Energy Substitution, Biased Technical Change, and the Economy-Wide Energy Rebound: A Normalized CES Estimation for Japan

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This version: August 27, 2026

We estimate an energy-extended Constant Elasticity of Substitution (CES) production function for Japan's aggregate economy to examine how high energy demand and low domestic energy sufficiency shaped supply-side production conditions from 1978 to 2019. Treating energy as an intermediate input and applying the "Normalized Supply-Side System Approach", we find a low elasticity of substitution for energy and a decelerating, time-varying energy-saving bias in technical progress. Our framework also quantifies an economy-wide rebound effect, an often-overlooked obstacle to the reduction of energy use that has rarely been investigated for the case of Japan: on average, 39% of energy efficiency gains over the sample period are offset by a subsequent unintended increase in energy consumption. These results are robust to extensive checks, including grid searches over initial values, alternative nesting structures, bootstrapped errors, addressing endogeneity concerns, and trend-filtering methods. Allowing for smooth technological regime shifts improves the model fit and reveals a sharp reversal toward accelerating energy-saving technical progress after the Fukushima accident in 2011. Yet, the rebound estimate simultaneously increases to nearly 50% in the improved model. Further decomposition of energy inputs into clean and fossil-based components indicates low interfuel substitutability, suggesting a limited flexibility to switch toward a greener energy mix. Overall, our empirical findings indicate that Japan's supply-side structure and its technical progress are insufficient to support sustained energy–growth decoupling in the long run, leaving the economy vulnerable to external energy supply conditions.

JEL: O44; O47; Q41; Q43

Keywords: energy substitution elasticity, energy-saving technical change, economy-wide rebound effect, energy-extended CES function, energy decoupling, energy efficiency

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1 Introduction

In 2023, Japan ranked among the world's five largest consumers of primary energy, with demand of 17.4 exajoules, behind only China, the United States, India, and Russia (Statista, 2023). Yet Japan possesses limited domestic energy resources and has long relied heavily on imported fossil fuels. Between 1978 and 2019, fossil fuel imports accounted for around 89% of its total energy supply on average (IEA, 2022b). A recent series by the Institute of Energy Economics, Japan, reviews the evolution of the country's energy markets and policies, highlighting its persistently low energy self-sufficiency and the central role of energy security in national policymaking (Koyama, 2024a, 2024b, 2024c, 2024d). At the same time, Japan has pledged to achieve carbon neutrality by 2050 and to reduce emissions by 45% by 2030 relative to 2013 levels (Kurachi et al., 2022). These ambitions raise a fundamental question: To what extent are such targets compatible with Japan's underlying production structure and its dependence on energy?

This study examines how Japan's dependence on energy imports and limited domestic energy resources have shaped aggregate production conditions on the supply side between 1978 and 2019. In particular, we investigate Japan's long-run capacity to decouple economic growth from energy consumption. To this end, we estimate an energy-augmented Constant Elasticity of Substitution (CES) production function for the Japanese aggregate economy using the "Normalized Supply-Side System Approach" developed by Klump et al. (2007a).

Our framework identifies three mechanisms governing Japan's long-run energy demand. First, the energy substitution elasticity measures the ease with which energy can be replaced by non-energy inputs. Second, time-varying biased technical change determines whether technological progress reduces or increases energy's relative cost share. Third, the economy-wide rebound effect captures the extent to which potential energy savings from efficiency improvements are offset by induced increases in energy use.

We model Japan's production using an aggregate gross-output function. Unlike previous energy-extended CES studies that employ primary fossil-energy inputs, such as Hassler et al. (2021), we measure energy as an intermediate input using total final energy consumption. Energy therefore enters the production function at the final-consumption stage, where producers purchase it at market prices. This specification brings the analysis closer to actual energy use on the aggregate supply side and enables us, in subsequent robustness analyses, to distinguish between clean and dirty energy components and to exclude unproductive residential household energy consumption from the energy input.

Our baseline results highlight structural constraints on Japan's ability to decouple economic growth from energy demand. Intermediate energy is a gross complement to capital and labor, implying only limited possibilities for substituting non-energy inputs for energy. The estimated energy substitution elasticity is low, at approximately 0.34. At the same time, the energy-saving bias of technical progress decelerates over time, weakening the contribution of technological improvements to reducing energy's cost share. The average economy-wide rebound effect amounts to approximately 39%, indicating that more than one-third of the potential energy savings generated by efficiency improvements are offset by additional energy consumption. Taken together,

low substitutability, decelerating energy-saving technical change, and a substantial rebound effect constrain Japan's ability to reduce long-run energy demand and increase its vulnerability to fluctuations in global energy prices. This finding holds across multiple robustness checks and model extensions.

We follow Chirinko and Mallick (2017) and apply Hodrick-Prescott (HP) and Baxter-King (BK) filters to isolate long-term trends and avoid biases from cyclical fluctuations in the data. The estimated energy substitution elasticity remains low and even declines in the filtered specifications, reinforcing our baseline results and suggesting that Japan's limited capacity to substitute away from energy is a persistent long-run feature.

Two major historical events during our sample period, the bursting of Japan's asset-price bubble in 1991 and the Fukushima Daiichi accident in 2011, may have triggered shifts in the technological regime and thereby induced medium-term changes within the longer-run technological trajectory. Both events were associated with substantial changes in Japan's economic and energy-policy environment. To account for such regime shifts, we introduce breaks in the curvature of the time-varying technology functions and allow for smooth transitions, following Manu et al. (2022). These more flexible specifications improve model fit and yield three main insights. First, the rate of energy-augmenting technical progress declines sharply during the 1990s and, together with weak primary-factor-augmenting technical progress, coincided with Japan's prolonged period of low economic growth, commonly referred to as the lost decade. Second, weak energy-augmenting technical progress during the 2000s generates a temporary shift toward an energy-using bias. Third, Japan returns to a rapidly accelerating energy-saving technological bias in the early 2010s. However, allowing for greater flexibility in technical progress also raises the estimated average rebound effect to around 50%. Thus, approximately half of the potential energy savings generated by efficiency improvements are offset by additional energy use over the sample period. Without measures to mitigate this rebound effect, Japan therefore risks substantially eroding the projected energy savings associated with the improvement in energy efficiency observed after 2011.

The economy-wide rebound effect consequently remains an important obstacle to rapidly decoupling energy demand from economic growth in Japan. Expanding domestic renewable-energy supply could reduce dependence on imported fossil fuels while supporting Japan's long-term emissions targets, even in the presence of a substantial rebound effect. Following Papageorgiou et al. (2017) and Jo (2024), we therefore disaggregate total final energy consumption into non-fossil (clean) and fossil-fuel (dirty) components and investigate both the scope for long-run interfuel substitution and the direction of technical change between clean and dirty energy. Our results indicate that clean and dirty energy sources are gross complements. Consequently, even if clean energy becomes relatively cheaper through carbon pricing or technological progress, it does not readily replace fossil fuels. We further find no significant technical progress biased toward clean energy; instead, the interfuel bias continues to favor fossil-fuel savings. At the same time, fossil-fuel demand remains strongly affected by the rebound effect, thereby weakening both decarbonization efforts and the broader objective of decoupling energy demand from economic growth.

To place the Japan-specific results in a broader context, we replicate the analysis for the United States, a common benchmark in energy-extended CES studies (e.g., Frieling & Madlener, 2017a; Hassler et al., 2021), using the same data sources. Despite the United States' substantially lower average energy-import dependence of 26.8% over the sample period, reflecting its abundant domestic energy resources, the two countries exhibit similar energy substitution elasticities. This similarity suggests that Japan's low elasticity may primarily reflect the prevailing level of technology rather than its particular factor endowments, polices or institutions. Differences between the two countries in the stylized evolution of energy intensity and energy cost shares instead appear to be driven mainly by energy-augmenting-technical progress, which has decelerated considerably more strongly in Japan since the late 1970s.

Finally, we conduct a broad set of additional robustness checks. These include (i) a manual grid search over alternative starting values to ensure that the non-linear estimation algorithm converges to a global solution; (ii) excluding non-productive residential household energy consumption from the total energy input; (iii) testing alternative CES nesting structures; (iv) assessing the precision of the parameter estimates using bootstrapped, resampled standard errors; and (v) addressing potential endogeneity in the baseline specification by estimating a Generalized Method of Moments (GMM) model using lagged variables and a time trend as instruments. All robustness checks support the reliability of our main findings.

The remainder of the paper is structured as follows. Section 2 introduces related literature. Section 3 describes the data and stylized facts of the Japanese aggregate economy. Section 4 presents the CES supply-side system approach and derives the bias in technical progress and the economy-wide rebound equations. Section 5 presents the baseline results, while Section 6 includes a range of robustness checks. Section 7 concludes and presents policy conclusions.

2 Related Literature

Our study is related to various strands of literature. It builds on the literature applying and extending the Normalized Supply-Side System Approach, as introduced by Klump et al. (2007a). This approach estimates a system of simultaneous equations, incorporating all first-order conditions along with the non-linear CES function, and is commonly applied to two-factor CES value-added functions (e.g., Herrendorf et al., 2015; Klump et al., 2007b; León-Ledesma et al., 2010; Manu, 2022; Manu et al., 2022). León-Ledesma et al. (2010) show through Monte Carlo simulations that the system approach outperforms single-equation estimations in simultaneously identifying factor-augmenting technical progress and the substitution elasticity. Diamond et al. (1978) assert that a non-unity substitution elasticity and biased technical change cannot be identified simultaneously, a result known as the "impossibility theorem" (León-Ledesma et al., 2010, p.1331). León-Ledesma et al. (2010) also stress the importance of normalization. Theoretically, normalization enables the economic interpretation of parameters by anchoring the elasticity of substitution, defined as a point elasticity, at benchmark values for output, inputs, and the marginal rate of substitution. Without it, CES functions are scale-dependent and potentially circular functions of the substitution elasticity itself, as demonstrated by de La Grandville and Klump (2000), rendering the results less robust.

Since these traditional two-factor CES functions investigate only the primary factor relationship for the value-added production, they miss an open economy's dependence on imports of intermediate energy resources. The efficiency and relative price of intermediate energy inputs can affect the use and productivity of primary factors and thus be a source of overall productivity and economic growth (Cobbold, 2003).[1]

A sub-category of CES studies extends the basic primary factor model by incorporating energy input as a third factor. These studies focus primarily on the elasticity of substitution between energy and capital or, more generally, between energy and primary factors. While numerous empirical studies use short-term industrial cross-sectional or panel data to inform calibrated climate-economy models (e.g., Antoszewski, 2019; Baccianti, 2013; Henningsen et al., 2019; Kemfert & Welsch, 2000; van der Werf, 2008), fewer focus on long-term country-level time series. The evidence is still mixed, but especially the long-term studies point to a complementary and hence limiting relationship that energy imposes on primary factors. Lagomarsino (2020) provides a recent review of the empirical work in this context. Stern and Kander (2012), as well as Kander and Stern (2014), apply a CES framework to 200 years of Swedish data. Their model features biased but exogenous technical progress and employs a gross output function that incorporates energy costs into GDP, allowing for consistent treatment of energy as both a final and intermediate input. They find that energy-augmenting technical progress slowed after 1900 and nearly halted after 1950. The long-term energy substitution elasticity in Sweden is below unity, with values of 0.65 and 0.69 according to the study. Inspired by Acemoglu et al. (2012), who incorporate the exhaustibility of resources in a model of directed technical change, Hassler et al. (2021), and later Hassler et al. (2022), develop an empirical energy-extended CES model for the United States (1949–2018), where technical change is biased and endogenously driven by R&D investments. They highlight the role of energy as a scarce resource for economic growth, reflected by the empirical finding of a near-zero substitution elasticity between energy and non-energy inputs. Energy and non-energy inputs are almost perfect complements. Since the 1970s, technical change has focused on saving energy to overcome the constraints imposed by energy and in response to rising fossil fuel prices, particularly during the oil crisis. The low energy substitution elasticity in Hassler et al. (2021, 2022) is explained by the estimation technique, which is based on fossil fuel price shocks. Despite the long period under investigation, the authors interpret the estimated energy substitution elasticity as a short-term parameter. This highlights the context dependence of estimated CES parameters. The country case, historical context, and length of the time series are important factors that CES researchers should consider when

[1] In a recent value-added CES study, Herrendorf et al. (2015) acknowledge that "[w]hile [...] often abstracted from, [intermediate inputs] can be quantitatively important, in particular in small open economies that import most of the resources and many of the agricultural and manufactured intermediate goods that they use." (p. 108). Following Herrendorf et al. (2015) two assumptions must be met for the "value-added" concept to be in line with the characteristics of the data. First, the share of intermediate inputs in gross output is constant over time. Second, primary and intermediate inputs explain gross output in a Cobb-Douglas type function. In other words, the substitution elasticity between energy and the composite input is at unity. Several empirical studies have already demonstrated that the energy cost share exhibits a long-term decreasing trend across multiple countries (Csereklyei et al., 2016; Kander & Stern, 2014; Smulders & de Nooij, 2003; Stern & Kander, 2012). Based on the stylized facts in our study, we can confirm that the countries under investigation over the period 1978-2019 exhibit a non-constant and declining energy cost share. Our empirical results provide an ex-post justification for the gross output CES, as we can also reject the second assumption of a unity substitution elasticity.

interpreting the empirical parameters. This calls for further CES studies, such as ours, that not only provide new country evidence, as seen in the case of Japan, but also situate themselves in the timely context by explicitly normalizing the production function and defining a baseline technology level.

A working paper series by Frieling and Madlener (2016, 2017a, 2017b) applies the basic principles of Klump et al.'s (2007a) estimation approach to an energy-extended CES function for the countries of Germany, the United States, and the United Kingdom. These papers are therefore closely related to our empirical baseline setup. Aside from focusing on a different country, our study's methodology goes several steps beyond the series to capture energy's actual properties for the aggregate production process, including modifying the output measure (see Berndt et al., 1993; Stern & Kander, 2012) to aggregate gross output and hence incorporating final energy as an intermediate input or assuming time-varying technical progress to capture a more realistic energy efficiency trend over time. As pointed out by Meran (2019), one would expect, according to the second law of thermodynamics, that energy-augmenting technical progress cannot grow at a constant rate but must eventually reach an upper bound. Moreover, we adopt recent developments on the CES normalization procedure and incorporate a range of state-of-the-art advancements within the empirical CES literature as additional robustness checks (see Section 6). Furthermore, in contrast to Frieling and Madlener (2016, 2017a, 2017b), our study investigates not only the empirical energy substitution elasticity but also the bias in technical progress and addresses the empirical economy-wide rebound effect. In doing so, we position our study within two distinct strands of research in the field of energy economics.

The first strand examines biased or directed technical change, such as Aghion et al. (2016), Inoue et al. (2022), and Popp (2002, 2019). Popp (2019) provides a review. We are aware of only one empirical study that examines the energy bias in technical progress within the Japanese context. Fukunaga and Osada (2009) apply a Translog production function to investigate the energy bias over time. This early contribution only covered data up to 2008. The authors identify an energy bias that persists until the end of their sample, characterized by energy use. However, despite rising global energy prices during the 2000s, they find no evidence of a switch to energy-saving technical progress. Our study extends the investigation period up to 2019 and confirms the earlier study's finding that there is indeed no regime switch in technology before the Fukushima accident in 2011 (see Section 6.2).

The second strand includes empirical studies dedicated to a paradox first described by Jevons (1865) in the context of coal production reveal that greater steam engine efficiency reduced coal use per unit of output. Yet, total coal consumption increased due to expanded production (see Klitgaard, 2022). There must be a counteracting mechanism, which is subsumed in what is today known as the energy rebound effect, that erodes the energy-saving effect of technical progress. The sum of all direct and indirect mechanisms offsetting energy savings at an aggregate economy level is defined as the economy-wide rebound (Brockway et al., 2017b). A large economy-wide rebound effect implies that energy use and economic growth may remain closely linked, even if technical progress is energy-saving. Brockway et al. (2021) conduct a meta-study encompassing 33 empirical studies, 21 of which used CGE (Computable General Equilibrium) models and 12

employed other macroeconomic or econometric approaches, similar to those used in our study. Their findings suggest that, on average, at least half of potential energy savings are lost to rebound effects. Still, there is considerable uncertainty regarding the empirical magnitude of the economy-wide rebound effect. Saunders et al. (2021) summarize 40 years of energy efficiency research, noting persistent uncertainty in measuring rebound effects and concluding that they may significantly offset energy savings. Reviews by York et al. (2022), Stern (2020), Colmenares et al. (2020) and Madlener and Turner (2016) concur that there is a wide variation in rebound estimates across methods, countries, and time frames.

We recognize the need for further empirical investigations of the economy-wide rebound effect, especially in the context of our country case, Japan, where empirical evidence for the economy-wide rebound effect is scarce thus far. Existing evidence for Japan is largely limited to multi-country studies dedicated to investigating the economy-wide rebound (see e.g. Adetutu et al., 2016; Wei et al., 2019). Saunders (2008) is the first to demonstrate analytically how CES production parameters can be used to quantify the energy rebound effect. He finds that the (KL)E nesting structure, where capital and labor are grouped separately from energy, is the most "rebound flexible," capable of capturing a full range of positive rebound outcomes. Other nesting structures often imply automatic backfire, resulting in a rebound of over 100%. Crucially, the elasticity of substitution between energy and non-energy inputs determines the rebound magnitude: the more easily inputs can be substituted, the larger the rebound, as the economy can more flexibly respond to energy efficiency improvements and relative price changes. In advanced economies, the rebound from output expansion is relatively modest due to energy's comparatively small share of costs. Three empirical studies, Brockway et al. (2017b)[2], Zhang and Lin Lawell (2017), as well as Ullah and Khan (2022), follow Saunders' (2008) CES-based rebound framework for a set of multiple countries. However, none of these studies are able to identify precise CES parameter estimates, which is most likely related to the papers' statistically weak single-equation approach, as noted by Henningsen and Henningsen (2011). The confidence interval for the energy substitution elasticity is large, and the estimated economy-wide rebound effect exhibits a wide range, indicating high uncertainty in its actual magnitude. Additionally, the mentioned empirical CES-based rebound studies focus on the energy substitution elasticity but do not aim to simultaneously identify the empirical energy-augmenting technical progress, which is an essential factor in the economy-wide rebound effect. Instead, the authors abstract from the energy-related technology parameter by normalizing it to unity (Ullah & Khan, 2022; Zhang & Lin Lawell, 2017) or zero (Brockway et al., 2017b). Sorrell (2014) highlights the limited empirical evidence on the direction of energy-biased technical change, which limits the reliable estimation of rebound effects in CES studies. Since our methodological approach enables the identification of precise estimates of the energy substitution elasticity, as well as time-varying factor-augmenting technical progress functions that determine the technological bias, our study advances the technique and the reliability of the CES-based economy-wide rebound estimation.

[2]In a subsidiary paper, Brockway et al. (2017a) assemble the various empirical model specifications CES econometricians have a priori to consider (or test) and provide recommendations. Heun et al. (2017) demonstrate the challenges of CES estimations and show the divergent policy implications these a priori choices can result in.

3 Data & Stylized Facts

Our data for output, capital and labor are taken from the Penn World Tables, PWT (2023), version 10.01. Output is measured as real GDP at constant 2017 national prices (in millions of 2017 US dollars). The capital stock is measured at constant 2017 national prices (in millions of 2017 US dollars). Labor is measured in millions of total hours worked, calculated as the product of engaged persons and average annual working hours. The output deflator is calculated by dividing nominal GDP (in millions of US dollars) by real GDP (in millions of 2017 US dollars). PWT measures the labor share in GDP, which we use to calculate labor compensation. The choice of data sources in this study enables a consistent comparison of Japan's supply-side characteristics with those of other industrialized countries, such as the US, below.

The IEA (2022b) World Energy Balances provides data on final energy consumption.[3] We are interested in the productive use of final energy for goods and services. Data on final energy consumption is disaggregated in different carriers, including coal, oil products, electricity, natural gas, renewables & waste, and heat. The sum of all carriers is our total final energy consumption measure. The IEA (2022a) Energy Prices and Taxes database hosts data for final energy prices for three sectors: industry, energy generation, and households. Here, we use industry prices for the construction of a "productive" aggregate final energy price based on the aggregate supply-side. The price data is available for different energy carriers. We follow Sato et al. (2019) and Schulte et al. (2016) in calculating the final energy price as a weighted average of carrier prices. The weight is defined by each carrier's share of total energy use at the aggregate level of the economy. We use prices in nominal US$ to apply the same PWT deflator corresponding to the other non-energy factor prices. The IEA (2022b) World Energy Balances provides data on final energy consumption.[4] We are interested in the productive use of final energy for goods and services. Data on final energy consumption is disaggregated in different carriers, including coal, oil products, electricity, natural gas, renewables & waste, and heat. The sum of all carriers is our total final energy consumption measure. The IEA (2022a) Energy Prices and Taxes database hosts data for final energy prices for three sectors: industry, energy generation, and households. Here, we use industry prices for the construction of a "productive" aggregate final energy price based on the aggregate supply-side. The price data is available for different energy carriers. We follow Sato et al. (2019) and Schulte et al. (2016) in calculating the final energy price as a weighted average of carrier prices. The weight is defined by each carrier's share of total energy use at the aggregate level of the economy. We use prices in nominal US$ to apply the same PWT deflator corresponding to the other non-energy factor prices. To match energy consumption by carrier with the corresponding price data, final coal consumption is valued using steam coal

[3] We deliberately do not adjust energy input for its quality, neither physically (see e.g. Brockway et al., 2017b, who use exergy data) nor economically (via Divisia indexation as applied by Stern and Kander, 2012) as this conflicts with the estimated factor augmenting technical parameters. Since the interpretation of technology parameters is a key focus of this study, our objective is to capture both embodied and disembodied technical change in our estimates.

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prices, crude oil and oil products using light fuel oil prices, electricity and heat using electricity prices, and natural gas using natural gas prices.

We drop the category renewables & waste. This category has a comparatively small weight in the total final energy consumption (2.4% in 2019) and is a heterogeneous mixture of renewable sources for which no matching price categories exist. Weights of the remaining carrier types are adjusted to sum to one accordingly. With the complete series of energy prices, we compute a fixed-weight energy price index, which holds the weights constant and mitigates potential endogenous interrelations between quantities and prices. To account for trends in the price series, we use a geometric average of the carrier share as a fixed weight. Our final sample spans the period from 1978 to 2019, thereby excluding the exceptional disruptions associated with the COVID-19 pandemic from 2020 onward.

We follow Berndt et al. (1993) and Stern and Kander (2012) in modifying the economic output measure to "gross output" Y by adding final energy costs (as product of the real final energy prices P_E and final energy quantities E) to GDP, each in year t. The measure is not intended to reconstruct national-accounts gross output; rather, it restores consistency between an energy-augmented production function and an output concept that does not net out the intermediate input explicitly included in the production function.

$$Y_t = GDP_t + P_{E,t}E_t \tag{1}$$

We normalize our data to index-based values. Hence, our input and output data are no longer scale-dependent. A switch from GDP to gross output will affect parameter estimates only if the index-based values deviate from each other. Fitted parameters will not change if gross output is only different from GDP by a constant multiplicative factor. We will return to the advantages of CES normalization in the methodology section(Brockway et al., 2017a).

Based on the income approach and the modified output measure, we can now adjust factor income shares by the value of intermediate energy costs. We use the labor share data provided by PWT (2023) to calculate real labor compensation, denoted as $COMP$. The modified labor share $s_{L,t}$ is hence:

$$s_{L,t} = \frac{COMP_t}{Y_t} \tag{2}$$

The final energy share in gross output s_E is given by:

$$s_{E,t} = \frac{p_{E,t}E_t}{Y_t} \tag{3}$$

Following the standard income approach, the modified capital share is calculated as a residual in total gross output value:

$$s_{K,t} = 1 - s_{L,t} - s_{E,t} \tag{4}$$

Figure 1 presents key stylized facts for Japan over the sample period. Plot (a) shows the modified gross output and GDP indexed to 1. Plot (b) illustrates the cost shares of capital, labor, and energy in gross production. Plot (c) zooms in on energy's cost share to highlight its fluctuations,

while plot (d) breaks down the energy share into fossil (non-electric) and non-fossil (electric) components.

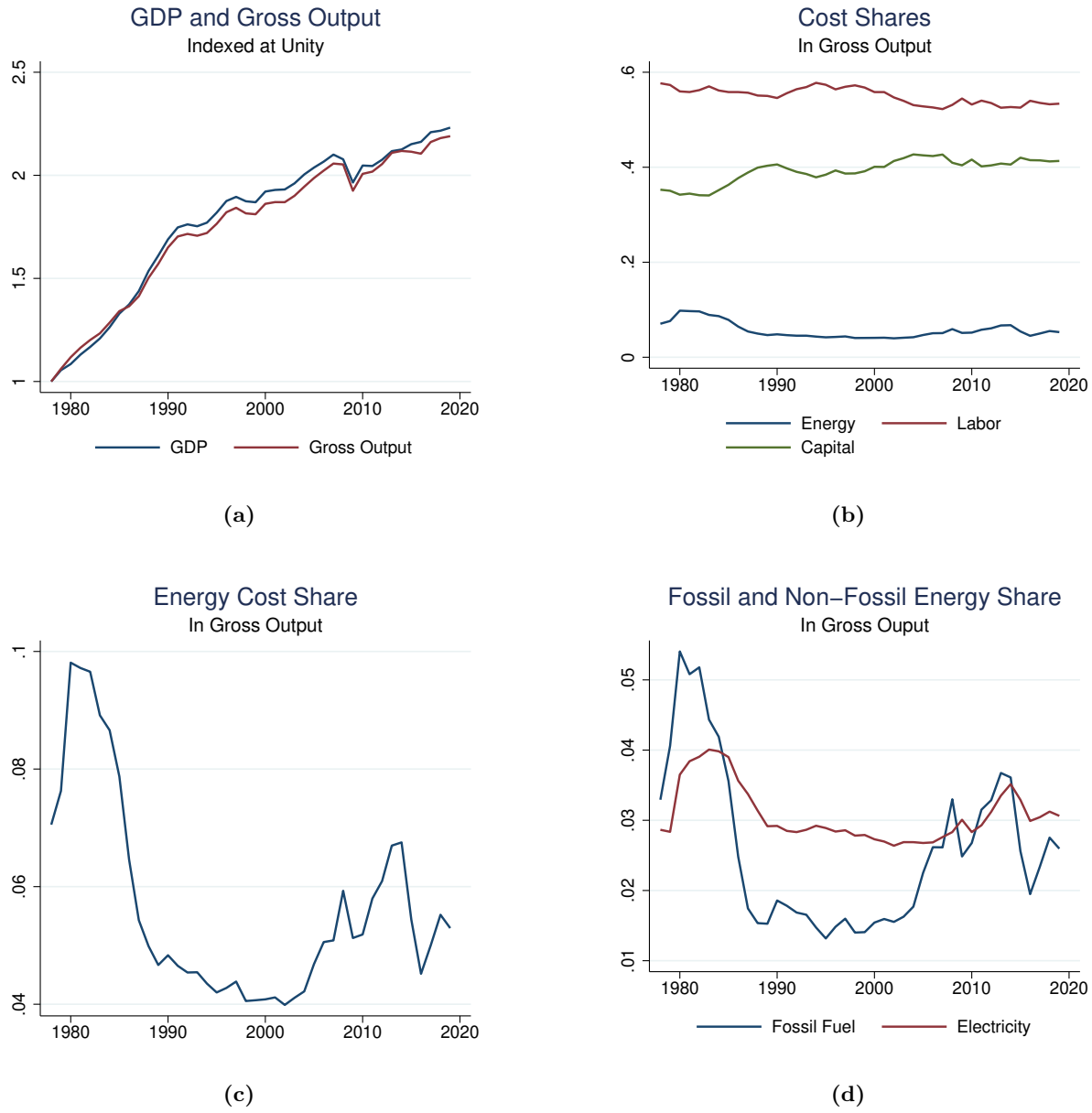


Fig. 1: GDP, Gross Output and Factor Shares. Note: The figure shows the stylized facts in Japan from 1978 to 2019. Plot (a) illustrates GDP and modified gross output (GDP plus energy costs), each indexed at unity. Plots (b), (c), and (d) show the cost shares of production factors in modified output. *Source:* PWT (2023), IEA (2022a) Energy Prices, IEA (2022b) World Energy Balances, and own calculations.

Gross output and GDP move closely together, although gross output tends to grow more rapidly during periods of rising energy costs and more closely approximates value added when energy costs are low. Throughout the sample period, the energy cost share remains small relative to those of capital and labor. Nevertheless, as the analysis later demonstrates, energy plays an important complementary and constraining role in shaping the marginal productivity of the primary inputs.

Japan's economy expanded steadily until the late 1980s before entering a prolonged period of

weak growth following the collapse of the asset-price bubble in 1991. This period, commonly referred to as the "lost decade," extended into the early 2000s. Over the sample period, the energy cost share exhibits a U-shaped pattern. It peaked during the second oil crisis in the late 1970s, declined sharply throughout the 1980s, and remained low during the 1990s. From the early 2000s onward, it rose again, driven by increases in global fossil-fuel prices associated with the United States' invasion of Iraq, concerns about peak oil, and rising demand from emerging markets such as China. Despite this increase, the energy cost share did not return to the levels observed in the 1970s.

The disaggregated energy cost shares show that fossil fuels largely drive the overall dynamics of the energy sector. The electricity share follows a broadly similar pattern but is more stable, remaining close to 3%. Following the 2011 Fukushima disaster and the subsequent shutdown of nuclear power plants, Japan once again became heavily dependent on fossil-fuel imports. After a temporary decline in the late 2000s, the fossil-fuel cost share increased steadily after 2011. A similar, though less pronounced, increase is also visible in the electricity cost share.

4 Methodology

4.1 Modeling an Energy-Extended CES Function

We model final energy as an intermediate input entering a gross output function. We, therefore, estimate an energy-extended CES function with factor-augmenting technology. Assuming constant returns to scale, our baseline CES function takes the following functional form:

$$\frac{Y_t}{Y_0} = \left[(1-\alpha_0) \left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}} \frac{N_t}{N_0} \right)^{\frac{\sigma-1}{\sigma}} + \alpha_0 \left(\frac{\Gamma_{E,t}}{\Gamma_{E,0}} \frac{E_t}{E_0} \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{5}$$

Where gross output Y over time t is explained by the intermediate final energy input in production E_t and the non-energy primary inputs N_t. We keep the notion N_t for simplicity in the following section. For the empirical estimation, we will assume that N_t constitutes a composite input of capital and labor that can take different functional forms. The capital-labor combination is nested within the CES function. Separating capital and labor from intermediate energy follows the separability assumption that the primary factors, combined as a composite, are enabled together by intermediate energy. Still, the combination of primary factors in producing value-added itself is independent of the energy input.

Factor-specific technical progress for non-energy and energy is captured in parameters $\Gamma_{N,t}$ and $\Gamma_{E,t}$, respectively. Note that we assume the technical progress related to the non-energy primary inputs is Hicks-neutral. This assumption facilitates the direct interpretation of the bias in technical progress by comparing the factor-specific technical progress rates related to energy with those of the primary factors.

All variables and parameters are normalized to their baseline values, denoted by the subscript 0. The parameter α_0 represents the normalized distributional weight of energy in the production function. The parameter $\sigma \in [0, \infty)$ denotes the Hicks elasticity of substitution between energy

and the non-energy composite, hereafter referred to as the energy substitution elasticity. It measures the percentage change in factor proportions induced by a one-percent change in the marginal rate of technical substitution, or equivalently in the factor price ratio. Energy and non-energy inputs are gross substitutes when $\sigma > 1$ and gross complements when $\sigma < 1$ (see Acemoglu, 2002; Acemoglu et al., 2012). Meran (2019) discusses the consistency of CES production functions with the physical laws governing energy use, arguing that "[t]hermodynamic limits of production must enter climate policy models by a priori constraints that are derived from physical laws" (p. 64). In economic terms, this implies that producing a positive level of output always requires a positive amount of energy. If production is impossible at zero energy input, energy and the remaining production factors should be gross complements, implying an elasticity of substitution below unity, while energy-augmenting technical progress should be non-linear or bounded from above.

We normalize the production function in line with the extensive empirical literature on conventional CES estimation (see Section 2). For all trending variables, including factor quantities and output, we use the geometric mean as the normalization baseline. The corresponding reference point in time is given by the arithmetic mean of the sample period, which allows the technological parameters to be interpreted meaningfully as average rates of technical progress around the "normal" technological level. Normalization at sample averages also provides an important econometric advantage: under the so-called Cost-Share Theorem, the distributional factor weights can be calibrated directly using average factor cost shares. This reduces the number of freely estimated parameters and thereby facilitates identification of the factor-augmenting technical-progress parameters and the substitution elasticity.

For the factor cost shares, we follow Herrendorf et al. (2015), who recommend using the geometric mean. This choice is particularly relevant in our setting because the stylized facts for both countries reveal a persistent decline in the energy cost share over time, implying a corresponding increase in the relative importance of primary factors throughout the sample period. Using the geometric mean allows this systematic shift in factor weights to be reflected appropriately in the normalized production function.

4.2 Time-Varying Energy-Saving Bias in Technical Progress

Sorrell (2014) emphasizes that energy-augmenting technical progress is not inherently energy-saving. Depending on the substitution elasticity and the augmentation of other non-energy inputs, the relative augmentation of energy can be either saving or using, in terms of energy's share in economic costs. We investigate the direction of biased technical progress affecting energy's marginal productivity and relative cost share. If factors are paid their marginal product, the relative energy cost share is defined (see León-Ledesma et al., 2010, pp. 1333 ff.) as:

$$\Theta = \frac{s_{E,t}}{1 - s_{E,t}} = \frac{\alpha_0}{1 - \alpha_0} \left[\left(\frac{E_t / E_0}{N_t / N_0} \right) \left(\frac{\Gamma_{E,t} / \Gamma_{E,0}}{\Gamma_{N,t} / \Gamma_{N,0}} \right) \right]^{\frac{\sigma - 1}{\sigma}} \tag{6}$$

If $\Gamma_{E,t}$ grows faster than $\Gamma_{N,t}$, technical progress is relatively energy-augmenting. The effect of relative energy-augmenting technical progress on its relative share in output is given via the first

derivative:

$$\frac{\partial \Theta}{\partial \left(\frac{\Gamma_{E,t}/\Gamma_{E,0}}{\Gamma_{N,t}/\Gamma_{N,0}}\right)} = \frac{\sigma-1}{\sigma}\frac{\alpha_0}{1-\alpha_0}\left(\frac{E_t/E_0}{N_t/N_0}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{\Gamma_{E,t}/\Gamma_{E,0}}{\Gamma_{N,t}/\Gamma_{N,0}}\right)^{-\frac{1}{\sigma}} \tag{7}$$

Relative energy-augmenting technical progress will be relatively energy-saving (energy-using) and non-energy input using (non-energy input saving) in Hicks' sense if the elasticity of substitution is lower (higher) than one, $\sigma < 1 (\sigma > 1)$. In other words, relative energy-augmentation is biased towards energy, in terms of lowering its relative share, only if $\sigma < 1$. The endogenous theory of directed technical change developed by Acemoglu et al. (2012) describes that the bias of technical progress responds to two opposing mechanisms. The market size effect stimulates technical change that uses cheaper and more abundant inputs, while the price effect spurs the development of technologies that favor the more expensive input. Which effect dominates is determined by the elasticity of substitution between the two inputs.

$$\frac{\partial\left(\frac{s_{E,t}}{1-s_{E,t}}\right)}{\partial\left(\frac{\Gamma_{E,t}/\Gamma_{E,0}}{\Gamma_{N,t}/\Gamma_{N,0}}\right)} \begin{cases} < 0 & \text{for } \sigma < 1 \\ = 0 & \text{for } \sigma = 1 \\ > 0 & \text{for } \sigma > 1 \end{cases} \tag{8}$$

Assuming $\Gamma_{E,t}$ grows with rate g_E and $\Gamma_{N,t}$ with g_N over time, then – depending on $\sigma < 1$ or $\sigma > 1$ – we can define the direction of biased technical progress by:

$$g_E(t) - g_N(t) \begin{cases} < 0 \\ > 0 \end{cases} \tag{9}$$

The bias in technical change may not follow a constant trend. To account for potential thermodynamic constraints, we model both technology parameters with a time-varying progress rate following Box and Cox (1964) and the examples in other CES production function estimations (e.g., Klump et al., 2007a, 2007b; Manu, 2022; Manu et al., 2022; Serrano-Quintero, 2023). The Box-Cox transformation relaxes the constraint of constant growth rates by introducing an additional curvature parameter, allowing for a more flexible representation of data. The curvature parameter captures the pace of technical progress, allowing for the investigation of a time-varying trend in technology. The technical progress $\Gamma_{i,t}$ is then measured at the normalization point with a time-varying average growth rate:

$$\frac{\Gamma_{i,t}}{\Gamma_{i,0}} = e^{g_i(t)} \quad \text{with} \quad g_i(t) = \frac{\gamma_i}{\eta_i} t_0 \left(\left(\frac{t}{t_0}\right)^{\eta_i} - 1\right) \tag{10}$$

where $i \in (N, E)$ defines one or more production factors for which the technical progress rate is augmenting. Due to the normalization, we can interpret γ_i as technical progress rates at the baseline point. Parameter η_i is a curvature parameter that captures the shape of the technology function. For $\eta_i = 1$, the function delivers constant (linear) growth rates. $\eta_i > 1$ captures accelerating technical change, and the two specifications $\eta_i = 0$ (log-linear) and $\eta_i < 0$ (hyperbolic)

stand for decelerating technical progress that is bounded from above.

$$\frac{\partial g_i(t)}{\partial t} = \gamma_i \left(\frac{t}{t_0}\right)^{\eta_i - 1} = \begin{cases} \to \infty, & \text{for } \eta_i > 1 \text{ and } t \to \infty; \quad \textit{accelerating} \\ \gamma_i, & \text{for } \eta_i = 1; \quad \textit{constant} \\ \to 0, & \text{for } \eta_i < 1 \text{ and } t \to \infty; \quad \textit{decelerating} \end{cases} \tag{11}$$

4.3 Economy-Wide Rebound Derivation

Next, we introduce equations to calculate the economy-wide rebound R. Following Saunders (2008), it is defined by the (here normalized) elasticity of energy consumption as a response to energy-augmenting technical progress:

$$R_t = 1 + \frac{\Gamma_{E,t}/\Gamma_{E,0}}{E_t/E_0} \frac{\partial E_t/E_0}{\partial \Gamma_{E,t}/\Gamma_{E,0}} \tag{12}$$

Energy-augmenting technical progress may reduce the relative price of energy, inducing substitution toward energy-intensive production. At the same time, lower effective energy costs can increase output and thereby raise energy demand. The economy-wide rebound effect can therefore be decomposed into the sum of a total substitution effect, π_s, and a total output effect, π_o. Assuming

$$\frac{E_t}{E_0} \equiv \frac{E_t/E_0}{Y_t/Y_0} \frac{Y_t}{Y_0} \tag{13}$$

the rebound effect can be decomposed into the substitution (intensity) effect and the output effect:

$$R_t = 1 + \pi_{s,t} + \pi_{o,t} \tag{14}$$

Where the intensity effect is

$$\pi_{s,t} = \frac{\Gamma_{E,t}/\Gamma_{E,0}}{(\frac{E_t/E_0}{Y_t/Y_0})} \frac{\partial(\frac{E_t/E_0}{Y_t/Y_0})}{\partial(\Gamma_{E,t}/\Gamma_{E,0})} \tag{15}$$

and the output effect is

$$\pi_{o,t} = \frac{\Gamma_{E,t}/\Gamma_{E,0}}{Y_t/Y_0} \frac{\partial(Y_t/Y_0)}{\partial(\Gamma_{E,t}/\Gamma_{E,0})} \tag{16}$$

Appendix A shows the detailed derivation of $\pi_{s,t}$ and $\pi_{o,t}$. The intensity effect requires the optimal condition from which we can derive the energy demand function. It can be derived as a function of the substitution elasticity between energy and the non-energy input.

$$\pi_{s,t} = \sigma - 1 \tag{17}$$

By construction of the CES production function, the substitution effect is constant over time. In the empirical estimation below, we therefore define it as the average of the annual energy substitution effects over the sample period. Sorrell (2014) emphasize the importance of this parameter for the magnitude of the rebound effect. The greater the ease of substitution, the larger the rebound effect, because the economy can adjust more flexibly to changes in energy

efficiency and relative energy prices. Given our theoretical CES production function with N and E as input factors, the output effect can be derived as

$$\pi_{o,t} = \frac{\alpha_0 \left(\frac{\Gamma_{E,t}}{\Gamma_{E,0}} \frac{E_t}{E_0}\right)^{\frac{\sigma-1}{\sigma}}}{(1-\alpha_0)\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}} \frac{N_t}{N_0}\right)^{\frac{\sigma-1}{\sigma}} + \alpha_0 \left(\frac{\Gamma_{E,t}}{\Gamma_{E,0}} \frac{E_t}{E_0}\right)^{\frac{\sigma-1}{\sigma}}} \tag{18}$$

The output effect over time is hence a function of the effective energy input in year t, weighted by its output elasticity and relative to a weighted sum of all effective factor inputs. The level effect of the constant energy substitution elasticity and the time-varying output effect determine the economy-wide rebound over time:

$$R_t = 1 + \pi_{s,t} + \pi_{o,t} = \sigma + \frac{\alpha_0 \left(\frac{\Gamma_{E,t}}{\Gamma_{E,0}} \frac{E_t}{E_0}\right)^{\frac{\sigma-1}{\sigma}}}{(1-\alpha_0)\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}} \frac{N_t}{N_0}\right)^{\frac{\sigma-1}{\sigma}} + \alpha_0 \left(\frac{\Gamma_{E,t}}{\Gamma_{E,0}} \frac{E_t}{E_0}\right)^{\frac{\sigma-1}{\sigma}}} \tag{19}$$

A key advantage of our estimation approach is that it jointly identifies the substitution elasticity, σ, and time-varying factor-augmenting technology functions. This allows us to calculate the time-dependent economy-wide rebound effect directly from the estimated CES parameters.[5]

In the empirical analysis below, we replace the theoretical non-energy input N with a functional form describing the relationship between the primary factors, capital and labor, nested within the energy-extended CES function. In principle, this inner nest may take different functional forms. Here, we assume a CES relationship between capital and labor. Accordingly, when calculating the empirical output effect, N is replaced by the nested primary-factor composite introduced in the following section.

A further useful feature of the normalized CES framework concerns the choice of the normalization point. We define the baseline technology level at the sample averages. By construction, the normalized CES function is independent of the substitution elasticity σ at this normalization point, because the terms inside the brackets of Eq. (5) equal unity. Consequently, the output effect evaluated at the normalization point (that is, at the average technology level) reduces to the normalized distributional weight of energy, α_0, which corresponds to the average energy cost share.

$$\bar{\pi}_o = \frac{\alpha_0}{(1-\alpha_0)+\alpha_0} = \alpha_0 \tag{20}$$

The average economy-wide rebound (i.e., at the normalization point) is hence the sum of energy substitution elasticity and the output elasticity. We estimate the former and insert the latter directly from the data as the average of the energy cost share.

$$\bar{R} = 1 + \bar{\pi}_s + \bar{\pi}_o = \sigma + \alpha_0 \tag{21}$$

[5]While straightforward, this direct approach may overlook second-order output effects arising from changes in the composition of effective primary factors induced by improvements in energy efficiency. Using the Implicit Function Theorem (IFT), Saunders (2008) derives an output effect that accounts for more complex interactions between the energy-augmenting technical parameter and the non-energy components of production.

4.4 Empirical Estimation Approach

We incorporate the primary factors, capital and labor, in empirical form for the non-energy input N. Capital K and labor L constitute a composite input in the inner nest of a two-stage nested CES function. There is no a priori justification to assume capital and labor exhibit a substitution elasticity of unity. Instead, we assume a CES-in-CES structure following Brockway et al. (2017b), Frieling and Madlener (2016, 2017a, 2017b), and Heun et al. (2017). Various empirical analyses in the context of conventional two-factor CES functions have shown that the elasticity of substitution between capital and labor is below unity, especially in the case of United States data (see Knoblach et al., 2020, for a meta-study and Klump et al., 2012, for a survey). Therefore, we model the composite input in the inner nest as a CES function. We maintain the assumption of neutral technical progress, augmenting the comprehensive composite input, which enables a direct interpretation of biased technical change between the intermediate and primary inputs.

$$\frac{N_t}{N_0} = \left(\beta_0 \left(\frac{K_t}{K_0} \right)^{\frac{\lambda-1}{\lambda}} + (1-\beta_0) \left(\frac{L_t}{L_0} \right)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}} \tag{22}$$

Consequently, we estimate a gross-output CES function of the (KL)E structure. It aligns with most climate economic models for policymaking and assumes that the capital-labor relationship is separable from the intermediate energy input. Furthermore, as Saunders (2008) shows in an investigation of various energy-extended production functions, the (KL)E structure is the most "rebound-flexible." Taking logs and including error terms ϵ_Y, our empirical CES model takes the following form:

$$\ln\left(\frac{Y_t}{Y_0}\right) = \ln(\zeta) + \frac{\sigma}{\sigma-1} \ln\left[(1-\alpha_0) \left(\beta_0 \left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}} \frac{K_t}{K_0} \right)^{\frac{\lambda-1}{\lambda}} + (1-\beta_0) \left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}} \frac{L_t}{L_0} \right)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda(\sigma-1)}{\sigma(\lambda-1)}} + \alpha_0 \left(\frac{\Gamma_{E,t}}{\Gamma_{E,0}} \frac{E_t}{E_0} \right)^{\frac{\sigma-1}{\sigma}} \right] + \varepsilon_Y \tag{23}$$

Parameter $\lambda \in [0, \infty)$ captures the substitution elasticity between capital and labor. Subscripts 0 indicate the values of respective variables at the point of normalization. Parameter $\alpha_0 \in (0,1)$ is the distribution parameter for the energy input at the normalization point. Parameter $\beta_0 \in (0,1)$ defines the distributional weight of capital at the normalization point within the inner nest. $\Gamma_{N,t}$ is hence composite-augmenting technical progress.

Due to the data's stochastic nature and the production function's non-linearity, an additional factor must be introduced with $E[\zeta] = 1$ (Klump et al., 2007b). It captures and mitigates the scaling problem that can arise from independently measuring the geometric average for output and input. Due to the non-linearity of a CES production function, the normalization point of output may not coincide with the geometric averages of input variables (this would always be the case in a linear Cobb-Douglas function). Therefore, $\zeta \neq 1$ takes up the non-linear deviation of the CES function of its nested log form $\zeta = 1$ at the fixed point of normalization.

We assume perfect markets for goods and factors. Firms minimize costs given the real gross

output Y_t, the price of output $p_{Y,t}$, and the prices (rental rates) for production factors for capital, labor, and final energy, respectively.

$$\min_{K_t,L_t,E_t} \; r_t K_t + w_t L_t + p_{E,t} E_t \quad \text{s.t.} \quad F(K_t, L_t, E_t) > Y_t \tag{24}$$

where r_t, w_t, $p_{E,t}$ are the real prices of capital, labor, and final energy deflated by $p_{Y,t}$. Given this optimization problem, we can derive three first-order conditions for each factor. We estimate a system of simultaneous equations comprising the first-order conditions and the non-linear CES function. We list the respective first-order conditions in Appendix B. As pointed out by León-Ledesma et al. (2010), the system estimation, developed by Klump et al. (2007a), avoids the pitfalls of the Impossibility Theorem (Diamond et al., 1978) that emerge when both the substitution elasticity and the non-neutral technology parameter of a CES production function should be simultaneously identified in a single equation estimation.[6] We execute Zellner's (1962) seemingly unrelated regressions (in a non-linear version) using the *nlsur* command in Stata and apply the feasible generalized non-linear least squares (*fgnls*) estimator.[7] The empirical method accounts for cross-parameter constraints and correlation across equations' error terms. In each estimation round, we explicitly ensure that the algorithm achieves convergence. The numerical estimators can be sensitive to initial values. In the baseline setup, we choose initial values that are not close to potential corner solutions to avoid the numerical algorithm getting stuck (Heun et al., 2017). The initial values are 0.01 for all technical growth rates, g_i; 0.5 for all curvature parameters, η_i; value 1 for ζ; and 0.1 for σ and 0.7 for λ. Our post-estimation diagnostics are based on the log-likelihood (*ll*), Akaike and Bayesian information criteria (*AIC* and *BIC*), as well as the root-mean-square-error (*rmse*). Standard errors are robust.

In summary, the Normalized Supply-Side System Approach facilitates the simultaneous identification of all unobservable supply-side parameters due to (1) cross-equation parameter constraints, (2) allowing for cross-equation correlations in the error terms, (3) setting a specific function for the technical progress, (4) including additional information on the optimal factor demand via factor prices and first-order-conditions and (5) normalization at sample averages and inserting distribution parameters directly from the data.

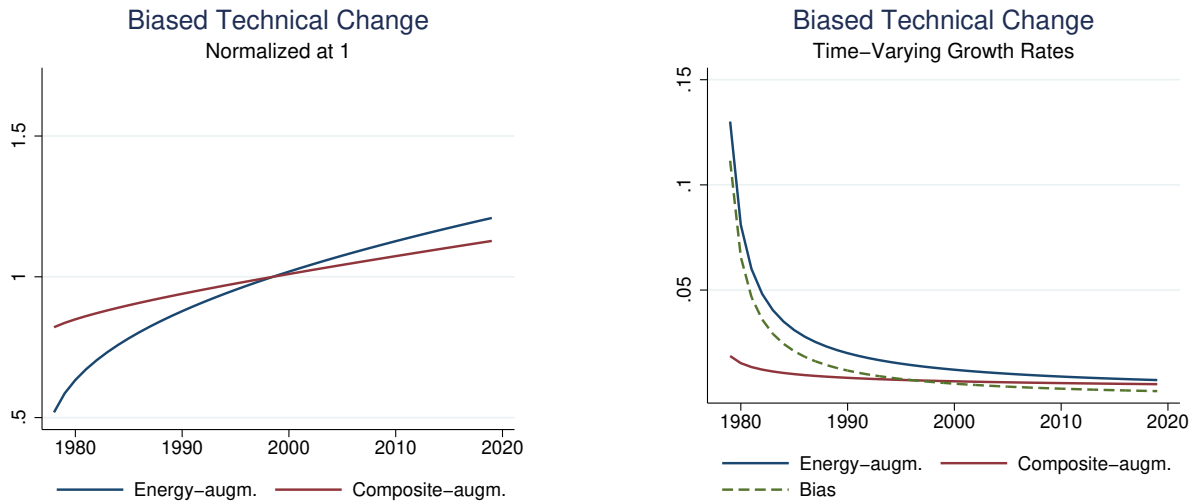
5 Baseline Empirical Results

Table 1 provides our baseline empirical results. Parameter ζ is close to its expected value at unity. The point estimate for σ is 0.336. Parameter λ is close to but above unity. A Wald test of the null $\lambda = 1$ shows that the model statistically rejects Cobb-Douglas in the inner nest for the Japanese case. We calibrate α_0 and β_0 at values 0.054 and 0.416, respectively, following the (geometric) average cost shares of energy in gross output and capital within value-added cost.

[6] We estimate the non-linear CES function as a single equation and cannot identify precise and economically reasonable parameter estimates. Results are available upon request.

[7] We test the non-linear least squares (*nls*) and the iterative feasible generalized non-linear least squares, (*ifgnls*) as well. The latter fails to converge. The *nls* estimator provides qualitatively similar results to the reported *fgnls*. The energy substitution elasticity generally shows a higher magnitude when the nls estimator is applied but the *ll*, *AIC* and *BIC* criteria advocate the *fgnls* estimator across each model. Non-linear least squares results are suppressed for brevity. They are available upon request.

The technical augmentation of primary factors, the composite-augmenting technical change, grows with a rate γ_N of 0.7% in Japan. Energy-augmenting technical progress grows at a rate γ_E of 1.3% in Japan. Investigating the curvatures of time-varying technical progress rates, Figure 2 plots the factor-augmenting technical progress functions normalized at unity in plot (a) and as technical growth rates, including the bias in technical change, as a dashed line in (b). Japan's technical energy-augmentation decelerates over time. Parameter η_E is 0.15 and insignificantly different from zero. The long-term trend of composite-augmenting technical progress is also decelerating in Japan, with a curvature η_N of 0.62. Over the sample period, energy-augmenting technical growth rates are consistently larger than their composite-augmenting counterparts. Technical energy-augmentation dominates in relative terms, and given our estimate of σ below unity, the bias in technology is energy-saving over the sample period. Japan's energy-augmenting technical progress exhibits relatively high growth rates in the early years following the second oil crisis, but declines rapidly in the initial phase of the sample period. This rapid deceleration of energy augmentation is mirrored in the energy-bias trend, which drops steeply before stabilizing at a low and nearly constant level.



(a) **(b)**

Fig. 2: Biased Technical Change in Normalized Levels and Growth Rates. Note: The figure displays our estimated factor-augmenting technical progress, indexed at unity in plot (a) and growth rates in plot (b). The blue line corresponds to energy-augmenting technical progress, while the red line corresponds to primary factor-augmenting technical progress. The dashed line in plot (b) represents the time-varying bias in technical progress rates, as defined in Eq. (9). *Source:* Own estimations.

Not only is the energy-saving bias in technical growth rates decelerating in Japan over the long run, but a substantial share of the potential energy savings generated by energy-augmenting technical progress is also offset by the economy-wide rebound effect. Based on our baseline estimates and the corresponding rebound equations, we calculate an average economy-wide rebound effect of 39% over the sample period. Thus, on average, more than one-third of the potential energy savings from energy-augmenting technical progress are offset by substitution and output effects. The output effect corresponds to the average energy cost share and amounts

to only 5.5%, implying that the rebound effect in Japan is dominated by the substitution effect.[8]

Figure C.1 in the Appendix depicts the corresponding economy-wide rebound effect as a function of time, following Eq. (19). The rebound trajectory mimics the energy cost share over time. The trajectory, however, indicates an incomplete U-shape of the rebound effect with an increasing magnitude as of the 2000s. By offsetting energy-saving benefits through technical progress, this rebound dynamic contributes to the rising energy cost share over the same period.

Table 1: Baseline Results

σ	0.336***	[0.332:0.341]
λ	1.018***	[1.010:1.026]
γ_E	0.013***	[0.010:0.015]
η_E	0.155	[-0.092:0.402]
γ_N	0.007***	[0.006:0.007]
η_N	0.624***	[0.499:0.748]
ζ	1.068***	[1.042:1.094]
α_0	0.055	
β_0	0.416	
$\ell\ell$	375.101	
AIC	-736.202	
BIC	-724.038	
$rmse_{CES}$	0.016	
$rmse_{FOC_E}$	0.157	
$rmse_{FOC_K}$	0.046	
$rmse_{FOC_L}$	0.058	
$\sigma = 1$	0.000	
$\lambda = 1$	0.000	
$1 + \pi_s$	0.336	
π_o	0.055	
R	0.391	

Note: The estimation results in the table are based on 42 observations of the countries' aggregate economies over the period 1978-2019. We apply the *fgnls* estimator. Standard errors are robust. Numbers in brackets indicate the 95% confidence interval. The abbreviations $\ell\ell$, AIC, and BIC refer to the log-likelihood and the Akaike and Bayesian information criteria, respectively. The *rmse* provides information on the root mean square error of the estimated equations. The table also reports p-values for a Wald test with the respective null hypotheses $\sigma = 1$ and $\lambda = 1$. Asterisks *, **, and *** indicate the 10%, 5%, and 1% significance levels, respectively. We also include the average long-term economy-wide rebound effect for the baseline estimation results with the *fgnls* estimator. $1 + \pi_s$ is the substitution effect in decimal values, π_o the average output effect, and R the economy-wide rebound effect as the sum of the two. Detailed derivations are included in Appendix A.

Figure C.2 in the Appendix shows the fit of our equation system. Plot (a) depicts the predicted normalized gross output (in logs) and (b) the predicted energy cost share. We observe that the

[8] We later verify these magnitudes by re-estimating the substitution and output effects using the Implicit Function Theorem (IFT) approach developed by Saunders (2008); see Appendix E. The resulting rebound magnitudes are very similar across the two approaches. The substitution effect remains unchanged, while the output effect is slightly higher at 7.2%. Consequently, the total economy-wide rebound effect is also marginally higher, at 40.8%.

baseline model accurately predicts the long-term trends of both dependent variables. Our model follows a long-term declining trend in the energy cost share since the late 1970s and predicts a U-shaped energy cost share, with a turnaround in the early 2000s, followed by an increasing share until the end of our sample period. Given the complementary relationship between the primary factors and intermediate energy, the long-term decelerating energy-bias in technical progress, and the non-negligible (increasing) economy-wide rebound effect, Japan's economy is unable to reduce energy demand as a coping mechanism to rising global energy prices in the second half of our sample period. The low magnitude of the energy-saving bias may explain the predicted increase in Japan's energy share in the second half of the sample period. Japan is exposed to rising fossil fuel prices but lacks the technical capacity to conserve energy.

In the presence of non-stationary macroeconomic variables and a technological trend, we must ensure that the error terms in our production function estimation do not have a unit root. Manu et al. (2022) interpret the error terms of the first-order conditions as economic wedges, i.e., distortions from the equilibrium condition in production, i.e., as taxes, factor price dispersion, inefficient mark-ups, (financial) frictions, sticky prices/wages, adjustment costs, etc. These "wedges" should be stationary to exclude spurious estimation results. We perform an Augmented Dickey Fuller (ADF) test on the error term series in each equation of our equation system. While we cannot reject the ADF for each first-order condition, we can reject the null hypothesis and non-stationary error terms in the CES production. We take comfort in this fact since the CES is our main objective function.

6 Robustness Checks

6.1 Energy Substitution: The Long-Term of It

We assume partial equilibrium and optimal cost-minimizing behavior in the baseline model, such that our estimates capture long-run production conditions. Whereas previous empirical country-level CES studies often rely on time series spanning up to two centuries to identify equilibrium parameter values, our analysis is limited to 42 years. This constraint is primarily driven by data availability, particularly for final-energy factor prices in the Japanese economy, and makes our estimates more susceptible to short-run cyclical deviations from long-run equilibrium. Temporary frictions and business-cycle fluctuations can alter relative energy prices without inducing an immediate adjustment in production processes. As Chirinko and Mallick (2017) show, failing to remove such short-run variation can generate downward-biased estimates of substitution elasticities. Manu (2022) confirms this pattern for Japanese macro-sectors and labor skill groups. Her results support the standard view that long-run substitution elasticities tend to exceed their short-run counterparts, particularly for capital and labor, because capital is quasi-fixed in the short run. For energy-extended CES production functions, however, the effect of filtering out short-run fluctuations has not yet been systematically examined.

To ensure that our estimated substitution effect reflects long-run dynamics despite the relatively short 42-year sample, we therefore test whether cyclical variation biases the energy substitution elasticity downward. We apply two low-pass filters—the Hodrick-Prescott (HP) and Baxter-King

(BK) filters—to all model variables: output, capital, labor, energy, and their respective factor shares. Because Chirinko and Mallick (2017) note that there is no consensus on the appropriate HP smoothing parameter, we consider values of 800 and 1200 for robustness. Applying the BK filter reduces the effective sample to 36 observations because the method trims a three-year window from each end of the annual time series.

Table D.2 in the Appendix reports the results. Removing transitory variation improves both the log-likelihood and the information criteria relative to the baseline specification. As expected, the capital-labor substitution elasticity rises above unity under the HP filter, indicating greater flexibility over the long run. By contrast, the BK filter produces a slightly lower capital-labor elasticity, just below unity, possibly reflecting the loss of observations caused by the required trimming. More importantly, the estimated energy substitution elasticity remains close to the baseline value across all filtered specifications. Under the HP filter, the long-run estimates of σ are 0.29 for a smoothing parameter of 800 and 0.26 for a smoothing parameter of 1200, suggesting a slight decline in energy substitutability once cyclical variation is removed. The BK filter yields an estimate of 0.36, almost identical to the baseline estimate. These results indicate that short-run fluctuations do not materially bias our baseline estimate of the energy substitution elasticity. The complementarity between capital, labor, and intermediate energy therefore persists—and, in some specifications, even strengthens—once cyclical variation is removed, reinforcing the view that Japan's production structure remains strongly energy-dependent over the long run.[9]

6.2 Technology Regime Switches

Following Koyama (2024a, 2024b, 2024c, 2024d) economic policies in Japan have historically placed varying emphasis on energy security and efficiency, which has influenced institutional and technological conditions. After Japan's asset-price bubble collapse in 1991 and the onset of the "lost decade," energy security lost priority. The 2011 Great East Japan Earthquake and the Fukushima Daiichi accident led to the shutdown of nuclear plants and renewed reliance on fossil fuel imports. As a result, energy security and climate commitments under the Paris Agreement became more pressing, placing energy efficiency back at the center of policy. While our baseline model captures a time-varying trend in technical progress, the functions may not fully reflect medium-term policy shifts. Accounting for these differences in a technical model could provide deeper insights into the trajectory of biased technical change and impact estimates of energy substitution elasticity, and consequently, the magnitude of economy-wide rebound effects. Lagomarsino (2020) highlights the lack of recognition of structural breaks in the previous energy-extended CES literature. A gap in the literature that we attempt to fill.

By incorporating dummy variables, we follow Manu et al. (2022) and introduce smooth tran-

[9]We also propose a more granular interpretation of Japan's relatively low long-run energy substitution elasticity. Drawing on Koh and Santaeulàlia-Llopis (2022), who show that firms adjust capital-labor substitution elasticities countercyclically and become more flexible during recessions, we extend this argument to energy. Japan experienced prolonged weak growth during the 1990s and a pronounced contraction during the 2008 financial crisis. During such periods, heightened energy vulnerability may have induced firms to temporarily increase substitutability between energy and other inputs as a coping mechanism. Filtering out this short-run flexibility may therefore help explain why the estimated long-run energy substitution elasticity is lower than in the unfiltered baseline.

sitions in the curvature parameter in the Box-Cox (1964) technology model. The curvature parameter can change across sub-periods while keeping the level of the technical progress rate. This method has the advantage of keeping the whole sample of yearly observations without breaking the sample into smaller sub-samples. We chose the years for structural breaks in 1991 and 2011 based on the historical events and stylized trajectory of the energy cost share. We expect a smooth transition in the energy-augmenting technical progress in the early 1990s and early 2010s.[10] The technology function, including two structural breaks, takes the following form:

$$\log \Gamma_t^I + \log \Gamma_t^{II} + \log \Gamma_t^{III} = g \left\{ \begin{array}{r} \frac{t_{90}}{\eta_E^I} \left[\left(\frac{(1-D_{91})t + D_{91} t_{90}}{t_{90}} \right)^{\eta_E^I} - 1 \right] + \\ D_{91} \frac{t_{90}}{\eta_E^{II}} \left[\left(\frac{(1-D_{11})t + D_{11} t_{10}}{t_{90}} \right)^{\eta_E^{II}} - 1 \right] + \\ D_{11} \frac{t_{10}}{\eta_E^{III}} \left[\left(\frac{t}{t_{10}} \right)^{\eta_E^{III}} - 1 \right] \left(\frac{t_{10}}{t_{90}} \right)^{\left(\eta_E^{II} - 1\right)} \end{array} \right. \tag{25}$$

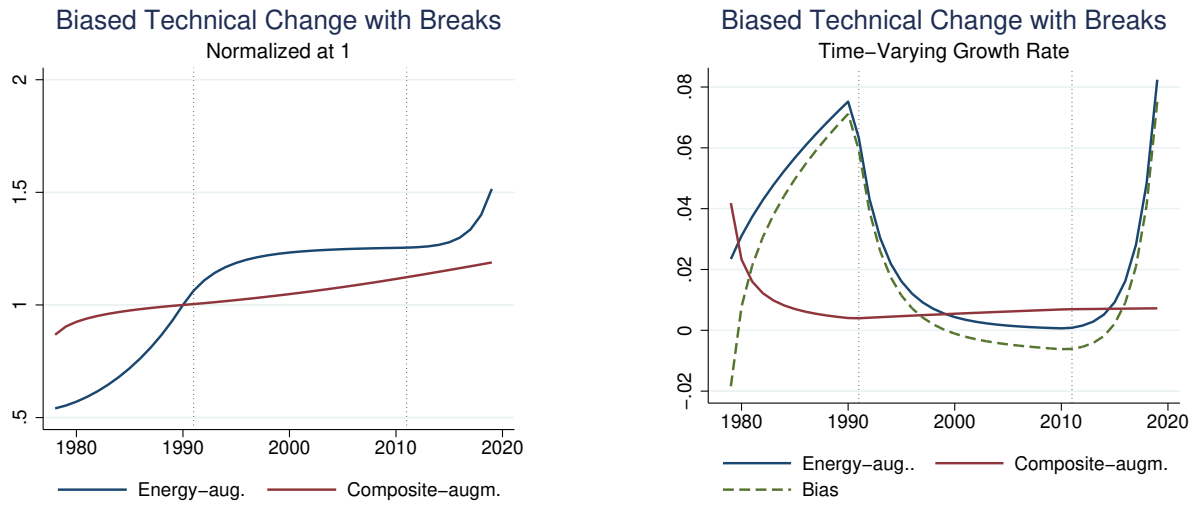
Where t_{90} and t_{10} refer to the values of variable t in 1990 and 2010. Dummies D_{91} and D_{11} equal 0 until 1990 and 2010, respectively, and 1 thereafter. It follows that $\log \Gamma_t^I$ defines the augmenting technical change until 1990. It starts from a level below zero and ends up at zero in $t \geq 1990$; $\log \Gamma_t^{II}$ equals zero until 1990 and determines the augmented technical change from 1991 to 2010; $\log \Gamma_t^{III}$ continues from that level as of 2011.

Table D.3 in the Appendix reports the results. Compared to the baseline model, allowing for technical smooth transitions improves the $\ell\ell$ as well as the *AIC* and *BIC* criteria. Figure C.3 in the Appendix plots again the model fit for the CES function and the energy cost share. For the latter, our model predictions are closer to the observations and depict at least a slightly declining energy share as of the early 2010s.

Figure 3 depicts the evolution of technical progress in normalized levels in panel (a) and growth rates in panel (b). The dashed line in panel (b) shows the bias in technical progress over time. Except for the first two years of the sample, 1978 and 1979, technical progress in Japan is biased toward energy saving and accelerates throughout the 1980s. During this period, strongly accelerating energy-augmenting technical progress ($\eta_E^I = 1.31$) coincides with decelerating primary-factor-composite-augmenting technical progress ($\eta_N^I = 0.11$). From the 1990s onward, however, energy-augmenting technical progress decelerates sharply and follows a hyperbolic trajectory

[10] To provide statistical support for the choice of break points, we examine the error terms of an AR(1) process fitted to energy-augmenting technical progress. Visual inspection of these residuals suggests a structural break in the early 1990s, but no clearly identifiable subsequent break. This provides support for modeling a regime shift in 1991, coinciding with Japan's transition into a prolonged low-growth period. To assess the timing of a potential second break, we re-estimate the model using alternative break years. Model fit, evaluated using the log-likelihood ($\ell\ell$), *AIC*, and *BIC*, changes only marginally across these specifications, while the qualitative results remain robust. Importantly, all tested specifications indicate that the technical-progress bias does not switch back before the 2010s. We therefore set 2011 as the year of the second smooth transition.

($\eta_E^{II} = -4.48$).[11] As a result, the energy-saving bias weakens and turns temporarily energy-using during the 2000s.



(a) **(b)**

Fig. 3: Biased Technical Change in Normalized Levels and Growth Rates including Breaks. Note: The figure displays our estimated factor-augmenting technical progress, including structural breaks in 1991 and 2011, indexed at unity in plot (a) and in growth rates in plot (b). The blue line corresponds to energy-augmenting technical progress, while the red line corresponds to primary factor-augmenting technical progress. The dashed line in plot (b) represents the time-varying bias in technical progress rates, as defined by Eq. (9). *Source:* Own estimations.

Following the Fukushima accident, energy-augmenting technical progress accelerates strongly again, with an estimated curvature parameter of $\eta_E^{III} = 22.28$. Technical augmentation of the primary-factor composite also accelerates, but considerably less strongly, with $\eta_N^{III} = 1.19$. The precise curvature of the resulting energy-saving bias remains somewhat uncertain because η_N^{III} is estimated imprecisely: its confidence interval of $[-1.939, , 4.315]$ encompasses both hyperbolic and accelerating trajectories. Based on the point estimates, however, the bias in technical progress shifts back toward energy saving in the early 2010s and subsequently accelerates rapidly. The estimated technology trajectory therefore reveals a pronounced post-2011 shift that breaks with the long-run pattern identified in the baseline model and is temporally consistent with the structural transformation of Japan's energy system following Fukushima. The shutdown of nuclear power generation and the resulting renewed reliance on fossil-fuel imports appear to have strengthened incentives for energy-saving technical change.

At the same time, the more flexible technology specification and improved model fit yield a

[11] It is well established that weak productivity growth of primary factors contributed to Japan's low-growth regime during the 1990s (see, e.g., Hayashi and Prescott, 2002). The coincidence of rapidly decelerating energy augmentation with Japan's post-1990 slowdown raises the possibility that energy-side constraints complemented the better-known weakness in primary-factor productivity. Establishing the quantitative contribution of this channel, however, would require a dedicated growth-decomposition exercise. Nakajima and Matsushima (2022) attribute Japan's low-growth trajectory after 1990 partly to the low embodied quality of the country's energy mix and to a decline in its energy acquisition capacity, represented by a fall in societal-scale Energy Return on Investment. By identifying energy and its technological properties as a potential constraint on Japan's economic activity during the 1990s, our study therefore points to an additional possible explanation for secular stagnation in an economy with low energy self-sufficiency.

higher estimated energy substitution elasticity of 0.43. This increased substitutability also raises the average economy-wide rebound effect to 48.6%. Hence, almost half of the potential energy savings generated by improvements in energy efficiency are offset by substitution and output responses. The economy-wide rebound effect therefore poses a substantial challenge to Japan's recent efforts to reduce aggregate energy demand.

6.3 Fuel Switching as a Solution?

The economy-wide rebound effect remains a major obstacle to decoupling energy demand from economic growth in Japan. Following the Fukushima disaster and the subsequent shutdown of domestic nuclear power plants, Japan became increasingly reliant on fossil-fuel imports, thereby intensifying the risk that rebound effects undermine its emissions-reduction targets. Expanding domestic renewable-energy supply offers a potential way forward. It could reduce dependence on imported fossil fuels while supporting long-term decarbonization, even in the presence of a substantial rebound effect. As the share of clean energy increases, additional energy demand generated by rebound effects would become less carbon-intensive, potentially turning rebound from a constraint on decarbonization into a "clean growth engine."

Mortha and Arimura (2024a, 2024b) identify electrification as a key strategy for replacing fossil fuels, but caution that rising electricity prices and Japan's post-Fukushima return to fossil-fuel imports may hinder this transition in the manufacturing sector. Using plant-level data from 2004 to 2022, they find strong one-way substitutability: electricity can replace fossil fuels, whereas changes in fossil-fuel prices do not significantly affect electricity demand in the short run.

Motivated by these findings, we examine the relationship between clean energy—defined as non-fossil sources such as electricity and renewables—and dirty energy, comprising fossil fuels such as oil, coal, and natural gas. We disaggregate Japan's total energy use into clean and dirty components and embed an interfuel nest within the CES production function. This framework allows us to estimate long-run interfuel substitutability (see Stern, 2012, for a meta-analysis) and to identify potential biases in technical progress across fuel types. Our approach builds on Papageorgiou et al. (2017), who pioneered CES-based estimates of clean-dirty energy substitutability, and Jo (2024), who applied a similar framework to the French manufacturing sector. Both studies estimate substitution elasticities above unity, indicating that clean and dirty energy inputs are gross substitutes. Their findings support a relatively optimistic view of green growth, as they imply that clean energy can replace fossil fuels in response to favorable changes in relative prices. The normalized CES-in-CES model comprises four production factors and takes the following form:

$$\ln\left(\frac{Y_t}{Y_0}\right) = \ln\zeta + \frac{\sigma}{\sigma-1}\ln\left[(1-\alpha_0)\left(\beta_0\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}}\frac{K_t}{K_0}\right)^{\frac{\lambda-1}{\lambda}} + (1-\beta_0)\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}}\frac{L_t}{L_0}\right)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{(\sigma-1)\lambda}{(\lambda-1)\sigma}}\right.$$
$$\left. +\alpha_0\left(\omega_0\left(\frac{\Gamma_{C,t}}{\Gamma_{C,0}}\frac{E_{C,t}}{E_{C,0}}\right)^{\frac{\varpi-1}{\varpi}} + (1-\omega_0)\left(\frac{\Gamma_{D,t}}{\Gamma_{D,0}}\frac{E_{D,t}}{E_{D,0}}\right)^{\frac{\varpi-1}{\varpi}}\right)^{\frac{(\sigma-1)\varpi}{(\varpi-1)\sigma}}\right] + \varepsilon_Y \tag{26}$$

Where

$$\frac{E_t}{E_0} = \left(\omega_0 \left(\frac{\Gamma_{C,t}}{\Gamma_{C,0}} \frac{E_{C,t}}{E_{C,0}} \right)^{\frac{\varpi-1}{\varpi}} + (1-\omega_0) \left(\frac{\Gamma_{D,t}}{\Gamma_{D,0}} \frac{E_{D,t}}{E_{D,0}} \right)^{\frac{\varpi-1}{\varpi}} \right)^{\frac{\varpi}{(\varpi-1)}} \tag{27}$$

We disaggregate total energy use, E_t, into clean energy, $E_{C,t}$, and dirty energy carriers, $E_{D,t}$. These two energy subcategories form a second inner CES nest. The parameters $\Gamma_{C,t}$ and $\Gamma_{D,t}$ capture factor-augmenting technical progress within the interfuel nest and therefore provide information on the direction of interfuel-biased technical change. Specifically, they indicate whether clean or dirty energy inputs are relatively saved within the total energy mix and how total energy-augmenting technical progress is distributed between clean and dirty energy carriers.

The parameter σ continues to denote the substitution elasticity between the non-energy and energy composite inputs in the outer nest. In the baseline model, measuring energy as aggregate total final energy consumption implicitly assumes perfect substitutability across all energy carriers. Because this strong assumption may also affect the estimated substitution elasticity in the outer nest, the extended model provides an additional robustness check for our baseline results.

The parameter ω denotes the bidirectional interfuel substitution elasticity between electricity and non-electric fossil final-energy carriers. We retain the same initial values as in the baseline estimation and set the initial value of ω to 0.7. We also test starting values above unity, but these consistently yield statistically and economically implausible results. The corresponding first-order conditions form a five-equation system, including the CES production function, and are reported in Appendix B. The estimation results are presented in Table D.4 in the Appendix.

Clean and dirty energy sources are gross complements in Japan, with an estimated interfuel substitution elasticity of $\omega = 0.63$. This stands in contrast to the high substitutability reported by Papageorgiou et al. (2017) and Jo (2024), suggesting that Japan is characterized by relatively rigid interfuel substitution. Our findings are instead consistent with Mortha and Arimura (2024a, 2024b). Even when clean energy becomes relatively cheaper—for example, through carbon pricing or technological progress—it does not substantially replace fossil fuels. This pattern is consistent with what the literature describes as the "Displacement Paradox" (York et al., 2022): clean-energy technologies do not necessarily displace existing fossil-fuel technologies but may instead be added alongside them (see York et al., 2022; York, 2006; York and Bell, 2019). York (2012) shows that, since 1960, the typical cross-country pattern has been that growth in non-fossil energy sources has not substantially reduced fossil-fuel consumption but has instead added to total energy supply.

For Japan, we find no statistically significant clean-energy-augmenting technical progress. By contrast, dirty-energy-augmenting technical progress is positive and significant, although it decelerates over time. Hence, we detect no measurable efficiency gains in clean-energy use over the sample period, while the bias of technical progress within the interfuel nest is directed toward saving fossil fuels. Given the limited substitutability of dirty energy, Japan exhibits a fossil-fuel-saving bias in interfuel technical change that gradually increases the relative share of clean energy in the total energy mix over the long run. This result is consistent with Sato (2013), who

examine the interfuel relationship between electricity and fossil fuels in Japanese industries over 1973–2008 and identify electricity-using technical progress in several industries.

Because clean-energy-augmenting technical progress is not significantly different from zero, while efficiency improvements are concentrated in the dirty-energy component, fossil-fuel efficiency emerges as the main driver of the overall energy-augmenting technical progress identified in the baseline model. It is therefore also the primary source of the economy-wide rebound effect. As a consequence, the rebound effect continues to undermine both Japan's decarbonization efforts and the broader objective of decoupling energy demand from economic growth.

6.4 Comparison with the United States Economy

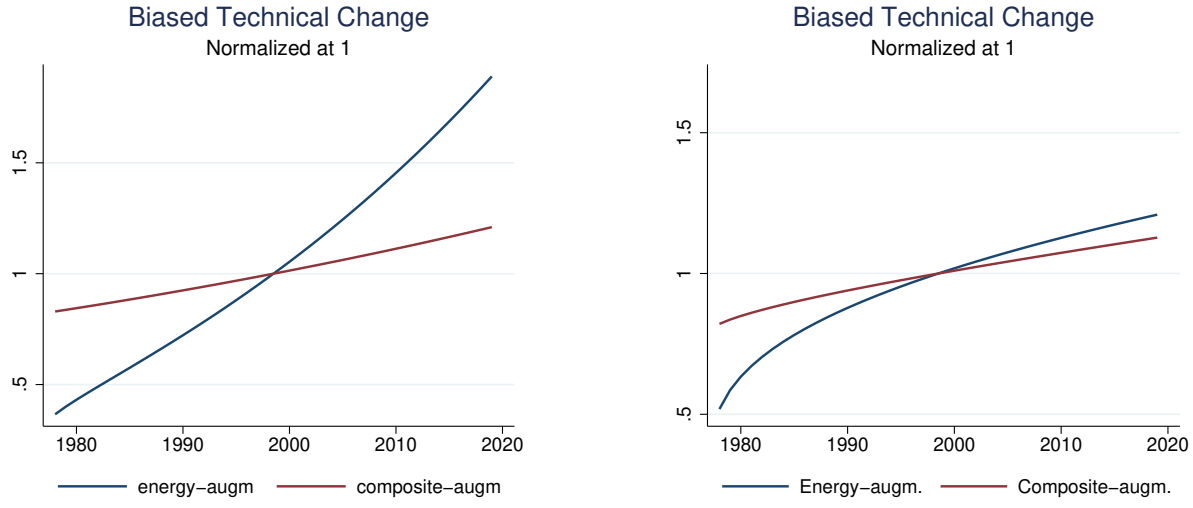
One advantage of our flexible CES-in-CES structure and the underlying data source is that they support a multi-country application and allow supply-side production parameters to be compared across economies. We use the United States as a benchmark. By the late 1970s, Japan and the United States were both highly industrialized economies operating at broadly comparable technological levels, which facilitates an approximate comparison of scale-dependent CES parameter estimates after normalization. In both cases, the production functions are normalized at country-specific sample averages, representing comparable reference points in terms of technological development. Moreover, several energy-extended CES studies already exist for the United States (e.g. Frieling & Madlener, 2017a; Hassler et al., 2021), making it a well-established benchmark. Data preparation follows the same procedure described in Section 3. The comparison therefore provides additional context and robustness for our Japan-specific results.

Figure C.4 in the Appendix compares the two countries. Panel (a) shows energy intensity, defined as final energy consumption relative to gross output, while panel (b) reports the energy cost share in gross output. Japan starts from a lower level of energy intensity in 1978, but its energy intensity subsequently declines at a slower pace. Despite its higher energy intensity, the United States exhibits an energy cost share that is similar to Japan's in both level and trajectory. This reflects differences in energy prices: the United States has access to relatively inexpensive domestic fossil fuels, whereas Japan is more exposed to higher fossil-fuel import prices on global markets. We therefore examine how these differences in energy-related stylized facts are reflected in the aggregate supply-side parameters of the two economies. To this end, we re-estimate the baseline equation system for the United States and repeat the same robustness checks. As for Japan, we normalize the U.S. production function at its sample averages, thereby reducing differences in scale and facilitating comparison of the estimated supply-side parameters. Table D.5 in the Appendix reports the empirical results. Based on the geometric average cost shares of energy in gross output and capital within value-added costs, we calibrate α_0 and β_0 to 0.051 and 0.39, respectively. The parameter ζ is close to its expected value of unity. According to a Wald test, the capital-labor substitution parameter in the inner nest differs statistically from unity, i.e., $\lambda = 1$, only at the 10% significance level. Most importantly, the estimated energy substitution elasticity of 0.29 is close to Japan's estimate of 0.34.

For the United States, we estimate primary-factor-augmenting technical progress of approxi-

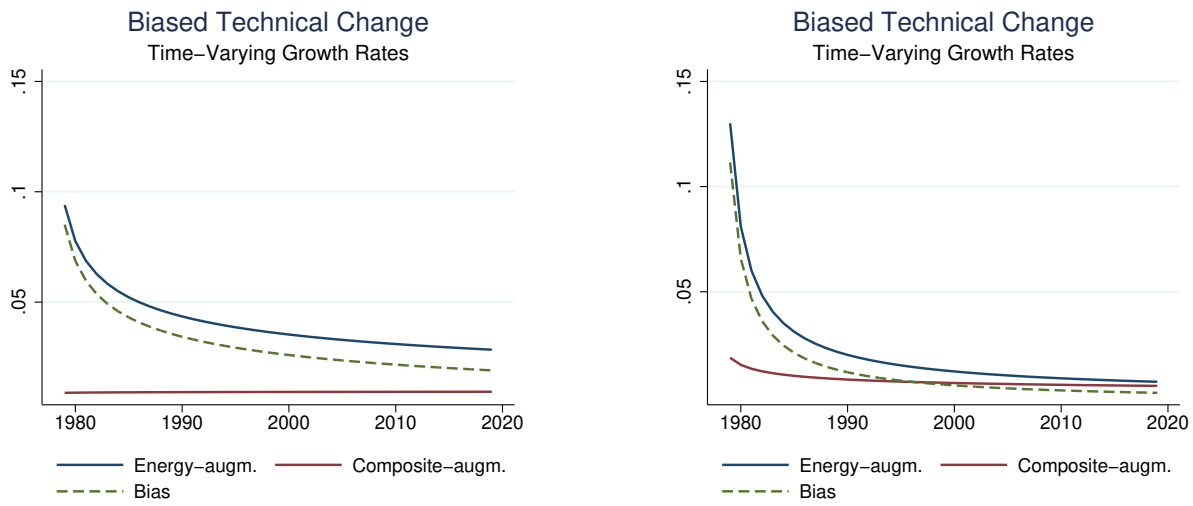
mately 1%, with a slightly accelerating curvature parameter of 1.1, and energy-augmenting technical progress of 2.8%, which gradually decelerates with a curvature parameter of 0.61. Figures 4 and 5 compare these technological trajectories with those of Japan by plotting the time-varying factor-augmenting technical progress functions in levels and growth rates, respectively. Throughout the sample period, both countries exhibit a persistent energy-saving bias: energy-augmenting technical progress exceeds primary-factor-augmenting technical progress while energy and primary factors remain gross complements. The dynamics of this bias, however, differ substantially. In Japan, the energy-saving bias declines rapidly, driven by a pronounced slowdown in energy-augmenting technical progress. In the United States, by contrast, the energy-saving bias decelerates more gradually, despite a slightly increasing rate of primary-factor-composite-augmenting technical progress. Thus, despite differences in factor endowments and Japan's substantially lower energy self-sufficiency, the United States achieves comparatively higher levels of relative energy efficiency and a stronger long-run energy-saving effect.

Two main takeaways emerge from the country comparison. First, both industrialized economies exhibit similar energy substitution elasticities, suggesting that this parameter may be driven more strongly by an economy's technological level than by differences in factor endowments, policies or institutions. This interpretation is consistent with Knoblach and Stöckl (2020), who emphasize that the substitution elasticity should be viewed as an endogenous rather than an "immutable deep parameter" (p. 21). As in Japan, the substitution effect also contributes substantially to the economy-wide rebound effect in the United States. Second, the main divergence between the two countries lies in the evolution of technical progress. Japan's energy-saving bias decelerates more rapidly over time, indicating that Japan performs comparatively worse in reducing energy requirements over the sample period.



(a) United States **(b)** Japan

Fig. 4: Biased Technical Change in Normalized Levels, United States and Japan. Note: The figure displays our estimated factor-augmenting technical progress, separated by the United States and Japan and indexed at unity. The blue line corresponds to energy-augmenting, and the red line corresponds. *Source:* Own estimations.



(a) United States **(b)** Japan

Fig. 5: Biased Technical Change Growth Rates, United States and Japan. Note: The figure displays our estimated factor-augmenting technical progress, separated by the United States and Japan, along with their corresponding growth rates. The blue line corresponds to energy-augmenting, and the red line corresponds to primary factor-augmenting technical progress. The dashed line in plot (b) represents the time-varying bias in technical progress rates, as defined in Eq. (9). *Source:* Own estimations.

6.5 Additional Robustness Checks

To ensure the robustness of our baseline analysis, we conduct a series of additional checks. Because the objective function in non-linear system estimation may exhibit flat regions and local extrema, the numerical algorithm can be sensitive to the choice of initial parameter values. We therefore perform two manual grid searches to increase the likelihood of identifying a global solution. First, following Henningsen and Henningsen (2012), we systematically vary the initial parameter values, a standard robustness procedure in the system-estimation literature. We evaluate the resulting specifications using the *rmse*, log-likelihood ($\ell\ell$), *AIC*, *BIC*, and the economic plausibility of the parameter estimates, excluding solutions that indicate local optima or economically implausible outcomes (see Lagomarsino, 2020, for criteria commonly applied in energy-augmented CES studies). Second, we fix the capital-labor substitution elasticity in the inner nest at a range of alternative values while freely estimating the remaining parameters. This approach, originally proposed by Sato (1967) to improve the performance of nested CES estimations, has subsequently been applied by Frieling and Madlener (2016, 2017a, 2017b). Consistent with their findings, extreme values of the inner-nest elasticity, close to zero or one, generate unstable or "ill-behaved" parameter estimates. Across a range of economically plausible values, however, the estimated energy substitution elasticity and technology parameters remain stable. This stability indicates that the inner capital-labor composite can be separated from energy in the outer nest and supports the reliability of our baseline estimates.

As recommended by Hassler et al. (2021), we additionally exclude residential energy consumption by private households, which does not constitute a productive intermediate input, from both aggregate energy consumption and the corresponding energy-price calculations (see Section 3).

Table D.8 in the Appendix reports the results. They are qualitatively identical to the baseline estimates, indicating that the inclusion of unproductive residential energy consumption does not materially bias the identified role of intermediate energy on the aggregate supply side.

Nesting capital and labor in the inner nest is economically intuitive because together they constitute value added, whereas energy enters as an intermediate input that enhances the ability of the primary factors to generate output. According to Saunders (2008), this is also the only rebound-flexible CES nesting structure and therefore represents the natural choice for our baseline specification. Nevertheless, despite the large number of energy-extended CES panel studies discussed in Section 2, there is no *a priori* reason to assume that our nesting structure is the only empirically feasible, or necessarily the best-fitting, specification. This issue relates to the "separability assumption" underlying nested CES production functions. Lagomarsino (2020, 2021) discuss the various empirical approaches developed in the multi-factor CES literature to identify which factors can be treated as separable and which nesting structure best fits the data. We adopt a straightforward comparison based on (1) the log-likelihood ($\ell\ell$) and the *AIC* and *BIC* of the complete equation systems, (2) the *rmse* of the CES production function as our primary objective function across alternative nests, and (3) the economic interpretability of the resulting parameter estimates.

Following Sato (1967), the two factors that are technologically most similar and hence most substitutable should be combined in the inner nest to form a genuine composite input. We therefore test the alternative (LE)K and (KE)L structures. In the (LE)K specification, labor and energy jointly represent the inputs required to operate the production infrastructure and together substitute for or complement the capital stock. In the (KE)L specification, capital and energy form the inner composite: intermediate energy enables capital to operate, and the resulting composite substitutes for or complements labor in the outer nest. The latter structure is particularly relevant for Japan, where population aging has increasingly constrained labor supply since the 1990s and may have strengthened the need to replace labor with non-labor production factors. The parameters γ_N and η_N continue to capture time-varying technical progress in the inner nest. In the (LE)K structure, γ_K and η_K capture capital-augmenting technical progress in the outer nest, whereas in the (KE)L structure, γ_L and η_L capture labor-augmenting technical progress. Table D.6 in the Appendix reports the corresponding estimates.

Although we cannot reject the alternative nesting structures outright, both perform worse than the baseline specification in terms of the log-likelihood and the *AIC* and *BIC* of the full equation system. The same conclusion emerges for the CES production function itself: the baseline (KL)E structure yields the lowest *rmse*. The alternative specifications nevertheless provide two additional insights. First, Japan's capital-augmenting technical progress is negative over the sample period, reducing the efficiency of the primary factors and appearing to be an important driver of the dominant energy-saving bias identified in the baseline model. Second, capital and energy are more substitutable within the inner nest than labor and energy. Following Sato's (1967) rationale, this supports the interpretation of the (KE)L structure as a genuine composite-input specification. In this case, energy-enabled capital in the (KE) composite complements labor in the outer nest, with an estimated elasticity of approximately 0.6 (see Manu, 2022, for

a more granular analysis of Japan's capital-labor substitution elasticity across sectors and skill levels).

We further follow Heun et al. (2017) and assess the precision of our parameter estimates using bootstrapped, resampled standard errors. Table D.7 in the Appendix shows that the 95% confidence intervals provide relatively narrow upper and lower bounds for most parameter estimates and remain within economically plausible ranges. In particular, the confidence interval for σ, ranging from 0.246 to 0.427, supports the estimated magnitude of the energy substitution elasticity. By contrast, the capital-labor elasticity and the curvature parameters governing technical change are identified with considerably less precision.

Finally, we address endogeneity concerns that are common in aggregate production-function estimation, particularly the possibility that capital investment and labor employment respond endogenously to expected or realized productivity shocks or output developments. We therefore estimate the non-linear equation system using GMM, instrumenting all factor inputs, expressed in logarithms, with their lagged values. In alternative GMM specifications, we augment these instruments with lagged gross output and a time trend. The three GMM models are reported in Table D.9 in the Appendix. The resulting estimates are qualitatively consistent with the baseline model. The energy substitution elasticity is slightly lower but remains close to the baseline estimate. Moreover, the curvature of energy-augmenting technical progress is identified more precisely, as reflected in a narrower confidence interval, while continuing to indicate a decelerating trajectory.

7 Conclusion

This study investigates Japan's aggregate supply side from 1978 to 2019 using a normalized, energy-extended CES production function. Energy use in aggregate production is modeled as an intermediate input in a gross-output framework, where it substitutes for or complements the primary factors generating value added. Applying the supply-side system estimation approach of Klump et al. (2007a), we jointly identify the elasticity of substitution between energy and non-energy inputs and a time-varying energy-saving bias in technical progress. This simultaneous identification of the CES parameters also allows us to quantify a scarcely investigated phenomenon in the aggregate Japanese economy: the economy-wide energy rebound effect. Our baseline results reveal low energy substitutability, a gradually decelerating energy-saving bias in technical progress, and an average economy-wide rebound effect of 39%. Together, these supply-side characteristics constrain Japan's ability to reduce energy demand, particularly in the context of rising global energy prices during the second half of our sample period. Japan therefore remains vulnerable to fluctuations in international energy markets and increases in fossil-fuel prices, as illustrated by concerns over peak oil and surging demand from China in the early 2000s. This vulnerability is reflected in the pronounced, nearly U-shaped evolution of Japan's energy cost share over time, which rises again during the latter part of the sample. A broad set of robustness checks supports these baseline findings.

Allowing for medium-term shifts in the technological regime reveals a temporary move toward

an energy-using bias in the early 2000s, followed by a renewed shift toward an energy-saving bias in the early 2010s after the Fukushima accident, with a strongly accelerating tendency. However, under these more flexible technology specifications, our estimates indicate that around 50% of the potential energy savings generated by energy-augmenting technical progress are offset by the economy-wide rebound effect. Given this substantial obstacle to decoupling, we further investigate Japan's ability to substitute clean (non-fossil) for dirty (fossil) energy. If such substitution were sufficiently flexible, the rebound effect would pose a smaller threat to both Japan's dependence on fossil-fuel imports and its emissions-reduction targets. Using a four-factor CES-in-CES framework, we find that clean and dirty energy carriers are gross complements, implying that clean energy tends to augment rather than displace fossil fuels. This result contrasts with Papageorgiou et al. (2017) and Jo (2024), both of whom find a gross-substitute relationship between clean and dirty energy carriers. Our Japan-specific findings are instead consistent with York et al.'s (2022) "Displacement Paradox." The four-factor specification further shows that fossil-fuel-saving technical progress within the interfuel nest is the main driver of the economy-wide rebound effect.

A direct comparison with the United States yields a similar estimated energy substitution elasticity. This suggests that the substitution parameter may be shaped more strongly by the technological level of advanced economies than by differences in factor endowments, policies, or institutions. The main cross-country difference lies in the evolution of technical progress: Japan's energy-saving bias decelerates more rapidly than that of the United States, suggesting potential for future catch-up in energy-saving technical change. Using low-pass filtering techniques, we further confirm that the estimated energy substitution elasticity is not materially biased by short-run business-cycle fluctuations and that its low magnitude persists in Japan's long-run trend.

Taken together, our findings point to a combination of low energy substitutability, decelerating energy-saving technical progress, and a substantial economy-wide rebound effect. These structural characteristics raise doubts about the ease with which Japan can achieve the highly ambitious targets set out in its Strategic Energy Plan. Even an expansion of domestic renewable-electricity generation and the gradual reopening of nuclear power plants (Kurachi et al., 2022) may, over the long run, complement rather than fully replace fossil-fuel imports. This does not imply that Japan should scale back its renewed emphasis on energy efficiency since the 2010s. Rather, our results suggest that policy should simultaneously facilitate substitution away from energy in response to price incentives and mitigate the technology-induced substitution toward energy that contributes significantly to the rebound effect. In this context, Freire-González and Ho (2022) recommend four policy instruments that, preferably implemented as part of a coordinated strategy, can help contain rebound effects: a carbon tax, an energy production tax, an emissions trading system, and changes in consumption patterns. Beyond rebound mitigation, the observed "Displacement Paradox" could also be addressed by increasing substitutability between clean and dirty energy through targeted investment. As Stöckl (2020) demonstrates theoretically, greater flexibility in substituting among energy carriers can provide an effective alternative to further improvements in energy efficiency. Because higher interfuel substitutability

is associated with a declining fossil-fuel share, this approach offers a potential pathway for reducing fossil-fuel dependence similar to fossil-fuel-saving technical change, but without generating the same rebound implications.

Finally, our analysis points to several avenues for future research. The estimated CES parameters provide a natural basis for a growth-decomposition exercise aimed at identifying which production-side components have contributed most strongly to Japan's long-term stagnation. We show that primary-factor-augmenting technical progress is weak since the 1990s and that this weakness further compounds by sharply decelerating energy augmentation. A decomposition of the individual growth contributions could therefore quantify the role of effective energy input in Japan's low-growth regime. A further natural extension is to replicate the analysis for additional countries. The dataset used here supports comparative work across a broad range of industrialized economies. Future studies could examine whether European countries exhibit systematically different patterns in energy substitution, technological bias, and rebound effects relative to Japan and the United States, and whether substantial heterogeneity exists within Europe itself. Finally, the estimation strategy itself could be extended by applying the three-stage least squares approach of Herrendorf et al. (2015) to the normalized CES equation system. This method uses lagged variables as instruments and can produce consistent estimates in simultaneous-equation systems with autocorrelated errors, but has not yet been applied to energy-extended CES production functions.

Appendix

A Derivation of the Substitution and Output Effect

Appendix A shows our derivations of the Substitution (Intensity) and the Output Effect. We drop time subscripts for brevity.

Intensity Effect

We start with our baseline CES model

$$Y = \left[(1-\alpha)(\Gamma_N N)^{\frac{\sigma-1}{\sigma}} + \alpha(\Gamma_E E)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{A.1}$$

Assuming the economic optimality condition

$$\frac{MP_E}{MP_N} = \frac{P_E}{P_N} \tag{A.2}$$

We can derive an expression for the energy intensity

$$\frac{E}{Y} = \frac{N}{Y}\left(\frac{(1-\alpha)}{\alpha}\frac{P_E}{P_N}\right)^{-\sigma}\left(\frac{\Gamma_E}{\Gamma_N}\right)^{\sigma-1} \tag{A.3}$$

Taking the partial derivative of this energy intensity with respect to Γ_E yields

$$\frac{\partial(E/Y)}{\partial\Gamma_E} = \frac{N}{Y}\left(\frac{(1-\alpha)}{\alpha}\frac{P_E}{P_N}\right)^{-\sigma}(\sigma-1)\left(\frac{\Gamma_E}{\Gamma_N}\right)^{(\sigma-2)}\frac{1}{\Gamma_N} \tag{A.4}$$

We know the substitution (intensity effect) is defined by

$$\pi_s = \frac{\Gamma_E}{(E/Y)}\frac{\partial(E/Y)}{\partial\Gamma_E} \tag{A.5}$$

Inserting Eq. (A.4) in (A.5) yields

$$\pi_s = \frac{\Gamma_E}{(E/Y)}\frac{\partial(E/Y)}{\partial\Gamma_E} = \frac{\Gamma_E}{(E/Y)}\frac{N}{Y}\left(\frac{(1-\alpha)}{\alpha}\frac{P_E}{P_N}\right)^{-\sigma}(\sigma-1)\left(\frac{\Gamma_E}{\Gamma_N}\right)^{\sigma-2}\frac{1}{\Gamma_N} \tag{A.6}$$

Which reduces to the final expression of the substitution effect

$$\pi_s = \frac{\Gamma_E}{(E/Y)}\frac{\partial(E/Y)}{\partial\Gamma_E} = \sigma - 1 \tag{A.7}$$

Output Effect

We start with our baseline CES model

$$Y = \left[(1-\alpha)(\Gamma_N N)^{\frac{\sigma-1}{\sigma}} + \alpha(\Gamma_E E)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{A.8}$$

And facilitate the derivation by defining that

$$T = (1-\alpha)(\Gamma_N N)^{\frac{\sigma-1}{\sigma}} + \alpha(\Gamma_E E)^{\frac{\sigma-1}{\sigma}} \tag{A.9}$$

So,

$$Y = [T]^{\frac{\sigma}{\sigma-1}} \tag{A.10}$$

Taking the partial derivative with respect to Γ_E yields

$$\frac{\partial Y}{\partial \Gamma_E} = \frac{\sigma}{\sigma-1}\,[T]^{\frac{\sigma}{\sigma-1}-1}\,\frac{\partial T}{\partial \Gamma_E} \tag{A.11}$$

Where the last term is again a partial derivative of T with respect to Γ_E

$$\frac{\partial T}{\partial \Gamma_E} = \alpha\frac{\sigma-1}{\sigma}(\Gamma_E E)^{\frac{\sigma-1}{\sigma}-1}E \tag{A.12}$$

Eq. (A.11) and Eq. (A.12) taken together, we get the full expression of $\frac{\partial Y}{\partial \Gamma_E}$

$$\frac{\partial Y}{\partial \Gamma_E} = \frac{\sigma}{\sigma-1}\,[T]^{\frac{\sigma}{\sigma-1}-1}\,\alpha\frac{\sigma-1}{\sigma}(\Gamma_E E)^{\frac{\sigma-1}{\sigma}-1}E \tag{A.13}$$

Which reduces to

$$\frac{\partial Y}{\partial \Gamma_E} = \alpha\,[T]^{\frac{\sigma}{\sigma-1}-1}\,(\Gamma_E E)^{\frac{\sigma-1}{\sigma}-1}E \tag{A.14}$$

The output effect is defined by

$$\pi_o = \frac{\Gamma_E}{Y}\frac{\partial Y}{\partial \Gamma_E} \tag{A.15}$$

Inserting Eq. (A.14), we get

$$\pi_o = \frac{\Gamma_E}{Y}\frac{\partial Y}{\partial \Gamma_E} = \frac{\Gamma_E}{[T]^{\frac{\sigma}{\sigma-1}}}\alpha\,[T]^{\frac{\sigma}{\sigma-1}-1}\,(\Gamma_E E)^{\frac{\sigma-1}{\sigma}-1}E \tag{A.16}$$

After two additional algebraic steps of

$$\pi_o = \alpha[T]^{-1}(\Gamma_E E)^{\frac{\sigma-1}{\sigma}-1}\Gamma_E E \tag{A.17}$$

And

$$\pi_o = \alpha[T]^{-1}(\Gamma_E E)^{\frac{\sigma-1}{\sigma}} \tag{A.18}$$

We get our final equation for the output effect

$$\pi_o = \frac{\Gamma_E}{Y}\frac{\partial Y}{\partial \Gamma_E} = \frac{\alpha(\Gamma_E E)^{\frac{\sigma-1}{\sigma}}}{(1-\alpha)(\Gamma_N N)^{\frac{\sigma-1}{\sigma}} + \alpha(\Gamma_E E)^{\frac{\sigma-1}{\sigma}}} \tag{A.19}$$

B First-Order-Conditions

Regarding the first-order conditions, two approaches are established in the empirical literature. One uses factor cost shares as dependent variables (Manu et al., 2022), and the second uses factor prices on the left-hand side (e.g., Herrendorf et al., 2015). Both approaches implicitly account for different potential sources of endogeneity. We test both options in our baseline models, leading to similar results and mitigating the fear of endogeneity problems in our estimates. Here, we display the first-order conditions used for the reports in our study.

CES-in-CES (corresponding to Eq. 23)

$$\ln(s_{E,t}) = \ln(\alpha_0) + \frac{\sigma-1}{\sigma}\left[\ln\left(\frac{\Gamma_{E,t}}{\Gamma_{E,0}}\right) + \ln(\delta) + \ln\left(\frac{E_t/E_0}{Y_t/Y_0}\right)\right] + \varepsilon_{s_{E,t}} \tag{B.1}$$

$$\begin{aligned}\ln(s_{K,t}) = \ln((1-\alpha_0)\beta_0) - \frac{\sigma-1}{\sigma}\ln\left(\frac{Y_{GO,t}}{Y_{GO,0}}\right) + \frac{\sigma-1}{\sigma}\ln(\zeta) + \frac{\lambda-1}{\lambda}\ln\left(\frac{K_t}{K_0}\right) + \frac{\lambda-1}{\lambda}\ln\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}}\right) \\ + \left(\frac{\sigma-\lambda}{\sigma(\lambda-1)}\right)\ln\left(\beta_0\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}}\frac{K_t}{K_0}\right)^{\frac{\lambda-1}{\lambda}} + (1-\beta_0)\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}}\frac{L_t}{L_0}\right)^{\frac{\lambda-1}{\lambda}}\right) + \varepsilon_{s_{K,t}}\end{aligned} \tag{B.2}$$

$$\begin{aligned}\ln(s_{L,t}) = \ln((1-\alpha_0)(1-\beta_0)) - \frac{\sigma-1}{\sigma}\ln\left(\frac{Y_{GO,t}}{Y_{GO,0}}\right) + \frac{\sigma-1}{\sigma}\ln(\zeta) + \frac{\lambda-1}{\lambda}\ln\left(\frac{L_t}{L_0}\right) + \frac{\lambda-1}{\lambda}\ln\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}}\right) \\ + \left(\frac{\sigma-\lambda}{\sigma(\lambda-1)}\right)\ln\left(\beta_0\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}}\frac{K_t}{K_0}\right)^{\frac{\lambda-1}{\lambda}} + (1-\beta_0)\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}}\frac{L_t}{L_0}\right)^{\frac{\lambda-1}{\lambda}}\right) + \varepsilon_{s_{L,t}}\end{aligned} \tag{B.3}$$

CES-in-CES with Disaggregated Energy (corresponding to Eq. 26)

$$\begin{aligned}\ln(s_{C,t}) = \ln(\alpha_0\omega_0) - \frac{\sigma-1}{\sigma}\ln\left(\frac{Y_t}{Y_0}\right) + \frac{\sigma-1}{\sigma}\ln(\zeta) + \frac{\varpi-1}{\varpi}\ln\left(\frac{E_{C,t}}{E_{C,0}}\right) + \frac{\varpi-1}{\varpi}\ln\left(\frac{\Gamma_{C,t}}{\Gamma_{C,0}}\right) \\ + \left(\frac{(\sigma-1)\varpi}{(\varpi-1)\sigma}\right)\ln\left(\omega_0\left(\frac{\Gamma_{C,t}}{\Gamma_{C,0}}\frac{E_{C,t}}{E_{C,0}}\right)^{\frac{\varpi-1}{\varpi}} + (1-\omega_0)\left(\frac{\Gamma_{D,t}}{\Gamma_{D,0}}\frac{E_{D,t}}{E_{D,0}}\right)^{\frac{\varpi-1}{\varpi}}\right) + \varepsilon_{s_{C,t}}\end{aligned} \tag{B.4}$$

$$\begin{aligned}\ln(s_{D,t}) = \ln(\alpha_0(1-\omega_0)) - \frac{\sigma-1}{\sigma}\ln\left(\frac{Y_t}{Y_0}\right) + \frac{\sigma-1}{\sigma}\ln(\zeta) + \frac{\varpi-1}{\varpi}\ln\left(\frac{E_{D,t}}{E_{D,0}}\right) + \frac{\varpi-1}{\varpi}\ln\left(\frac{\Gamma_{D,t}}{\Gamma_{D,0}}\right) \\ + \left(\frac{(\sigma-1)\varpi}{(\varpi-1)\sigma}\right)\ln\left(\omega_0\left(\frac{\Gamma_{C,t}}{\Gamma_{C,0}}\frac{E_{C,t}}{E_{C,0}}\right)^{\frac{\varpi-1}{\varpi}} + (1-\omega_0)\left(\frac{\Gamma_{D,t}}{\Gamma_{D,0}}\frac{E_{D,t}}{E_{D,0}}\right)^{\frac{\varpi-1}{\varpi}}\right) + \varepsilon_{s_{D,t}}\end{aligned} \tag{B.5}$$

$$\ln(s_{K,t}) = \ln((1-\alpha_0)\beta_0) - \frac{\sigma-1}{\sigma}\ln\left(\frac{Y_t}{Y_0}\right) + \frac{\sigma-1}{\sigma}\ln(\zeta) + \frac{\lambda-1}{\lambda}\ln\left(\frac{K_t}{K_0}\right) + \frac{\lambda-1}{\lambda}\ln\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}}\right) + \left(\frac{\sigma-\lambda}{\sigma(\lambda-1)}\right)\ln\left(\beta_0\left(\frac{\Gamma_{K,t}}{\Gamma_{K,0}}\frac{K_t}{K_0}\right)^{\frac{\lambda-1}{\lambda}} + (1-\beta_0)\left(\frac{\Gamma_{L,t}}{\Gamma_{L,0}}\frac{L_t}{L_0}\right)^{\frac{\lambda-1}{\lambda}}\right) + \varepsilon_{s_{K,t}} \tag{B.6}$$

$$\ln(s_{L,t}) = \ln\left((1-\alpha_0)(1-\beta_0)\right) - \frac{\sigma-1}{\sigma}\ln\left(\frac{Y_t}{Y_0}\right) + \frac{\sigma-1}{\sigma}\ln(\zeta) + \frac{\lambda-1}{\lambda}\ln\left(\frac{L_t}{L_0}\right) + \frac{\lambda-1}{\lambda}\ln\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}}\right) + \left(\frac{\sigma-\lambda}{\sigma(\lambda-1)}\right)\ln\left(\beta_0\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}}\frac{K_t}{K_0}\right)^{\frac{\lambda-1}{\lambda}} + (1-\beta_0)\left(\frac{\Gamma_{N,t}}{\Gamma_{N,0}}\frac{L_t}{L_0}\right)^{\frac{\lambda-1}{\lambda}}\right) + \varepsilon_{s_{L,t}} \tag{B.7}$$

C Additional Figures

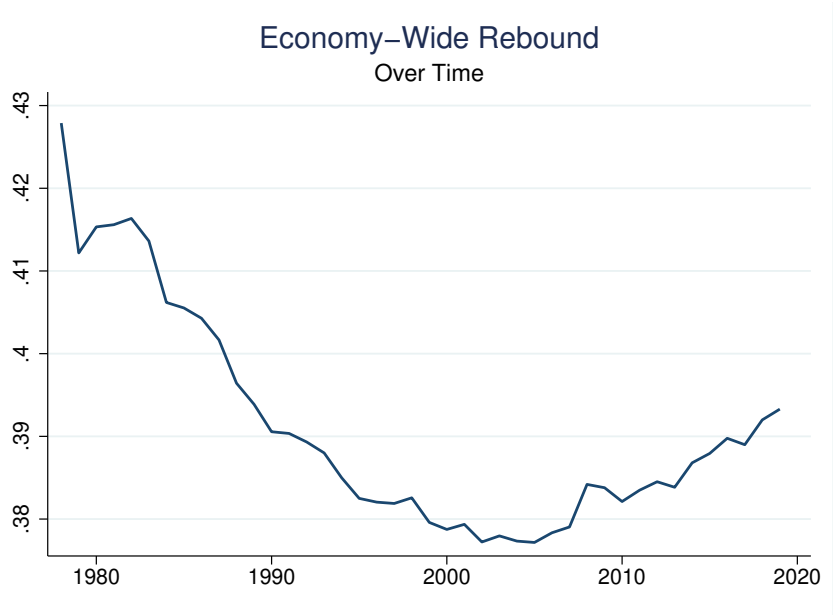
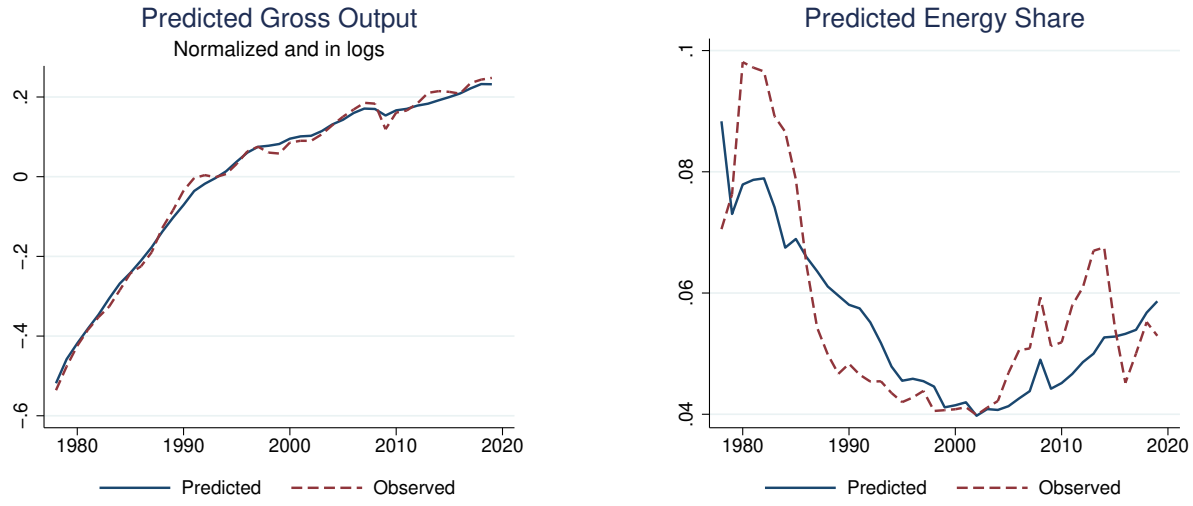
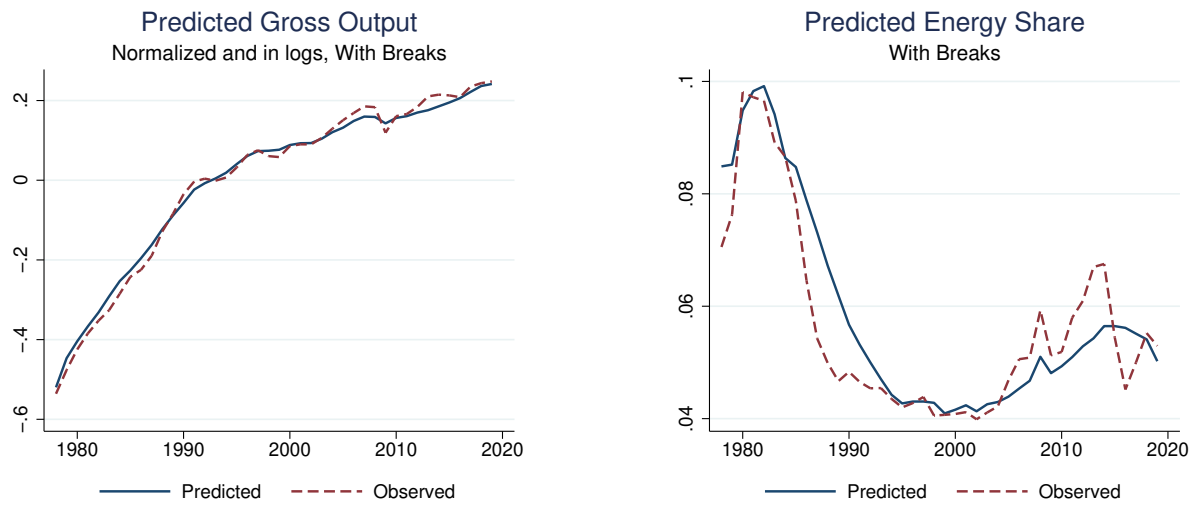


Fig. C.1: Japan's Economy-Wide Rebound Effect Over Time. Note: The figure displays the estimated economy-wide rebound over time corresponding to Eq. (19). *Source:* Own estimations.



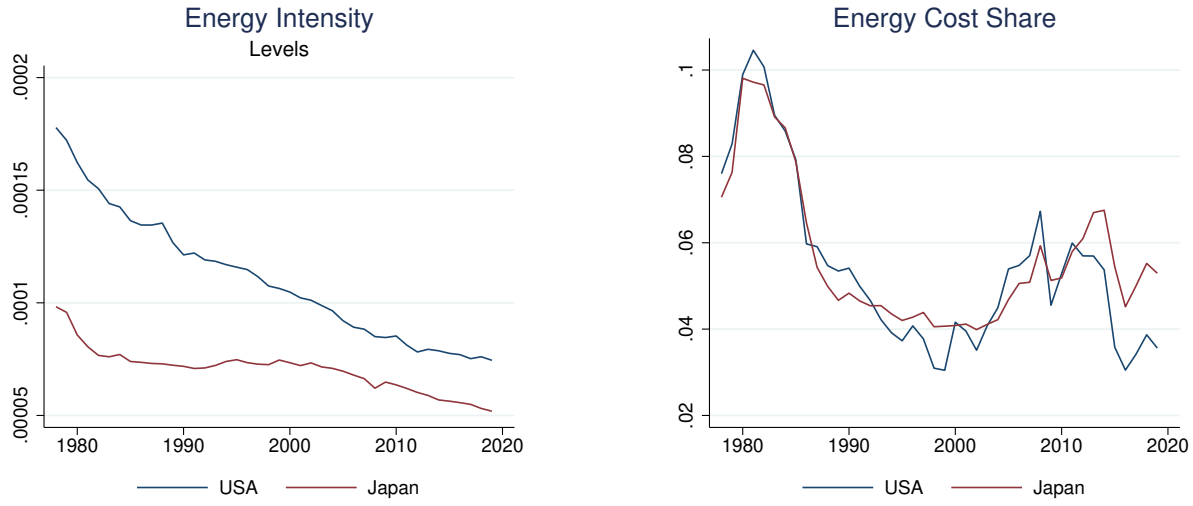
(a) **(b)**

Fig. C.2: Energy Cost Share and Gross Output, Predicted (Baseline Model). Note: The figure displays the predicted gross output (normalized at sample averages and in logs) in (a) and the predicted energy cost share in (b) in correspondence with our baseline model. *Source:* PWT (2023), IEA (2022a) Energy Prices, IEA (2022b) World Energy Balances, and own calculations.



(a) **(b)**

Fig. C.3: Energy Cost Share and Gross Output, Predicted (with Breaks). Note: The figure displays the predicted gross output (normalized at sample averages and in logs) in (a) and the predicted energy cost share in (b) in correspondence with our empirical equation system model, including structural breaks in the technology function in 1991 and 2011. *Source:* Own estimations.



(a) **(b)**

Fig. C.4: Energy Intensity and Energy Share, United States and Japan. Note: The figure displays the energy intensity in (a) and energy cost share in gross output in (b). *Source:* Own estimations.

D Additional Tables

Table D.2: Results based on HP & BK Filtered Data

Filter	HP (800)	HP (1200)	BK
σ	0.293*** [0.275:0.311]	0.262*** [0.246:0.278]	0.359*** [0.316:0.403]
λ	1.258*** [1.230:1.286]	1.205*** [1.159:1.252]	0.913*** [0.895:0.931]
γ_E	0.013*** [0.012:0.013]	0.012*** [0.012:0.013]	0.007*** [0.005:0.009]
η_E	0.421*** [0.357:0.485]	0.500*** [0.449:0.550]	-0.899*** [-1.352:-0.445]
γ_N	0.007*** [0.007:0.007]	0.007*** [0.007:0.007]	0.007*** [0.007:0.007]
η_N	0.676*** [0.657:0.695]	0.707*** [0.690:0.724]	0.726*** [0.609:0.843]
ζ	1.011*** [1.010:1.012]	1.011*** [1.010:1.013]	1.018*** [1.012:1.024]
$\ell\ell$	611.896	603.141	289.300
AIC	-1209.791	-1192.282	-564.601
BIC	-1197.627	-1180.118	-553.516
$rmse_{CES}$	0.003	0.003	0.019
$rmse_{FOC_E}$	0.088	0.074	0.113
$rmse_{FOC_K}$	0.008	0.013	0.067
$rmse_{FOC_L}$	0.008	0.012	0.051
$\sigma = 1$	0.000	0.000	0.000
$\lambda = 1$	0.000	0.000	0.000

Note: Estimation results in the table are based on 42 observations of the countries' aggregate economies over the period 1978–2019. We apply the *fgnls* estimator. Standard errors are robust. Numbers in brackets indicate the 95% confidence interval. The abbreviations $\ell\ell$, AIC, and BIC are the log-likelihood and the Akaike and Bayesian information criterion, respectively. The *rmse* provides information on the root mean square error of the estimated equations. The table also reports p-values for a Wald test with the respective null hypotheses $\sigma = 1$ as well as $\lambda = 1$. Asterisks *, **, and *** indicate the 10%, 5%, and 1% significance levels, respectively.

Table D.3: Smooth Transitions in Technical Progress

σ	0.427***	[0.424:0.431]
λ	0.948***	[0.871:1.025]
γ_E	0.074***	[0.059:0.089]
η_E^I	1.536***	[1.073:1.999]
η_E^{II}	-4.175***	[-6.040:-2.310]
η_E^{III}	22.280***	[13.518:31.042]
γ_N	0.004***	[0.003:0.005]
η_N^I	-0.074	[-0.282:0.134]
η_N^{II}	1.623***	[1.191:2.054]
η_N^{III}	1.188	[-1.939:4.315]
ζ	0.940***	[0.898:0.982]
$\ell\ell$	418.193	
AIC	-814.386	
BIC	-795.271	
$rmse_{CES}$	0.018	
$rmse_{FOC_E}$	0.124	
$rmse_{FOC_K}$	0.042	
$rmse_{FOC_L}$	0.069	
$\sigma = 1$	0.000	
$\lambda = 1$	0.260	

Note: Estimation results in the table are based on 42 observations of the countries' aggregate economies over the period 1978–2019. We apply the *fgnls* estimator. Standard errors are robust. Numbers in brackets indicate the 95% confidence interval. The abbreviations $\ell\ell$, AIC, and BIC are the log-likelihood and the Akaike and Bayesian information criterion, respectively. The *rmse* provides information on the root mean square error of the estimated equations. The table also reports p-values for a Wald test with the respective null hypotheses $\sigma = 1$ as well as $\lambda = 1$. Asterisks *, **, and *** indicate the 10%, 5%, and 1% significance levels, respectively.

Table D.4: Interfuel Substitution

σ	0.336***	[0.331:0.340]
λ	1.347***	[1.292:1.403]
ϖ	0.634***	[0.457:0.810]
γ_C	-0.000	[-0.001:0.001]
η_C	-1.745*	[-3.535:0.045]
γ_D	0.017***	[0.011:0.023]
η_D	-0.063	[-0.482:0.356]
γ_N	0.008***	[0.007:0.008]
η_N	0.554***	[0.469:0.638]
ζ	1.012***	[1.007:1.018]
$\ell\ell$	422.847	
AIC	-825.695	
BIC	-808.318	
$rmse_{CES}$	0.016	
$rmse_{FOC_{EI}}$	0.045	
$rmse_{FOC_{NEI}}$	0.317	
$rmse_{FOC_K}$	0.031	
$rmse_{FOC_L}$	0.045	
$\sigma = 1$	0.000	
$\lambda = 1$	0.000	

Note: Estimation results in the table are based on 42 observations of the countries' aggregate economies over the period 1978–2019. We apply the *fgnls* estimator. Standard errors are robust. Numbers in brackets indicate the 95% confidence interval. The abbreviations $\ell\ell$, AIC, and BIC are the log-likelihood and the Akaike and Bayesian information criterion, respectively. The *rmse* provides information on the root mean square error of the estimated equations. The table also reports p-values for a Wald test with the respective null hypotheses $\sigma = 1$ as well as $\lambda = 1$. Asterisks *, **, and *** indicate the 10%, 5%, and 1% significance levels, respectively.

Table D.5: Results for the United States Supply-Side

σ	0.294***	[0.290:0.298]
λ	1.008***	[1.000:1.015]
γ_E	0.028***	[0.026:0.030]
η_E	0.606***	[0.433:0.779]
γ_N	0.010***	[0.010:0.011]
η_N	1.138***	[0.984:1.293]
ζ	1.043***	[1.008:1.079]
α_0	0.051	
β_0	0.39	
$\ell\ell$	371.137	
AIC	-728.273	
BIC	-716.109	
$rmse_{CES}$	0.023	
$rmse_{FOC_E}$	0.213	
$rmse_{FOC_K}$	0.068	
$rmse_{FOC_L}$	0.073	
$\sigma = 1$	0.000	
$\lambda = 1$	0.053	

Note: Estimation results in the table are based on 42 observations of the countries' aggregate economies over the period 1978–2019. We apply the *fgnls* estimator. Standard errors are robust. Numbers in brackets indicate the 95% confidence interval. The abbreviations $\ell\ell$, AIC, and BIC are the log-likelihood and the Akaike and Bayesian information criterion, respectively. The *rmse* provides information on the root mean square error of the estimated equations. The table also reports p-values for a Wald test with the respective null hypotheses $\sigma = 1$ as well as $\lambda = 1$. Asterisks *, **, and *** indicate the 10%, 5%, and 1% significance levels, respectively.

Table D.6: Different Nesting Structures

	(LE)K	(KE)L
σ	0.917*** [0.886:0.947]	0.598*** [0.588:0.609]
λ	0.444*** [0.373:0.515]	0.933*** [0.923:0.944]
γ_N	0.037*** [0.026:0.047]	-0.006*** [-0.008:-0.004]
η_N	0.353*** [0.177:0.529]	2.414*** [1.609:3.220]
γ_L		0.020*** [0.019:0.021]
η_L		0.735*** [0.658:0.813]
γ_K	-0.047*** [-0.063:-0.031]	
η_K	0.322*** [0.096:0.548]	
ζ	1.003*** [1.000:1.006]	0.995*** [0.992:0.998]
$\ell\ell$	360.428	350.728
AIC	-706.857	-687.456
BIC	-694.693	-675.292
$rmse_{CES}$	0.021	0.020
$rmse_{FOC_E}$	0.180	0.258
$rmse_{FOC_K}$	0.036	0.092
$rmse_{FOC_L}$	0.025	0.036

Note: Estimation results in the table are based on 42 observations of the countries' aggregate economies over the period 1978–2019. We apply the *fgnls* estimator. Standard errors are robust. Numbers in brackets indicate the 95% confidence interval. The abbreviations $\ell\ell$, AIC, and BIC are the log-likelihood and the Akaike and Bayesian information criterion, respectively. The *rmse* provides information on the root mean square error of the estimated equations. The table also reports p-values for a Wald test with the respective null hypotheses $\sigma = 1$ as well as $\lambda = 1$. Asterisks *, **, and *** indicate the 10%, 5%, and 1% significance levels, respectively.

Table D.7: Bootstrapped Resampled Standard Errors

σ	0.336***	[0.246:0.427]
λ	1.018***	[0.755:1.281]
γ_E	0.013***	[0.007:0.018]
η_E	0.155	[-0.660:0.970]
γ_N	0.007***	[0.006:0.007]
η_N	0.624***	[0.264:0.983]
ζ	1.068***	[0.970:1.166]
$\ell\ell$	375.101	
AIC	-736.202	
BIC	-724.038	
$rmse_{CES}$	0.016	
$rmse_{FOC_E}$	0.157	
$rmse_{FOC_K}$	0.046	
$rmse_{FOC_L}$	0.058	
$\sigma = 1$	0.000	
$\lambda = 1$	0.893	

Note: Estimation results in the table are based on 42 observations of the countries' aggregate economies over the period 1978–2019. We apply the *fgnls* estimator. Standard errors are robust. Numbers in brackets indicate the 95% confidence interval. The abbreviations $\ell\ell$, AIC, and BIC are the log-likelihood and the Akaike and Bayesian information criterion, respectively. The *rmse* provides information on the root mean square error of the estimated equations. The table also reports p-values for a Wald test with the respective null hypotheses $\sigma = 1$ as well as $\lambda = 1$. Asterisks *, **, and *** indicate the 10%, 5%, and 1% significance levels, respectively.

Table D.8: Excluding Residential Energy Consumption

σ	0.360***	[0.355:0.365]
λ	0.959***	[0.895:1.024]
γ_E	0.015***	[0.012:0.018]
η_E	0.289*	[-0.001:0.579]
γ_N	0.006***	[0.006:0.007]
η_N	0.445***	[0.335:0.555]
ζ	1.006***	[0.969:1.043]
$\ell\ell$	346.668	
AIC	-679.335	
BIC	-667.171	
$rmse_{CES}$	0.060	
$rmse_{FOC_E}$	0.066	
$rmse_{FOC_K}$	0.201	
$rmse_{FOC_L}$	0.019	
$\sigma = 1$	0.000	
$\lambda = 1$	0.215	

Note: The estimation results in the table are based on 42 observations of the countries' aggregate economies over the period 1978–2019. We apply the *fgnls* estimator. Standard errors are robust. Numbers in brackets indicate the 95% confidence interval. The abbreviations $\ell\ell$, AIC, and BIC are the log-likelihood and the Akaike and Bayesian information criterion, respectively. The *rmse* provides information on the root mean square error of the estimated equations. The table also reports p-values for a Wald test with the respective null hypotheses $\sigma = 1$ as well as $\lambda = 1$. Asterisks *, **, and *** indicate the 10%, 5%, and 1% significance levels, respectively.

Table D.9: Baseline Model with GMM Estimator and Instruments

	Version 1	Version 2	Version 3
σ	0.261*** [0.253:0.269]	0.282*** [0.281:0.283]	0.200*** [0.198:0.201]
λ	1.318*** [1.287:1.350]	1.311*** [1.282:1.339]	1.328*** [1.296:1.360]
γ_E	0.011*** [0.009:0.013]	0.013*** [0.012:0.014]	0.011*** [0.010:0.012]
η_E	0.383*** [0.145:0.622]	0.479*** [0.351:0.607]	0.501*** [0.312:0.690]
γ_N	0.007*** [0.006:0.007]	0.006*** [0.005:0.006]	0.007*** [0.007:0.008]
η_N	0.285*** [0.138:0.433]	0.037 [–0.082:0.155]	0.505*** [0.438:0.573]
ζ	1.020*** [1.013:1.026]	1.029*** [1.025:1.032]	1.018*** [1.013:1.022]
K_{t-1}	yes	yes	yes
L_{t-1}	yes	yes	yes
E_{t-1}	yes	yes	yes
Y_{t-1}	no	yes	no
t	no	no	yes

Note: Estimation results in the table are based on 42 observations of the countries' aggregate economies over the period 1978–2019. We apply the *gmm* estimator with the usual default options in Stata. Standard errors are robust. Numbers in brackets indicate the 95% confidence interval. Asterisks *, **, and *** indicate the 10%, 5%, and 1% significance levels, respectively. K_{t-1}, L_{t-1}, E_{t-1}, Y_{t-1}, and t indicate the applied instruments in each estimation.

E Rebound according to the Implicit Function Theorem

Based on the IFT and a CD-in-CES production function structure, Saunders (2008) derives equations for the long-term of η_s and η_o. The IFT avoids the empirical difficulty of simultaneously identifying the energy substitution elasticity and energy-augmenting technical progress. Via the IFT, the final equations for the substitution and the output effect are functions of observable cost shares and the energy substitution elasticity only. Moreover, the output effect captures second-order effects that energy efficiency can impose on other production factors in the CES function. The essential idea is that energy-augmenting technical progress not only affects output per se but also induces second-order effects on primary factors (or energy), which in turn affect output again. The second-order effects are implicit functions of energy-augmentation within the output effect equation. Saunders' (2008) derivations are not directly applicable here since he assumes primary factors are nested in a Cobb-Douglas function. Brockway et al. (2017b) and Ullah and Khan (2022) follow Saunders (2008) and derive the long-term equations for the substitution- the output and the economy-wide rebound as the sum of the former two based on a CES-in-CES structure. [12] Table E.2 presents the respective equations and empirical results. The substitution effect is a function of energy's substitution elasticity σ. The output effect is a complex function of energy's cost share, the capital share in the value-added nest, and σ. We see again that the economy-wide rebound depends on the magnitude of σ. The output effect of energy contributes relatively little. Even more importantly, the output effect based on the IFT is similar to the direct estimation approach provided in our study above. We conclude that the second-order effects on output induced by energy-augmenting technical progress are negligible.

Table E.2: Long-Term Economy-Wide Rebound

$1+\pi_s$	π_o	$1+\pi$
σ	$\left(\frac{s_E}{1+s_E+s_K}\right)\left(\frac{1+2\left(\frac{1-\sigma}{\sigma}\right)}{1+\left(\frac{1-\sigma}{\sigma}\right)}\right)$	$\frac{(1+s_E+s_K)+s_E\left(1+2\left(\frac{1-\sigma}{\sigma}\right)\right)}{(1+s_E+s_K)\left(1+\left(\frac{1-\sigma}{\sigma}\right)\right)}$
0.336	0.072	0.408

Note: Equations borrowed from Ullah and Khan (2022). In the long run, Saunders (2008) assumes flexible output and input quantities and holds real input prices fixed.

[12] Ullah and Khan (2022) and Brockway et al. (2017b) equations of different structure. However, we confirm that they lead to the same rebound results

Acknowledgments

The authors thank Georg Dürnecker, Vanessa Christiansen, Kenichi Ueda, and Matthias Schlegl, as well as participants at the Sophia Institute for Human Security, Sophia University, Tokyo (November 2024), the 70th CARF Seminar at the Center for Advanced Research in Finance, University of Tokyo (November 2025), and the virtual Japan-Tokyo Resource and Environmental Economics (J-TREE) Seminar Series (June 2026), for their valuable comments and suggestions.

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