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Abstract

In growth theory, a greater-than-one elasticity of substitution between clean and dirty energy is among key necessary conditions for long-run green economic growth. Using parametric specifications, Papageorgiou et al. (2017) provide first estimates of this fundamentally important inter-energy substitution elasticity. We extend their work by relaxing restrictive functional-form assumptions about production technologies using flexible nonparametric methods. We find that the technological substitutability between clean and dirty energy inputs may not be that strong, especially in the case of a final-goods sector for which the inter-energy elasticity of substitution statistically exceeds one for at most a third of industries/countries. Hence, the favorability of technological conditions for long-run green growth may not be corroborated by the cross-country empirical evidence as strongly as previously thought.

Keywords: aggregate production function, clean and dirty energy, cross-country analysis, elasticity of substitution, environmental policy, green growth

JEL Classification: O44, O47, Q54, Q58

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1 Introduction

In many neoclassical and endogenous growth models (e.g., Acemoglu et al., 2012), a strong technological substitutability between clean and dirty energy sources is one of the key "necessary condition" factors for the sustainable long-run green economic growth. Generally, the feasibility (at least theoretically) of such a long-run green growth directly depends on the substitution elasticity between clean and dirty energy being greater than one regardless of whether the technical change is neutral, directed or absent altogether. Papageorgiou et al. (2017) have recently reported first estimates of this fundamentally important inter-energy substitution elasticity using novel industry-level data from 26 countries during the 1995–2009 period.[1] Under the CES functional-form assumption, they estimate aggregate production functions and find strong evidence that the substitution elasticity between clean and dirty energy inputs is well above one in both the electricity generation and nonenergy final-goods production sectors thereby concluding about favorability of conditions for green growth.

In this paper, we complement Papageorgiou et al.'s (2017) work by taking a fresh look at the robust measurement of the degree of inter-energy substitutability. While desirably parsimonious, their parametric CES specifications may lack sufficient flexibility to adequately model production technologies which could result in biased and misleading findings. Therefore, we employ kernel-based nonparametric methods to estimate aggregate production functions. In doing so, we seek to mitigate potential model misspecification risks inherent in Papageorgiou et al.'s (2017) parametric specifications due to their reliance on *a priori* assumptions about (i) the functional form of the input-output relationship, (ii) the Hicks-neutral (temporal) technical change, and (iii) the additive time-invariant country/industry heterogeneity. Lastly but not least importantly, by the virtue of using a nonparametric formulation of production technologies, we obtain heterogeneous measures of the substitution elasticity between clean and dirty energy across industries and countries which enables us to test technological favorability of the green growth conditions at the observation level. We also formally test for correct parametric model specification.

2 Nonparametric Elasticity of Substitution

In line with Papageorgiou et al. (2017), we estimate separate aggregate production functions for the (single-industry) electricity and (multi-industry) nonenergy sectors. These nonparametric functions are respectively given by (in logs)

$$\log Y_{it} = f_i\big(\log KC_{it}, \log KD_{it}, D_{T,it}\big) + \epsilon_{it} \tag{2.1}$$

and

$$\log Y_{ijt} = h_{ij}\big(\log L_{ijt}, \log K_{ijt}, \log MS_{ijt}, \log EC_{ijt}, \log ED_{ijt}, D_{T,ijt}\big) + \varepsilon_{ijt}, \tag{2.2}$$

[1] We use their data available in the *Review*'s data archive.

where indices i, j and t correspond to the country, industry and year, respectively; and D_T is an ordered discrete time variable with the rest of (continuous) covariates being defined as in Papageorgiou et al. (2017): KC – clean energy production capacity, KD – dirty energy production capacity, K – physical capital, L – labor, MS – intermediate inputs, EC – clean energy input, ED – dirty energy input, Y – generated electricity in (2.1) or the final product value in (2.2).

The above equations are essentially the nonparametric generalizations of those estimated by Papageorgiou et al. (2017):[2] the CES electricity production function and the CES-in-Cobb-Douglas final-goods production function respectively given by eqs. (4) and (8) in their paper. Not only do our nonparametric specifications in (2.1)–(2.2) make no functional form assumptions but they are also more flexible because they let the time enter the production function in an unrestricted way thereby allowing both the neutral and input-augmenting technical changes. Furthermore, we relax the assumption about additivity of cross-sectional heterogeneity (customarily modeled as fixed effects) by specifying country/industry-specific nonparametric aggregate production functions $f_i(\cdot)$ and $h_{ij}(\cdot)$ which accommodates arbitrary heterogeneity among cross-sectional units.

Unlike in parametric CES specifications, our models (2.1)–(2.2) do not identify a single elasticity of substitution parameter for clean and dirty energy inputs. To measure the substitutability between the two, we use the popular Allen–Uzawa partial elasticity of substitution (especially suitable for production models with more than two inputs). For a generic production function in levels $Y = F(X_1, \dots, X_P)$, it is symmetrically defined for any two inputs q and $s(\neq q)$ as

$$\sigma_{qs} = \frac{\sum_{p=1}^{P} X_p F_p}{X_q X_s} \frac{\mathrm{C}_{qs}}{\det \overline{\mathbf{H}}} \quad \text{and} \quad \overline{\mathbf{H}} = \begin{bmatrix} 0 & F_1 & \dots & F_p \\ F_1 & F_{11} & \dots & F_{1P} \\ \vdots & \vdots & \ddots & \vdots \\ F_P & F_{P1} & \dots & F_{PP} \end{bmatrix}, \tag{2.3}$$

where F_p and F_{pp} are the first- and second-order partial derivatives of $F(\cdot)$ for $p = 1, \dots, P$; and $\overline{\mathbf{H}}$ is the bordered Hessian matrix with C_{qs} denoting the cofactor of its F_{qs} element. Positive/negative values of σ_{qs} indicate net substitutes/complements. We apply this formula to production functions (2.1)–(2.2)[3] to compute elasticity of substitution between the clean and dirty energy generation capacity/capital in the electricity sector (KC and KD) and the clean and dirty energy usage in the nonenergy final-goods production sector (EC and ED), respectively. Importantly, obtained are observation-specific measures of the inter-energy substitutability.

2.1 Estimation and Inference

We rely on recent advances in the generalized kernel regression estimation with mixed data (Racine & Li, 2004) to feasibly estimate country/industry-varying production functions $f_i(\cdot)$ and $h_{ij}(\cdot)$ in

[2]Throughout our analysis, we follow their modeling choices (except for the parametric formulation of equations) as closely as feasible.

[3]By recovering the derivatives of production functions in level from their estimated log-derivatives.

(2.1)–(2.2) without the need for sample cell-splitting on the basis of country/industry. Concretely, we model these functions as $f_i(\cdot) = f(\cdot, D_{I,it})$ and $h_{ij}(\cdot) = h(\cdot, D_{I,ijt}, D_{J,ijt})$, where D_I and D_J are the unordered discrete variables categorizing countries and industries, respectively. In its spirit, such an approach echoes the estimation of fully saturated models with country and/or industry dummies. However, in practice we do not need to employ such binary indicators of which there are too many; the use of two categorical index variables D_I and D_J in the kernel estimation suffices so long as we recognize their *unordered* nature.[4] Further, unlike fully saturated parametric or cell-split nonparametric models, our approach allows using relevant information from "similar" country/industry cells during the estimation.

We estimate nonparametric production functions via local-quadratic fitting which readily yields observation-specific estimates of the first- and second-order gradients necessary to evaluate the Allen–Uzawa substitution elasticities. Essentially, we estimate observation-specific translog production functions. The optimal bandwidths are selected via the data-driven leave-one-cross-section-out cross-validation suitable for panel data.

Although the local-polynomial estimator that we employ is asymptotically normal (Li & Racine, 2007), it is well-known that asymptotic inference for nonparametric estimators is often unreliable in finite samples due to biases as well as the first-order asymptotic theory's poor ability to approximate the distribution of estimators in finite samples (Horowitz, 2001). Bootstrap however provides means not only to reduce the estimator's finite-sample bias (and hence finite-sample MSE) but also to account for higher-order moments in the sampling distribution. In order to conduct statistical inference, we therefore resort to wild residual block-bootstrap[5] which accounts for the panel structure of the data by allowing for the error correlation within cross-sectional clusters. Both models (2.1)–(2.2) are bootstrapped 499 times to construct percentile confidence bounds[6] for each observation-specific estimate of the elasticity of substitution between clean and dirty energy.

2.2 Model Specification Testing

Besides directly comparing our substitution elasticity estimates to those reported by Papageorgiou et al. (2017), we also formally discriminate between their and our models by means of Ullah's (1985) model specification test. Namely, we test their parametric specifications (the null hypotheses)—the CES electricity production function [eq. (4)] and the CES-in-Cobb-Douglas nonenergy final-goods production function [eq. (8)]—against our respective nonparametric alternatives in (2.1) and (2.2). The test is essentially a nonparametric likelihood-ratio test based on comparison of the restricted and unrestricted models (also see Fan et al., 2001; Lee & Ullah, 2003) with the corresponding residual-based test statistic given by $T_n = (RSS_0 - RSS_1)/RSS_1$, where RSS_0 and RSS_1 are the residual sums of squares under the (restricted parametric) null and the (unrestricted nonparametric)

[4] A luxury one cannot afford in a parametric model.

[5] A "block" is defined at the country level for the electricity sector and at the country-industry level for the nonenergy sector.

[6] These percentile confidence intervals may be *a*symmetric around the point estimate.

Table 1. Nonparametric Estimates of the Inter-Energy Substitution Elasticity: Electricity Sector

Capital Measure	*Percentiles of Point Estimates* 10th	25th	Median	75th	90th	*Share of Sample (%)* $\neq 0$	>1
Generation Capacity	–2.947	0.059	1.786	2.749	4.605	88.72	69.23
	(–3.993, –2.386)	(–0.002, 1.148)	(1.756, 1.887)	(2.639, 2.842)	(4.387, 5.698)		
Apprx. Real Capital Stock	–0.275	1.467	1.943	3.328	5.245	54.73	58.58
	(–7.247, 1.263)	(–1.051, 1.865)	(1.500, 2.663)	(1.963, 4.498)	(2.479, 10.570)		

The two-sided 95% percentile block-bootstrap confidence intervals in parentheses. The second-to-last (last) column reports the share of observations for which the point estimates are statistically different from zero (greater than unity) at the 5% significance level using two-sided (one-sided) percentile bootstrap confidence intervals.

Table 2. Nonparametric Estimates of the Inter-Energy Substitution Elasticity: Nonenergy Sector

Production Function Type	*Percentiles of Point Estimates* 10th	25th	Median	75th	90th	*Share of Sample (%)* $\neq 0$	>1
Value Added	–2.760	–0.803	0.061	1.082	3.165	75.85	17.36
	(–3.138, –2.745)	(–0.831, –0.745)	(0.057; 0.092)	(1.062, 1.133)	(2.983, 3.246)		
Gross Output	–6.655	–1.821	0.310	2.525	7.420	77.15	29.16
	(–6.601; –5.901)	(–1.830; –1.639)	(0.283, 0.346)	(2.432, 2.568)	(7.120, 7.792)		

The two-sided 95% percentile block-bootstrap confidence intervals in parentheses. The second-to-last (last) column reports the share of observations for which the point estimates are statistically different from zero (greater than unity) at the 5% significance level using two-sided (one-sided) percentile bootstrap confidence intervals.

alternative, respectively. Intuitively, the test statistic is expected to converge to zero under the null and is positive under the alternative; hence the test is one-sided. To approximate the null distribution of T_n, we use wild block-bootstrap by resampling residuals from the restricted models.

3 Empirical Results

Tables 1 and 2 summarize our nonparametric point estimates of the elasticity of substitution between clean and dirty energy in the electricity and nonenergy sectors, respectively. We estimate the aggregate production technology for each of these sectors twice. In the case of an electricity sector, we use two alternative measures of physical capital KC and KD: the net generation capacity and the approximate real fixed capital stock. For the nonenergy final-goods production sector, we first estimate the gross production function and then the value-added production function with the appropriately adjusted output measure and the intermediate input MS omitted from the right-hand side of equation. For details on these empirical specifications, see Papageorgiou et al. (2017).

Our results point to a non-negligible heterogeneity in the degree of substitutability between clean and dirty energy inputs across industries and countries, which can also be vividly seen in Figures 1–2 that plot kernel densities of our inter-energy elasticity of substitution estimates. Nonparametric estimates include both statistically significant and insignificant positive and negative values (shares of significant estimates are reported in the second-to-last columns of Tables 1–2). To facilitate direct comparability of Papageorgiou et al.'s (2017) and our results, we also compute Allen–Uzawa

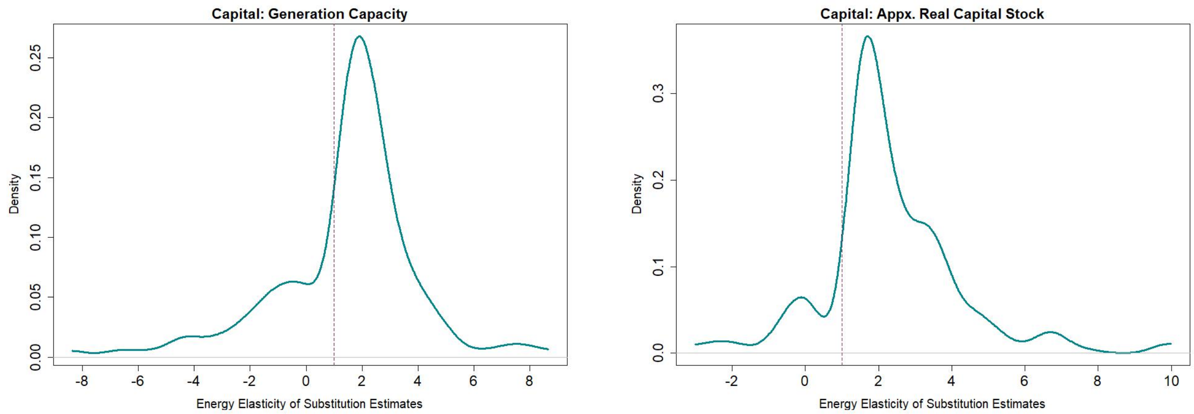

Figure 1. Density of the Inter-Energy Elasticity of Substitution Estimates: Electricity Sector

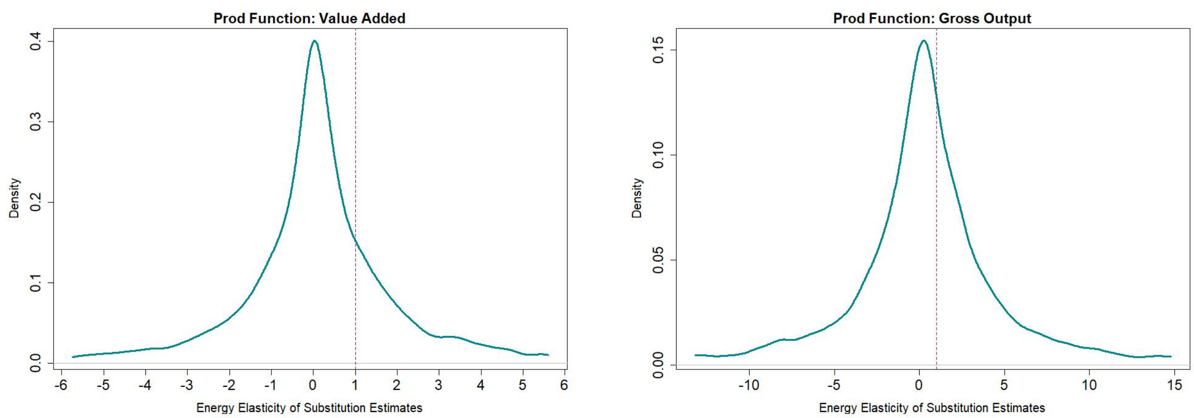

Figure 2. Density of the Inter-Energy Elasticity of Substitution Estimates: Nonenergy Sector

partial elasticities of substitution between clear and dirty energy implied by their main parametric specifications in eqs. (4) and (8) evaluated at their reported parameter estimates. Expectedly, given Papageorgiou et al.'s (2017) functional choices for production functions, the implied inter-energy partial substitution elasticities are all constant (i.e., same for the entire sample) and, in case of the electricity sector, are equal to the corresponding "σ" parameters reported in their paper. Table 3 summarizes their implied substitution elasticities. From Tables 1–2, our *median* nonparametric point estimates of the partial elasticity of substitution are in the range of 1.79–1.94 for the electricity generation sector and 0.06–0.31 for the nonenergy sector. While these median estimates are fairly on a par with Papageorgiou et al.'s (2017) *fixed parameter* estimates for the electricity sector, they are however significantly different in case of the nonenergy final-goods sector, with their implied partial elasticity ranging from 8.2 to 16.6 in contrast to ours that is relatively close to zero.

To allow a more "level playing field" comparison of Papageorgiou et al.'s (2017) and our results, instead of considering quantitative differences in the magnitudes of their parametric and our (more flexible) nonparametric estimates, we rather focus on qualitative differences in the conclusions.[7]

[7]As evident from Table 3, Papageorgiou et al.'s (2017) conclusions continue to hold even when focusing on *partial*

Table 3. Inter-Energy Elasticity of Substitution Estimates
Implied in Papageorgiou et al. (2017)

Model	σ Elasticity	Partial Elasticities
	Electricity Sector (CES)	
Generation Capacity	1.840 / 1.948	1.840 / 1.948
Apprx. Real Capital Stock	1.734 / 1.852	1.734 / 1.852
	Nonenergy Sector (CES-in-Cobb-Douglas)	
Value Added	2.868	8.189
Gross Output	2.888	16.636

The "σ" parameter is Papageorgiou et al.'s (2017) substitution elasticity measure of choice. Their values are the same as those in the first two columns of Tables 3, 4 and 6 in Papageorgiou et al. (2017). The last column reports the implied Allen-Uzawa partial elasticities.

Specifically, since our ultimate research question of interest is centered on examining the potential for long-run green growth, the possibility of which depends on technological substitution elasticity between clean and dirty energy sources being above one, we primarily aim our attention at testing the latter condition. That is, we formally test if the inter-energy partial elasticity of substitution is statistically greater than one. Given our "greater than" alternative, we reject the null of substitution elasticity being equal one if the corresponding *one*-sided 95% percentile bootstrap lower bound exceeds unity. We perform such a test at the observation level; the results are reported in the far right columns of Tables 1 and 2. We find that, for the electricity sector, the elasticity of substitution between clean and dirty energy statistically exceeds one for 59–69% of the sample. The results are however less encouraging in the case of nonenergy sector where we find the evidence of a greater-than-one elasticity of substitution for 17–29% of observations only.

Before drawing final conclusions, we also formally test Papageorgiou et al.'s (2017) parametric specifications against our preferred nonparametric ones in (2.1)–(2.2) using a nonparametric model specification test. Table 4 reports the corresponding bootstrap p-values. We reject the CES specification of the electricity generation production function at the conventional 5% level when using a net generation capacity proxy for physical capital [Papageorgiou et al.'s (2017) preferred measure for this sector]. In the case of a nonenergy final-goods sector, the evidence against a parametric specification is even more convincing with the p-values being virtually zero, which helps explain dramatic differences between our partial substitution elasticity estimates for the sector and those implied by Papageorgiou et al.'s (2017) CES-in-Cobb-Douglas specification.

4 Concluding remarks

Overall, our results lend strong support in favor of a more flexible nonparametric modeling of aggregate production technologies, especially in the case of a nonenergy final-goods sector. Employing

elasticities.

Table 4. Model Specification Tests

Model	p-value
Electricity Sector	
Generation Capacity	0.01996
Apprx. Real Capital Stock	0.11063
Nonenergy Sector	
Value Added	0.00000
Gross Output	0.00000

Reported are the block-bootstrap p-values for Ullah's (1985) test. The null in each case is the corresponding Papageorgiou et al.'s (2017) CES specification tested against the alternative of a nonparametric function.

such nonparametric methods, we find that the (partial) substitution elasticity between clean and dirty energy inputs in the electricity generation is statistically greater than one only for about two thirds of observations. The evidence of a strong inter-energy substitutability is even weaker for the final-goods sector with the corresponding elasticity statistically exceeding unity for at most a third of the sample. Hence, the favorability of technological conditions for long-run green growth may not be corroborated by the cross-country empirical evidence as strongly as priorly thought.

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