WORKING PAPER

ON THE ELASTICITY OF SUBSTITUTION BETWEEN CLEAN AND DIRTY ENERGY: RECONCILING EMPIRICAL ESTIMATES AND THEIR IMPLICATIONS FOR MODEL CALIBRATION

Thomas Lebbe
Freddy Heylen

April 2026
2026/1140

GHENT UNIVERSITY

Department of Economics

Faculty of Economics and Business Administration
Campus Tweekerken, St.-Pietersplein 5, 9000 Ghent - BELGIUM

On the elasticity of substitution between clean and dirty energy: Reconciling empirical estimates and their implications for model calibration

Thomas Lebbe [a,b,*] and Freddy Heylen [a]

[a] Department of Economics, Ghent University
[b] Research Foundation Flanders

April 2026

Abstract

Estimates of the elasticity of substitution between clean and dirty energy - and the values assumed in theoretical models - vary from less than 0.5 to as high as 10, creating substantial uncertainty about climate policy effectiveness and the feasibility of green growth.

This paper develops an encompassing empirical specification that nests both low and high elasticity estimates and applies it to macroeconomic data from 13 OECD countries over 1980–2020. Holding countries' energy-related technology and infrastructure constant, the estimated elasticity of substitution remains well below 1, indicating limited short-run responsiveness of energy inputs to relative price changes. Allowing technology and infrastructure to respond to price changes, the estimated elasticity rises to between 2 and 3, a plausible long-run value. Without any controls, estimates reach as high as 6, greatly overstating true substitutability.

We conclude that price-based policies alone, such as carbon taxes, are insufficient to trigger early-stage energy transitions. Investments in clean technology and infrastructure are essential, as they increase both the share of clean energy and the elasticity of substitution. Our findings can also guide the calibration of energy-augmented macroeconomic models. The elasticity values imposed in these models appear more often too high than too low.

---

[*] Corresponding author: Thomas Lebbe, Department of Economics, Ghent University, Sint-Pietersplein 6, 9000 Ghent, Belgium. E-mail: Thomas.Lebbe@UGent.be.

The authors are grateful to Brent Bleys, Selien De Schryder, Marthe Mareels, Marten Ovaere, Luca Pensieroso, Ko Sugiura, Jakub Verschoore, and participants at macroeconomics seminars at Ghent University for useful comments and suggestions during the development of this paper. Thomas Lebbe gratefully acknowledges support from the Research Foundation Flanders.

1. Introduction

Current literature reveals significant parameter uncertainty in climate-economic models, in particular about the elasticity of substitution between clean and dirty energy inputs at the macro level. Table 1 reports empirical estimates ranging from less than 0.5 to more than 4. In theoretical models we see values being imposed that can even go to 10. The uncertainty surrounding this elasticity underscores the complexity of modeling the energy transition and its associated emissions.

Reducing parameter uncertainty is essential for policymakers and society at large. First, carbon pricing is regressive, and the degree of regressivity is directly tied to the responsiveness of the demand for clean and dirty energy to price changes. When the elasticity of substitution is high, the energy transition can be achieved with less stringent policy interventions, resulting in lower levels of regressivity. Conversely, when the elasticity is low, carbon prices must be set very high to induce energy producers to switch to clean inputs (Acemoglu et al., 2012; Mattauch et al., 2015).

Second, as noted by Stern (2012), Acemoglu et al. (2012) and Papageorgiou et al. (2017), the elasticity of substitution determines whether green growth is feasible. When the elasticity is below unity, dirty and clean energy are complements. An increase in clean energy input may then also make investment in dirty energy more profitable, causing both inputs to expand. Achieving zero emissions may then require reducing total energy demand and lower economic growth. This is fundamentally at odds with the green growth premise of decoupling carbon emissions from growth. With an elasticity above unity, the opposite occurs. Policy actions like a carbon price or other developments that reduce the relative price of clean energy will increase demand for clean inputs more than proportionally. Total revenues from the production of clean energy will then rise, and the use of dirty inputs falls while the economy maintains its growth.

The above-mentioned price and revenue effects apply at a given level of technology in the energy sectors. Over time, however, they may influence the evolution of technology. In principle, this could enable a complete transition to clean inputs and an emissions-free economy. In the directed technical change framework of Acemoglu et al. (2012), rising clean-sector revenues induce all researchers to shift their efforts from dirty to clean technologies. This shift further lowers the relative price of clean inputs, reinforcing the transition. A higher substitution elasticity strengthens this dynamic: it reduces optimal carbon prices and shortens the period during which policy is needed. In a less extreme setting, Mattauch et al. (2015) model clean technical progress and its response to price changes through learning-by-doing and knowledge spillovers as clean energy production gradually expands. Although Mattauch et al. do not require an initial elasticity of substitution above 1, a higher elasticity in their model likewise accelerates the energy transition and reduces the required policy intensity. Under the learning-by-doing mechanism, however, policy interventions must remain permanent, as demand for dirty inputs persists.

Table 1. Elasticity of substitution between clean and dirty energy in the literature

Empirical estimates	**Elasticity**
Lanzi and Sue Wing (2010)	1.6 (energy sector)
Pelli (2012)	0.51 (electricity)
Papageorgiou et al. (2017)	
- Production function approach	1.8 (electricity)
	2.9 (non-energy industries)
- Cost-function approach	0.4 (non-energy industries)
Jo and Miftakhova (2024)	> 1.8 and increasing in the clean to dirty energy ratio
Jo (2025)	3.1
Schwerin (2025)	4.3
Imposed values	**Elasticity**
Babiker et al. (2003)	0.5 – 1
Acemoglu et al. (2012)	3.0 – 10
Pottier et al. (2014)	0.5 – < 1
Fried (2018)	1.1 – 3
Hart (2019)	4.0
Freire-Gonzàlez and Ho (2019)	1.0
Karydas and Zhang (2019)	0.7
IMF (2022)	0.2 – 0.5 (manufacturing, short-run)
Coenen et al. (2024)	1.8
Campiglio et al. (2024)	3.0
Kotlikoff et al. (2024)	≥ 2.0
Bretschger et al. (2025)	1.5 – 4.0
Allen et al. (2025)	1.1 – 1.2 (short-run)

Given the critical importance of the elasticity of substitution and whether it lies below or above unity, the wide range of estimated and calibrated parameters – between 0.2 and 10 in Table 1 – is concerning. It implies that many model-based and real-world outcomes are possible, limiting modelers' and policymakers' ability to predict policy effects. This further amplifies uncertainty about the future global climate.

This paper makes three contributions. First, we bring structure in the multitude of values for the elasticity of substitution between clean and dirty energy. Starting from a theoretical framework, we derive an encompassing empirical specification for the ratio of clean to dirty energy inputs that nests both high and low elasticity estimates as special cases. This specification is strongly inspired by the literature on estimating the parameters of CES production functions, which traditionally focuses on the distinction between labor and capital. Exploiting the analogous binary distinction between clean and dirty energy, we draw on the estimation techniques and findings from this literature. Most inspiring is the work of Klump et al. (2007, 2012) and León-Ledesma et al. (2010, 2013), who show the importance of incorporating factor-biased technical change in CES functions, and address the joint estimation of elasticities and technology parameters.

Second, we estimate our specification using macroeconomic data from 13 OECD countries over four decades, 1980–2020. Controlling for countries' energy-related technology and infrastructure in the regression, the estimated elasticity of substitution remains well below 1. We interpret this as the short-run elasticity of substitution – the response of the ratio of clean to dirty energy inputs to a relative price change for given technology and infrastructure. By contrast, when we only control for initial levels of technology and infrastructure, but allow technology to respond to price changes, the estimated elasticity rises to between 2 and 3. We consider this a plausible long-run elasticity. A brief look at the empirical literature reveals that existing studies do generally not account for these different perspectives, despite their considerable importance.

Our findings are in line with the basic theoretical predictions of Acemoglu et al. (2012) and Mattauch et al. (2015), among others, that changes in the relative price of clean energy may in the longer run also affect relative quantities through their impact on the development of clean technology and knowledge. The distinction between a short-run and a long-run effect induced by technological responses has been made previously by Hassler et al. (2021).[1,2]

Our results, however, cast doubt on the short-run elasticity values above 1, as recently assumed for example by Allen et al. (2025). The results also challenge the high elasticities of substitution (≥ 3) assumed by Acemoglu et al. (2012) and many others, when they additionally model technology as endogenous to price changes. This combination appears to double-count the same mechanism. We empirically obtain elasticity values above 3 only in specifications without controls. In such specifications, the estimated elasticity may absorb not only induced technological change, but also the impact of any initial cross-country difference in energy-related technology and infrastructure, thereby strongly overstating the true substitutability.

A challenge in estimating elasticities of substitution at the macro level is to find appropriate instruments for the relative price of clean to dirty energy. As part of the empirical contribution of this paper, our results suggest that the global solar PV panel price per megawatt of capacity and lagged carbon tax rates may serve as valid candidates.

A corollary of our findings is that technology and infrastructure are central to the substitutability between dirty and clean energy inputs: the elasticity of substitution is expected

---

[1] The focus of Hassler et al. (2021) is on dirty energy-saving technology. They show that this took off after the oil shocks of the 1970s. More recently, Känzig and Williamson (2025) empirically confirmed the impact of fossil fuel prices on energy-saving technology in a structural VAR setting for the US. However, none of these authors make the distinction between clean and dirty energy.

[2] More general, this distinction can be considered as an application of Le Chatelier's principle (Samuelson, 1947), where the long-run reaction to a shock is more elastic than the short-run response, as the relevance of initial-state constraints vanishes over time. Jacobs (2023, 2025) demonstrates the same mechanism in the context of the adoption of automation technologies.

to rise as countries expand their clean-energy capacity. This aligns with the argument of Mattauch et al. (2015), who contend that far-reaching substitution of dirty with clean energy inputs becomes feasible only as infrastructure for low-carbon energy use expands over time. Bretschger et al. (2025) highlight the importance of this mechanism in a theoretical model, while Jo and Miftakhova (2024) provide empirical support for it in the French manufacturing sector. As a third contribution, we estimate our empirical model in rolling time windows. We confirm a positive association between the share of clean energy in total energy and the macro elasticity of substitution, with both variables showing a clear rise over time.

The broader policy implication of our findings is that price-based policies alone, such as carbon taxes, are insufficient to trigger early-stage energy transitions; their impact is modest and slow when the composition of energy supply lacks the flexibility to respond. Investments in clean technology and infrastructure are essential, as they may raise both the share of clean energy and the elasticity of substitution.

The remainder of this paper is organized as follows. Section 2 derives our empirical model to estimate the elasticity of substitution between clean and dirty energy. Our specification can be seen as a generalization of the current literature, where we account for both the level of technology and the relative rate of technical progress in clean energy. In Section 3 we discuss our data. In Section 4 we report our empirical results. Section 5 concludes the paper and summarizes its main implications for policy and the calibration of energy-augmented macroeconomic models.

2. Model and empirical specification

In Section 2.1, we start from a theoretical framework to derive a general empirical specification that allows us to estimate the elasticity of substitution between clean and dirty energy under alternative restrictions. Section 2.2 reviews frequent estimation methods and how they deal with those restrictions. We also briefly discuss four related empirical studies. We clarify how chosen methods and imposed restrictions may affect the reported results.

2.1. Model

Our starting point is optimal behavior by an energy bundler in country i and year t. The energy bundler aggregates all energy demand in the economy and works in a perfectly competitive environment.[3] The bundler takes input and output prices as given, and chooses the combination of clean and dirty energy inputs that allows to meet a given total demand for energy $E_{i,t}$ at minimal cost. Production is constrained by the limited substitutability between

---

[3] This assumption may be somewhat controversial, but it is permissible since we do allow for markups and imperfect market characteristics within the underlying dirty and clean energy input sectors.

clean and dirty energy and related technologies. In brief, the bundler's objective is to choose clean and dirty energy inputs to minimize the following:

$$P_{i,t}^{E_C} E_{i,t}^C + P_{i,t}^{E_D} E_{i,t}^D$$

subject to producing the required quantity $E_{i,t}$. Output is modeled as a CES composite of clean and dirty inputs incorporating factor-augmenting technical change:

$$E_{i,t} = \left[\left(A_{i,t}^C E_{i,t}^C \right)^{\frac{\sigma-1}{\sigma}} + \left(A_{i,t}^D E_{i,t}^D \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

Alongside total energy demand and output $E_{i,t}$, we define $E_{i,t}^C$ and $E_{i,t}^D$ as the quantities of clean and dirty energy inputs, $P_{i,t}^C$ and $P_{i,t}^D$ as their respective prices, and $A_{i,t}^C$ and $A_{i,t}^D$ as their factor-augmenting technology levels, all defined in country i and year t. The elasticity of substitution is denoted by σ. In line with the literature we assume that technology follows a loglinear trend, with $\gamma_{i,j}$ the rate of technical progress which may differ by energy type:

$$A_{i,t}^j = A_{i,0}^j e^{\gamma_{i,j}(t-t_0)}$$

for $j \in \{C, D\}$. It then follows that:

$$E_{i,t} = \left[\left(A_{i,0}^C e^{\gamma_{i,C}(t-t_0)} E_{i,t}^C \right)^{\frac{\sigma-1}{\sigma}} + \left(A_{i,0}^D e^{\gamma_{i,D}(t-t_0)} E_{i,t}^D \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

Throughout our discussion, we will refer to $A_{i,t}^C$ and $A_{i,t}^D$ as technology levels. It should be clear, however, that these parameters also relate to the available infrastructure. The electric grid, in particular, acts as a constraint on clean energy production. While innovation in clean energy can increase efficiency, its total supply remains limited by grid capacity. In other words, efficiency gains in the clean energy sector will not translate into higher output once the electric grid is saturated. Similarly, dirty energy augmenting technologies (such as more efficient coal power) rely on fuel supply chains, plants, and transmission lines. Without adequate infrastructure, factor-augmenting technologies may thus not be fully effective. Even more, in the spirit of Acemoglu et al. (2012), the available infrastructure may determine the direction of innovation and technological development.

Solving the energy bundler's constrained optimization problem, yields the following first-order condition for the relative demand of clean versus dirty energy:

$$\ln\left(\frac{E_{i,t}^C}{E_{i,t}^D}\right) = \sigma \ln\left(\frac{P_{i,t}^{E_D}}{P_{i,t}^{E_C}}\right) + \sigma \ln\left(\frac{\pi_i^C}{\pi_i^D}\right) + (\sigma - 1)\left(\gamma_{i,C} - \gamma_{i,D}\right)(t - t_0) \tag{1}$$

where π_i^C and π_i^D are constants related to the initial levels of technology $A_{i,0}^C$ and $A_{i,0}^D$ and σ. More precisely, $\pi_i^C = \left(A_{i,0}^C\right)^{(\sigma-1)/\sigma}$ and $\pi_i^D = \left(A_{i,0}^D\right)^{(\sigma-1)/\sigma}$.

Estimation of Equation (1) is quite straightforward. On the LHS we have the dependent variable, the log ratio of clean to dirty energy inputs. On the RHS we find our parameter of interest as a direct coefficient on the log ratio of energy prices. The larger the elasticity, the more responsive the energy ratio will be to changes in relative prices. The second term is a country-specific constant, and the last term a country-specific time trend.

The theoretical relevance of different initial levels of clean and dirty technology quite naturally pushes towards using country-fixed effects in empirical work. Country-specific time trends are needed to capture the fact that some countries are advancing more rapidly in clean relative to dirty technologies. Moreover, they allow for incorporating catch-up effects documented in studies on innovation and technological change (e.g. Berlingieri, 2020). In line with this, Acemoglu et al. (2006) and Westmore (2014) find different growth rates of innovation depending on economies' distance to the technological frontier.

A small note is that the last term in Equation (1) captures only the net technological growth rate, i.e. the difference between clean and dirty rates of technical progress. We lose some information as a rising net growth rate could be due to either faster technical progress in clean energy or slower technical progress in the dirty energy sector. To simplify notation, net growth in clean energy technology $\gamma_{i,C} - \gamma_{i,D}$ is noted by γ_i. Summarizing, we obtain the following empirical specification for country i and year t.

$$\ln\left(\frac{E_{i,t}^{C}}{E_{i,t}^{D}}\right) = \alpha_i + \sigma \ln\left(\frac{P_{i,t}^{E_D}}{P_{i,t}^{E_C}}\right) + (\sigma - 1)\gamma_i T_t + v_{i,t} \tag{2}$$

with α_i a country-specific fixed effect, reflecting initial stocks of technology (and infrastructure), $\gamma_i T_t$ a time trend with country-specific loading, and $v_{i,t}$ the error term of the regression. Note that the elasticity of substitution also determines the impact of the net rate of technical progress on the energy ratio. Faster technical progress in clean energy only promotes its relative input when clean and dirty energy are substitutes ($\sigma > 1$). In contrast, when the two types of energy are complements ($\sigma < 1$), technical progress that boosts the effective supply of clean energy will induce firms to also raise the quantity of dirty energy incorporated in their production. Consequently, CO_2 emissions will rise.

2.2. Implications for related empirical analysis and studies

In this section, we highlight how alternative empirical specifications and estimation techniques affect the resulting estimates. Three issues are crucial. We begin by outlining them and then briefly review four studies that, like ours, directly estimate the elasticity of substitution: Papageorgiou et al. (2017), Jo (2025), Jo and Miftakhova (2024), and Schwerin (2025). None of these studies addresses all three issues. This need not be problematic, but it has implications for the interpretation and use of their results.

A first issue concerns the relationship between α_i and γ_i, on the one hand, and σ, on the other. Following Mattauch et al. (2015), a growing number of authors have emphasized the crucial role of infrastructure provision to facilitate the low-carbon transformation (see e.g. Papageorgiou et al., 2017; Kemp-Benedict, 2018; Jo and Miftakhova, 2024). Far-reaching substitution of dirty with clean energy inputs may only be possible as infrastructure and technology for the use of low-carbon energy sources expand over time.[4] A high σ may therefore be associated with – or even depend on – the structural factors behind a high α_i and/or γ_i. Consequently, omitting α_i and/or γ_i from the empirical specification may imply a substantially higher estimate of σ, reflecting not only price-induced substitution but also the impact of structural differences across countries in available technology and infrastructure that are not accounted for in the empirical specification.

A second issue concerns the effects of price movements on the energy mix that operate through changes in technology. As shown by Acemoglu et al. (2012) and Mattauch et al. (2015), relative price changes may trigger technological development in favor of clean energy. If such induced technological change is not accounted for in the equation, the estimated σ may incorporate this longer-run effect and – again – increase.

An important third concern is endogeneity. Because energy quantities and prices are often determined jointly, credible estimation of the elasticity of substitution and identification of the causal impact of relative price changes on demand, require valid instruments for relative prices. These should capture exogenous supply shifts. Without instrumentation, price movements may be driven by unobserved demand factors, inducing a positive correlation between the price and the regression error term, and thereby biasing the estimated σ.

The between estimator (B.E.)

Based on a survey of the interfuel substitution literature, Stern (2012) concludes that the between estimator should be the preferred technique for estimating the long-run elasticity of substitution. We tend to disagree. The between estimator uses time-averaged transformed series of the variables and exploits only cross-sectional variation. It cannot accommodate country-specific fixed effects nor heterogeneous technology growth rates. It is easy to show that this may inflate the estimated elasticity of substitution and overstate true substitutability.

Building on the conditional demand function for energy in Equation (2), the time-averaged transformation implies:

---

[4] As we have mentioned before, no matter how large the drop in the relative price of clean energy, the response in clean energy use will be small if the electric grid is saturated. Similarly, a lack of adequate charging capacity restricts the use of electric vehicles. And as long as technical barriers prevent the substitution of coal or natural gas with electric heating in high-temperature furnaces, the response in fuel use will remain small. Jo and Miftakhova (2024) test – and confirm – this hypothesis in the French manufacturing sector. They incorporate a Variable Elasticity of Substitution (VES) production function as developed by Revankar (1971) and observe that the elasticity of substitution responds positively to the penetration of clean energy.

$$\overline{\ln\left(\frac{E_i^C}{E_i^D}\right)} = \alpha_i + \sigma \overline{\ln\left(\frac{P_i^{E_D}}{P_i^{E_C}}\right)} + (\sigma - 1)\gamma_i \bar{T} + \bar{v}_i \qquad (3)$$

$$= \kappa_i + \sigma \overline{\ln\left(\frac{P_i^{E_D}}{P_i^{E_C}}\right)} + \bar{v}_i \qquad (3')$$

with $\bar{x}_i = \left(\frac{1}{T}\right) \sum_{t=1}^{T} x_{i,t}$ and $\kappa_i = \alpha_i + (\sigma - 1)\gamma_i \bar{T}$.

In a setting with N countries i and T observations per country, time-averaging reduces the available observations from NxT to N. It will then be impossible to account for country-specific initial technology levels captured by α_i and heterogeneous technology growth rates γ_i. As discussed above, neglecting these parameters may shift the influence of initial cross-country differences and induced technological change that affect the ratio of clean to dirty energy inputs into the second term on the right-hand side of equation (2), implying a much higher estimate of the elasticity.

As a suboptimal alternative, one could first drop the distinction between α_i and γ_i and combine them into κ_i as in (3'). Alternatively, one might impose technological neutrality by setting $\gamma_i = 0$. Even then, given the limited data, only a small set of country group-specific or region-specific values for κ_i could be estimated, rather than country-specific values.

The preceding discussion does not, however, imply that the between estimator is without merit. It helps illustrate the consequences of ignoring cross-country differences in technology levels and growth rates. It explains in part why we will find much higher estimates of this elasticity with the between estimator and in cross-sectional studies more generally (see Section 4 - Results).

The within estimator (F.E.)

The F.E. estimator, in contrast, does account for country-specific initial stocks of technology (and infrastructure). However, in its standard specification, it also ignores the impact of technology growth within each country. To the extent that such growth is induced by changes in relative energy prices within a country, the F.E. estimate may absorb this and come closest to measuring the long-run elasticity of substitution, in the spirit of Hassler et al. (2021). By extending the regression with country-specific time effects or trends, thereby controlling for induced technological developments, a lower estimated σ will emerge. Again following the interpretation of Hassler et al. (2021), this would measure only short-run effects of relative price changes.

This brings us back to the four empirical studies mentioned above. Papageorgiou et al. (2017) estimate an aggregate CES production function including labor, capital, intermediate materials and services, and clean and dirty energy. They use panel data covering up to 26 countries and 28 industries in 1995-2009. Jo (2025) and Jo and Miftakhova (2024) focus on a panel of French manufacturing firms in 1994-2015. Jo (2025) also recovers an estimate for the elasticity at the aggregate level from her micro results. Schwerin (2025) exploits a global aggregate time series of fossil versus renewable energy and their prices in 1800-2012. The latter three studies also adopt the cost-minimization approach that we described in Section 2.1.

When we review these studies in light of our general specification in Equation (2), a few observations emerge. First, in their specifications underlying the estimates that we report in Table 1, only Papageorgiou et al. (2017) include cross-section specific fixed effects. Jo (2025) and Jo and Miftakhova (2024) control for industry fixed effects, but they do not include firm-level fixed effects. Schwerin (2025) has no panel data. Second, none of these four studies accounts for cross-sectional differences in the rates of technical progress in clean and dirty energy (γ_i). Papageorgiou et al. (2017) and Schwerin (2025) only allow neutral technical progress. In Equations (1) and (2) their approach would impose $\gamma_{i,C} = \gamma_{i,D}$ and $\gamma_i = 0$. Jo (2025) and Jo and Miftakhova (2024) do allow for different rates γ_C and γ_D, but the difference is assumed to be common across all firms, which explains the lack of subscript i. Their approach implies a common time trend or common time fixed effects: technical progress is factor-biased, but common across the cross-sections. When the cross-sectional units relate to different sectors or feature different countries, this approach is clearly restrictive. In the case of countries, this approach also rules out catching-up dynamics. From their initial level of technology countries would grow in parallel, never catching up in technology.

As discussed above, these restrictions are not without empirical consequences. First, without fixed effects, initial cross-sectional differences in energy-related technology and infrastructure may be absorbed by the estimated elasticity, biasing perceived substitutability upward. Second, ignoring cross-sectional differences in the rates of technical progress in clean and dirty energy will also raise the estimated elasticity, as it may then incorporate the longer-run effects of price movements on the energy mix operating through induced innovation and technological change. The estimated elasticity of substitution would then capture both the direct (short-run) price impact and the indirect (long-run) price impact through induced clean technical progress.[5] There is nothing inherently wrong with this, however. We defined the resulting estimate as the closest measure of the long-run elasticity of substitution. A problem arises, though, if the resulting high estimate of σ is imposed in theoretical models that treat technology as endogenous to price changes, such as Acemoglu et al. (2012). In that case, the same mechanism may be counted twice, leading to overly optimistic assessments of the effects of price changes.

Endogeneity and the need for instrumental variables

As we highlighted above, appropriate identification of causal effects requires the use of valid instruments for relative prices. A well-known challenge in the literature is finding such

---

[5] This conclusion is consistent with Leon-Lédesma et al. (2015), who show that when technological change in CES functions is mis-specified, the estimated elasticity of substitution tends to be systematically higher.

instruments. Papageorgiou et al. (2017) for example report no IV estimates due to a lack of exogenous instruments. Schwerin (2025) instead focuses on long-run equilibrium rather than this identification issue. Jo (2025) and Jo and Miftakhova (2024) avoid the problem by estimating the elasticity of substitution at the micro level of French manufacturing firms. They employ changes in aggregate energy prices to create valid instruments. A contribution of our paper is to provide valid instruments for estimating the elasticity of substitution from macro data. These instruments are the global solar PV panel price per megawatt of capacity and the lagged carbon tax rate (see the next section).

3. Data

In this section we discuss the data used for our analysis. It contains information on our choice of energy quantities and prices, the assumptions and adjustment we made to the original data series, and information on the variables we use as instruments for the relative energy price.

Our data consist of a panel of 13 countries – the six founding members of the European Union, the four Nordic countries, and three Anglo-Saxon countries (USA, UK, Canada). The time dimension of this panel is quite large, with 41 annual data points from 1980 to 2020. Including more countries would substantially shorten the time dimension of the panel.[6] Given our focus on long-run relationships, we prioritize a longer time series over a wider cross-section.

Table 2 and Figures 1 and 2 show the main data. We report various statistical indicators for the data overall, as well as along the time and cross-sectional dimensions. Variation along these dimensions is necessary for precise estimation using the within and between estimators.

Energy prices are real and expressed in 2015 euros per kWh of energy. They are end-use prices, including all involved taxes and subsidies. Clean energy is derived from nuclear and renewable sources. Clean energy prices (P_{E_C}) are the average of household and industry electricity prices.[7] Dirty energy is produced by burning coal, oil and gas. Dirty energy prices (P_{E_D}) are a weighted average of the commodity prices of these three fossil fuels. Following recent literature, energy quantities (E_C, E_D) are expressed in their energy potential. Metric tonnes for coal, barrels for oil and cubic meters for gas are converted into kWh. Table A1 in Appendix A contains the adopted energy conversion factors. This approach seems natural as clean energy comes in the form of electricity and the energy unit used in electricity is kWh. It also explains why all prices are expressed as euros per kWh of energy.

A look at the data immediately reveals several interesting patterns. First, considering Figures 1 and 2 and the size of the coefficient of variation in Table 2, cross-country differences are clearly larger in clean energy shares than in relative energy prices. The Nordic countries and France stand out with the highest clean energy share in 2020, ranging from more than 40%

---

[6] Including seven additional countries would shift the start year to 1995, rather than 1980.

[7] We have considered different weighting schemes between industry and households, but these weighted series do not differ in any significant way from a simple unweighted average.

(Denmark) to even more than 70% (Sweden). In all other countries the clean energy share was still below 30% in 2020. In the Netherlands and Luxembourg even below 15%. Second, whereas the variation in the clean energy shares is dominated by structural differences across countries (between variation), the variation in relative prices is more evenly driven. Both structural cross-country differences and within-country changes over time matter. As is clear from a comparison of between and within standard deviations, the cross-country differences are mainly due to differences in clean energy prices. For the within-country changes, however, volatility in dirty energy prices is relatively more important. Third, as to energy inputs, countries differ more in clean energy than in dirty energy consumption.

Table 2 - Description of included variables and summary statistics

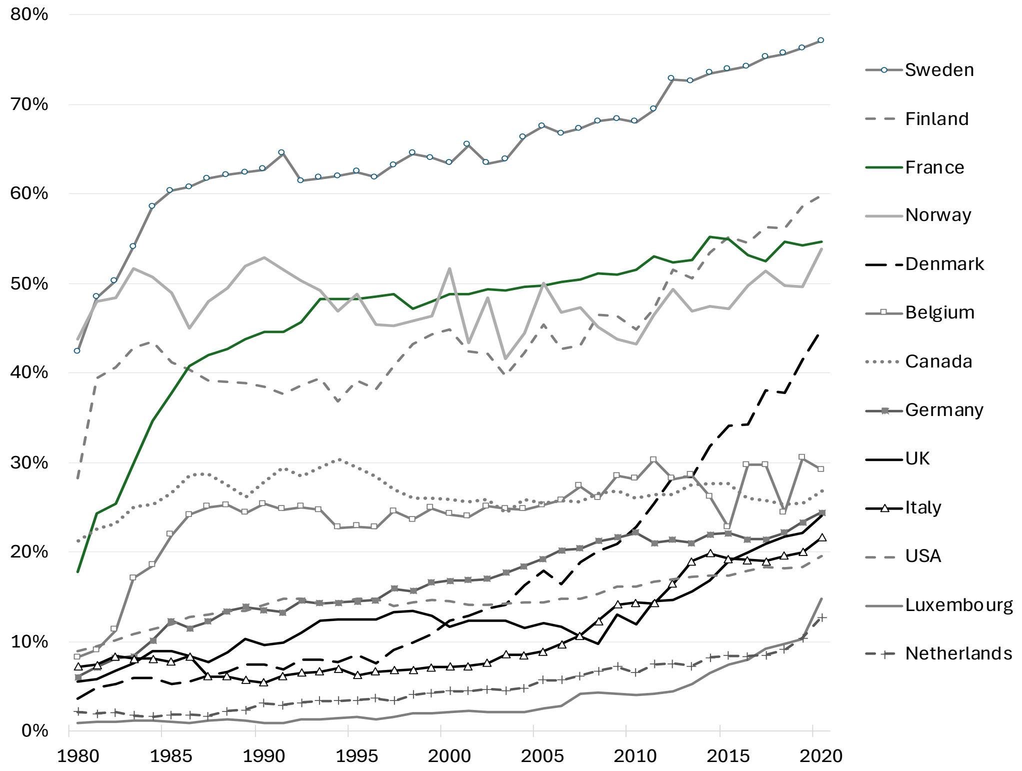
Variable		Mean	Std. dev.	Coeff. of variation	Observations
P_{E_D}/P_{E_C}	overall	0.1537	0.0843	0.548	N = 533
	between	0.1537	0.0509	0.331	n = 13
	within	0.0	0.0687		T = 41
P_{E_c}	overall	0.1132	0.0423	0.374	N = 533
	between	0.1132	0.0352	0.311	n = 13
	within	0.0	0.0254		T = 41
P_{E_D}	overall	0.0159	0.0081	0.509	N = 533
	between	0.0159	0.0017	0.107	n = 13
	within		0.0079		T = 41
$E_c/(E_C + E_D)$	overall	0.2566	0.193	0.752	N = 533
	between	0.2566	0.192	0.748	n = 13
	within	0.0	0.058		T = 41
$\ln(E_c)$	overall	11.99	2.034	0.170	N = 533
	between	11.99	2.064	0.172	n = 13
	within	0.0	0.443		T = 41
$\ln(E_D)$	overall	13.40	1.615	0.121	N = 533
	between	13.40	1.673	0.125	n = 13
	within	0.0	0.134		T = 41

Notes and data sources:

Energy prices are real and expressed in 2015 euros per kWh of energy. They are end-use prices, including all involved taxes and subsidies. Clean energy prices (P_{E_C}) are the average of household and industry electricity prices. Dirty energy prices (P_{E_D}) are a weighted average of the commodity prices for fossil fuels (by market: North America, Europe) and weighted by share of fossil fuel. Involved fuels are coal, oil and gas. Sources: International Energy Agency (IEA, World Energy Balances), World Bank Commodity Price Data (The Pink Sheet).

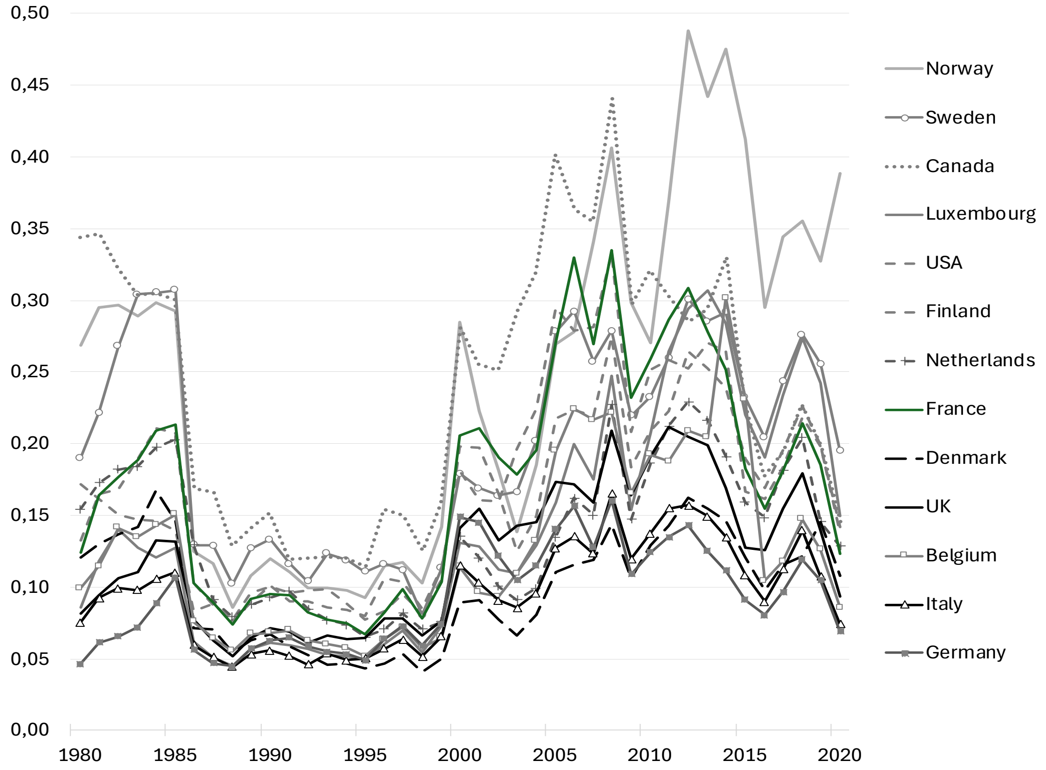
Energy quantities are expressed in their energy potential in kWh. Clean energy includes nuclear and renewable energy. Metric tonnes for coal, barrels for oil and cubic meters for gas are converted into kWh, which is also the energy unit used for electricity. See the data in Table A1 in Appendix A. This conversion also explains why all prices are expressed in euros per kWh. Quantities are expressed in logarithms to allow for meaningful comparison between (very) large and small countries. Source: International Energy Agency (IEA, World Energy Balances).

Fig 1 - Clean energy shares across our panel



Note: Series are organized by decreasing order of clean energy shares in 2020.
Description and data sources: see main text and notes below Table 2.

Fig 2 – Relative price of dirty to clean energy



Note: Series are organized by decreasing order of relative dirty energy price in 2020.

Instrments

We highlighted the importance of good instruments in Section 2.2. In our analysis, we employ two instruments that affect the relative final price of clean versus dirty energy from the supply side. The first one is the one-year lagged carbon tax rate, measured in real 2015 euros per tonne of CO_2. The second reflects the change in the global real price of solar photovoltaic (PV) panels per megawatt of capacity. Appendix A shows the data. Here we report the basics.

Carbon tax data are taken from Dolphin and Xiahou (2022), who improve upon the widely used Metcalf and Stock (2020) data by accounting for the fact that carbon taxes and emission permit prices do not act uniformly throughout the economy. Not all sectors are affected by these policies. By using weights that reflect each sector's size, they obtain an effective carbon tax rate for a country, which is generally lower than the rates reported by Metcalf and Stock (2020). This is important when analyzing data at the macro level: using the unweighted carbon prices might bias their estimated effect on quantities.

Our second instrument has been constructed by applying the growth rate of the global price of solar PV panels, from 1981 onward, to the country-level price of clean energy in 1980. Technically, the instrument for the clean energy price in country i at time t is computed as

$$P^{IV}_{Ec,i,t} = P_{Ec,i,1980} \cdot IPV_t \quad \text{with } IPV_{1980} = 1, \text{and } t = 1980, \dots, 2020.$$

In this equation $P_{Ec,i,1980}$ is the price of clean energy in country i in 1980 and IPV_t an index reflecting the global real solar PV panel price in year t relative to 1980. We will define this instrument as the "global solar cost-indexed initial clean energy price". A similar approach of incorporating higher level price movements has been adopted by e.g. Marin and Vona (2021) and Jo (2025). Jo applied the growth rate of national energy prices in France to pre-sample firm-level prices to mitigate the endogeneity of firm-level energy prices. The data for the real price of solar PV panels have been processed by 'Our World in Data'. Underlying sources are IRENA (2024), Nemet (2009) and Farmer and Lafond (2016). The clean energy price in each country in 1980 has been obtained from the sources listed below Table 2.

From a theoretical point of view, we can justify the use of these two instruments. The carbon tax rate captures part of government intervention in the pricing of dirty energy. A concern could be that governments endogenously respond to changes in the ratio of clean to dirty energy in their country. However, by lagging the implemented carbon tax rate, and recognizing that tax changes are often decided at least one year in advance, we strongly reduce this potential endogeneity.

Global solar PV panel prices are exogenous as they are dependent on the development of R&D and price formation in the solar sector worldwide. As panels become more efficient, their cost per watt of capacity decreases, inducing a price decline for clean energy. This can then act as an impetus for shifting to clean energy. The reverse is not true: a shock to the ratio of clean to dirty energy in an individual country in our sample will have a negligible impact on innovation in PV technology and the global price of solar PV panels. A concern with the use of this instrument could be that individual country shocks are part of a broader common adjustment, for example related to European regulation, such that world solar panel prices may also be affected. The importance and generality of this concern over our whole sample, however, remain open questions.

To assess the strength and validity of our instruments, we carry out appropriate empirical tests. The results are reported and briefly discussed alongside the IV regressions in the next section. Anticipating these results, we note that our chosen instruments pass the tests. Additionally, our results are robust to alternative instrument specifications. Furthermore, we note that for all our estimated relationships with a time dimension, we reject the null hypothesis of no cointegration. This implies that our estimated regressions capture an equilibrium relationship between the variables involved.

4. Results

In this section, we first report the baseline results using the between and within estimators. We then expand the estimated equation to incorporate country-specific time trends as in Equation (2). Last, building on arguments by Mattauch et al. (2015), Bretschger et al. (2025), and empirical work by Jo and Miftakhova (2024), we explore a corollary of our results: the positive association between the clean energy share and the elasticity of substitution.

4.1. Between and within estimation results

Table 3 contains our estimation results for 13 OECD countries in 1980-2020. Column (1) fully confirms our expectation to see the highest estimated elasticity from the between estimator ($\sigma = 6$). Our estimate is in the middle of the range assumed by Acemoglu et al. (2012).[8] In column (2) we introduce country-specific fixed effects to account for cross-country differences in the initial state of technology (and infrastructure). It brings down the estimated elasticity to about 2.3. Following up on our earlier discussion, this estimate is likely to provide the best measure of the long-run elasticity of substitution in the sense of Hassler et al. (2021). It may incorporate the effects on relative energy inputs of longer-run technological developments induced by changes in relative energy prices within a country. Further extending the regression in column (2) by including common time effects, for example to capture the impact of technological developments at the global level, did not materially change the results. It led to an estimated σ of 2.11.[9]

---

[8] Adding regional dummies for the Nordic group and for the euro area implies an estimated σ equal to 5.3.

[9] An explanation may be that these global technological developments are already incorporated by our use of the global price of solar PV panels as instrument for the relative price of clean energy.

Table 3. Empirical analysis of the log ratio of clean versus dirty energy (1980-2020) [1, 2]

	Between estimation (1)	Within estimation (2)	Within estimation with country-specific differential technical progress (3)	(4)
constant	10.7^{***}	3.82^{***}	-0.69^{***}	-1.91^{***}
	(3.75)	(0.92)	(0.34)	(0.28)
$\ln\left(P_{E_D}/P_{E_C}\right)_{i,t}$	6.00^{***}	2.26^{***}	0.30^{***}	0.38^{***}
	(1.96)	(0.41)	(0.09)	(0.08)
$Nuclear\ share_{i,t}$				1.89^{***}
				(0.29)
Coefficient on country-specific time trend Belgium			0.010	0.006
Canada			-0.003	-0.003
Denmark			0.066^{***}	0.065^{***}
Finland			0.013^{***}	0.019^{***}
France			0.017^{***}	0.002
Germany			0.023^{***}	0.019^{***}
Italy			0.031^{***}	0.032^{***}
Luxemburg			0.055^{***}	0.052^{***}
Netherlands			0.047^{***}	0.045^{***}
Norway			-0.010^{***}	-0.012^{**}
Sweden			0.020^{***}	0.026^{***}
UK			0.021^{***}	0.015^{***}
US			0.007^{*}	0.002
Observations	13	520	520	520
Country fixed effects	no	yes	yes	yes
Time fixed effects	-	no	no	no
R^2 adjusted	0.331	0.436	0.974	0.974
Kleibergen-Paap underidentif. [3]	0.15	0.00	0.00	0.00
Kleibergen-Paap weak ident.[4]	6.17	11.2	12.9	13.3
Hansen J-test statistic [5]	-	0.13	0.51	0.63
Cointegration [6]	-	yes	yes	yes

Notes : 1. Estimated HAC standard errors in brackets. * p<0.1; ** p<0.05; *** p<0.01.

2. As instruments we use the 1-year lagged carbon tax rate and the global solar cost-indexed initial clean energy price.
3. Kleibergen-Paap (2006) underidentification test, p-value: the null hypothesis is that the model is underidentified (weak instruments).
4. First-stage rk Wald F-statistic. Observed values in columns (2)-(4) are above the rule-of-thumb threshold of 10, indicating sufficient first-stage relevance.
5. Hansen J-test of overidentifying restrictions, p-value. The null hypothesis that the instruments are valid cannot be rejected.
6. Results have been derived from applying the cross-sectionally augmented IPS (CIPS) test to the residuals of the regressions (Pesaran, 2007). The test always rejects the null hypothesis of a unit root in the residuals. Details are available upon request.

Introducing country-specific time trends, the third column accounts for technological developments within individual countries over time. As expected, we observe a further decline in the estimated elasticity to well below 1. Since this regression controls for country-specific technology (and infrastructure) levels, as well as technological developments, the estimated

0.3 can be interpreted as the short-run elasticity of substitution in the sense of Hassler et al. (2021). This value is close to the estimated or imposed values of Pelli (2012), Pottier et al. (2014), IMF (2022), and Papageorgiou et al. (2017) when they adopt a cost-function approach. But it is far below the imposed short-run elasticity by Allen et al. (2025). Column (4) extends the regression of column (3) with the share of nuclear energy. It has the expected positive sign and is highly significant, but it leaves our main findings unchanged.

Robustness

Beyond the controls for common time effects across countries and the share of nuclear energy included in Table 3, we conducted several other robustness checks. First, as another extension and attempt to control for country-specific technology, we included the accumulated public low-carbon R&D stock per capita in each country. Underlying data are provided by the International Energy Agency (IEA, Energy Technology R&D Budgets). This additional variable was at most marginally significant – at the 10% level. Adding it, did not affect our main results.

Second, we tested the impact of including or excluding individual countries. Dropping single countries from our sample never had a notable impact on the estimation results. Re-estimating the equation in column (2) with only 12 instead of 13 countries never led to values significantly different from 2. Results varied between 1.99 and 2.45.

Third, we considered alternative instruments for the relative price of dirty to clean energy. In response to the earlier concern that the global price of solar PV panels may be correlated with shocks to countries' clean-to-dirty energy input ratios if these shocks are part of a broader adjustment, we introduced the one-period lag of this variable as instrument. As a second variation, we added the (annualized) oil supply news shock of Känzig (2021) as instrument. A third variation more explicitly accounted for the impact of oil supply disruptions related to conflicts in the Middle East in the period since 1980. We captured this by a dummy equal to 1 in 1980-88 (Iran-Iraq war), 1990-91 (Gulf War) and 2011 (Arab Spring and civil war in Libya). Finally, we considered the lagged real effective exchange rate of the dollar as additional instrument. When the dollar strengthens, oil and dirty energy become more expensive in other currencies. This will dampen global demand for dirty energy with downward pressure on its price.[10] Evidence for this causal effect has been reported by among others De Schryder and Peersman (2015) and Beckmann et al. (2020). Including these alternative or additional instruments never changed our main findings. Appendix B summarizes the obtained elasticity estimates.[11] They remain close to 2 in the within-specification of column (2), and well below 1 in the within-specification with country-specific time trends of column (3).

---

[10] We used lagged data of the dollar exchange rate to exclude reverse causal effects from oil price changes to the value of the dollar.

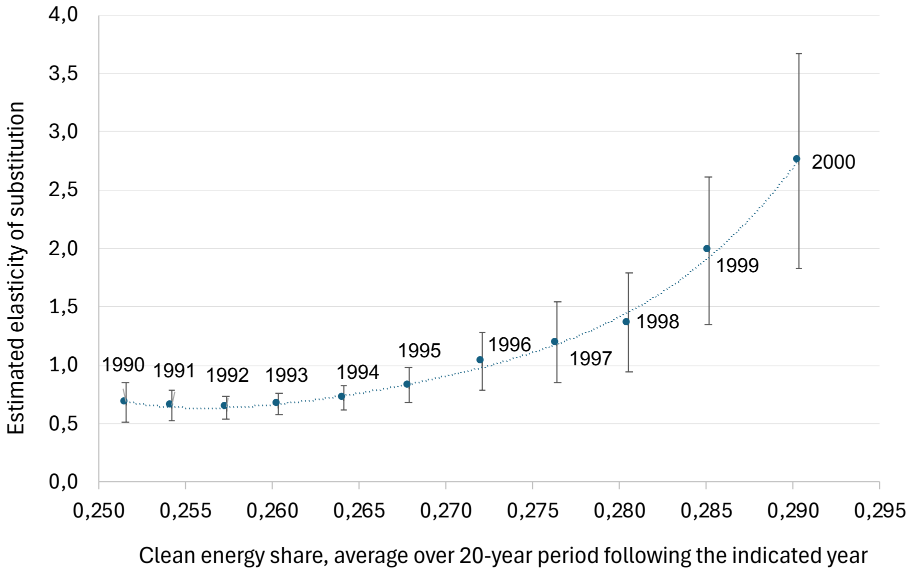
[11] More details are available upon request.

4.2. Time-varying elasticity of substitution

The less we controlled for α_i and γ_i in the previous section, the stronger was the estimated response of the clean-to-dirty energy input ratio to relative price changes. This suggests a positive association between the scale of clean infrastructure and technology – and the corresponding share of clean energy – and the elasticity of substitution. This empirical observation aligns with the argument of Mattauch et al. (2015), who contend that far-reaching substitution of dirty by clean energy inputs becomes feasible only as infrastructure for low-carbon energy sources expands over time. Jo and Miftakhova (2024) provide empirical support for this mechanism in the French manufacturing sector.

To directly test this hypothesis at the macro level, we re-estimated the regression reported in column (2) in Table 3 using rolling 20-year windows. The first window concerns 1990-2010, the last one is 2000-2020.[12] Figure 3 reports the results. It relates the estimated elasticity of substitution and the corresponding 90% confidence interval to the average share of clean energy in total energy use over the 20-year window. The expected positive association is clearly visible. Another striking result is that at the early stages of the energy transition – that is, at low levels of clean infrastructure and technology, reflected in low shares of clean energy in total energy use – plausible values for the long-run elasticity of substitution are significantly below 1. In this case, clean and dirty energy inputs are complements, and the price mechanism will be ineffective at reducing emissions. For the elasticity to be significantly above 1, a clean energy share of more than 28% appears to be required. Estimated over the most recent period, we find an elasticity of 2.75.

Figure 3. Rolling window estimation results



Note: Point estimates are indicated by dots, 90% confidence intervals are shown for each point estimate.

---

[12] Lack of time variation in the carbon tax instrument over 1980-1990 (it is zero in all countries) made it impossible to start the rolling window estimations before 1990. The last regression includes a covid dummy for 2020.

5. Conclusions

For the design of effective climate policies and the feasibility of green growth, the elasticity of substitution between clean and dirty energy is crucial. A key threshold is whether it lies below or above 1. The existing literature, however, reveals considerable uncertainty: reported empirical estimates and the values assumed in theoretical models vary widely, from less than 0.5 to more than 3, and in some cases up to 10.

This paper develops an encompassing empirical specification that nests both low and high elasticity estimates as special cases and applies it to macroeconomic panel data from 13 OECD countries over 1980–2020. A central question is whether one controls for a country's initial level of energy-related technology and infrastructure, as well as for country-specific rates of technical progress in clean and dirty energy. Since theory predicts that changes in the relative price of clean and dirty energy may themselves induce technological change, the treatment of these factors is decisive for estimation and interpretation.

When we control for these elements using country-specific fixed effects and country-specific time trends – thereby identifying the effect of relative price changes holding technology and infrastructure constant – the estimated elasticity of substitution is well below 1. We interpret this as a short-run elasticity. In contrast, when induced technological change is not controlled for, the estimated elasticity rises to between 2 and 3, which we interpret as a plausible long-run elasticity incorporating the effects of price-induced technological adjustment. Finally, in the absence of any controls, estimated elasticities reach values as high as 6, which give an overly optimistic picture of true substitutability, as the effect of any omitted factor influencing the clean-to-dirty energy ratio is then absorbed into the elasticity estimate.

A corollary of our findings is that the elasticity of substitution is positively correlated with the scale of clean energy infrastructure and technology, and with the induced share of clean energy in total energy use. Estimating our model over rolling 20-year windows, we find suggestive evidence for this hypothesis. A related and striking observation is that at early stages of the energy transition – characterized by low levels of clean energy infrastructure and technology and clean energy shares below 28% – plausible values for even the long-run elasticity of substitution are significantly below 1. In this case, clean and dirty energy inputs behave as complements rather than substitutes, implying that the price mechanism alone will be ineffective at reducing emissions.

Our findings have clear implications for society and policy. At the beginning of the clean energy transition, countries have very limited possibilities to replace dirty energy via the price mechanism. When technology and infrastructure are not yet in place, the elasticity of substitution is far below 1, and clean and dirty inputs may be complements. In this setting, carbon taxation or subsidies have limited impact on shifting demand, and reducing emissions may require negative growth of output and energy use. As a result, carbon taxes at this stage are likely to be ineffective and highly regressive. With higher levels of technical progress in clean energy and supporting infrastructure, however, the elasticity of substitution increases, enabling a more cost-effective and less regressive use of carbon taxes. Our findings thus highlight the central role of investment in green technology and infrastructure, particularly for countries at an early stage of the transition. Building up these capabilities is necessary to move beyond the tipping-point at which clean energy becomes self-reinforcing, after which carbon pricing becomes more effective in accelerating the transition at lower social (less regressive) cost.

Last, our results provide guidance for the calibration of energy-augmented macroeconomic models. To study short- or near-term scenarios, the results suggest the use of an elasticity of substitution well below 1. The choices made by IMF (2022) are in line with this suggestion. Allen et al. (2025), however, impose a value above 1, which our results would consider as too high. In models for long-run analysis that do not explicitly incorporate an endogenous technological response to relative price changes, it appears warranted to impose an elasticity of substitution of around 2 or 3. By contrast, in models that account for the state of technology and allow for its endogenous response to relative price changes, substantially lower values seem appropriate. In this respect, the elasticities between 3 and 10 assumed by Acemoglu et al. (2012) and many others (e.g. Fried, 2018; Hart, 2019; Campiglio et al., 2024; Bretschger et al., 2025) appear too high. Modeling endogenous technological change while simultaneously assuming a (very) high elasticity of substitution risks double-counting the same mechanism.

References

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

Acemoglu, D., Aghion, P., & Zilibotti, F. (2006). Distance to frontier, selection, and economic growth. *Journal of the European Economic association*, 4, 37-74.

Allen, T., Boullot, M., Dées, S., de Gaye, A., Lisack, N., Thubin C., & Wegner, O. (2025). Using short-term scenarios to assess the macroeconomic impacts of climate transition. *Energy Economics*, https://doi.org/10.1016/j.eneco.2025.108663.

Babiker, M. H., Metcalf, G. E., & Reilly, J. (2003). Tax distortions and global climate policy. *Journal of Environmental Economics and Management*, 46, 269-287.

Beckmann, J., Czudaj, R. L., & Arora, V. (2020). The relationship between oil prices and exchange rates: Revisiting theory and evidence, *Energy Economics*, https://doi.org/10.1016/ j.eneco.2020.104772.

Berlingieri, G. et al. (2020), "Laggard firms, technology diffusion and its structural and policy determinants", *OECD Science, Technology and Industry Policy Papers,* No. 86, OECD Publishing, Paris.

Bretschger, L., Leuthard, M., & Miftakhova, A. (2025). Boosting sluggish climate policy: Endogenous substitution, learning, and energy efficiency improvements, *Environmental and Resource Economics*, 88, 3905–3947.

Campiglio, E., Spiganti, A., & Wiskich, A. (2024). Clean innovation, heterogeneous financing costs, and the optimal climate policy mix. *Journal of Environmental Economics and Management*, https://doi.org/10.1016/j.jeem.2024.103071.

Coenen, G., Lozej, M., & Priftis, R. (2024). Macroeconomic effects of carbon transition policies: an assessment based on the ECB's New Area-Wide Model with a disaggregated energy sector. *European Economic Review*, 167, 104798.

Davis, S. J., Caldeira, K., & Matthews, H. D. (2010). Future CO2 emissions and climate change from existing energy infrastructure. *Science*, 329(5997), 1330-1333.

De Schryder, S., Peersman, G. (2015). The US dollar exchange rate and the demand for oil. *Energy Journal,* 36, 263-285.

Dolphin, G., & Xiahou, Q. (2022). World carbon pricing database: sources and methods. *Scientific Data*, 9(1), 573.

Farmer, J.D. and Lafond, F. (2016). How predictable is technological progress? *Research Policy*, 45*,* 647-665.

Freire-González, J., & Ho, M. S. (2019). Carbon taxes and the double dividend hypothesis in a recursive-dynamic CGE model for Spain. *Economic Systems Research*, 31, 267-284.

Ha-Duong, M., Grubb, M. J., & Hourcade, J. C. (1997). Influence of socioeconomic inertia and uncertainty on optimal CO2-emission abatement. *Nature*, 390(6657), 270-273.

Hart, R. (2019). To everything there is a season: Carbon pricing, research subsidies, and the transition to fossil-free energy. *Journal of the Association of Environmental and Resource Economists,* 6*,* 349–389.

Hassler, J., Krusell, P., & Olovsson, C. (2021). Directed technical change as a response to natural resource scarcity. *Journal of Political Economy,* 129, 3039-3072.

IMF (2022). Near-term macroeconomic impact of decarbonization policies. *World Economic Outlook,* International Monetary Fund. Washington D.C., October, 71-95.

IRENA (2024). *Renewable Power Generation Costs in 2023*, International Renewable Energy Agency, Abu Dhabi.

Jacobs, A. (2023). Capital-augmenting technical change in the context of untapped automation opportunities. *Mathematical Social Sciences*, 123, 155–166.

Jacobs, A. (2025). The rise of the 1% and the fall of the labor share: An automation-driven doom loop? *National Bank of Belgium Working Paper*, No 475.

Jo, A. (2025). Substitution between clean and dirty energy with biased technical change. *International Economic Review*, 66, 883-902.

Jo, A., & Miftakhova, A. (2024). How constant is constant elasticity of substitution? Endogenous substitution between clean and dirty energy. *Journal of Environmental Economics and Management*, 125, 102982.

Känzig, D.R. (2021) The macroeconomic effects of oil supply news: Evidence from OPEC announcements. *American Economic Review*, 111, 1092-1125.

Känzig, D. R. & Williamson, C.T. (2025) Unraveling the drivers of energy-saving technical change. *NBER Working Paper Series*, No 34511.

Karydas, C., & Zhang, L. (2019). Green tax reform, endogenous innovation and the growth dividend. *Journal of Environmental Economics and Management*, 97, 158-181.

Kemp-Benedict, E. (2018). Investing in a green transition, *Ecological Economics,* 153, 218-236.

Kleibergen, F., & Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, 133, 97–126.

Klump, R., McAdam, P., & Willman, A. (2007). Factor substitution and factor-augmenting technical progress in the United States: a normalized supply-side system approach. *The Review of Economics and Statistics*, 89, 183-192.

Klump, R., McAdam, P., & Willman, A. (2012). The normalized CES production function: theory and empirics. *Journal of Economic surveys*, 26, 769-799

Lanzi, E., & Sue Wing, I. (2010). Directed technical change in the energy sector: an empirical test of induced directed innovation, *Working paper for the Conference on Sustainable Resource Use and Economic Dynamics (SURED 2010).*

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

León-Ledesma, M. A., McAdam, P., & Willman, A. (2015). Production technology estimates and balanced growth. *Oxford Bulletin of Economics and Statistics*, 77, 40-65.

Marin, G., & Vona, F. (2021). The impact of energy prices on socioeconomic and environmental performance: Evidence from French manufacturing establishments, 1997–2015. *European Economic Review,* 135, 103739.

Mattauch, L., Creutzig, F. & Edenhofer, O. (2015). Avoiding carbon lock-in: Policy options for advancing structural change. *Economic Modelling*, 50, 49-63.

Metcalf, G. E., & Stock, J. H. (2020, May). Measuring the macroeconomic impact of carbon taxes. In *AEA papers and Proceedings,* 110, 101-106.

Nemet, G.F. (2009). Interim monitoring of cost dynamics for publicly supported energy technologies. *Energy Policy,* 37, 825-835.

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

Pelli, M. (2012). The elasticity of substitution between clean and dirty inputs in the production of electricity. *Working paper for the Conference on Sustainable Resource Use and Economic Dynamics (SURED 2012)*

Pesaran, M. H. (2007), A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22, 265–312.

Pottier, A., Hourcade, J. C., & Espagne, E. (2014). Modelling the redirection of technical change: The pitfalls of incorporeal visions of the economy. *Energy Economics*, 42, 213-218.

Revankar, N. S. (1971). A class of variable elasticity of substitution production functions. *Econometrica*, 61-71.

Samuelson, P. A. (1947). *Foundations of Economic Analysis.* Harvard University Press.

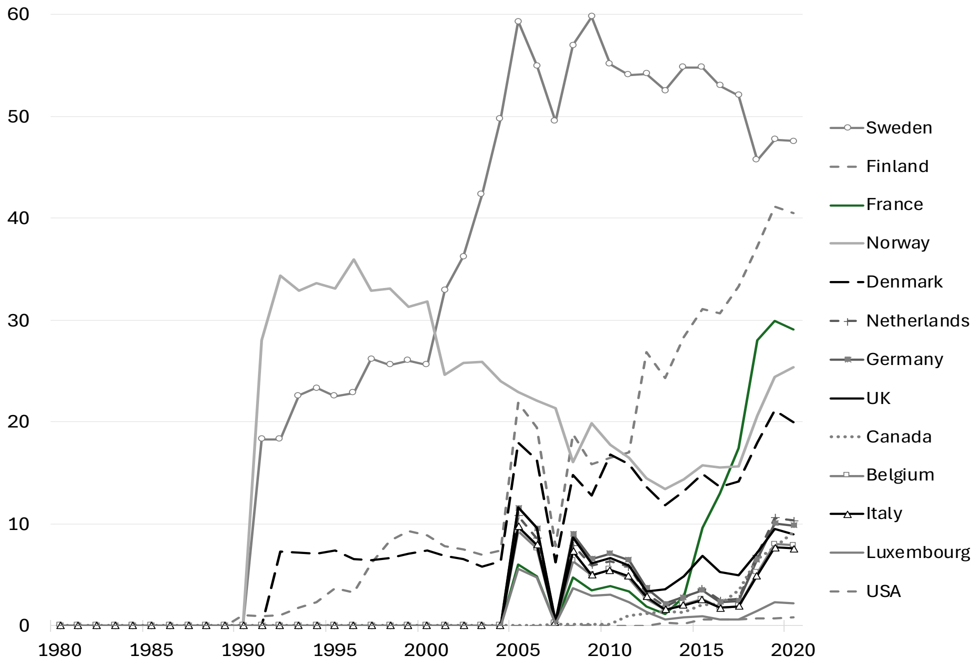
Schwerin, H. (2025). Long-run substitutability between fossil and renewable energy: global evidence 1800–2012. *Empirical Economics*, 69, 129–148.

Stern, D. (2012). Interfuel substitution: a meta-analysis. *Journal of Economic Surveys*, 26, 307-331.

Westmore, B. (2014). Policy incentives for private innovation and maximising the returns. *OECD Journal: Economic Studies*, vol. 2013(1), 121-163.

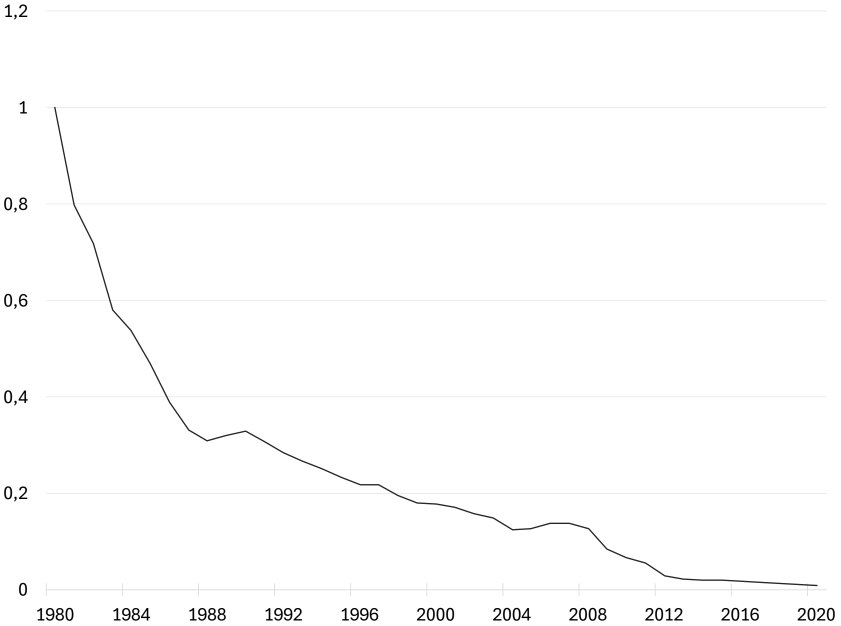
Appendix A: Instrumental variables

Figure A1. Carbon tax rate (real 2015 euros per tonne CO_2).



Source: Dolphin and Xiahou (2022).
Note: Series are organized by decreasing order of carbon tax in 2020.

Figure A2. Index for the global price of solar PV panels (real, per megawatt of capacity, 1980=1).



Source: Our World in Data (https://ourworldindata.org/grapher/solar-pv-prices, global price index).
Note: Multiplication of this index with the country-specific price of clean energy in 1980 generates data per country. We refer to the main text for more details and motivation.

Table A1 - Average energy conversion factor

Fossil fuel	Energy conversion factor
Coal	1 metric tonne = 8141 kWh
Oil	1 barrel = 1700 kWh
Gas	1 million British thermal units = 293 kWh

Source: Energy Education – University of Calgary and Breeze (2015)

Appendix B: Estimated elasticity of substitution – results from alternative specifications and/or adopted instruments

	Within estimation (Table 5, column 2)	Within estimation with country-specific time trends (Table 5, column 3)
Reported result (Table 5)	2.26**	0.30***
Adding common time fixed effects	2.11**	0.83***
Lagging the global solar PV panel price related variable as instrument	2.31***	0.30***
Adding Känzig oil supply news shocks as instrument	1.81***	0.21**
Adding a conflict dummy as instrument	2.14***	0.23***
Adding the lagged real effective exchange rate of the dollar as instrument	2.21***	0.28***

Note: See robustness section in the main text for more details on the alternative specifications or instruments.