Substitution between Clean and Dirty Energy Inputs - A Macroeconomic Perspective*

Chris Papageorgiou†
International Monetary Fund

Marianne Saam
Centre for European
Economic Research (ZEW)

Patrick Schulte
Centre for European
Economic Research (ZEW)

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Abstract

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

JEL Classification: O44; O47; Q54; Q58.

Keywords: Clean and dirty energy inputs; aggregate elasticity of substitution; CES function; cross-country sectoral data; environmental policy.

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†Corresponding author. email: cpapageorgiou@imf.org; address: 700 19th Street NW, Washington DC.

1 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 only be effective 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. Recently, Acemoglu, Aghion, Bursztyn, and Hemous (2012) (AABH thereafter) formulate 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 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 CO2 is increased as a result of using fossil fuels (coal, oil, natural gas).

An elasticity of substitution between clean and dirty production tasks is a concept that allows to represent conditions for clean growth in an elegant and parsimonious way within a growth model. But this elasticity is too abstract for being estimated based on input and output 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 promoting long-run green growth. This role is similar to that of the elasticity of substitution between clean and dirty production in a two-factor production model.

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 impacts the model's long-run predictions. Under plausible conditions, an elasticity of substitution between clean and dirty energy inputs within the energy aggregate that exceeds one is a necessary condition for long-run green growth in the absence of technical change. But even in the presence of technical change, an elasticity of substitution below one implies properties of the production function that are adverse to achieving long-run green growth.

Most of the existing empirical literature has estimated partial elasticities of substitution between capital and energy and between different fuels. Meanwhile evidence on the substitution parameter between total clean and dirty energy inputs at the macroeconomic level 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 of macroeconomic production functions. In doing so, we account for the fact that substitution between clean and dirty inputs takes a different form within the electricity-generating sector itself.

We set out to develop an empirical approach to estimate the substitution parameter between clean and dirty energy inputs from CES production functions using available macroeconomic data and interpret it through the lens of growth models. In assessing whether an energy input is clean or dirty, we use a binary distinction: clean energy inputs are those not causing CO2 emissions, while 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 $1995-2009$. Our key finding is that the substitution parameter estimates are significantly greater than unity; around 2 for the electricity-generating sector and close to 3 for the non-energy industries. These results are in contrast to the majority of existing studies obtaining elasticity estimates that are low (mostly below unity). Our larger elasticity estimates are consistent with conditions favorable for promoting green growth.

The rest of the paper is organized as follows. Section 2 presents the theoretical underpinnings. Section 3 discusses empirical evidence on substitution between energy inputs. The methodology and the estimable equations obtained based on production theory are presented in Section 4. The dataset used in the empirical analysis is briefly discussed in Section 5 while Section 6 presents estimates of the elasticity of substitution between clean and dirty energy inputs in the electricity and non-energy industries. Section 7 concludes with some directions for future research.

2 Theoretical Foundations

2.1 The Role of Substitution Parameters in Models of Green Growth

Inspired by recent work in endogenous growth theory, the aim of our paper is to empirically identify parameters affecting substitution between clean and dirty production at the macroeconomic level. 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. While summarizing all relevant dimensions of clean-dirty substitution within a single parameter (as in AABH) does not seem feasible empirically, we consider that 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 negative has already been a bit better established than any evidence on the elasticity of substitution between clean and dirty energy inputs within the energy aggregate. 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 total 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 that can at the same time be estimated from available macroeconomic data. In Section 2.2 and 2.3, we discuss how the properties of prototypical CES production functions influence the prospects of long-run growth in theoretical approaches taking into account clean and dirty energy inputs. Section 2.4 gives examples of previous theoretical work using the kind of elasticity parameters we discuss.

2.2 Two-Factor Production Technology

We first discuss a two-factor production function where final output Y is produced from intermediates from the clean sector Y_C and intermediates from the dirty sector Y_D. This setting is similar to the one used by AABH. Output of clean intermediates depends on inputs X_C (that we do not specify any further) and a technology parameter A_C: $Y_C = A_C X_C$. Output of dirty intermediates depends on inputs X_D and a technology parameter A_D: $Y_D = A_D X_D$. Only the production of dirty intermediates generates emissions, which depending on the interpretation can be assumed proportional to X_D or Y_D (Both kinds of assumptions are used in the literature depending on the interpretation given to the sectoral output, see also Brock and Taylor (2005)). The production function has a constant elasticity of substitution:

$$Y = \left[\beta(A_C X_C)^{\psi} + (1-\beta)(A_D X_D)^{\psi}\right]^{\frac{1}{\psi}} . \tag{1}$$

In line with AABH, we call $\sigma = 1/1-\psi$ in this two-factor setting the elasticity of substitution between output from the clean and the dirty production sector, or shortly, the elasticity of substitution between clean and dirty production. We speak of ψ as the *substitution parameter* between the clean and the dirty production, with $-\infty < \psi < 1$.

In the absence of technical change, long-run green growth is only possible if the economy is able to grow infinitely while dirty inputs Y_D are bounded. With Y_D fixed at some maximal level, the long-run growth rate of consumption is

$$g = \lim_{Y_C \to \infty} \frac{\dot{Y}}{Y} - \frac{\dot{I}}{I}, \tag{2}$$

where I is a measure of investment and intermediate input, expressed in units of final output. If the growth of I is nonnegative, a necessary (but generally not sufficient) condition for long-run growth is

$$\lim_{Y_C \to \infty} \frac{\dot{Y}}{Y} > 0. \tag{3}$$

If Y_D is to be bounded, long-run growth is only possible if the marginal productivity of Y_C has a positive limit. It is well-known that this is the case for $\psi > 0$. For $\psi = 0$, output is unbounded even with bounded Y_D, but the marginal product of Y_C converges to zero, which prevents growth in the long-run. With $\psi < 0$, output is bounded if Y_D is bounded (for a proof with capital and labor as inputs see e.g. Klump and Preissler (2000)).

The ratio of the marginal products of X_C and X_D valued in units of final output is:

$$\frac{\frac{\partial Y}{\partial X_C}}{\frac{\partial Y}{\partial X_D}} = \frac{\beta}{1-\beta}\left(\frac{X_C}{X_D}\right)^{\psi-1}\left(\frac{A_C}{A_D}\right)^{\psi}. \tag{4}$$

If $\psi < 0$, the relative marginal product of inputs into clean production declines more than proportionally if the ratio of clean of clean to dirty inputs X_C/X_D increases. If $\psi > 0$, it declines less than proportionally.

Long-run green growth becomes technically feasible in the presence of neutral technical change irrespective of the substitution parameter if emissions are proportional to inputs into dirty production X_D. If emissions are proportional to output of the dirty sector Y_D, long-run green growth is impossible for $\psi \leq 0$ for the same reason as without technical change. With emissions proportional to inputs into dirty production, it will now depend on the cost structure and incentives in a model whether growth in the use of dirty inputs will stop at a sufficiently low level to halt climate change. If the elasticity of substitution between clean and dirty production is smaller than one and dirty inputs are bounded, the income share of clean intermediates Y_C would converge to zero under perfect competition. This is unlikely to be a sustainable situation even under policy invention. It is impossible to give up or ban the use of dirty inputs at some point because they represent an essential input. In this setting, it is likely that restricting the use of dirty inputs will also reduce the use of clean inputs, thus the use of inputs altogether (To our knowledge an exact model with neutral technical change or labor-augmenting technical change and this kind of production function has not been formulated). On the contrary, with an elasticity of substitution larger than one, it is possible to completely switch to clean inputs and to sustain their growth in the long-run.

Technical progress that is directed to the use clean energy inputs is considered in theory as well as in practice as one of the most important conditions for long-run green growth. As with neutral technical change, long-run green growth is impossible with $\psi \leq 0$ if emissions are proportional to intermediates produced in the dirty sector Y_D. If emissions are proportional to input to dirty production X_D, long-run green growth is technically feasible at any value of the substitution parameter. But directed technical change affects the relative demand for clean and dirty inputs in opposite ways for low and high substitution (i.e., for ψ smaller and larger than zero, see Equation 4).

With an elasticity of substitution σ larger than one ($\psi > 0$), technical progress in clean production raises the relative demand for clean inputs. With an elasticity of substitution lower than one ($\psi < 0$), the demand for inputs into the clean sector would rise following a relative increase in the level of technology in *dirty* production. In models of endogenous directed technical change, technical change is ceteris paribus directed to the more expensive input.[1] With $\psi > 0$, this property tends to support self-propelling clean progress as soon as it is profitable. Progress directed towards clean production will under perfect competition in the final and intermediate sector raise the relative price of inputs into the clean sector and thus further raise the profitability of clean progress. With $\psi < 0$, the converse is true, clean progress will raise the relative price of inputs into dirty production and thus reduce the relative profitability of clean intermediates. In the model by AABH, this leads to parallel progress in the clean and dirty sector in the long-run if $\psi < 0$ and in consequence also to an increase of inputs into both sectors.

2.3 Four-Factor Production Technology with Energy Aggregate

We now consider production functions with inputs that can be measured at the macroeconomic level. For the non-energy (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 the rest of the economy. Modeling the electricity sector and not the other parts of the energy sector is in line with our estimation

[1] See also Acemoglu (2008).

strategy, which provides estimates for the electricity sector only. Both functions formulated in this section will serve to discuss substitution properties relevant for long-run green growth. More restricted versions of the function will then be presented in Section 4 to estimate the substitution parameters related to clean energy.

Final output is represented as a CES aggregate of a composite of capital and labor and an energy composite of clean energy E_{FC} and dirty energy E_{FD}.[2] Non-energy inputs have a common technology parameter A_F. Clean and dirty energy inputs have specific factor-augmenting technology parameters A_{FC} and A_{FD}

$$Y_F = \left\{ \gamma A_F^{\phi} [\alpha K^{\chi} + (1-\alpha) L^{\chi}]^{\frac{\phi}{\chi}} + (1-\gamma)[\beta (A_{FC} E_{FC})^{\psi_F} + (1-\beta)(A_{FD} E_{FD})^{\psi_F}]^{\frac{\phi}{\psi_F}} \right\}^{\frac{1}{\phi}}. \quad (5)$$

We consider as long-run green growth a situation in which the inputs of capital and clean energy are increased, while labor and dirty energy input cannot exceed some upper limit. Since the clean and dirty intermediate inputs are now not those produced in the clean and in the dirty sector, but are considered to represent the energy inputs directly, emissions are always assumed to be proportional to dirty energy input E_{FD}. In this production function, $\sigma_F = 1/1 - \psi_F$ 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-factor elasticity of substitution for the case of more factors. But for long-run growth, the constant parameter values and not the partial elasticities matter, so we focus on the substitution parameter ψ_F.

Without technical progress, 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 the case if the substitution parameters χ and ψ_F are positive. The substitution parameter of the upper-level CES function, ϕ, does not need to be positive.[3] We assume here that capital is produced in a closed economy from final output, such that pollution from producing capital is already taken into account.

[2] Materials are omitted. The empirical estimation will be carried out with and without materials.

[3] To see this, consider the case of a steady state where K and E_C grow at the same rate.

With technical change, long-run green growth is always technically feasible in this setting, because we consider A_{FD} as a parameter that increases the efficiency in the use of dirty energy inputs. Emissions are proportional to E_{FD}. But as in the previous section, increasing clean energy input per dirty energy input reduces the relative marginal product of clean energy input more than proportionally if $\psi < 0$. (Since both energy inputs are within the same CES subaggregate, Equation 4 holds just replacing X_C, X_D by E_{FC}, E_{FD}.). With directed technical change, one observes the same effect on relative demand for clean and dirty inputs as in the case with two factors. But more complex interactions may arise from this if all three technology parameters are endogenous.

Now we turn to modeling the electricity sector. We assume that the final sector does not produce electricity itself but buys it from the electricity sector. Meanwhile the final sector directly produces energy from dirty sources. 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 in the electricity sector. 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 zero (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} (which means clean energy input to the final sector) is modeled as a CES production function of clean production capacity K_{EC} in that sector and dirty production capacity K_{ED}:[4]

$$E_{FC} = A_E \left(\omega(A_{EC}K_{EC})^{\psi_E} + (1-\omega)(A_{ED}K_{ED})^{\psi_E}\right)^{\frac{1}{\psi_E}} . \quad (6)$$

The parameter ψ_E now represents the substitution parameter between clean and dirty capac-

[4]Since it is well-known that clean energy production has higher fixed cost and lower marginal cost than dirty production, one may object that the production function should account for these characteristics and should not treat clean and dirty inputs in electricity production in a symmetrical way. Production functions that will arise from such a construction, however, imply restrictions that predetermine the elasticity of substitution. In many cases, the elasticity of substitution converges to one as one of the input intensities increases (see e.g. Revankar (1971) for a so-called VES function and Gerlagh and Lise (2005) for an application to energy inputs). Thus we prefer the CES specification.

ity in the electricity-generating sector. The corresponding elasticity of substitution equals $\sigma_E = 1/1 - \psi_E$. If capacity and fuels are used in a fixed ratio, fuels and capacity are affected by substitution in an identical way. In the absence of technical change, the substitution parameter within the capital-labor aggregate χ and the substitution parameters within the energy aggregate, ψ_E and ψ_F, have to be positive in order for long-run green growth to be possible. Moreover, a constant growth rate of output from the electricity sector is a precondition for a constant growth rate of clean energy input in the final sector. Long-run green growth in the electricity sector is in turn only possible if $\psi_E > 0$. Our aim is to estimate the substitution parameters ψ_E and ψ_F and thus the corresponding two-factor elasticities of substitution σ_E and σ_F.

2.4 Clean-Dirty Substitution in Existing Theoretical Models

Estimates for substitution parameters related to energy are needed for the calibration of a multitude of models on growth and the environment ranging from abstract models deriving general theorems on growth and welfare to large CGE models used for policy evaluation. For the predictions of almost any model that features some element of production with constant returns and technical change, it is essential to know the sign of one or several substitution parameters related to energy or pollution. This section gives a brief overview of representative models using production functions involving substitution parameters between clean and dirty outputs or inputs.

The recent paper by AABH models substitution, green growth and optimal policy in a setting that has many parallels with other models of directed technical change. These models inspired empirical research to take a closer look at the connection between growth and factor substitution (e.g. Klump, McAdam, and Willman (2007), Krusell, Ohanian, Ríos-Rull, and Violante (2000), Duffy, Papageorgiou, and Perez-Sebastian (2004)). We discuss the paper by AABH in some more detail since it summarizes the role substitution plays for green growth elegantly within a single parameter.

While the literature on environmental policy first developed from a microeconomic perspective, in recent years it has increasingly focused on macroeconomic questions.[5] The paradigm of directed technical change is a general modeling framework based on the idea of induced innovation going back to Hicks (1932), who in the same book defined his concept of an elasticity of substitution. In its most widely used contemporary version, the theory of directed technical change has been developed by Acemoglu (1998, 2002).

In their work 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, as in Section 2.2. 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 two degree Celsius. According to simulations in the paper, this would only be possible with a very high elasticity of substitution between clean and dirty production, laying around ten. The threshold for long-run green growth being technically feasible is one, but the policy to enforce this would not be optimal for elasticities only slightly above one. From the perspective of growth theory, the elasticity between clean and dirty production modeled by AABH represents a very general single measure on which the possibilities of green growth in an economy crucially depend. Of course, there are few inputs in the economy that are exclusively produced with clean or dirty energy. The authors mention that a more realistic interpretation would be to consider the inputs as clean and dirty tasks of production.

In a CGE model, Otto, Löschel, and Dellink (2007) use a CES utility function to aggregate utility from energy-intensive and energy-nonintensive goods. Technical change can be directed to capital used in these two sectors. Again the elasticity of substitution between the two products (now within the utility function) plays a crucial role for green growth.

More common in the theoretical literature is the modeling of substitution between capital and energy, dirty energy inputs and clean energy inputs within the energy aggregate, or

[5]Two excellent surveys on technical change and other macroeconomic issues in environmental economics have been contributed by Popp, Newell, and Jaffe (2010) and Fischer and Heutel (2013).

both in the same model. The production structures used in these models are closer to the ones discussed in the previous section. In a model of endogenous growth, Bovenberg and Smulders (1996) assume an elasticity of substitution between capital and pollution that is smaller than one. In an early model of induced technical change, Goulder and Schneider (1999) use a multilevel CES function that builds a CES aggregate of carbon-intensive and alternative energies. In the ENTICE model, which is based on Nordhaus' DICE model (Nordhaus 1994), Popp (2004) models substitution between knowledge and fuels in energy production in a CES function along with technological progress increasing the efficiency of fuel use. While most models assume a CES function, the study by Gerlagh and Lise (2005) is one of the few papers to use a VES function in a CGE model. The function has an elasticity of substitution between fossil fuel and other energy sources that is by assumption larger than one but is converging to one if the intensity of one energy input increases infinitely.

Based on the approach of Acemoglu (2007), Gans (2012) analyses the effect of an emission cap on directed technical change and growth. Total energy input is a CES aggregate of fossil fuel and alternative energy input and factor-augmenting progress may increase the efficiency of each of them. 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 one, the baseline assumption being that it is equal or larger than one. If an elasticity of substitution smaller than one was assumed, the emission cap would reduce innovation incentives for both factor-augmenting technologies. In a DSGE model analyzing welfare loss through climate change and the potential of a carbon tax to reduce it, Golosov, Hassler, Krusell, and Tsyvinski (2014) use a CES energy aggregate with three inputs, coal, oil and non-fossil energy. Assuming alternatively elasticities of substitution within the 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.

Given the difficulties to estimate substitution parameters of energy input and to postulate their stability over time, 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 non-renewable resources or causing excessive pollution (Bretschger and Smulders 2012). But again this poses the empirical challenge to identify the parameters relevant for these other channels.

3 Review of the Empirical Literature

3.1 Interfuel Substitution

While there is to our knowledge no previous econometric estimation with the explicit goal to identify 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. This literature that emerged in the 1970s aimed at explaining the economic implications of the oil crisis. Specifically, the goal was to assess how oil could be substituted by coal, gas and electricity or by more energy-efficient production methods in light of prohibitively high oil prices. The focus of this literature is thus quite different from our focus. The first studies exploited substitution of fuels at given capacities in the electricity sector (Atkinson and Halvorsen 1976) as well as long-run substitution estimated from cross-country data for the electricity sector (Griffin 1977) and the non-energy sector (Pindyck 1979). Fuss (1977) reports cross-price elasticities that are higher within fossil fuels than between fossil fuels and electricity. These studies all use some variant of the translog function.

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) argues that it is important to differentiate between fuels used for energy purposes and fuels used for non-energy purposes in the estimation of interfuel substitution elasticities. Steinbuks (2012) introduces a further differentiation of fuel use for energy purposes in different manufacturing processes. Heating processes account for more than two thirds of total energy consumption in manufacturing. In these processes, positive shares of all four energy inputs (petroleum, coal, gas, electricity) are observed, while other processes 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.[6] 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 (Stern 2012). Already in early studies, the difference between cross-section and time series estimates has been interpreted as reflecting long-run versus short-run elasticities (Griffin and Gregory 1976). Moreover, elasticities are lower at higher levels of aggregation. Elasticities involving electricity tend to be smaller than those between two fossil fuels.

In summary, the empirical approach used in the earlier interfuel substitution literature was primarily based on estimates of Allen elasticities or Morishima elasticities of substitution from translog cost functions. These studies were not undertaken in view of testing predictions of growth theory and the results obtained are not directly comparable to the substitution parameters we study here. Still the interfuel substitution literature represents the empirical work that is most closely related to ours.[7]

3.2 Substitution between Clean and Dirty Energy Inputs

The older interfuel literature did not use a binary distinction of clean and dirty energy inputs. While it suggests that substitution between fossil fuels and electricity may be limited, it does not offer predictions for the elasticity parameters we are interested in.

[6] The shadow elasticity is as symmetric ratio elasticity that represents the average of the asymmetric Morishima elasticities. It restricts cost to be constant. The Morishima elasticity in turn represents the difference between the cross-price and the own-price elasticity. The most popular partial elasticity has for a long time been the Allen/Uzawa elasticity of substitution, which divides the cross price elasticity by the cost share of the factor varying in price.

[7] Some exceptions to the use of translog functions in empirical research on energy-related substitution are found in the literature on capital-energy substitution, e.g. Kemfert (1998) and Van der Werf (2008). Recently Hassler, Krusell, and Olovsson (2012) estimate a nested CES function for capital, labor and energy based on quantity and price data for the US. Capital-labor substitution is assumed to be unity and short-run substitution between this composite and fossil fuels is found to be close to zero. Energy-saving technical change appears to have reacted strongly to the oil crisis and exhibits a negative medium-run correlation with technical change directed towards other inputs. The parsimonious specification in this study and the perspective on long-run growth are close to our approach, with the main difference that we focus on substitution between clean and dirty energy inputs and that we do not estimate directed technical change.

To our knowledge, there is only one previous study focusing on an empirical determination of the elasticity of substitution between clean and dirty energy inputs. Pelli (2012) extends the model developed by AABH to a multi-sector setting. For the electricity sector, he then introduces several assumptions that allow the calibration of the non-US elasticities from the US elasticity. The calibrated elasticities for the electricity sector concentrate around 0.51.

A small number of other studies obtain a substitution parameter between total clean and dirty energy input as a byproduct, most of them also using simulation instead of econometric methods. One of the scarce pieces of econometric evidence is found in the study by Lanzi and Sue Wing (2010). Investigating directed technical change in the energy sector, they develop a dynamic model in which energy demand is satisfied with production derived from renewable and fossil-fuel energy. While the main purpose of the paper is to investigate whether clean innovation reacts to rising fossil fuel prices, the estimating equation also yields a value for the elasticity of substitution between clean and dirty inputs in the energy sector of 1.6. The econometric estimate for a panel of OECD countries is obtained under the particular assumptions of the steady state of a model of directed technical change. Pottier, Hourcade, and Espagne (2014) cast doubt on the possibility to measure 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 non-fossil (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 here 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 nor 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 pointed out in this quote is a critical one for renewable energy. In energy production, the difficulties in storing energy from renewable sources leads to a misalignment in time and space with electricity demand. Mattauch, Creutzig, and Edenhofer (2012) 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. The two-factor elasticity of substitution does not express the level of relative average or marginal productivity. Rather a high elasticity of substitution means that the relative marginal productivity of an input does not decline much if it is used in increasing relative intensity.

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 first be installed 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 not only compared to renewables but also compared 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 (e.g. the cement production). And in transportation the internal combustion engine still represents the dominant technology to which current infrastructure is mainly adapted (Mattauch, Creutzig, and Edenhofer 2012). On the other hand, structural change may reduce the weight of dirty production processes in the economy. At macroeconomic level it is therefore a priori 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.

4 Estimation

In this section we discuss our choice of empirical methodology as well as the econometric specifications used for the electricity and non-energy sectors.

4.1 Methodology

In this paper we estimate the elasticity of substitution between clean and dirty energy inputs directly from aggregate production functions following an established empirical literature.[8] Specifically, we estimate nested CES specifications using nonlinear estimation. Mindful of the challenges related with nonlinear estimation (see e.g. León-Ledesma, McAdam, and 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 factor accumulation and the limited number of observations in the energy sector make the simultaneous identification of elasticities of substitution and biased factor-augmenting technical change for more than two factors of production difficult. It may be easier when imposing first-order conditions or using direct measures of technical change in combination with a steady state assumption (as in Lanzi and Sue Wing (2010)), but each of these approaches implies other restrictions not needed in our approach. We consider an estimation with neutral technological change as a useful starting point.[9]

[8]The CES aggregate production function estimation was revived from earlier work traced back to the 1970s by Duffy and Papageorgiou (2000) and Duffy, Papageorgiou, and Perez-Sebastian (2004). Subsequently, a collection of substantial work on the CES aggregate production function was published in a special issue of the *Journal of Macroeconomics* (2008).

[9]The meta-analysis by Stern (2012) found mixed results from omitting technical change from the energy

It is important to recognize here that 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 are sympathetic to 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 energy price and its marginal productivity or any measure derived from it including mark-ups.

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 energy. Within a CES function for the energy aggregate, the limiting marginal productivity of both clean and dirty energy inputs is constant in the limit if the elasticity of substitution exceeds one. Against this background, our main estimation strategy relies on input and output quantities only. But we certainly view our work as complementary to existing work using first-order conditions. A robustness check presented in Section 6.3 suggests that these alternative methodological choices require further research.

4.2 Empirical Specifications for the Electricity Sector

For the electricity sector, we use the production function formulated in Equation 6. Imposing neutral technical change, we obtain the following regression equation:

$$\ln Y_{it} = a_i + dt + \frac{1}{\psi} \ln \left(\omega K_{Cit}^{\psi} + (1-\omega) K_{Dit}^{\psi} \right) + \varepsilon_{it}, \tag{7}$$

where i denotes the country, t denotes the year, and ε is the error term.[10] As discussed in Section 2.3, 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.

sub-model, with a tendency towards a negative effect on the shadow elasticities of substitution between fuels.

[10] The subscript E for the electricity-generating sector from Section 2.3 is dropped in the current section and Section 6.1, since both sections deal with the electricity sector only.

We conduct a robustness check assuming a unitary elasticity of substitution between capital and fuel in electricity generation, similar to the function used by Stokey (1996). The resulting Cobb-Douglas-in-CES specification is the following:

$$\ln Y_{it} = a_i + dt + \frac{1}{\psi} \ln \left(\omega K_{Cit}^{\psi} + (1-\omega)(K_{Dit}^{\alpha} E_{Dit}^{1-\alpha})^{\psi} \right) + \varepsilon_{it}, \tag{8}$$

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

Nonlinear estimation accounts in the most exact way for the properties of the CES function, yet it is more difficult to implement because of numerical problems. As a robustness check we estimate a variant of the translog function, the so-called Kmenta approximation, which represents a linear first-order approximation of Equation 7 around $\psi = 0$ (Kmenta 1967):

$$\ln Y_{it} = a_i + dt + \omega \ln K_{Cit} + (1-\omega) \ln K_{Dit} + (1-\omega)\frac{\psi}{2}(\ln K_{Cit} - \ln K_{Dit})^2. \tag{9}$$

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 to obtain the following specification for linear estimation:

$$\ln y_{it} = a_i + dt + \beta_1 \ln k_{it} - \beta_2 (\ln k_{it})^2 + \varepsilon_{it}. \tag{10}$$

From the parameter estimates, we can compute the CES parameters in the following way:

$$\sigma = \beta_1(1-\beta_1)/(\beta_1(1-\beta_1) - 2\beta_2) \tag{11}$$

$$\omega = \beta_1. \tag{12}$$

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

4.3 Empirical Specifications in the Non-Energy Sector

We choose a baseline specification that allows to identify the substitution parameter between clean and dirty energy inputs within the energy aggregate ψ and assumes a value of zero for the other substitution parameters specified in Equation (5). This parsimonious strategy is close to the one used by Hassler, Krusell, and Olovsson (2012) with the difference that they estimate substitution between energy and non-energy inputs. Additionally, we impose neutral technical change and include other material and service inputs than energy in some variants estimated. Ideally we would observe gross output and all relevant inputs (capital, labor, clean energy, dirty energy and the other intermediate inputs) with the reliability of national accounts data. Since our data only allow for 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 e.g. used in 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 the following:

$$\begin{aligned} \ln Y_{ijt} = a_i + a_j + dt + (1-\alpha-\gamma-\theta)\ln L_{ijt} + \alpha \ln K_{ijt} \\ + \theta \ln MS_{ijt} + \gamma\left[\frac{1}{\psi}\ln\left(E^{\psi}_{Cijt} + E^{\psi}_{Dijt}\right)\right] + \varepsilon_{ijt}, \end{aligned} \tag{13}$$

where Y_{ijt} represents gross output in country i and industry j, t is a time trend, L_{ijt} denotes labor input, K_{ijt} is the capital input, MS_{ijt} represents intermediate materials and services input and E_{Cijt} and E_{Dijt} represent the clean and dirty energy inputs.[11] 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 non-energy industries to estimate an aggregate production function for the non-energy (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 towards

[11] All specifications for value added plus energy cost follow in a straightforward way and are not written down here. The subscript F for the non-energy sector from Section 2.3 is dropped in the current section and Section 6.2, since both deal with the non-energy sector only.

sectors with a higher share of clean energy inputs. We run a robustness check relaxing the assumption of a unitary elasticity between the energy aggregate and the remaining inputs. This results in the following function for logarithmic gross output:

$$\ln Y_{ijt} = a_i + a_j + dt + \frac{1}{\phi} \ln \left[\gamma \left(K_{ijt}^{\alpha} MS_{ijt}^{\theta} L_{ijt}^{(1-\alpha-\theta)} \right)^{\phi} + (1-\gamma) \left(E_{Cijt}^{\psi} + E_{Dijt}^{\psi} \right)^{\frac{\phi}{\psi}} \right] + \varepsilon_{ijt}. \tag{14}$$

Again $\sigma = \frac{1}{1-\psi}$ is the elasticity of substitution of interest. On the other hand, $\sigma_{KLM,E}$ which is equal to $\frac{1}{1-\phi}$, represents the elasticity of substitution between the energy and the non-energy aggregate. As for the electricity sector, we also run a robustness check with a linear approximation of the baseline CES-in-Cobb-Douglas form:

$$\ln \frac{Y_{ijt}}{L_{ijt}} = a_i + a_j + dt + \beta_1 \ln \frac{K_{ijt}}{L_{ijt}} + \beta_2 \ln \frac{E_{Cijt}}{L_{ijt}} + \beta_3 \ln \frac{E_{Dijt}}{L_{ijt}} + \beta_4 \left(\ln \frac{E_{Dijt}}{E_{Cijt}} \right)^2 + \beta_5 \ln \frac{MS_{ijt}}{L_{ijt}} + \varepsilon_{ijt}, \tag{15}$$

where $\beta_2 = \beta_3$. The CES-in-Cobb-Douglas parameters can then be derived as:

$$\begin{aligned} \alpha &= \beta_1 \\ \gamma &= 2\beta_2 \\ \theta &= \beta_5 \\ \sigma &= 1/(1 - \beta_4/8\beta_3). \end{aligned}$$

5 Data

Estimation of both electricity and non-energy sector specifications make use of input and output data that are mainly taken from the World-Input-Output Database (WIOD) and the GGDC Productivity Level database. The WIOD, a new cross-country data set constructed in a project funded by the European Commission, makes available for the first time internationally comparable fuel use data together with standard productivity data at the level of up to 35 industries. It covers a time period of 15 years (1995 - 2009).[12] The WIOD and the GGDC Productivity Level Database use the same industry classification system (NACE

[12] A detailed description of the contents and the construction of the database can be found in Timmer (2012) and Dietzenbacher, Los, Stehrer, Timmer, and de Vries (2013).

1.1), cover nearly the same industries and are constructed in a methodologically similar way which allows their consistent combination.[13] From the GGDC Productivity Level Database industrial Purchasing Power Parities (PPPs) for up to 30 countries can be taken to convert monetary variables from the WIOD into internationally comparable units. For the construction of the data set for the electricity generating sector the EU KLEMS database (March 2011 release), the IEA Electricity Information Statistics database and the EIA Annual Energy Outlook are used in addition.[14] The raw data taken from all sources are summarized in Table 1.

5.1 Electricity Sector

To estimate substitution possibilities between clean and dirty electricity generation we need input and output information for both types of production processes. As output measure 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 approximated by another physical measure: 'net installed technology-specific generation capacity' in megawatt (MW).[15] It is important to emphasize that this measure is not tautological to physical output since an equivalence only holds under uninterrupted production and ideal conditions as for example discussed by Söderholm (2001).

Still, installed capacity is not measured in units that are homogeneous in cost. The installed capacity should be strongly correlated with monetary capital employed, since installing additional generation capacity requires additional investments. On the other hand, it

[13]The sources and methods used in the construction of the GGDC Productivity Level Database are described by Inklaar and Timmer (2008). The database complements the WIOD by providing Purchasing Power Parities. The Groningen Growth and Development Center, which maintains the GGDC Productivity Level Database, also has a leading role in the consortium responsible for the construction of the WIOD database.

[14]The sources and methods used in the construction of the EU KLEMS database are described by O'Mahony and Timmer (2009).

[15]The IEA defines the net installed generation capacity as: "It is the maximum active power that can be supplied, continuously, with all plants running, at the point of outlet to the network." (IEA / OECD 2013). It has been used frequently as a capital input proxy in the electricity sector, see e.g. Dhrymes and Kurz (1964), Atkinson and Halvorsen (1976), Bopp and Costello (1990), Söderholm (2001), Färe, Grosskopf, Noh, and Weber (2005), Considine and Larson (2012), Pettersson, Söderholm, and Lundmark (2012).

should be 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, using approximated real capital stocks for a robustness check.

These 'real' clean and dirty capital stocks are derived by valuing installed capacities with technology specific investment cost estimates published by the US Energy Information Agency.[16] 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. The monetary values derived from this source are then normalized in such a way that the clean and the dirty capital stocks together equal the capital stocks obtained from EU KLEMS for the electricity sector in order to ensure consistency with the remaining monetary input and output data. We classify installed capacities of nuclear, hydro, geothermal, solar, ocean and wind power plants as clean capacities and the remaining ones as dirty capacities.

EU KLEMS, however, does not contain capital stock data for sector 40x of the NACE 1.1 classification (the electricity sector) but only for the more aggregate sector E. Meanwhile it contains capital compensation data of sector 40x. We use the capital compensation data to approximate the capital stock of sector 40x by assuming that the capital compensation per unit of capital is identical for all of the subsectors of sector E. This requires the assumption of identical capital structures in the electricity, gas and water supply industries, what might be not too misleading given their overall similarity. Monetary variables are deflated and converted into dollar using price indices and PPPs from sector E (see next section for details on the use of PPPs). Table 2 summarizes the variables available. The data set exhibits up to 390 observations (15 years and 26 countries).

A limitation of our approach is the way our data account for trade in energy inputs and for private energy consumption. Electricity supply to households is included in the electricity

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

sector. Gas supply is not included and neither gasoline supply for transport, since we exclude the industry 'coke, refined petroleum and nuclear fuel' (NACE 23) with an extremely high dirty-to-clean ratio of inputs from the non-energy sector. We include imported energy inputs but we do not account for the fact that imported electricity may cause emissions at production in other countries. The average ratio of imported electricity to generated electricity lies below 30 percent in all countries observed except Luxembourg, in a number of countries even below 10 percent.

5.2 Non-Energy Industries

Three steps are undertaken to construct the data for the non-energy sector from the WIOD and the GGDC Productivity Level Database. First, 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 a 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, services and materials input aggregates. These are not given in WIOD directly but can be derived from its use tables. Following the EU KLEMS methodology (O'Mahony and Timmer 2009), energy intermediate inputs (IIE) are defined as all energy mining products (produced by sector 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 materials inputs (IIM). This classification can be applied one to one to the WIOD Use tables at purchasers prices.[17]

In a third step, the nominal values in local currency are transformed into real values of a common currency (in our case real 1997 US$). This requires using the PPPs from the GGDC

[17] Comparing the IIE, IIS and IIM values which we obtain through this procedure with the IIE, IIS and IIM values given in the EU KLEMS database from 2008 shows rather small differences, which are also present in total intermediate or value added numbers that exist in both databases. However, since the EU KLEMS database exhibits values for IIE, IIS and IIM only in its first version and only covers a limited number of countries we decided to stick to the data derived from WIOD.

Productivity Level Database in combination with price indices from WIOD.[18] This is done through a two-step procedure which uses the PPP values, $PPP_{k,i,1997}$, and the price indices, $P_{k,i,t}$, for gross output (GO), value added (VA), intermediate inputs (II) and the capital stock (K). Technically, the conversion factors, $PPP_{k,i,t}$, are derived by

$$PPP_{k,i,t} = \frac{P_{k,i,1997}}{P_{k,i,t}} \frac{1}{PPP_{k,i,1997}}, \tag{16}$$

where $k \in \{\text{GO, VA, II, K}\}$, i stands for the country industry combinations available and t denotes time. Multiplying the nominal values with these conversion factors then yields real values. In this procedure, the $PPP_{GO,i,t}$ are used to convert the gross output time-series, the $PPP_{VA,i,t}$ are used to convert the value added time-series, the $PPP_{II,i,t}$ are used to convert all intermediate input time-series and the $PPP_{K,i,t}$ are applied to convert the real fixed capital stock data.

In combination, these three steps lead to a data set containing the variables necessary for our analysis. They are summarized in Table 3. The part of our data set relevant for the analysis of the non-energy sector then contains observations for 19 countries (AUS, AUT, BEL, CZE, DEU, DNK, ESP, FIN, FRA, GBR, HUN, IRL, ITA, JPN, NLD, PRT, SVN, SWE, USA), 28 industries (see Table 4) and the time between 1995 and 2007, resulting in a nearly balanced panel of 6914 observations.[19]

[18]The two databases, WIOD and GGDC, exhibit small differences in their industry coverage. WIOD contains data for the industries 17t18, 19, 50, 51, 52, 60, 61, 62 and 63, whereas the GGDC database contains PPPs for three aggregates of these nine industries (17t19, G and 60t63). To cope with this, two options are at hand, either the WIOD industry data are aggregated and then matched with the GGDC values or the aggregate PPP values are directly used for their subsectors. The second approach allows to maximize the number of observations, however, it requires assuming the validity of using aggregate PPPs directly for subsectors. Here, the second approach is chosen since we believe that the measurement error introduced by this assumption can be neglected.

[19]We drop observations of Luxembourg, because of several extreme values, as well as the industries 'wood and of products of wood and cork' (20), 'coke, refined petroleum and nuclear fuel' (23), 'other water transport' (61), 'other air transport' (62) and 'real estate activities' (70). Industries 61 and 62 are neglected since nearly no observations are available for them in the raw data. Industries 20, 23 and 70 show extreme ratios of clean to dirty energy use, thereby picking up energy use which is not relevant to our analysis (e.g usage of wood as a raw material in the production of furniture).

6 Results

In this section we present the results of the empirical analysis for the electricity sector and non-energy industries followed by a discussion of our main findings in 6.3.

6.1 Electricity Sector

We start by estimating the CES function in Equation 7 for the electricity-generating sector. Output is measured as electricity generation (in GWh units), and inputs are measured as clean and dirty installed generation capacity (in MW units).We first employ nonlinear estimation (nonlinear least squares) that relies on nonlinear optimization methods to search for the parameter values that minimize the residual sum of squares and to estimate the confidence intervals of these estimates. The 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.[20]

In addition to nonlinear least squares, we also run OLS regressions after linearizing the CES function using the linear Kmenta approximation. We do that to confirm that nonlinear and linear estimation do not obtain drastically different estimates of the key parameters. Results from the two estimation methods are reported in columns 1-2 and 3-4 of Table 5, respectively. Both variants control for country fixed effects by using country dummies and also running first-difference regressions.

For the electricity-generating sector, we obtain estimates of the substitution parameter ψ between clean and dirty capacity of around 0.46. Reassuringly, we obtain very similar estimates for ψ using nonlinear and linear least squares. The estimates imply an elasticity of substitution between clean and dirty generation capacity of about 1.8 (a ψ value of zero 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 necessary condition for long-term clean growth of the electricity sector is fulfilled, even in the absence of technical

[20]To reduce the extent of nonlinearity, we perform estimation and tests on ψ instead on 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, and Willman 2015). Degenerate results where the numerical search either does not converge or finds a ψ larger than one are discarded from the bootstrap.

change.

In Table 6 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 OLS. It is important to note here though that the scope of this sensitivity analysis is limited by the lack of plant cost data across fuels used.

Finally, we relax the assumption of a two-factor CES function, which implicitly assumes fixed proportions of all other inputs. The Cobb-Douglas-in-CES specification shown in Equation 8 allows for 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 two as reported in Table 7. However, it is also the case that the estimate of the distribution parameter ω becomes more unstable across specifications.

As it is well-known, results of non-linear estimation procedures maybe sensitive to the choice of starting values of the estimation parameters. To validate the robustness of our results towards this issue, we follow Klump, McAdam, and Willman (2007) as well as Henningsen and Henningsen (2012) and employ an extensive grid search; our search algorithm performs the nonlinear estimation routine repeatedly using different starting values of the estimation parameters. Figure 1 and Figure 2 graphically illustrate the results we obtain for the electricity sector specifications. While some starting value combinations do not converge, or converge to local minimums, the large majority of grid searches performed confirm that our baseline estimation results constitute in each case the global minimum in terms of the residual sum of squares.

6.2 Non-Energy Industries

The main specification we employ for non-energy 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 13. Consistent with the previous analysis in the electricity sector we use both nonlinear and linear estimation methods. As discussed in Section 4.3, we use two alternative dependent variables, gross output and value added plus intermediate energy input.

Results are presented in Table 8 (columns 1-2 report nonlinear estimation results; columns 3-4 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.[21] They imply elasticities of substitution between clean and dirty energy inputs within the energy aggregate up to the value of three. One reason why we observe a larger difference in the estimates between nonlinear and linear estimation than we did for the electricity sector may be that the data for different industries exhibit higher dispersion.

So far we have assumed a unitary elasticity of substitution between energy and non-energy inputs. Since a large literature, most recently Hassler, Krusell, and Olovsson (2012), finds evidence of a lower elasticity, we also attempted to estimate a more general two-level CES specification based on Equation 14, where only the aggregate of capital, labor and non-energy intermediates remain in a Cobb-Douglas structure and the substitution parameter between energy and non-energy aggregates can take any value. It turns out that identifying two elasticities in a highly nonlinear function is challenging. The elasticity of substitution between energy and non-energy inputs estimated with augmented value added as dependent variable does not differ significantly from one (i.e., ϕ does not differ from zero). With gross output as dependent variable, we observe implausible parameter estimates: a negative elasticity of substitution between clean and dirty energy inputs and a distribution parameter γ of non-energy input close to zero (Table 9). Since the distribution parameter γ and the substitution parameter ψ are both insignificant in this case, we consider that problems of collinearity have been aggravated through the identification of an additional parameter.

Once again, we employ an extensive grid search. The results obtained for the non-energy industry specifications can be found in Figure 3 and Figure 4. Again, for all specifications the grid searches strongly confirm our estimation results.

[21] As an approximation around $\psi = 0$ the Kmenta approximation is known to bias elasticity parameters of CES functions towards one.

6.3 Discussion

In the theoretical discussion we have highlighted that an elasticity of substitution larger than one 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. We argue moreover that 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 one significantly, both in the electricity-generating sector, where we measure production capacities as inputs, and in the energy aggregate of non-energy 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. First, issues of endogeneity were very 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. Second, our underlying assumption of trend stationarity in the data series used in the analysis cannot be confirmed because for our nonlinear panel data models asymptotic theory and estimation methods do not yet exist for nonstationary time-series (see e.g., Wagner, 2008).[22] We take comfort in the fact that the dimension of our data set for the non-energy sector (13 years, 532 country-industry cells) resembles that of a micro panel data set (small time series, large cross-section dimension) for which issues of nonstationarity are typically not a major concern and not evaluated.[23] Third, while our data are novel, data limitations are still a constraining factor to the estimation. Therefore future

[22]In contrast, 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 (Kao 1999, Phillips and Moon 1999). This is because panel estimators average across individuals and the information in the independent cross-section data leads to a stronger signal than in the time-series case.

[23]Indeed, tests using a between estimator (group means) indicate that our results are driven to a large part by cross-sectional variation. These results are available by the authors upon request.

work with expanded data will certainly enrich the analysis.

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 downwards because of particularly severe market distortions for energy.[24] 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 possibility. We reestimate the substitution parameter between clean and dirty energy inputs for non-energy industries imposing first-order conditions and using available price data (see Appendix for details on price data construction and estimation). Using Seemingly Unrelated Regression (SUR), we obtain an elasticity of substitution within the energy aggregate of 0.43 (Table 10). Controlling for time trends or alternatively for country and industry fixed effects, the result is not significantly different from zero anymore. Still more research may be needed to contrast in a methodologically rigorous way estimations with and without FOCs, in the potential presence of a bias to FOCs that can be unknown and non-constant.

7 Conclusion

In the context of growth models with neoclassical production functions, the elasticity of substitution between clean and dirty energy inputs is a central parameter in assessing the conditions necessary for long-run green growth. In this paper we produce 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 a novel data source, namely the World-Input-Output-Database (WIOD), we construct industry level data for a panel of up to 26 countries covering clean and dirty inputs. Third, we present evidence that the elasticity of substitution

[24] Examples are the result obtained by Pelli (2012) and the conjecture formulated by Pottier, Hourcade, and Espagne (2014), both pointing to values of the elasticity of substitution within an energy aggregate of 0.6 or below.

between clean and dirty energy inputs within the energy aggregate of the non-energy 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 for the elasticity of substitution between clean and dirty capacity in the electricity-generating sector and values close to 3 for the elasticity of substitution between clean and dirty energy inputs within the energy aggregate of non-energy 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 production 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 result from employing plant level data. Instead of using a binary distinction between clean and dirty fuels, future research on non-energy industries could also use fuel-specific data on actual emissions to develop specifications of technology that accounts for unwelcome by-products such as carbon emissions. This could account for a more precise estimation by recognizing that not all energy inputs causing emissions are equally dirty.

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Table 1: Data Description

Variable Description and Unit of Measurement
World Input-Output Database
Gross output at current basic prices (in millions of national currency)
Gross value added at current basic prices (in millions of national currency)
Intermediate inputs at current purchasers prices (in millions of national currency)
Use of products by industry at current purchasers prices (in millions of national currency)
Real fixed capital stock (1995 prices)
Total hours worked by persons engaged
Price levels gross output (1995 = 100)
Price levels value added (1995 = 100)
Price levels intermediate inputs (1995 = 100)
Labor compensation (in millions of national currency)
Capital compensation (in millions of national currency)
Price levels of gross fixed capital formation (1995=100)
Emission relevant energy use by fuel type (in TJ)
GGDC Productivity Level Database
Purchasing Power Parities for country industry combinations (national currency per US$, 1997)
EU KLEMS March 2011 Update (only for industry 40x)
Capital compensation (in millions of national currency)
IEA Electricity Information Statistics
Net electricity production by generation technology (GWh) - Total plants
Net electrical capacity by generation technology (MW) - Total plants
Fuel input by fuel type (TJ) - Total plants
EIA Annual Energy Outlook
Capital Cost by generation technology (in current US$ per kW)

Notes: TJ = terajoule, GWh = gigawatt hour, MW = megawatt, kW = kilowatt.

Table 2: Variable Description of the Electricity Sector Database

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)

Notes: TJ = terajoule, GWh = gigawatt hour, MW = megawatt.

Table 3: Variable Description of the Non-Energy Sector Database

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

Notes: TJ = terajoule.

Table 4: Sectoral Coverage

Sector	Code	WIOD	GGDC	KLEMS	IEA	Sample
Total industries	TOT	x	x			
Agriculture, hunting, forest, fish.	AtB	x	x			1
Mining and quarrying	C	x	x			1
Food , beverages and tobacco	15t16	x	x			1
Textiles, textile, leather and footwear	17t19		x			
Textiles and textile	17t18	x				1
Leather, leather and footwear	19	x				1
Wood and of wood and cork	20	x	x			
Pulp, paper, printing and publishing	21t22	x	x			1
Coke, refined petroleum and nuclear fuel	23	x	x			
Chemicals and chemical	24	x	x			1
Rubber and plastics	25	x	x			1
Other non-metallic mineral	26	x	x			1
Basic metals and fabricated metal	27t28	x	x			1
Machinery, nec	29	x	x			1
Electrical and optical equipment	30t33	x	x			1
Transport equipment	34t35	x	x			1
Manufacturing nec; recycling	36t37	x	x			1
Electricity, gas and water supply	E	x	x			
Electricity and gas	40			x	x	
Electricity supply	40x			x	x	2
Gas supply	402			x	x	
Wholesale trade and commission trade	51	x				1
Retail trade, except of motor vehicles;	52	x				1
Hotels and restaurants	H	x	x			1
Transport and storage	60t63		x			
Other Inland transport	60	x				1
Other Water transport	61	x				
Other Air transport	62	x				
Other Supporting and auxil. transp. act.	63	x				1
Post and telecommunications	64	x	x			1
Financial intermediation	J	x	x			1
Real estate activities	70	x	x			
Renting of m&eq and other busin. act.	71t74	x	x			1
Public admin and defence; social sec.	L	x	x			1
Education	M	x	x			1
Health and social work	N	x	x			1
Other community, social and personal services	O	x	x			1
Private households with employed persons	P	x	x			

Notes: 1 = sample of non-energy industries, 2 = electricity generating sector sample.

Table 5: 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
adj.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

Notes: z-statistics in parentheses. ***, **, *: Significantly different from 0 at the 1, 5, and 10 percent levels, respectively. Column 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 6: 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
adj.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

Notes: z-statistics in parentheses. ***, **, *: Significantly different from 0 at the 1, 5, and 10 percent levels, respectively. Column 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 7: 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
adj.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	2.034	2.810
N	390	364	338	312

Notes: z-statistics in parentheses. ***, **, *: Significantly different from 0 at the 1, 5, and 10 percent levels, respectively. All columns provide bootstrapped standard errors based on 400 replications with country as cluster variable. Specification 1 and 3 apply the Nonlinear Least Squares (NLS) estimator and include country dummies. Specification 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 8: Nonlinear Estimation and Kmenta Approximation of CES in Cobb-Douglas - Non-Energy 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***
	(7.45)	(6.65)	(7.78)	(7.04)
γ	0.260***	0.121***	0.258***	0.121***
	(6.23)	(5.10)	(6.15)	(4.88)
θ		0.565***		0.566***
		(15.45)		(16.54)
ψ	0.651***	0.654**	0.394***	0.276
	(3.28)	(2.27)	(2.97)	(1.41)
Country DV	Yes	Yes	Yes	Yes
Industry DV	Yes	Yes	Yes	Yes
$\psi = 0$	0.001	0.023	0.003	0.159
σ	2.868	2.888	1.651	1.382
adj. R^2	0.948	0.982	0.739	0.907
N	6914	6914	6914	6914

Notes: z-statistics in parentheses. ***, **, *: Significantly different from 0 at the 1, 5, and 10 percent levels, respectively. Columns 1 and 2 provide bootstrapped standard errors based on 400 replications with country and industry as cluster variables. Specification 1 and 2 apply the Nonlinear Least Squares (NLS) estimator and include country and industry dummy variables. Specification 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 $H_0 : \psi = 0$.

Table 9: Nonlinear Estimation of Two-level CES - Non-Energy Industries

	Two-level CES	
	VA + IIE	GO
d	0.010***	0.003**
	(4.14)	(2.37)
α	0.474***	0.191***
	(6.14)	(6.88)
θ		0.618***
		(18.37)
γ	0.679***	0.011
	(3.21)	(0.40)
ϕ	0.076	0.744**
	(0.25)	(2.49)
ψ	0.683***	1.477
	(3.12)	(1.03)
Country DV	Yes	Yes
Industry DV	Yes	Yes
$\phi = 0$	0.801	0.013
$\psi = 0$	0.002	0.304
$\sigma_{KLM,E}$	1.082	3.908
σ	3.153	-2.095
adj. R^2	0.948	0.982
N	6914	6914

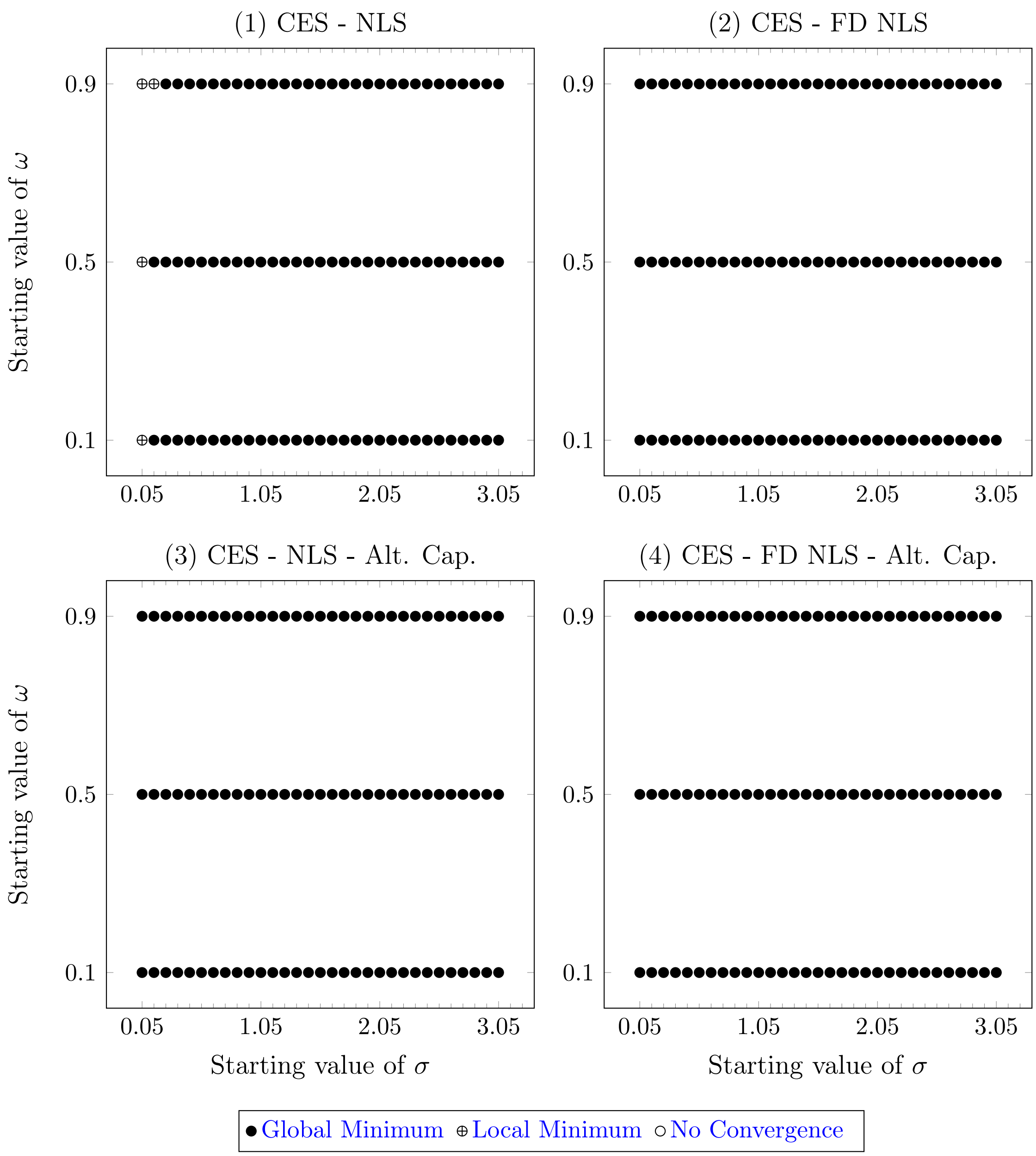
Notes: z-statistics in parentheses. ***, **, *: Significantly different from 0 at the 1, 5, and 10 percent levels, respectively. Column 1 provides bootstrapped standard errors based on 400 replications with country and industry as cluster variables. Specification 1 and 2 apply the Nonlinear Least Squares (NLS) estimator and include country and industry dummy variables. $\psi = 0$ reports the significance level of a Wald test with $H_0 : \psi = 0$. $\phi = 0$ reports the significance level of a Wald test with $H_0 : \phi = 0$.

Table 10: CES for Energy Subaggregate Price Based SUR Estimation - Non-Energy Industries

	CES for Energy Subaggregate		
	(1)	(2)	(3)
d_1		-0.001***	-0.001***
		(-28.53)	(-7.54)
d_2		-0.000***	-0.000***
		(-18.19)	(-6.31)
σ	0.433***	-0.099	-0.002
	(5.63)	(-1.32)	(-0.02)
Country DV	No	No	Yes
Industry DV	No	No	Yes
N	3220	3220	3220

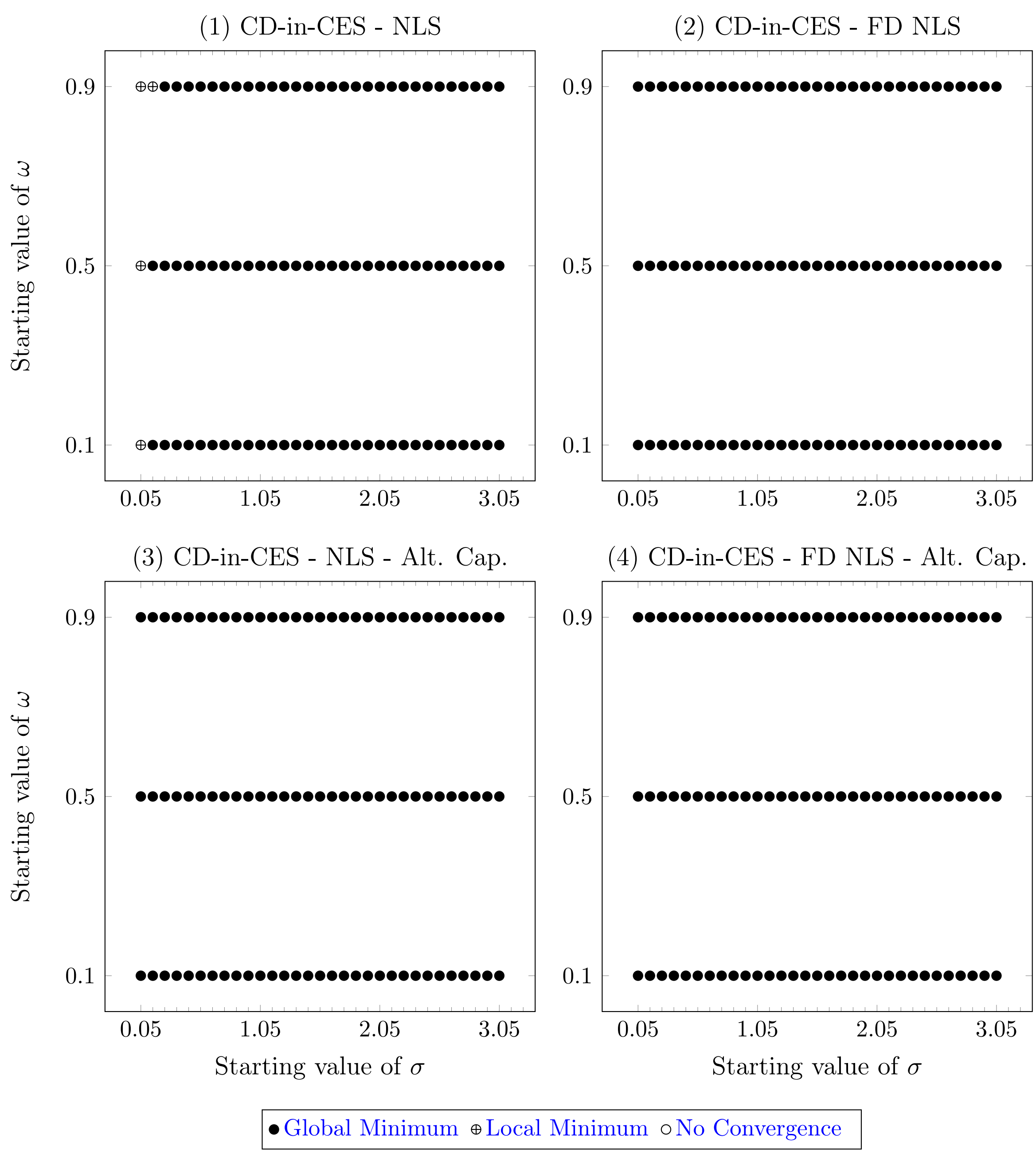
Notes: Heteroscedasticity- and autocorrelation-robust z-statistics in parentheses. ***, **, *: Significantly different from 0 at the 1, 5, and 10 percent levels, respectively. Specification 1 to 3 apply the Feasible Generalized Nonlinear Least Squares (FGNLS) estimator to the system of equations. Specification 2 and 3 include equation specific time trends. Specification 3 includes equation specific country and industry dummies.

Figure 1: Electricity Sector (Part I)



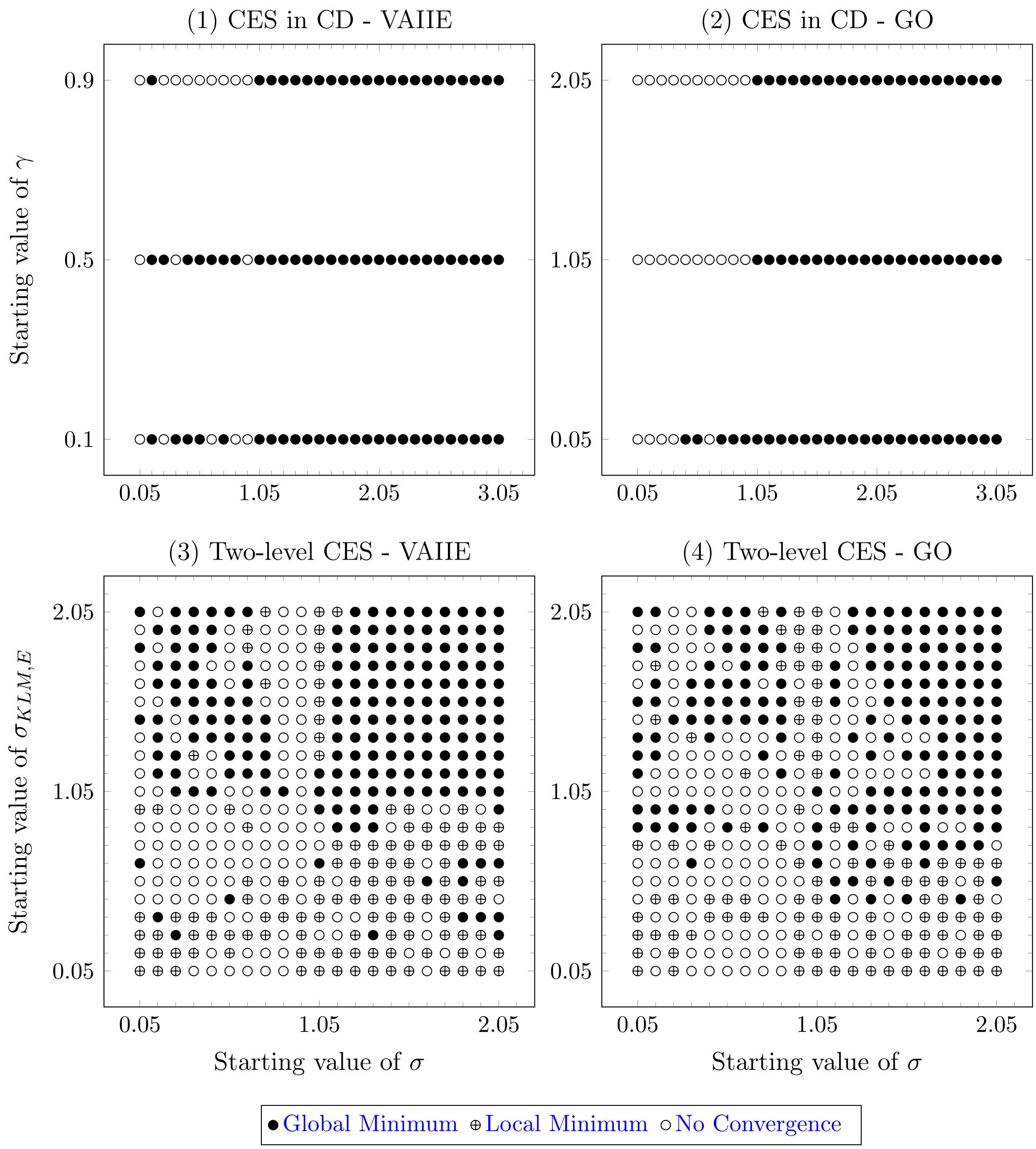
Notes: Results correspond to the nonlinear specifications of Table 5 and Table 6. For all combinations, the following starting values are used: $\delta = 0.01$. The markers indicate whether the respective combination has converged to the global or local RSS-minimum or has not converged at all. In (1) the global minimum has the following RSS-value: 2.14 and is obtained by the following vector of parameter estimates: $\delta = -0.001$, $\omega = 0.219$, $\psi = 0.456$. In (2) the global minimum has the following RSS-value: 1.54 and is obtained by the following vector of parameter estimates: $\delta = -0.003$, $\omega = 0.441$, $\psi = 0.486$. In (3) the global minimum has the following RSS-value: 2.06 and is obtained by the following vector of parameter estimates: $\delta = -0.009$, $\omega = 0.193$, $\psi = 0.423$. In (4) the global minimum has the following RSS-value: 1.60 and is obtained by the following vector of parameter estimates: $\delta = -0.009$, $\omega = 0.388$, $\psi = 0.459$.

Figure 2: Electricity Sector (Part II)



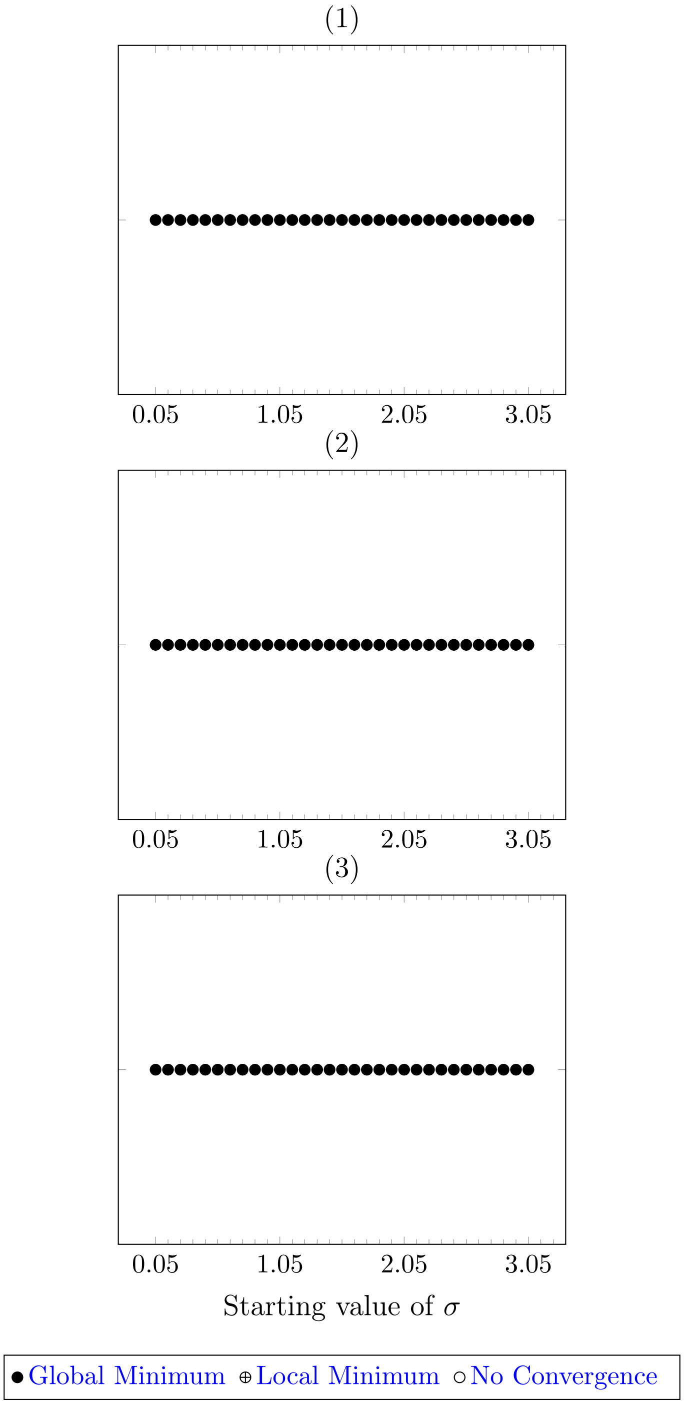
Notes: Results correspond to the nonlinear specifications of Table 7. For all combinations, the following starting values are used: $\delta = 0.01$ and $\alpha = 0.3$. The markers indicate whether the respective combination has converged to the global or local RSS-minimum or has not converged at all. In (1) the global minimum has the following RSS-value: 1.23 and is obtained by the following vector of parameter estimates: $\delta = 0.002$, $\omega = 0.487$, $\alpha = 0.437$, $\psi = 0.507$. In (2) the global minimum has the following RSS-value: 0.90 and is obtained by the following vector of parameter estimates: $\delta = 0.002$, $\omega = 0.707$, $\alpha = 0.379$, $\psi = 0.651$. In (3) the global minimum has the following RSS-value: 1.06 and is obtained by the following vector of parameter estimates: $\delta = -0.000$, $\omega = 0.010$, $\alpha = 0.346$, $\psi = 0.507$. In (4) the global minimum has the following RSS-value: 0.84 and is obtained by the following vector of parameter estimates: $\delta = -0.000$, $\omega = 0.004$, $\alpha = 0.310$, $\psi = 0.644$.

Figure 3: Non-Energy Industries (Part I)



Notes: Results correspond to the nonlinear specifications of Table 8 and Table 9. The markers indicate whether the respective starting value combination has converged to the global or local RSS-minimum or has not converged at all. For (1) additionally the following starting values are used: $\delta = 0.01$ and $\alpha = 0.3$. For (2) and (4), in addition $\theta = 0.5$. For (3) and (4), in addition, $\gamma = 0.2$. Not displayed are results for (3) and (4) where $\gamma = 0.8$. In (1) the global minimum has the following RSS-value: 1206 and is obtained by the following vector of parameter estimates: $\delta = 0.010$, $\alpha = 0.358$ $\gamma = 0.259$, $\psi = 0.651$. In (2) the global minimum has the following RSS-value: 352 and is obtained by the following vector of parameter estimates: $\delta = 0.002$, $\alpha = 0.186$ $\gamma = 0.120$, $\theta = 0.564$, $\psi = 0.653$. In (3) the global minimum has the following RSS-value: 1206 and is obtained by the following vector of parameter estimates: $\delta = 0.010$, $\alpha = 0.473$, $\gamma = 0.679$, $\phi = 0.075$, $\psi = 0.682$. In (4) the global minimum has the following RSS-value: 1206 and is obtained by the following vector of parameter estimates: $\delta = 0.010$, $\alpha = 0.191$, $\gamma = 0.011$, $\theta = 0.618$, $\phi = 0.744$, $\psi = 1.477$.

Figure 4: Non-Energy Industries (Part II)



Notes: Results correspond to the nonlinear specifications of Table 10. The markers indicate whether the respective combination has converged to the global or local RSS-minimum or has not converged at all. In (1) the global maximum has the following log-likelihood-value: -8651 and is obtained by the following vector of parameter estimates: $\sigma = 0.432$. In (2) the global maximum has the following log-likelihood-value: -3949 and is obtained by the following vector of parameter estimates: $\sigma = -0.098$. In (3) the global maximum has the following log-likelihood-value: -2014 and is obtained by the following vector of parameter estimates: $\sigma = -0.001$.

Appendix

Robustness using Factor Price Data for the Non-Energy Industries

To construct a data set containing price information in addition to the quantity data used in our main analysis, information on energy factor prices and energy cost shares is added. Cost values are derived by combining the available quantity data with price data taken from the IEA's Energy Prices and Taxes database. It provides energy prices in US$/toe for 14 different types of energy. These types include: 'steam coal', 'coking coal', 'automotive diesel fuel', 'electricity', 'high sulfur fuel oil', 'premium leaded gasoline', 'regular leaded gasoline', 'light fuel oil', 'liquefied petroleum gas', 'low sulfur fuel oil', 'natural gas', 'premium unleaded 95 RON', 'premium unleaded 98 RON', 'regular unleaded gasoline'. The prices include energy taxes and are calculated by converting national prices using international exchange rates. Prices for three different sectors are published: households, the industrial sector and the electricity generating sector. We use the industrial sector prices. Missing values are replaced with prices from the electricity generating sector (for a similar imputation see Serletis, Timilsina, and Vasetsky (2011)). The energy prices are converted from a tons of oil equivalent (toe) basis into a TJ basis to ensure a common physical unit between price and quantity data. A conversion factor given by the IEA of 1 toe = 0.041868 TJ is applied.

Using prices and quantities a cost variable for clean as well as for dirty energy is then generated. This is done by multiplying clean energy quantities by the electricity price.[25] For dirty energy sources the following procedure is applied: first, in order to maximize the available number of observations without neglecting available information, prices for four different energy carrier groups (coal, petroleum, oil, gas) are generated. The steam coal price is used as the coal price but is replaced by the coking coal price if the steam coal price is not available. For oil, the high sulfur fuel oil price is used as standard but is replaced by low sulfur fuel oil price or the light fuel oil price if necessary. In the case of gas the natural gas price is used, whereas for petroleum products there is only the automotive diesel fuel price

[25] Electricity represents on average 75 percent of clean energy used, thus using the electricity price might be an appropriate proxy.

available. Subsequently, these four price approximations are used to price four groups of energy quantities. The coal price is applied to 'hard coal', 'lignite', and 'coke'; the petroleum price is used for 'diesel', 'gasoline', 'jet fuel', 'other petroleum products' and 'naphtha'; the oil price is applied to the 'light fuel oil', 'heavy fuel oil' and 'crude oil' quantities; the gas price is used for 'natural gas' and 'other gases'. The sum of these energy cost values is then divided by the total sum of energy use, which gives the average energy price for a given year and entity.

We choose the most parsimonious specification possible to estimate the elasticity of substitution between clean and dirty energy inputs from Equation 5, exploiting the fact that the separability of the production function allows to estimate elasticities from the energy subaggregate alone (Fuss 1977). Taking the first-order conditions for clean and dirty energy inputs from the production function in Equation 13 and rearranging yields the following system of equations:

$$\ln\left(\frac{p_{Cit}E_{Cit}}{p_{Cit}E_{Cit}+p_{Dit}E_{Dit}}\right) = (1-\sigma)\ln\left(\frac{p_{Cit}}{p_{Eit}}\right)+\varepsilon_{it} \tag{17}$$

$$\ln\left(\frac{p_{Dit}E_{Dit}}{p_{Cit}E_{Cit}+p_{Dit}E_{Dit}}\right) = (1-\sigma)\ln\left(\frac{p_{Dit}}{p_{Eit}}\right)+\nu_{it}. \tag{18}$$

We estimate these equations using Seemingly Unrelated Regression (SUR), first following the function used in the previous section and then adding a time trend and country and industry dummies, aiming to capture nonneutral technological progress and country idiosyncrasies, respectively. Results are presented in Table 10.