0.574	1.000	1.000
					(0.270)	(0.220)		
$\boldsymbol{\omega}$	0.365	0.466	0.444	0.383	0.287	0.275	0.353	0.492
	(0.163)	(0.0834)	(0.0838)	(0.146)	(0.159)	(0.113)	(0.115)	(0.113)
Regressors	23	23	23	23	23	23	23	23
Obs	226	226	226	171	226	226	351	91
Regions	14	14	14	14	14	14	22	7

Standard errors are in parentheses. $\psi < 1$ indicates that ψ is restricted, and hence standard errors are not shown if $\hat{\psi} \to 1$ (an invlogit function is used in this case).

A perfect (or high) long-run elasticity seems most appropriate for an economic model with a standard CES function. Figure 2 shows the residual sum of squares (RSS) for the main specification using a differenced (2.1) with different exogenous values of substitution parameter ψ, indicating rapidly declining performance as ψ decreases below 1. The main results are also robust to country omission and different time frames (see Appendix A for a discussion).

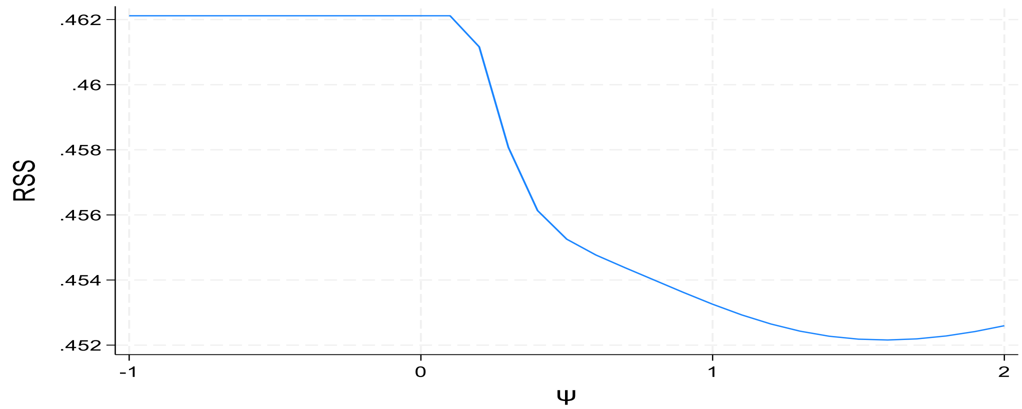

FIGURE 3: RESIDUAL SUM OF SQUARES (RSS) FOR THE MAIN SPECIFICATION FOR VALUES OF SUBSTITUTION PARAMETER ψ

Table 4 shows the results for the VES specifications. Note that when estimate $\hat{\alpha}$ approaches zero, as for most specifications, (2.3) approaches (2.1) with $\psi = 1$, so the results are almost the same as for CES. The central estimates for the specifications *Nuclear* and *CapDelay* imply the elasticity falls to 7.7 and 1.5 when the W&S and dirty inputs are equal (so the elasticity is $1 + \hat{\beta}$), but the standard errors are very large. Due to small values of $\hat{\alpha}$ and large values of $\hat{\beta}$ (which implies the high elasticity persists), the regression estimates $\alpha\beta$ directly. The implied values of $\hat{\beta}$ are also shown.

TABLE 4 —NONLINEAR VES ESTIMATIONS

	Main	W&Scap	DirtyCost	MinW&S	Nuclear	CapDelay	Lenient	Strict
$\boldsymbol{\alpha}$	0.000	0.000	0.000	0.000	0.214	0.652	0.000	0.000
					(2.877)	(0.413)		
$\boldsymbol{\alpha\beta}$	1.943	1.145	1.251	1.610	1.440	0.337	1.830	1.032
	(1.285)	(0.384)	(0.424)	(0.997)	(6.136)	(0.697)	(0.922)	(0.465)
Implied $\boldsymbol{\beta}$	>999	>999	>999	>999	6.729	0.517	>999	>999
Regressors	23	23	23	23	23	23	23	23
Obs	226	226	226	171	226	226	351	91
Regions	14	14	14	14	14	14	22	7

Standard errors are in parentheses.

5. Comparison with previous literature

The theoretical approach owes a debt to Papageorgiou et al. (2017), who report a robust elasticity estimate of 2 undertaking supply-side regressions of clean, including hydro and nuclear, and dirty energy substitutability in electricity. But in my view, their analysis is problematic. Regarding their specification, I prefer to exclude hydro and nuclear in the clean aggregate, as I presume W&S will drive the clean transition. On their execution, while they (correctly in my view) note that Luxembourg should be excluded due to a high trade share, it is not. Excluding Luxembourg using their data and specifications changes their estimates for ψ from 0.46 to 2.05 for the levels regression and from 0.49 to 1.80 for the first difference regression, implying convex production functions as found in the current paper and highlighting the importance of checking dominance from a single region. Further, their approach to estimating standard errors from bootstrapping errors is unconvincing.[21]

Regarding previous estimates from changes in input shares induced by price changes (the price approach), used for example by Pelli (2012) who finds an elasticity of around 0.5, I see two reasons that help explain higher elasticity estimates in the current paper. First, in the price approach, every period where relative prices change "contributes" to the estimation. If price falls had no effect until the W&S price became sufficiently competitive, then including these periods would reduce the elasticity estimate. In contrast, the supply approach relies on changes in input shares. Consider a hypothetical with two regions: in one, W&S and dirty inputs (and total output) do not change despite price falls in W&S, and in

[21] Papageorgiou et al. (2017) use bootstrapped errors and discard generated data which lead to estimates of ψ greater than 1. While this approach ensures consistency with the isoelastic functional form in the generated data, it does not seem to be a conservative method to derive the standard error. Consider an estimate for ψ just under 1. Rejecting generated data which lead to an estimate of ψ greater than 1 means the derived standard error is likely very small by construction.

the other, W&S inputs increase with a substitution elasticity of 2. The price approach finds an elasticity estimate of about 1 (between 0 and 2), but the supply approach finds an elasticity estimate of 2 as the region which experiences no W&S adoption has only one data point and so has no effect on the estimated elasticity. Thus, the supply approach puts a higher weight on regions that have undergone a greater change in W&S inputs, which probably have a higher elasticity.

The second reason relates to the long-lived nature of generation assets: reductions in dirty capital to long-run levels (due to the uptake of W&S) may take many years, as power plants may continue to operate until their end-of-life or until refurbishment costs are required. In the price approach, this adjustment delay likely biases the elasticity downwards, as the change in input shares is lower than the long-run change. But in the supply approach, the direction of bias is likely upwards, as shown in the results. To illustrate, consider constant output as W&S inputs increase from 1 to 2 and then to 3, and long-run dirty inputs change from 10 to 9 to 9. The fact that 9 dirty inputs are still needed despite the increase in W&S input from 2 to 3 leads to convexity of the isoquant and a finite long-run elasticity. But if dirty inputs change from 10 to 9.5 to 9 due to adjustment delays, there is no convexity in the isoquant and the supply method will find perfect substitutability between W&S and dirty inputs.

6. Conclusion

A rapid clean transition in electricity will depend on how well wind and solar substitute for dirty electricity generation. This paper finds empirical support for using a high elasticity in economic models, at least for wind and solar shares up to 50% or so, exceeding previous empirical estimates but consistent with dispatch models of electricity. Dispatch models find that W&S introduces an integration cost on the system due to reduced utilisation of other generators: the empirical specification in the current paper can capture this effect but has limitations.

Estimating a long-run elasticity from a transition still in its early stages is difficult. The supply-side estimation approach in this paper probably overestimates the elasticity, as more weight applies to regions with a wide range of input shares and due to delays in capital adjustment. Future work could investigate variation in substitutability at different clean shares, strongly indicated by dispatch models, as the clean transition progresses and more data becomes available. Other possible extensions include substitutability in sub-national markets, consideration of the different emissions intensities of dirty technologies, and accounting for electricity storage and network integration.

APPENDIX A – FURTHER EMPIRICAL DISCUSSION

Levels versus difference regressions

The levels method is more efficient when the errors are serially uncorrelated, while the difference method is more efficient when the residuals follow a random walk (Wooldridge, 2010). The lumpy nature of capital investment and slow dynamics due to long-lived capital would lead to dependence of the error on historical values of independent variables. Indeed, there is a strong serial correlation in the residuals in the levels (as well as evidence of unit roots) but not in the difference method.[22]

STATA code for difference regressions

The following lines of code were run in STATA 18.

[22] Wooldridge test (null of no first-order correlation) rejects for levels residuals (p=0.0001) but not difference (p=0.5). Fisher-type tests for unit roots based on both Dickey-Fuller and Phillips-Perron do not reject null hypothesis (all panels contain unit roots), whether a lag is included or not.

Restricted CES ($\psi < 1$)[23]:

```
qui nl ( dLHS`z' = 1/invlogit({psi})*ln( ( {omega}*C`x'^invlogit({psi})+(1-{omega})*D`y'^invlogit({psi}) ) / ( {omega}*L.C`x'^invlogit({psi})+ (1-{omega})*L.D`y'^invlogit({psi}) ) ) +${TIME} ) if !missing(dLHS`z',C`x',D`y',L.C`x',L.D`y'), initial( psi 1 omega 0.5) vce(cluster country) iterate(200)
```

Unrestricted CES ($\psi < \infty$) and for *Nuclear* and *CapDelay* ($\hat{\psi} \ll 1$):

```
qui nl ( dLHS`z' = 1/{psi}*ln( ( {omega}*C`x'^{psi}+(1-{omega})*D`y'^{psi}) / ( {omega}*L.C`x'^{psi}+ (1-{omega})*L.D`y'^{psi}) ) +${TIME} ) if !missing(dLHS`z',C`x',D`y',L.C`x',L.D`y'), initial( psi 0.5 omega 0.5) vce(cluster country) iterate(200)
```

VES:

```
qui nl ( dLHS`z' = invlogit({a})*ln(D`y'/L.D`y') + (1-invlogit({a}))*ln( (C`x'+ {b}* D`y')/(L.C`x'+ {b}*L.D`y') ) + ${TIME}) if !missing(dLHS`z',C`x',D`y',L.C`x',L.D`y'), initial(a 0.01 b 1) vce(cluster country) iterate(200)
```

VES for *Nuclear* and *CapDelay* ($\hat{\alpha} \gg 0$) :

```
qui nl ( dLHS`z' = {a}*ln(D`y'/L.D`y') + (1-{a})*ln( (C`x'+ {b}* D`y')/(L.C`x'+ {b}*L.D`y') ) + ${TIME}) if !missing(dLHS`z',C`x',D`y',L.C`x',L.D`y'), initial(a 0.1 b 1) vce(cluster country) iterate(200)
```

Results for CES regressions with unrestricted substitution parameter ψ

TABLE 5 —NONLINEAR CES ESTIMATIONS FOR UNRESTRICTED *SUBSTITUTION PARAMETER* ψ

	Main	W&Scap	DirtyCost	MinW&S	Nuclear	CapDelay	Lenient	Strict
$\boldsymbol{\psi}$	1.591	2.099	2.043	1.387	0.826	0.574	2.264	2.570
	(0.777)	(0.653)	(0.463)	(0.665)	(0.270)	(0.220)	(1.169)	(0.945)
$\boldsymbol{\omega}$	0.565	0.838	0.750	0.530	0.287	0.275	0.819	0.929
	(0.320)	(0.135)	(0.0850)	(0.284)	(0.159)	(0.113)	(0.234)	(0.0749)
Regressors	23	23	23	23	23	23	23	23
Obs	226	226	226	171	226	226	351	91
Regions	14	14	14	14	14	14	22	7

Standard errors are in parentheses.

Robustness checks for outlier regions and changes in start/end years

The robustness of the main CES specification is tested in two ways, shown in Figure 4. First, each region is excluded from the panel, making 14 central estimates (“exclude 1 region”). Second, six estimates show results when the starting year changes from 2000 to 1997, 1998 or 1999 or the ending year is changed from 2020 to 2017, 2018 or 2019. Unsurprisingly, results are more sensitive to final years than initial years, as W&S uptake is recent. The only results outside one standard deviation of the main estimate are when the final year is 2017 or 2018. Note that

[23] Note the use of invlogit which restricts $0 < \psi < 1$ rather than $\psi < 1$, however negative values of $\hat{\psi}$ are never estimated when ψ is unrestricted.

standard errors for $\widehat{\psi}$ in these two regressions are large (0.97 and 1.45), and the estimates $\widehat{\omega}$ are very low (0.03 and 0.06), indicating potential difficulty in estimating ψ due to indeterminacy as ω approaches zero.

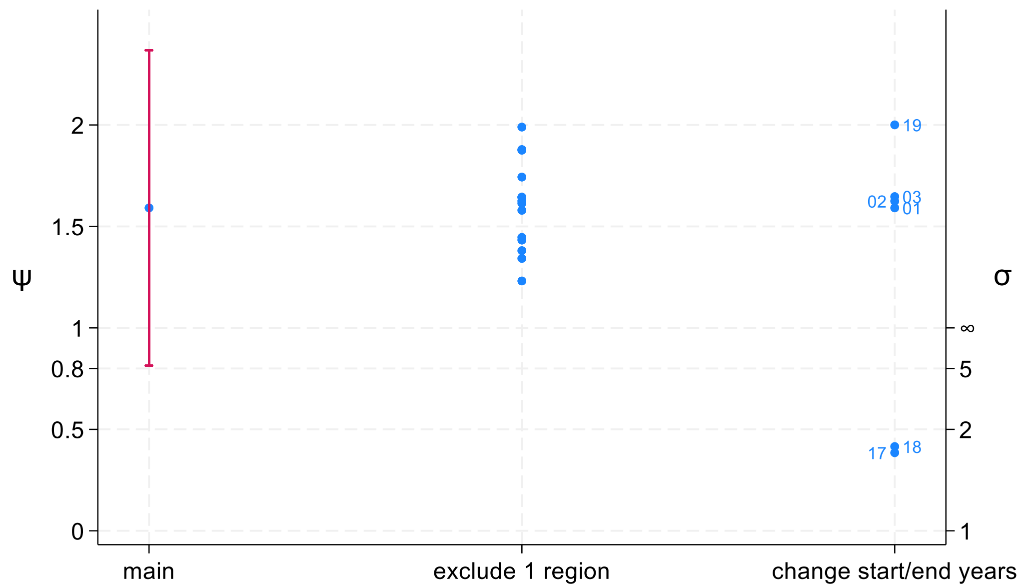

FIGURE 4: ROBUSTNESS CHECKS FOR THE MAIN CES SPECIFICATION

The primary y-axis shows estimates for the substitution parameter ψ and the secondary y-axis shows corresponding estimates for the elasticity of substitution σ. "main" shows the central estimates for the main CES regression and standard error. "exclude 1 region" shows ψ estimates when one region is excluded. "change start/end years" shows when the first year is 1997, 1998 or 1999, or the last year is 2017, 2018 or 2019.

REFERENCES

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. *American economic review*, *102*(1), 131-166.

Aleti, S., & Hochman, G. (2020). Non-Constant Elasticity of Substitution and Intermittent Renewable Energy. *Agricultural and Resource Economics Review*, *49*(2), 321-359.

Ambec, S., & Crampes, C. (2012). Electricity provision with intermittent sources of energy. *Resource and Energy Economics*, *34*(3), 319-336.

Ambec, S., & Crampes, C. (2019). Decarbonizing electricity generation with intermittent sources of energy. *Journal of the Association of Environmental and Resource Economists, 6*(6), 1105-1134.

Hirth, L., Ueckerdt, F., & Edenhofer, O. (2015). Integration costs revisited–An economic framework for wind and solar variability. *Renewable Energy, 74*, 925-939.

Karagiannis, G., Palivos, T., & Papageorgiou, C. (2005). Variable elasticity of substitution and economic growth: theory and evidence. In *New trends in macroeconomics* (pp. 21-37): Springer.

Lanzi, E., & Sue Wing, I. (2011). *Directed technical change in the energy sector: an empirical test of induced directed innovation.* Paper presented at the WCERE 2010 Conference, mimeo.

León-Ledesma, M. A., McAdam, P., & Willman, A. (2010). Identifying the elasticity of substitution with biased technical change. *American economic review, 100*(4), 1330-1357.

Papageorgiou, C., Saam, M., & Schulte, P. (2017). Substitution between clean and dirty energy inputs: A macroeconomic perspective. *Review of Economics and Statistics*, *99*(2), 281-290.

Pelli, M. (2012). *The elasticity of substitution between clean and dirty inputs in the production of electricity.* Paper presented at the Proceedings of the Conference on Sustainable Resource Use and Economic Dynamics (SURED 2012), Ascona, Switzerland.

Stöckl, F., & Zerrahn, A. (2023). Substituting clean for dirty energy: A bottom-up analysis. *Journal of the Association of Environmental and Resource Economists*, *10*(3), 819-863.

Ueckerdt, F., Hirth, L., Luderer, G., & Edenhofer, O. (2013). System LCOE: What are the costs of variable renewables? *Energy, 63*, 61-75.

Wiskich, A. (2019). Decreasing substitutability between clean and dirty energy. *CAMA Working Paper No. 72/2019*. Retrieved from https://ssrn.com/abstract=3458743

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*: MIT press.