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Author(s): Chris Papageorgiou, Marianne Saam and Patrick Schulte

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SUBSTITUTION BETWEEN CLEAN AND DIRTY ENERGY INPUTS: A MACROECONOMIC PERSPECTIVE

Chris Papageorgiou, Marianne Saam, and Patrick Schulte*

Abstract—In macroeconomic models, the elasticity of substitution between clean and dirty energy inputs within the energy aggregate is a central parameter in assessing the necessary conditions for long-run green growth. Using new sectoral data in a panel of 26 countries, we formulate specifications of nested constant elasticity of substitution production functions that allow estimating this parameter for the first time. We present evidence that it significantly exceeds unity, a favorable condition for promoting green growth.

I. Introduction

ADVANCES in environment-friendly, clean technologies seem indispensable if disastrous climate change is to be prevented without compromising economic growth. Clean technological innovation will be effective only if there are economic incentives to reallocate resources from dirty to clean production. While incentives may depend on economic policies, they also depend on the production structure of an economy. In a wide range of models, the substitution parameter between clean and dirty energy inputs within the energy subaggregate of a macroeconomic production function has fundamental importance for the possibility of long-run green growth. In this paper, we propose parsimonious specifications of production functions to estimate this parameter and present the first macroeconomic evidence on it.

Acemoglu, Aghion, Bursztyn, and Hemous (2012; AABH hereafter) have formulated the relation between growth and pollution in the framework of endogenous growth theory, in which different assumptions about the production structure can be discussed in an analytically stringent way. Within this framework, the economy-wide elasticity of substitution between clean and dirty production tasks represents a parameter on which the potential of clean innovation to prevent a climate disaster crucially depends. Dirty production is considered to take place when the atmospheric concentration of CO_2 is increased as a result of the combustion of fossil fuels (coal, oil, natural gas).

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A two-input elasticity of substitution between clean and dirty production tasks as introduced by AABH is a concept that permits representing conditions for green growth in an elegant and parsimonious way within a growth model. But clean and dirty tasks cannot be identified in macroeconomic data. Considering a production function for final output with four factors (capital, labor, clean energy input, and dirty energy input), we argue that the elasticity of substitution between clean and dirty energy inputs within an energy aggregate plays a crucial role for the possibility of long-run green growth. Besides AABH, numerous other examples can be found in theoretical as well as in the applied CGE literature where substitution between clean and dirty production or substitution between clean and dirty energy inputs affects the model's long-run predictions. In the next section, we discuss the properties of production functions that are prototypical for these models.

Most of the existing empirical literature has estimated partial elasticities of substitution between capital and energy or between different fuels. Meanwhile, evidence on the substitution parameter between aggregate clean and dirty energy inputs remains scarce to date. In this paper, we make a first attempt to evaluate this parameter by estimating the elasticity of substitution between clean and dirty energy inputs within the energy aggregate of macroeconomic production functions. In assessing whether an energy input is clean or dirty, we use a binary distinction: clean energy inputs are those not causing CO_2 emissions, and dirty energy inputs are those causing such emissions. We exploit the new World Input-Output Database (WIOD), which provides cross-country data on energy use by fuel type in an industry classification consistent with available productivity data. The data for our analysis cover up to 26 countries for the years 1995 to 2009. Our key finding is that the estimates of the elasticity of substitution within the energy aggregate are significantly greater than unity—around 2 for the electricity-generating sector and close to 3 for the nonenergy industries. These results contrast with studies pointing to an elasticity of substitution below unity. Our larger elasticity estimates are consistent with conditions that allow green growth in the framework of growth theory.

The rest of the paper is organized as follows. Section II presents the theoretical underpinnings. Section III discusses empirical evidence on substitution between energy inputs. The methodology and the estimable equations obtained based on production theory are presented in section IV. The data set used in the empirical analysis is briefly discussed in section V. Section VI presents estimates of the substitution parameters between clean and dirty energy inputs in the electricity and nonenergy industries. Section VII concludes with some directions for future research.

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II. Theoretical Foundations

A. The Role of Substitution Parameters in Models of Green Growth

The predictions of neoclassical and endogenous growth models crucially depend on substitution parameters between inputs. In many cases, the predictions of the models are reversed if a substitution parameter changes its sign. For green growth, the substitution between capital and energy and the substitution between clean and dirty energy inputs are the most important dimensions. For three reasons, we choose to study the substitution of clean and dirty inputs within the energy aggregate. First, evidence that the substitution parameter between the aggregates containing capital and energy is low has already been a bit better established than any evidence on substitution between clean and dirty energy inputs. Second, doubts remain under which conditions substitution by capital is clean, since capital is a produced input. Third, if substitution by clean sources is strong within the energy aggregate, substitution between aggregate energy and other factors of production such as capital matters less for long-run green growth.

We formulate production functions containing substitution parameters that are important in the context of growth theory and at the same time can be estimated from available macroeconomic data. In section IIB, we discuss how the properties of prototypical constant elasticity of substitution (CES) production functions influence the prospects of long-run growth in theoretical approaches taking into account clean and dirty energy inputs. Section IIC gives examples of previous theoretical work using the kind of substitution parameters we discuss.

B. A Prototypical Macroeconomic Production Technology

In this paper we formulate variants of nested CES production functions that can be evaluated at the macroeconomic level. Their properties follow in a straightforward way from those of two-input CES functions.

For the nonenergy (or final) sector, we formulate a production function with four inputs that can be used to estimate the substitution parameter between clean and dirty inputs within the energy aggregate. For the electricity sector, we formulate a production function with two inputs that can be used to estimate the substitution parameter between clean and dirty electricity generation (proxied by production capacity). A separate electricity-generating sector is important because the substitution patterns that prevail in this sector can be expected to be very different from those in the rest of the economy. Modeling the electricity sector and not the other parts of the energy sector is in line with our estimation strategy, which provides estimates for the electricity sector only.

Final output is represented as a CES aggregate of a composite of capital K and labor L and a composite of clean energy input E_{FC} and dirty energy input E_{FD}. Nonenergy inputs have a common technology parameter A_F. Clean and dirty energy inputs have specific factor-augmenting technology parameters A_{FC} and A_{FD}:

$$Y_F = \left\{ (1-\gamma) A_F^{\phi} [\alpha K^{\chi} + (1-\alpha) L^{\chi}]^{\frac{\phi}{\chi}} + \gamma [\beta (A_{FC} E_{FC})^{\psi_F} + (1-\beta)(A_{FD} E_{FD})^{\psi_F}]^{\frac{\phi}{\psi_F}} \right\}^{\frac{1}{\phi}}. \tag{1}$$

We consider as long-run green growth a situation in which the inputs of capital and clean energy are increased, while dirty energy input cannot exceed some upper limit. Labor is held constant for simplification. Emissions are assumed to be proportional to dirty energy input E_{FD}. The parameter $\sigma_F = 1/1 - \psi_F$ is the elasticity of substitution between clean and dirty energy inputs within the energy aggregate of the final sector. In order to express an elasticity that characterizes substitution between clean and dirty energy inputs at the level of the final output function, we would have to choose a concept of partial elasticity, since there is no unique generalization of the two-input elasticity of substitution for the case of more inputs. But for long-run growth, the constant parameter values and not the partial elasticities matter, so we focus on the substitution parameter ψ_F, which may assume values between $-\infty$ and 1.

Without technical progress and with energy as an essential input ($\phi \leq 0$), a necessary condition for long-run green growth is that both subaggregates, the K-L aggregate and the energy aggregate, have a positive long-run growth rate. This is possible only if both χ and ψ_F are positive. (See online appendix section I. The case of energy being a nonessential input is trivial in the context of investigating substitution between clean and dirty energy inputs.) If we consider in contrast the situation with neutral technical progress, long-run green growth is always possible at the technological level. But with a negative substitution parameter ψ_F between clean and dirty energy, a relative increase in clean energy input drives down its relative price more than proportionally under competitive remuneration (see also Acemoglu, 2008):

$$\frac{P_{FC}}{P_{FD}} = \frac{\beta}{1-\beta} \left(\frac{A_{FC}}{A_{FD}} \right)^{\psi} \left(\frac{E_{FC}}{E_{FD}} \right)^{\psi - 1}. \tag{2}$$

This means that the cost share of clean energy in total energy cost also declines. Although the precise consequences for growth depend on the full model specifications, this is a situation that is unlikely to be sustainable in a market economy. The only other possibility for long-run green growth then remains a situation where the growing demand for energy services is satisfied exclusively from their increasing efficiency through technical progress. But the technological feasibility of long-run green growth with constant energy input does not necessarily preclude the existence of an economic incentive to increase the use of both energy inputs along the growth path. With positive ψ_F, it is possible to completely switch to clean energy inputs and sustain their growth in the long run. Their relative price also decreases in this case, but in a less-than-proportional way.

Technical progress that is directed to the use of clean energy input is considered in theory as well as in practice as one of the most important conditions for long-run green growth. With a positive substitution parameter ψ_F, technical progress increasing the relative efficiency of clean energy input A_{FC} more than the efficiency of dirty energy input raises the relative demand and the relative price for it (see equation [2]). With a negative substitution parameter ψ_F, the relative demand for clean energy input would rise following a relative increase in the efficiency of dirty energy input use, A_{FD}. In models of endogenous directed technical change, technical change is ceteris paribus directed to the more expensive input. With a positive ψ_F, this property tends to support self-propelling clean progress as soon as it is profitable. The precise results depend on the assumptions on the market for technology (see AABH for a similar case with two inputs into final production). With negative ψ_F, the converse is true: with each advance in clean technology, the profitability of dirty technical progress will rise. This mechanism is pushing technical progress toward neutrality in the long run. More complex interactions may arise if more than two technology parameters are endogenous. In summary, a positive substitution parameter ψ_F plays an important role for the possibility of long-run green growth without technical change, with neutral technical change, and with directed technical change.

We assume that the final sector does not produce electricity but buys its electricity (clean) input E_{FC} from the electricity sector. Meanwhile, the final sector is assumed to use primary dirty energy input E_{FD} directly. In the electricity-generating sector, we assume a more reduced production function than in the final sector. The share of labor income is negligible, and labor is not expected to be substitutable. Thus, we exclude labor from the production function. Moreover, we implicitly assume a fixed ratio between capital and fuel input. For clean electricity production, the cost for primary energy input is often 0 (e.g., sunlight, wind) or negligible. Thus, our assumption is more restrictive for dirty electricity production where there might be an economically meaningful trade-off between fuel use and investment in better capacity. Under these assumptions, the technology for generating electricity E_{FC} is modeled as a CES production function of clean production capacity K_{EC} in that sector and dirty production capacity K_{ED}:

$$E_{FC} = \left[\omega(A_{EC}K_{EC})^{\psi_E} + (1-\omega)(A_{ED}K_{ED})^{\psi_E}\right]^{\frac{1}{\psi_E}}. \quad (3)$$

The parameter ψ_E now represents the substitution parameter between clean and dirty capacity in the electricity-generating sector. The corresponding elasticity of substitution equals $\sigma_E = 1/1 - \psi_E$. In the absence of technical change, the substitution parameter ψ_E has to be positive in order for long-run green growth to be possible in the electricity sector (this result has been shown for the two-input CES function with capital and labor by Klump & de La Grandville, 2000) and the aggregate economy. With technical change, the evolution of the relative price for clean capacity depends on the substitution parameter in a way analogous to equation (2). Our aim is to estimate the substitution parameters ψ_E and ψ_F and thus the corresponding two-input elasticities of substitution σ_E and σ_F.

C. *Clean-Dirty Substitution in Theoretical Models*

While the literature on environmental policy developed from a microeconomic perspective, it has increasingly focused on macroeconomic questions (see Popp, Newell, & Jaffe, 2010, and Fischer & Heutel, 2013). The paradigm of directed technical change is a general modeling framework based on the idea of induced innovation going back to Hicks (1932). In its most widely used contemporary version, it has been developed by Acemoglu (1998, 2002). This theory inspired empirical research to take a closer look at the connection between growth and factor substitution (e.g., Krusell et al., 2000, and Duffy, Papageorgiou, & Perez-Sebastian, 2004).

AABH use this framework and the Schumpeterian model of green growth by Aghion and Howitt (1998) to place the question of long-run green growth in the center stage of modern neoclassical growth theory. A final good is produced from clean and dirty intermediate inputs with a CES technology. The intermediates are in turn produced using clean and dirty machines, which can be improved by invention. The main question is whether optimal policy will manage to redirect all scientists immediately to the clean sector and thus contain long-term climate change below 2°C. The threshold for long-run green growth being technically feasible is an elasticity of substitution above 1, but the policy to enforce this would not be optimal for values only slightly above 1. From the perspective of growth theory, the elasticity of substitution between clean and dirty production tasks modeled by AABH represents a quite general measure of substitution on which the possibilities of green growth in an economy crucially depend. Using a similar structure in a CGE model, Otto, Löschel, and Dellink (2007) assume a CES utility function to aggregate utility from energy-intensive and energy-nonintensive goods.

More common in the theoretical literature is the modeling of substitution between capital and energy, dirty and clean energy inputs within the energy aggregate, or both variants in the same model (see, e.g., Bovenberg & Smulders, 1996; Goulder & Schneider, 1999; Nordhaus, 1994; Popp, 2004). Gans (2012) analyzes the effect of an emission cap on directed technical change and growth. Contrary to more applied and complex models, the paper explicitly discusses the cases of an elasticity of substitution within the energy aggregate smaller and larger than 1, the baseline assumption being that it is equal to or larger than 1. With an elasticity of substitution smaller than 1, the emission cap would reduce innovation incentives for factor-augmenting technologies.

In a DSGE model analyzing welfare loss through climate change and the potential of a carbon tax to reduce it, Golosov et al. (2014) use a CES energy aggregate with three inputs: coal, oil, and nonfossil energy. Assuming alternatively elasticities of substitution within the energy aggregate of 0.95 and 2, they come to the conclusion that the difference between the market and the optimal allocation is much more pronounced with a higher elasticity.

Some theoretical work explicitly starts from the conservative assumption of low substitution possibilities and identifies other technological channels thought to make long-run growth possible without depleting nonrenewable resources or causing excessive pollution (Bretschger & Smulders, 2012). But again this poses the empirical challenge to identify the parameters relevant for these other channels.

III. Review of the Empirical Literature

While there is, to our knowledge, no previous econometric estimation with the explicit goal of identifying a substitution parameter between clean and dirty energy inputs using a binary distinction, there is a large literature on substitution of fuels at a more disaggregated level and on capital-energy substitution. Emerging in the 1970s in the light of high oil prices, this literature aimed at assessing how oil could be substituted by coal, gas, and electricity or more energy-efficient production methods. Its focus is thus quite different from our focus. Still, the interfuel substitution literature represents the empirical work that is most closely related to ours. Major early contributions were made by Atkinson and Halvorsen (1976), Fuss (1977), Griffin (1977), and Pindyck (1979). All of these studies, as well as most of the subsequent ones, use some variant of the translog function.[1] Methodological aspects that later studies paid attention to were the difficulty of estimating elasticities in the presence of concavity violations of the translog function, biases resulting from policies that regulate energy supply, and the structure of industrial fuel and energy consumption (Considine, 1989). Jones (1995) differentiates between fuels used for energy purposes and fuels used for nonenergy purposes. Steinbuks (2012) introduces a further differentiation of fuel use for energy purposes in different manufacturing processes, some of which require specific fuels.

Stern (2012) offers a systematic overview over the different partial elasticities used in the literature as well as a meta-analysis. For the meta-analysis, the estimates and computed elasticities from various studies are converted into so-called shadow elasticities.[2] The results show that cross-section estimates tend to be higher than panel estimates of the shadow elasticity of substitution, which are in turn higher than time series estimates (see also Griffin & Gregory, 1976). Moreover, elasticities are lower at higher levels of aggregation. Elasticities involving electricity tend to be smaller than those between two fossil fuels.

To our knowledge, only one previous study focuses on an empirical determination of the elasticity of substitution between clean and dirty energy inputs using a binary distinction. Pelli (2012) extends the model developed by AABH to a multisector setting. For the electricity sector, he then introduces several assumptions that allow the calibration of the non-U.S. elasticities from the U.S. elasticity. The calibrated elasticities for the electricity sector concentrate around 0.51. A small number of other studies obtain a substitution parameter between aggregate clean and dirty energy input as a by-product. Lanzi and Sue Wing (2010) find a value of 1.6 for the two-input elasticity of substitution between clean and dirty inputs in the energy sector from econometric estimation using a steady-state assumption. Pottier, Hourcade, and Espagne (2014) cast doubt on the possibility of measuring the elasticity of substitution between clean and dirty production modeled by AABH. What in their view comes closest to it in previous econometric research is the absolute value of the price elasticity of gasoline demand, for which they report a range of 0.3 to 0.6 from other studies. Several CGE models use assumptions on the elasticity of substitution between fossil fuels and nonfossil (in our sense "clean") fuels within the energy aggregate and report values obtained from fitting calibrated models. Goulder and Schneider (1999) use a value of 0.9 at the sectoral level, Popp (2004) a value of 1.6.

Since no more quantitative evidence is available, we also discuss some speculative conjectures expressed in previous research. Thinking about substitution between clean and dirty energy inputs from a macroeconomic perspective, one might consider that the productivity of energy does not depend much on its source or its intensity of pollution. As AABH argue: "For example, renewable energy, provided it can be stored and transported efficiently, would be highly substitutable with energy derived from fossil fuels. This reasoning would suggest a (very) high degree of substitution between dirty and clean inputs, since the same production services can be obtained from alternative energy with less pollution" (p. 135). The aspect of transportation and storage is a critical one for renewable energy. In electricity generation, the difficulties in storing energy from renewable sources lead to a misalignment in time and space with electricity demand. Mattauch, Creutzig, and Edenhofer (2015) consider that investments in better infrastructure (e.g., grid integration across large areas) could increase the substitution possibilities between clean and dirty energy production. Even in cases where demand is adequate to supply, the fixed costs are currently higher for clean energy plants than for dirty energy plants. Meanwhile, the variable costs of clean energy production are generally lower. One has to be careful not to interpret these properties in any simple way as evidence on the elasticity of substitution between clean and dirty energy inputs within the energy aggregate, since substitution

[1] Some exceptions to the use of translog functions are found in the literature on capital-energy substitution (e.g., Kemfert, 1998; Van der Werf, 2008).

[2] The shadow elasticity is a symmetric ratio elasticity that represents the average of the asymmetric Morishima elasticities. It restricts cost to be constant.

parameters are based not on levels of marginal productivity but on changes in marginal productivity.

Still, there are aspects thought to limit the ease of substitution between clean and dirty energy: if clean electricity generation involves both nuclear and renewable sources, the marginal productivity of investment into clean capacity may be declining. Capacity may be installed first in places where the supply of wind or sun is advantageous and then in less advantageous places. Moreover, fossil fuels with relatively low fixed but higher variable cost better serve as peak load fuels compared not only to renewables but also to nuclear energy (IEA/OECD NEA, 2010). If the ratio of clean to dirty energy inputs rises to high levels in the entire economy, clean energy production has to serve both base and peak demand and will experience declining efficiency.

In the energy-using sectors, a wide range of processes can be run using electricity, but some industrial processes require particular fossil fuels. And in transportation, the internal combustion engine still represents the dominant technology to which current infrastructure is mainly adapted (Mattauch et al., 2015). On the other hand, structural change may reduce the weight of dirty production processes in the economy. At a macroeconomic level, it is therefore uncertain whether the known cases of limited substitution lead to an overall low substitution between clean and dirty energy inputs. The aim of this paper is to provide first econometric evidence on this issue using an aggregate production function approach.

IV. Estimation

A. Methodology

We estimate the substitution parameter between clean and dirty energy inputs directly from aggregate production functions following an established empirical literature.[3] Specifically, we estimate nested CES specifications using nonlinear estimation. Mindful of the challenges related with nonlinear estimation (see, e.g., León-Ledesma, McAdam, & Willman, 2010), we also consider linear translog approximations as robustness checks.

Contrary to most of the theoretical literature, we assume technological change to be neutral. The nonlinear nature of the CES function, the collinear nature of time and input growth, and the limited number of observations in the energy sector make the simultaneous identification of elasticities of substitution and biased input-augmenting technical change for more than two inputs of production difficult.

An alternative to our aggregate production approach used quite extensively in the literature is estimation based on first-order conditions (FOCs) that assume perfect markets and equalize input prices with marginal products. While we recognize the importance of this work and the numerous methods developed to estimate marginal products from price accounting, we also want to flag that the underlying assumption of undistorted markets is questionable. Especially in the energy market, market distortions and measurement error can be large enough to cast doubt on the equality between the price of energy and its marginal productivity or any measure derived from it including markups.

Following the perspective of growth theory, it is not our primary interest to explore how the use of energy inputs reacts to changes in their prices. Rather, we are interested in whether the aggregate technological capabilities of an economy are such that it could replace dirty energy input with clean energy input without inducing or accelerating a decline of marginal productivity of clean energy. Against this background, our main estimation strategy relies on input and output quantities only.

B. Empirical Specifications for the Electricity Sector

For the electricity sector, we use the production function formulated in equation (3). Imposing neutral technical change, we obtain the following regression equation:

$$\ln Y_{it} = a_i + dt + \frac{1}{\psi} \ln \left(\omega K_{Cit}^{\psi} + (1-\omega) K_{Dit}^{\psi} \right) + \varepsilon_{it}, \tag{4}$$

where i denotes the country, t denotes the year, and ε is the error term.[4] As discussed in section IIB, our parameter of interest is ψ, the substitution parameter between clean and dirty production capacity, $\sigma = 1/1 - \psi$ representing the corresponding elasticity of substitution.

We conduct a robustness check assuming a unitary elasticity of substitution between capital and fuel within electricity generation from dirty sources. The resulting Cobb-Douglas-in-CES specification is

$$\ln Y_{it} = a_i + dt + \frac{1}{\psi} \ln \left(\omega K_{Cit}^{\psi} + (1-\omega) (K_{Dit}^{\alpha} E_{Dit}^{1-\alpha})^{\psi} \right) + \varepsilon_{it}, \tag{5}$$

where E_{Dit} represents fuel input used in dirty electricity generation.

As a robustness check to the nonlinear regression, we estimate a variant of the translog function, the so-called Kmenta approximation, which represents a linear first-order approximation of equation (4) around $\psi = 0$ (Kmenta, 1967):

$$\ln Y_{it} = a_i + dt + \omega \ln K_{Cit} + (1-\omega) \ln K_{Dit} + (1-\omega) \frac{\psi}{2} (\ln K_{Cit} - \ln K_{Dit})^2. \tag{6}$$

This expression can then be rewritten in per dirty capital units (indicated by lowercase variables) by subtracting $\ln K_{Dit}$ from both sides of the equation:

[3] The CES aggregate production function estimation was revived from earlier work traced back to the 1970s by Duffy and Papageorgiou (2000) and Duffy et al. (2004).

[4] The subscript E for the electricity-generating sector is dropped in this section and section VIA, since both sections deal with the electricity sector only.

$$\ln y_{it} = a_i + dt + \beta_1 \ln k_{it} - \beta_2 (\ln k_{it})^2 + \varepsilon_{it}. \quad (7)$$

The CES parameters are computed as $\sigma = \beta_1(1-\beta_1)/(\beta_1(1-\beta_1) - 2\beta_2)$ and $\omega = \beta_1$.

The disadvantage of the translog function is that its two-input elasticity of substitution converges to one for large input ratios and it satisfies the conditions of a neoclassical production function only locally.

C. *Empirical Specifications in the Nonenergy Sector*

We choose a baseline specification that allows identifying the substitution parameter between clean and dirty energy inputs within the energy aggregate ψ and assumes a value of 0 for the other substitution parameters specified in equation (1). This parsimonious strategy is close to the one that Hassler, Krusell, and Olovsson (2012) used, with the difference that they estimate substitution between energy and nonenergy inputs. In addition, we impose neutral technical change and include other material and service inputs besides energy in some variants estimated. Ideally, we would observe gross output and all relevant inputs with the reliability of national accounts data. Since our data allow for only a more approximate split of intermediate input into energy, on the one hand, and materials and services, on the other hand, we use two alternative dependent variables: value added plus energy cost (as used by, e.g., Van der Werf, 2008) and gross output. Written down for gross output, our baseline CES-in-Cobb-Douglas specification with constant returns to scale and neutral technical change is

$$\ln Y_{ijt} = a_i + a_j + dt + (1-\alpha-\gamma-\theta)\ln L_{ijt} + \alpha \ln K_{ijt} + \theta \ln MS_{ijt} + \gamma\left[\frac{1}{\psi}\ln\left(E^{\psi}_{Cijt} + E^{\psi}_{Dijt}\right)\right] + \varepsilon_{ijt}, \quad (8)$$

where Y_{ijt} represents gross output in country i and industry j, t is a time trend, L_{ijt} denotes labor input, K_{ijt} denotes capital input, MS_{ijt} denotes intermediate materials and services input, and E_{Cijt} and E_{Dijt} the clean and dirty energy inputs.[5] Note that contrary to the standard CES function, our specification for the energy subaggregate does not include multiplicative weights for the two input terms. The reason becomes intuitive when considering the case of infinite substitution: energy inputs are measured in homogeneous units of terajoules (TJ), and in the case of infinite substitution, we would expect the total productive services of energy inputs to be the unweighted sum of these inputs.

We use industry-level observations of the nonenergy industries to estimate an aggregate production function for the nonenergy (or final) sector. This approach implies that substitution between clean and dirty energy inputs can occur at three levels: industries can become cleaner over time, the same industries may have different levels of clean energy use in different countries, and a country's production can become cleaner by shifting resources toward sectors with a higher share of clean energy inputs.

We again run a robustness check with a linear approximation of the baseline CES-in-Cobb-Douglas form:

$$\ln\frac{Y_{ijt}}{L_{ijt}} = a_i + a_j + dt + \beta_1 \ln\frac{K_{ijt}}{L_{ijt}} + \beta_2 \ln\frac{E_{Cijt}}{L_{ijt}} + \beta_3 \ln\frac{E_{Dijt}}{L_{ijt}} + \beta_4\left(\ln\frac{E_{Dijt}}{E_{Cijt}}\right)^2 + \beta_5 \ln\frac{MS_{ijt}}{L_{ijt}} + \varepsilon_{ijt}, \quad (9)$$

where $\beta_2 = \beta_3$. The CES-in-Cobb-Douglas parameters can then be derived as $\alpha = \beta_1$, $\gamma = 2\beta_2$, $\theta = \beta_5$, and $\sigma = 1/(1 - \beta_4/8\beta_3)$.

V. Data

A. *Electricity Sector*

As output measure in the electricity sector, we choose physical output since real value added in this highly regulated sector may be influenced by many factors not related to productivity. Information on the electricity generated by technology is taken from the IEA Electricity Information Statistics. The main input measures, clean and dirty capital, are also approximated by a physical measure: net installed technology-specific generation capacity in megawatt (MW), a measure that has been used frequently as a capital input proxy in the electricity sector (see, e.g., Atkinson & Halvorsen, 1976; Söderholm, 2001; Färe et al., 2005).[6] We classify installed capacities of nuclear, hydro, geothermal, solar, ocean, and wind power plants as clean capacities and the remaining ones as dirty capacities.

It is expected that clean technologies have higher capital costs than dirty technologies, which in turn incur higher fuel costs. Since we have only limited information about clean and dirty installation cost per megawatt and, moreover, lose some data points in adding this information, we present estimations with capacity data as baseline results but provide robustness checks using approximated real capital stocks. They are derived by valuing installed capacities with technology-specific investment cost estimates published by the U.S. Energy Information Agency.[7] These estimates offer temporal variation since they are updated every year. But we need to assume that they are equal across countries since we do not have similar information for other countries. Table 1

[5] All specifications for value added plus energy cost follow in a straightforward way and are not written down here. The subscript F for the nonenergy sector is dropped in this section and section VIB, since both deal with the nonenergy sector only.

[6] The IEA defines the net installed generation capacity as "the maximum active power that can be supplied, continuously, with all plants running, at the point of outlet to the network" (IEA/OECD, 2013). This measure is not tautological to physical output since an equivalence holds only under uninterrupted production and ideal conditions, as, for example, discussed by Söderholm (2001).

[7] These values represent assumptions used in the Electricity Market Module of the Annual Energy Outlook: http://www.eia.gov/oiaf/archive.html.

Table 1.—Variable Description of the Electricity Sector Data

Variable Description and Unit of Measurement
Real fixed capital stock assigned to clean technologies (EIA based)
Real fixed capital stock assigned to dirty technologies (EIA based)
Electricity generation by all technologies (in GWh)
Net installed capacity of clean technologies (in MW)
Net installed capacity of dirty technologies (in MW)
Fuel input into dirty technologies (in TJ)

TJ = terajoule; GWh = gigawatt-hour; MW = megawatt.

summarizes the variables available. The data set exhibits up to 390 observations (26 countries for the period 1995 to 2009).[8]

B. *Nonenergy Industries*

Three steps are undertaken to construct input and output data for the nonenergy sector using information from the World Input-Output Database (WIOD) and the GGDC Productivity Level Database. First, emission-relevant energy use by fuel type is aggregated into a clean and a dirty aggregate. In doing so, we are adding up biogasoline, biodiesel, biogas, other renewables, electricity, heat production, hydro, geothermal, solar, wind, other sources, nuclear, and waste into the clean aggregate. All other types of energy-generating technologies sum up to the dirty aggregate. The second step deals with the construction of intermediate energy, service, and material input aggregates. These are not given in WIOD directly but can be derived from its use tables. Following the EU KLEMS methodology (O'Mahony & Timmer, 2009), energy intermediate inputs (IIE) are defined as all energy mining products (produced by sectors 10–12), oil refining products (23), as well as electricity and gas products (40) that are used as intermediate production inputs. Intermediate service inputs (IIS) are defined as all service products used (50–99), whereas all remaining products are classified as intermediate material inputs (IIM). This classification can be applied one to one to the WIOD use tables at purchasers' prices. In a third step, the nominal values in local currency are transformed into real values of a common currency (real 1997 $US) using the PPPs from the GGDC Productivity Level Database in combination with price indices from WIOD.

Table 2 summarizes the variables observed in the nonenergy sector. The data set contains observations for nineteen countries (Australia, Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Great Britain, Hungary, Ireland, Italy, Japan, Netherlands, Portugal, Slovenia, Sweden, and the United States), 28 industries, and the years 1995 to 2007 (see online appendix section II for details on coverage and PPPs).

[8] A limitation of our approach is the way our data account for trade in energy inputs and for private energy consumption; see online appendix section II.

Table 2.—Variable Description of the Nonenergy Sector Data

Variable Description and Unit of Measurement
Gross output at real 1997 U.S. dollars (PPP)
Gross value added at real 1997 U.S. dollars (PPP)
Intermediate energy input at real 1997 U.S. dollars (PPP)
Intermediate materials and service input at real 1997 U.S. dollars (PPP)
Real fixed capital stock at real 1997 U.S. dollars (PPP)
Total hours worked by persons engaged
Energy use of clean sources (in TJ)
Energy use of dirty sources (in TJ)

TJ = terajoule.

VI. Results

A. *Electricity Sector*

We start by estimating the CES function in equation (4) for the electricity-generating sector. Output is measured as electricity generation in gigawatt-hours (GWh), and inputs are measured as clean and dirty installed generation capacity in megawatts (MW). We first employ nonlinear least squares estimation that relies on nonlinear optimization methods to search for the parameter values that minimize the residual sum of squares and estimate the confidence intervals of these estimates. The production function is nonlinear in ψ, which appears as an exponent, and the elasticity of substitution within the energy aggregate σ is in turn nonlinear in ψ.[9]

In addition to nonlinear least squares, we also run OLS regressions after linearizing the CES function with the Kmenta approximation. We do that to confirm that nonlinear and linear estimation do not obtain drastically different estimates of the key parameters. Results from both estimation methods are reported in table 3. With both variants, we run a regression with country fixed effects (columns 1 and 3) and in first differences (columns 2 and 4).

For the electricity-generating sector, we obtain estimates of the substitution parameter ψ between clean and dirty capacity of around 0.46. The estimates using nonlinear and linear least squares are very similar. They imply an elasticity of substitution between clean and dirty generation capacity of about 1.8 (a ψ value of 0 would imply a unitary elasticity of substitution). In the perspective of growth theory, this value of the estimate of ψ would place us in the case where an important condition for long-term clean growth of the electricity sector is fulfilled, even in the absence of technical change.

In table 4, we use approximated real capital stocks, instead of capacities in MW, as input measures. The estimates of the elasticity of substitution change only marginally under both nonlinear and linear least squares. It is important to note

[9] To reduce the extent of nonlinearity, we perform estimation and tests of ψ instead of σ. Standard errors are bootstrapped with clusters at the country and, if applicable, the industry level. A parameter space that often exhibits multimodality and flat regions for the CES function is known to complicate estimation (León-Ledesma, McAdam, & Willman, 2015). Degenerate results where the numerical search either does not converge or finds a ψ larger than one are discarded from the bootstrap.

TABLE 3.—NONLINEAR ESTIMATION AND KMENTA APPROXIMATION OF CES: ELECTRICITY SECTOR

	CES		Kmenta	
	NLS	FD NLS	OLS	FD OLS
d	−0.001	−0.003	−0.001	−0.003
	(−0.67)	(−1.57)	(−0.50)	(−1.18)
ω	0.220**	0.442***	0.245***	0.451***
	(2.44)	(5.80)	(6.02)	(7.87)
ψ	0.457**	0.487***	0.446***	0.455***
	(2.09)	(3.65)	(3.39)	(9.87)
Country DV	Yes	No	Yes	No
Adjusted R^2	0.997	0.187	0.968	0.546
$\psi = 0$	0.037	0.000	0.002	0.000
σ	1.840	1.948	1.806	1.833
N	390	364	390	364

z-statistics in parentheses. Significantly different from 0 at ***1%, **5%, *10%. Columns 1 and 2 provide bootstrapped standard errors based on 400 replications with country as cluster variable. Specification 1 applies the nonlinear least squares (NLS) estimator and includes country dummies. Specification 2 applies the NLS estimator to a first-differenced version of the model. Specification 3 applies the OLS estimator and includes country dummies. Specification 4 applies the OLS estimator to a first-differenced version of the model. $\psi = 0$ reports the significance level of a Wald test with $H_0 : \psi = 0$.

TABLE 4.—NONLINEAR ESTIMATION AND KMENTA APPROXIMATION OF CES WITH AN ALTERNATIVE CAPITAL PROXY: ELECTRICITY SECTOR

	CES		Kmenta	
	NLS	FD NLS	OLS	FD OLS
d	−0.010***	−0.009***	−0.009***	−0.009***
	(−3.67)	(−3.92)	(−3.97)	(−3.35)
ω	0.193*	0.388***	0.203***	0.401***
	(1.68)	(3.57)	(4.01)	(6.39)
ψ	0.423*	0.460***	0.535**	0.441***
	(1.70)	(2.59)	(2.74)	(5.17)
Country DV	Yes	No	Yes	No
Adjusted R^2	0.997	0.053	0.965	0.555
$\psi = 0$	0.090	0.010	0.011	0.000
σ	1.734	1.852	2.152	1.789
N	338	312	338	312

z-statistics in parentheses. Significantly different from 0 at ***1%, **5%, *10%. Columns 1 and 2 provide bootstrapped standard errors based on 400 replications with country as cluster variable. Specification 1 applies the nonlinear least squares (NLS) estimator and includes country dummies. Specification 2 applies the NLS estimator to a first-differenced version of the model. Specification 3 applies the OLS estimator and includes country dummies. Specification 4 applies the OLS estimator to a first-differenced version of the model. $\psi = 0$ reports the significance level of a Wald test with $H_0 : \psi = 0$.

here, though, that the scope of this sensitivity analysis is limited by the lack of plant cost data across fuels used.

In the last specification, we consider the Cobb-Douglas-in-CES function introduced in equation (5) that allows substitution between dirty capacity and dirty fuels assuming a unitary elasticity. With this specification, the estimate of the elasticity of substitution between clean and dirty electricity generation rises to values above 2 as reported in table 5. However, it also turns out that the estimate of the distribution parameter ω becomes more unstable across specifications.

B. *Nonenergy Industries*

The main specification we employ for nonenergy industries is a production function that is CES in clean and dirty fuel input and Cobb-Douglas in the energy aggregate and other inputs based on equation (8). Consistent with the previous analysis in the electricity sector, we use both nonlinear and linear estimation methods. As discussed in section IVC, we use two alternative dependent variables: gross output and value added plus intermediate energy input.

TABLE 5.—NONLINEAR ESTIMATION OF COBB-DOUGLAS IN CES: ELECTRICITY SECTOR

	Main Capital Proxy		Alternative Capital Proxy	
	NLS	FD NLS	NLS	FD NLS
d	0.003	0.003	−0.000	−0.000
	(1.47)	(1.34)	(−0.19)	(−0.10)
α	0.437***	0.379***	0.347***	0.311***
	(6.33)	(4.03)	(5.72)	(3.60)
ω	0.488***	0.707***	0.010	0.005
	(4.83)	(10.08)	(0.14)	(0.37)
ψ	0.508***	0.651***	0.508***	0.644***
	(3.30)	(4.53)	(3.31)	(4.83)
Country DV	Yes	No	Yes	No
Adjusted R^2	0.999	0.525	0.999	0.500
$\psi = 0$	0.001	0.000	0.001	0.000
σ	2.031	2.867	2.032	2.810
N	390	364	338	312

z-statistics in parentheses. Significantly different from 0 at ***1%, **5%, *10%. All columns provide bootstrapped standard errors based on 400 replications with country as cluster variable. Specifications 1 and 3 apply the nonlinear least squares (NLS) estimator and include country dummies. Specifications 2 and 4 apply the NLS estimator to a first-differenced version of the model. $\psi = 0$ reports the significance level of a Wald test with $H_0 : \psi = 0$.

TABLE 6.—NONLINEAR ESTIMATION AND KMENTA APPROXIMATION OF CES IN COBB-DOUGLAS: NONENERGY INDUSTRIES

	CES in Cobb-Douglas		Kmenta	
	VA + IIE	GO	VA + IIE	GO
d	0.010***	0.003*	0.010***	0.002*
	(4.66)	(1.82)	(4.79)	(1.73)
α	0.359***	0.186***	0.360***	0.187***
	(7.43)	(6.63)	(7.78)	(7.04)
γ	0.260***	0.121***	0.258***	0.121***
	(6.22)	(5.05)	(6.15)	(4.88)
θ		0.565***		0.566***
		(15.46)		(16.54)
ψ	0.651***	0.654**	0.394***	0.276
	(3.29)	(2.26)	(2.97)	(1.41)
Country DV	Yes	Yes	Yes	Yes
Industry DV	Yes	Yes	Yes	Yes
$\psi = 0$	0.001	0.024	0.003	0.159
σ	2.868	2.888	1.651	1.382
Adjusted R^2	0.948	0.982	0.739	0.907
N	6,914	6,914	6,914	6,914

z-statistics in parentheses. Significantly different from 0 at ***1%, **5%, *10%. Columns 1 and 2 provide bootstrapped standard errors based on 400 replications with country and industry as cluster variables. Specifications 1 and 2 apply the nonlinear least squares (NLS) estimator and include country and industry dummy variables. Specifications 3 and 4 apply the OLS estimator and include country and industry dummy variables. $\psi = 0$ reports the significance level of a Wald test with $H_0 : \psi = 0$.

Results are presented in table 6 (columns 1 and 2 report nonlinear estimation results; columns 3 and 4 report OLS estimation results). The estimates for the substitution parameter ψ are significantly positive in all specifications except for the linear model for gross output.[10] They imply elasticities of substitution between clean and dirty energy inputs within the energy aggregate up to a value of 3. One reason that we observe a larger difference in the estimates between

[10] As an approximation around $\psi = 0$, the Kmenta approximation is known to bias elasticity parameters of CES functions toward 1.

nonlinear and linear estimation than we did for the electricity sector may be that the data for different industries exhibit higher dispersion.[11]

C. Discussion

In the theoretical discussion, we have highlighted that an elasticity of substitution larger than 1 within a CES energy aggregate in both the electricity sector and the final sector is a necessary condition for green long-run growth in the absence of technical change in the framework of neoclassical growth models. Even if neutral or endogenous directed technical change is assumed, the sign of the corresponding substitution parameters fundamentally affects the conditions for long-run green growth. Our empirical results support the view that the elasticity of substitution between clean and dirty energy inputs exceeds the value of 1 significantly in both the electricity-generating sector, where we measure production capacities as inputs, and the energy aggregate of nonenergy industries. We thus offer a first piece of econometric evidence on a parameter that was previously inferred from partial elasticities at a lower level of aggregation of energy, model calibration or conjectures.

Our empirical estimation is not without limitations. Issues of endogeneity were challenging to tackle since test statistics generally indicated that potential input instruments were not exogenous. Therefore, our results can be interpreted as associations, and claims of causation cannot be made. Moreover, the implicit assumption of trend stationarity in the data series used cannot be confirmed because for nonlinear panel data models with nonstationary time series, asymptotic theory and estimation methods do not yet exist (see, e.g., Wagner, 2008).[12] We take comfort in the fact that the dimension of the data for the nonenergy sector (13 years, 532 country-industry cells) resembles that of micropanel data with a small time series and a large cross-section dimension, for which issues of nonstationarity are typically not a major concern and not evaluated.

We started from the presumption that the use of first-order conditions in empirical research on fuel substitution may bias marginal products and thus might bias elasticity parameters downward because of particularly severe market distortions for energy. While fully exploiting the methods that may be most appropriate in the hypothetical absence of this bias lies beyond the scope of this paper, we run a first check to exploit this comparison. Estimating a seemingly unrelated regression (SUR) of FOCs, we obtain an elasticity of substitution within the energy aggregate of at most 0.43 (see online appendix section III). Still more research may be needed to contrast in a methodologically rigorous way estimations with and without FOCs, in the presence of a bias to FOCs that can be unknown and nonconstant.

[11] Section III in the online appendix contains sensitivity analysis with a more general CES function, which is, however, difficult to identify, and with different starting values for the nonlinear estimation, where we find that our results are robust.

[12] For the linear case of nonstationary panel data models, Phillips and Moon (1999) developed an asymptotic theory and show that panel spurious regressions, contrary to pure time-series spurious regressions, give a consistent estimate of the underlying parameter as both N and T tend to infinity.

VII. Conclusion

In the context of growth models with neoclassical production functions, the elasticity of substitution between clean and dirty energy inputs within the energy aggregate represents a central parameter in assessing the conditions necessary for long-run green growth. In this paper, we produce the first econometric evidence on this elasticity at the macroeconomic level.

Our contribution is threefold. First, we review the role of energy-related substitution parameters in variants of CES production functions that are prototypical for growth models. This leads us to formulate parsimonious specifications of production functions that can be used in econometric analysis. Second, using the World-Input-Output-Database as a novel data source, we construct industry-level data for a panel of up to 26 countries covering clean and dirty energy inputs. Third, we present evidence that the elasticity of substitution between clean and dirty energy inputs within the energy aggregate of the nonenergy sector and the elasticity of substitution between clean and dirty capacity in the electricity sector both exceed unity. More specifically, we find values around 2 in the electricity-generating sector and values close to 3 in nonenergy industries. This result contrasts with some low elasticities found in calibrations or conjectures inferred from the interfuel substitution literature.

While the analysis presented in this study is a useful first attempt and a good point of reference to evaluate the elasticity of substitution between clean and dirty energy inputs from a macroeconomic perspective, we hope that it can also serve as a launching pad for future work. A potential avenue for a more detailed estimation of substitution possibilities in the electricity-generating sector could be pursued by employing plant-level data. Instead of using a binary distinction between clean and dirty fuels, future research on nonenergy industries could also use fuel-specific data on actual emissions to develop specifications of technology that account for unwelcome by-products such as carbon emissions. This could provide a more precise estimation by accounting for the fact that not all energy inputs causing emissions are equally dirty.

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