The Aggregate Green Elasticity of Substitution*

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Abstract

I introduce a new empirical strategy to provide the first estimate of the aggregate elasticity of substitution between polluting and non-polluting energy. Exploiting variation in US states' energy mixes, I estimate an elasticity of 0.50 — much lower than most calibrations assume. Gross complementarity between energy sources complicates the green transition and significantly raises the economic costs of climate change. Despite rapid clean energy adoption, I find no evidence of increasing substitutability over time. A bottom-up model mapping invariant sectoral elasticities to their aggregate counterpart supports this result. These findings underscore the need for policies targeting green energy's economic suitability.

1 Introduction

As global fossil fuel consumption reaches record highs, questions regarding the feasibility of a transition to net-zero emissions become increasingly urgent. The macroeconomic literature broadly agrees that the success of a clean energy transition critically hinges on the

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economy's ability to substitute away from fossil fuels as cleaner alternatives become relatively cheaper. This substitutability is typically captured by the elasticity of substitution between clean and pollutant energy sources[1] in the aggregate production function. Yet, despite this parameter's central importance for climate policy evaluation, no empirical estimates of its value are currently available (Casey et al., 2023).

This paper fills that gap. I develop a novel empirical strategy to estimate the aggregate elasticity of substitution — that is, how the economy-wide ratio of pollutant to non-pollutant energy consumption responds to changes in these sources' relative prices, and apply it to the United States (US). I find a value of 0.50, well below unity, suggesting that clean and dirty energy sources act as complements in the aggregate production function. This estimate stands in stark contrast to typical macroeconomic calibrations, which assume gross substitutability by default. Compared to previous empirical work, my approach incorporates all energy consumed in the economy — rather than focusing only on specific sectors — and explicitly addresses the endogeneity between energy prices and technological efficiency. A key methodological innovation tackles the core challenge of measuring clean energy prices when estimating this elasticity.

My result fundamentally challenges prevailing views on the practicality of the green energy transition. In the framework of Acemoglu et al. (2012), which embeds directed technological change into the analysis of the energy transition, a low elasticity of substitution between clean and dirty energy sources — as I find — implies that a full transition to carbon-neutrality would bring economic growth to a halt. Moreover, clean energy subsidies, when used as the sole policy instrument, would be insufficient to eliminate fossil fuel use, rendering the current dominant policy approach in the US ineffective.

Recent quantitative studies further highlight the importance of the elasticity of substitution in shaping both the welfare consequences of climate change and the costs of transitioning away from fossil fuels. Cruz and Rossi-Hansberg (2024) project that reducing the elasticity from a baseline of 2.7 to 0.5 increases climate-induced welfare losses by 27% over the next century, even after accounting for adaptation through migration. Similarly, Hochmuth et al. (2025) show that clean energy transition policies disproportionately burden lower-income households, who face welfare losses 50% higher than their high-income counterparts due to the non-homothetic nature of energy demand. In their model, lowering the elasticity from 3 to 2 doubles the required carbon tax, exacerbating both the distributional impacts and the total transition costs. I show that the final energy demand elasticity actually lies below unity, reinforcing and amplifying their conclusions and suggesting that the welfare costs of

[1] I use the terms 'dirty', 'dark' and 'pollutant', and 'clean', 'green' and 'non-pollutant' interchangeably throughout. I define the concepts explicitly in section 2.

transitioning may be higher and more unequal than previously thought.

Estimating the elasticity of substitution between energy types from equilibrium conditions is challenging for two reasons. First, clean energy prices are not directly observed. Prior work has proxied clean energy use with electricity consumption, but this approach is inappropriate when studying energy aggregates because a substantial share of electricity remains carbon-intensive, reaching 58% in the US as recently as 2022. To address this problem, I exploit the connection between clean energy prices, the share of clean energy sources in electricity generation, and the final price of electricity. Incorporating this relationship into the first-order conditions for energy demand, I can control for clean energy prices and identify the aggregate elasticity. My parameter of interest is determined by the reaction of total energy composition to changes in the price of fossil fuels, but now relative to electricity prices. Crucially, identification also depends on the share of clean electricity, which pins down the elasticity of substitution between energy sources within the electricity generation sector itself. I find a sectoral elasticity of 0.52, which aligns closely with my aggregate estimate.

A second challenge stems from the endogeneity between prices and relative energy efficiency - unobserved to the econometrician (Grossman and Oberfield, 2022). To deal with this problem, I exploit the heterogeneity in US states' energy mixes and implement a shift-share design in the spirit of Bartik (1991). Specifically, I explore the variation in US states' fossil fuel consumption composition: the amount of natural gas, coal, and petroleum used both economy-wide and by the electricity generation sector itself. These differences generate heterogeneity in states' exposure to global fossil fuel price fluctuations, which in turn produce quasi-random variation in the relative price of dirty energy. Combining this with the US's electrical grid organization, defined by three largely separated interconnections, I can control for the evolution of clean electricity independently from state-level changes in the electricity market structure or in the suitability of green energy sources. Employing an instrumental variables strategy, I estimate the economy-wide elasticity of substitution from the equilibrium relationship previously derived.

A key conceptual innovation is that I account for all energy use in the economy, rather than limiting my attention to stationary business consumption. This distinction is crucial: residential and transportation use together account for 56% of total US energy consumption as of 2022. Building on Oberfield and Raval (2021), I develop a model that clarifies how sector-specific elasticities of substitution map into an aggregate elasticity when energy usage follows a nested structure — from electricity generation to final consumption. I show that existing micro-level elasticity estimates, when aggregated across sectors and weighted appropriately, imply a much lower economy-wide elasticity than is typically assumed. Using this framework, calibrated to the US economy in 2022, I recover the average elasticity of

substitution between direct fossil fuel usage and electricity for energy end-users[2]. This figure, 0.81, lies above the electricity-generation's elasticity but remains below unity, indicating greater flexibility in downstream sectors but still suggesting gross complementarity within final energy consumption.

Finally, I find no evidence of an increase in the aggregate elasticity of substitution over the past two decades, despite rapid growth in clean energy deployment. This surprising result suggests that the average technological ability to substitute between energy sources has remained relatively constant during this period. I therefore do not project substantial increases in the aggregate elasticity as clean energy adoption continues. While the source of adoption matters — electrifying transportation, for instance, would raise the aggregate elasticity more than an equivalent expansion in clean electricity production — neither development is likely to induce large shifts in the economy-wide capacity to substitute between energy types. Consequently, I conclude that policy must not only affect the relative price of clean energy but also actively enhance the technological capacity of the economy to substitute toward it. Such measures may target electricity production by, for example, improving the grid interconnection or by further incentivizing energy storage installation, as well as final energy consumption, with widespread deployment of electric vehicle charging stations or mass public transit expansions.

Related Literature. My work contributes to the literature studying the economic substitutability between different energy sources. Much of this literature has focused on the elasticity of substitution among fossil fuels — especially in the aftermath of the oil price shocks of the 1970s — and, to a lesser extent, between fossil fuels and electricity. Stern (2012) conduct a comprehensive meta-analysis of this body of work, documenting a wide range of elasticity estimates. In line with my findings, they conclude that substitution elasticities tend to decline with the level of aggregation, and that only fossil fuels appear to be significant substitutes at the macro level.

To my knowledge, Papageorgiou et al. (2017) provide the first peer-reviewed empirical analysis that explicitly distinguishes between energy sources based on their carbon intensities. Using industry-level data for a panel of OECD countries, they estimate substitution elasticities between energy inputs separately for the electricity generation and industrial sectors, finding values well above unity. However, they do not provide an aggregate elasticity estimate. My theoretical framework bridges this gap by deriving a mapping between sector-specific and economy-wide elasticities. I calibrate this formula to their sectoral-level figures,

[2]Sectors whose main purpose is not the production of secondary or higher forms of energy. This includes private and residential consumption.

combined with existing estimates for transportation and residential consumption, and data on American energy consumption for 2022, and find that they imply an aggregate elasticity of approximately 1.51, close to the policy-relevant threshold identified by Acemoglu et al. (2012) — below which clean energy subsidies lose their effectiveness as a stand-alone policy tool.

Methodologically, their approach differs from mine in important respects. They directly estimate the elasticity parameter from the production function via non-linear least squares, admittedly leaving endogeneity concerns unaddressed. In addition, their analysis omits air transport, residential consumption, road and rail vehicle use — which together account for a substantial share of total energy demand. In section 5.3, I discuss these differences in greater detail, and argue that the estimation strategy is the key driver of our diverging results. I also provide evidence that my estimate aligns more closely with observed patterns in the US clean energy transition: despite a significant fall in clean energy's relative price, its contribution to total energy consumption has grown at a relatively modest pace, implying a "realized elasticity" of around 0.34, well below unity.

Several recent papers introduce alternative estimation strategies but remain focused on specific sectors. Using plant-level data from France, Jo (2024) tackle the endogeneity problem using instrumental variables and report elasticities between electricity and primary fuels ranging from 1.4 to 3, depending on the instrument employed. Stöckl and Zerrahn (2023), by contrast, use simulations based on forecasted costs and technological efficiency parameters to trace out isoquants for electricity production. As long as some storage technology is available, they conclude that clean electricity sources can fully stand in for dirty energy alternatives. Otherwise, at higher shares of clean electricity, energy types become complementary — as I find. In practice, storage is still very limited in the US, representing less than 2% of total utility scale electricity as of 2024 (U.S. Energy Information Administration, 2025b), and is not evenly distributed across space - as they assume. Reassuringly, they conclude that a constant elasticity of substitution function is a reasonable representation of the underlying electricity production function, supporting the structure I adopt.

A parallel literature examines price elasticities of demand in private energy consumption. A large body of work has focused on gasoline consumption in particular. Kilian and Zhou (2024) are a recent example. They find a stable price elasticity of approximately 0.3 until 2015, declining to 0.2 thereafter. Davis and Kilian (2011) in turn analyze residential energy use and estimate a price elasticity for natural gas heating of around 0.34 in 1980, which drops substantially by 2000, to 0.1. They also find that, on average, households replace their heating systems only once every 17.5 years. These low price elasticities support the theory that clean and dirty energy sources are complementary factors of production (Hourcade et

al., 2012). Furthermore, the documented downward trend mirrors my findings on the time evolution of the aggregate elasticity of substitution.

Finally, a distinct but related line of research studies the long-run relationship between finite energy resources and economic growth, often highlighting the role of energy-saving technologies. Hassler et al. (2021), using a calibrated general equilibrium model, and Känzig and Williamson (2024), using time-series identification, emphasize the importance of innovation in sustaining growth when energy is a near-perfect complement to other inputs of aggregate production. The ability to replace fossil fuels with clean energy sources represents one such technological innovation. However, my analysis suggests that this channel of energy efficiency has played a limited role, underscoring instead the importance of broader advancements in energy-saving technologies.

Outline. This work is structured as follows. Section 2 lays out the macroeconomic framework that guides the empirical work. Section 3 describes the data used in my empirical exercise. Section 4 details the empirical methodology employed to account for clean energy prices, and the resulting identification strategy. The empirical results are provided in section 5. Section 6 introduces the bottom-up model that links aggregate estimates to their sectoral counterparts and examines the evolution of elasticities in the US over time. Lastly, section 7 concludes.

2 The Aggregate Elasticity of Substitution

I begin by outlining the theoretical framework underpinning my empirical analysis. Following the literature in environmental macroeconomics (Hassler et al., 2016; Lemoine, 2024) I posit that state-level output is a function of an energy composite, and other inputs, such as labor and capital. I formalize this by assuming that output follows a constant elasticity of substitution (CES) function of the form

$$Y_{i,t} = \left(H_{i,t}^{\frac{\eta-1}{\eta}} + E_{i,t}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \tag{1}$$

where $E_{i,t}$ and $H_{i,t}$ are the input aggregates for energy and other factors, respectively. η is the elasticity of substitution between $E_{i,t}$ and $H_{i,t}$.

The aggregate energy factor, $E_{i,t}$, is a composite of clean and dirty energy consumption, $E_{i,t}^C$ and $E_{i,t}^D$, respectively, so that

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

$A^D_{i,t}$ and $A^C_{i,t}$ are the share factors, which can change over time. This formulation thus explicitly accounts for changes in both overall and type-specific energy efficiency. My parameter of interest is $\sigma = d\ln \frac{E^D_{i,t}}{E^C_{i,t}} \Big/ d\ln \frac{P^C_{i,t}}{P^D_{i,t}}$, the elasticity of substitution between polluting and non-polluting economy-wide energy consumption. Implicitly, this nested CES formulation assumes that energy is separable from the other factors of production. Advantageously, to study σ I need not specify $H_{i,t}$ further, nor do I need to know the value of η.

I follow Papageorgiou et al. (2017) and define each energy factor as

$$E^X_{i,t} = \sum_{k \in \mathcal{K}_X} E^k_{i,t}, \quad X \in D, C \tag{2}$$

where D and C are dirty and clean aggregate energy consumption, respectively, and $\mathcal{K}_X$ their underlying energy sources. The differentiation between the two aggregates lies on their operational greenhouse gas emissions[3] (ghg). As a result, non-polluting energy is made up of nuclear, solar, geothermal, wind and hydropower. In turn, the constituents of the polluting aggregate are petroleum products, coal, natural gas and biomass. Following my definition, biofuels fall into petroleum products, and more generally, biomass is classified as a dirty energy source. Although in theory, biomass could be carbon neutral when considering its life-cycle emissions, this is hardly the case in practice[4].

Discussion About Modelling Assumptions. I do not make additional distinctions between energy sources, such as the coupling or not of battery storage. This reflects the idea that enhanced battery efficiency and increased availability are akin to increases in the elasticity of substitution. Improving energy storage capacity is a way of addressing the inherent intermittency of solar and wind power and, as a result, diminishes the need for fuel based back-up plants (Stöckl and Zerrahn, 2023). In the same spirit, additional considerations in energy planning, such as the cost of managing bio-hazardous waste or the pollution consequences of different types of drilling techniques, can also be captured in this framework through the energy efficiency parameters, $A^X_{i,t}$. In contrast, my framework does not explicitly model for other important considerations such as tail-risk or the role expectations play in the build up of energy infrastructure capacity (Kellogg, 2014), especially for clean energy.

Moreover, my formulation assumes perfect substitution within energy aggregates. Although this is the case physically — since fuel based energy generation always involves

[3]The term "operational emissions" contrasts with life-cycle emissions, with the latter including not just emissions arising from the use of energy, but also from the manufacturing of the underlying infrastructure — particularly relevant for renewable energy.

[4]For a discussion of this topic see MIT Climate Portal Writing and Gurgel (2024).

combustion, and fuel-conversion technologies do exist[5], this does not necessarily hold economically[6]. In particular, fuels' physical characteristics make them more suitable for certain economic activities. This, coupled with natural resource scarcity, generates the observed concentration in the energy consumption mix[7]. Notwithstanding, fuel switching, in particular between natural gas and petroleum in industrial settings and electricity generation, is generally regarded as high (Baumeister et al., 2024). Similarly, while electrons are perfectly fungible, the intermittency of solar and wind, or the distinct ramp-up capabilities of nuclear, mean that clean sources play different roles in electricity generation.

Despite these considerations, I choose to maintain the literature's formulation for comparability and practicality — I avoid having to estimate two latent parameters[8]. In addition, I ignore the differences in ghg intensity between fuels. While this may be an important consideration for short-run analysis, with current and projected carbon capturing capabilities, attaining carbon neutrality requires a significant decrease in all sources of polluting energy consumption (Pindyck, 2022).

Finally, focusing on state-level elasticity ignores cross-border energy substitution via trade (Moll et al., 2023). This concern is mitigated by the predominance of non-tradable energy use: in 2022, the transportation and residential sectors together accounted for over 74% of total energy expenditures. Furthermore, consistent with my empirical exercise, this framework accounts for electricity trade across states. As such, I believe that this set-up capture the dominant forces shaping aggregate substitutability between energy types.

[5]The production of synthetic gasoline for example is a well known procedure in history. The Nazi regime produced half of all its petroleum products during world war II from coal (U.S. Department of Energy, Office of Fossil Energy and Carbon Management, 2019).

[6]Although conceptually different from the constant elasticity formulation I use, Stern (2012) conducts a meta-analysis and finds that the cross-fuel elasticities were on average 1.74, 1.11 and 1.78 for coal and oil, coal and gas, and oil and gas, respectively.

[7]For example, petroleum, due to its high energy density, is the preferred fuel in transportation, with 70% of total US consumption in 2024 directed towards this use. In comparison, 90% of coal usage is directed to the electricity generation sector. This number decreases to 40% for natural gas with the remaining 60% used for primary consumption in other sectors (U.S. Energy Information Administration, 2024). Note that the purpose of this primary use may be the production of electricity in-house. 32% of natural gas was directly consumed by industrial plants at this time.

[8]To approximate the first-order movements in the dirty energy aggregate, I would need two share parameters — as the third one is defined residually. On top of this, to the best of my knowledge, there is no counterpart to the work of Stern (2012) for clean energy.

Equilibrium Conditions. I assume that states act as price-takers, so that aggregate dirty energy demand is represented by the following first-order conditions

$$E_{i,t}^D = (A_{i,t}^D)^{\sigma-1}\left(\frac{P_{i,t}^D}{P_{i,t}^E}\right)^{-\sigma} E_{i,t}, \tag{3a}$$

$$E_{i,t}^C = (A_{i,t}^C)^{\sigma-1}\left(\frac{P_{i,t}^C}{P_{i,t}^E}\right)^{-\sigma} E_{i,t}, \tag{3b}$$

where $P_{i,t}^C$ and $P_{i,t}^D$ are the prices of clean and dirty energy sources, respectively, and $P_{i,t}^E$ is the price of the energy index. Taking the ratio of the first-order conditions in equations (3a) and (3b), applying logs and taking differences, I find that

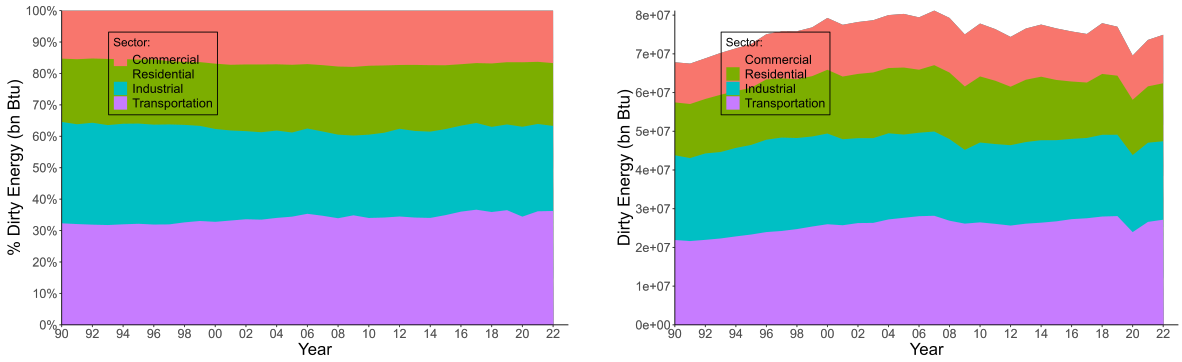
$$\widehat{\frac{E_{i,t}^D}{E_{i,t}^C}} = -\sigma\widehat{\frac{P_{i,t}^D}{P_{i,t}^C}} + (\sigma-1)\widehat{\frac{A_{i,t}^D}{A_{i,t}^C}}, \tag{4}$$

where $\widehat{Y_{i,t}} \equiv \ln Y_{i,t} - \ln Y_{i,t-1}$.

I choose to focus on the first-order conditions instead of the production function to circumvent the normalization difficulties of direct CES estimation discussed in León-Ledesma et al. (2010). Notwithstanding, estimating σ using equation (4) still requires solving two problems: *i*) measuring the price of clean energy, P^C, and *ii*) accounting for the endogeneity problem generated by the unobserved share parameters, $A_{i,t}^D$ and $A_{i,t}^C$. I propose solutions to each of these problems in section 4.1 and section 4.2, respectively. Lastly, by using log-differences instead of levels, I bypass the problem of harmonizing energy units across bundles.

2.1 Accounting for The Full Energy Spectrum

Unlike some of the empirical macroeconomics literature, my framework includes all energy use, not just stationary non-residential energy. To motivate this choice, figure 1 plots the evolution of total dirty energy consumption, direct and indirect, across end-using sectors for the US from 1990 to 2022. I follow the US Energy Information Administration's (EIA) sectoral definitions. Figure 1a displays the share of total consumption while figure 1b plots the absolute levels. In 2022, transportation and residential consumption together represented 56% of total polluting-energy usage, versus only 44% for the industrial and commercial sectors. As such, ignoring private and non-stationary energy usage could risk omitting an important share of total energy consumption. Importantly too, since 1990, industrial consumption of dirty energy has edged down while transportation's own consumption has risen. These contrasting dynamics point to the inadequacy of using industrial-specific energy elasticities



(a) Share of Total Consumption

(b) Absolute Values

Figure 1: Energy-using Sectors' Dirty Energy Consumption

Notes: The measure of dirty energy use includes both direct and indirect polluting energy consumption (through electricity). Dirty energy includes all petroleum products, coal, natural gas and biomass. It excludes non-combustible consumption.

in frameworks studying overall energy consumption dynamics, as in most macroeconomic models, further motivating my comprehensive framework.

3 Data

I employ data from the US Energy Information Administration's (EIA) State Energy Data System (SEDS) to measure annual energy consumption and expenditures at the state level in the contiguous United States. My sample excludes Alaska and Hawaii and incorporates the District of Columbia into Maryland. The SEDS provides consistent, comparable annual time series on states' energy production, use, and expenditures, derived from EIA surveys and complementary observational data. The dataset spans the period from 1990 to 2022.

Following the EIA's statistical energy balance methodology, I restrict attention to primary energy consumption — that is, energy used prior to any transformation into secondary or tertiary forms. For example, coal converted into synthetic gas and subsequently into electricity is recorded solely as coal consumption[9]. Accordingly, I consider the consumption of petroleum products instead of crude oil, which lacks direct end-use applications. Although the SEDS reports crude oil production, it does not report crude oil consumption; my focus on petroleum products therefore aligns with both the data and the conceptual framework presented in section 2.

I exclude non-combustible uses of combustible energy sources, which arise when energy inputs are consumed as material inputs — for example, in the production of feedstocks,

[9] U.S. Energy Information Administration (n.d.).

lubricants, or asphalt. Thus, my measures of energy use capture only consumption for heat and power generation[10]. Focusing on consumption (rather than production) and measuring it at the first point of use is consistent with the macroeconomic framework laid out in section 2, where energy enters the aggregate production function as an input. This approach also yields a direct mapping between fuel use and emissions.

Following standard practice in the macroeconomic literature (Hassler et al., 2016), I express all energy in British thermal units (Btu). For polluting energy, I apply the SEDS's time-varying, energy-specific conversion factors, which translate source-specific physical units (e.g., barrels, short tons) into Btus based on each fuel's average heat content. For clean energy, I adopt the EIA's fixed electricity-to-heat conversion rate of 3.412. All clean energy is first measured in kilowatt-hour (kWh) of electricity produced and then converted into Btus. This diverges from the EIA's convention only for nuclear energy, which has a different conversion factor. Although heat-based conversions are appropriate when comparing combustible inputs (as with fossil fuels), they are unsuitable for clean energy, which is consumed exclusively via electricity. Since my empirical exercises uses log growth rates, conversion factors matter only within energy categories. I define the price of dirty energy as the consumption-weighted average of the subcomponents' prices.

3.1 Accounting for Electricity Trade

My empirical strategy relies on state-level measures of aggregate primary energy consumption. However, the SEDS does not capture primary energy embodied in electricity imported from other states or abroad. Although SEDS reports electricity imports and exports, it does not identify their sources or destinations. Assuming identical energy mixes for produced and consumed electricity would bias primary consumption measures, as interstate electricity trade is non-negligible. Between 1990 and 2022, net imported electricity constituted, on average, 21% of total electricity consumed in net-importing states, while net-exporting states exported approximately 31% of their electricity production. In contrast, US net electricity imports from abroad represented only 1% of total electricity consumption.

To account for electricity trade, I implement a two-step procedure. First, I compute each state's (as well as Canada and Mexico's) primary energy mix used in electricity production and remove any primary energy associated with net electricity exports. Second, I partition the country into three distinct electricity pools — the Eastern, Western, and Texas grids — following U.S. Environmental Protection Agency (2024). These pools reflect grid infrastructure and the resulting limitations on interconnection and electricity trade[11]. I account

[10]Further details on variable construction are provided in section 1.1 of the supplemental appendix.

[11]For a depiction of the grid infrastructure as of 2025, see figure 1 of the supplemental appendix.

Table 1: Descriptive Statistics

	Energy Consumption												
	Coal (Tn BTU)		Gas (Tn BTU)		Petr (Tn BTU)		NP (Tn BTU)		P (Tn BTU)		Electricity (Bn kWh)	Pop (Mn)	GDP (Bn USD 2019)
	Og.	Adj.	Og.	Adj.	Og.	Adj.	Og.	Adj.	Og.	Adj.			
Avg	388	388	497	498	634	634	85	88	1,574	1,574	246	6	343
SD	383	366	666	665	701	702	92	93	1,560	1,600	226	7	419
Min	0	0	4	4	64	64	0^+	0^+	79	80	16	0^+	22
Max	1,695	1,694	4,750	4,760	4,498	4,498	626	668	10,111	10,127	1,622	40	3,230
Mdn	299	267	277	275	463	463	49	56	1,167	1,165	191	4	209
P25	71	109	147	147	200	200	19	19	642	580	85	2	85
P75	521	576	558	548	775	775	124	129	1,858	1,956	318	7	439
N	1,584	1,584	1,584	1,584	1,584	1,584	1,584	1,584	1,584	1,584	1,584	1,584	1,584
IQR	450	467	412	401	575	575	105	110	1,216	1,376	234	5	354

Notes: The dataset includes 48 states and spans 1990 to 2022. Energy and population data are from the EIA's SEDS. GDP data is from the BEA's Regional accounts data. All units are indicated in parenthesis. "Coal", "Gas", "Petr", indicate primary energy consumption of coal, naturas gas, and petroleum, respectively. "Electricity" depicts electricity consumption. "P" is pollutant energy primary consumption whereas "NP" is clean energy's. The subheaders "Adj." and "Og." indicate whether or not the values include primary energy consumption from electricity trade among US states, and with Canada, and/or Mexico, respectively. A "+" superscript indicates that the value was positive before rounding.

for trade across pools and within each region and allocate to net-importing states their proportional share of primary energy consumed indirectly through imported electricity. A full description of the procedure is provided in section 1.2 of the online appendix.

Descriptive statistics of the final dataset and of the primary energy consumption changes induced by my procedure are reported in table 1[12]. I further document the impact of my adjustments in section 1.2 of the supplemental appendix. On average, clean energy consumption increased by roughly 2% while dirty energy consumption rose by less than 1%. This differential primarily reflects the clean energy composition of Canadian electricity imports. Judging by the interquartile range, the cross-sectional variation in clean and dirty energy consumption increased slightly. Western states experienced more increases in dirty energy shares, whereas the majority of Mid-Atlantic and Eastern states saw reductions. The largest percentage drops occurred in Rhode Island and Delaware, where the clean energy share, in Btus of dirty energy, tripled on average. These states initially exhibited very low clean energy shares (less than 1% overall, and 2% in 2020).

Changes in polluting energy's composition, relevant for my empirical analysis, were modest. The most notable shift occurred in coal's share during 2020. Several states retired coal plants during the 2010s but continued to import electricity from coal-intensive states. For

[12]The "Og." sub-headers indicate the values of energy consumption without accounting for electricity trade. The values in sub-columns "Adj." include primary energy consumed indirectly through electricity imports.

example, California and Maine saw their coal shares double, starting from very low initial levels (less than 1%). Similar patterns emerged in Vermont and Massachusetts, which lack operational coal plants. These observations underscore that significant changes were confined to states with highly specialized generation infrastructure. By accounting for electricity trade, I incorporate primary energy indirectly imported from other states, thereby internalizing trade's effect on the energy consumption mix.

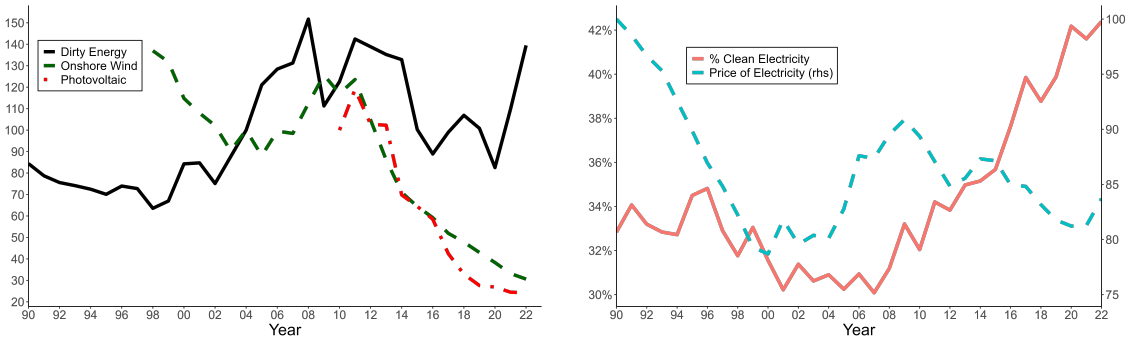
4 Empirical Approach

This section shows how I account for the price of clean energy and presents my identification strategy.

4.1 The Price of Clean Energy

The cost structures of fossil and renewable energy sources differ fundamentally. Fossil energy costs are largely driven by variable fuel expenses. Consistent with standard macroeconomic practice, I thus use fossil fuel prices to proxy for the price of dirty energy (Hassler et al., 2021). In contrast, renewable energy costs are predominantly shaped by upfront capital expenditures — including infrastructure, permitting, land acquisition, and financing — which are typically sunk and difficult to observe directly (Arkolakis and Walsh, 2024). Although the levelized cost of energy (LCOE) offers a long-run average cost estimate, its limited time-series coverage and sensitivity to state-specific policies and geographic factors prevents its consistent use in my analysis.

Nuclear power occupies a distinct position among clean energy sources. Unlike renewables, it requires a fuel component and has operational flexibility, allowing it to play both a baseload and lower frequency load-following roles. Consequently, its effective cost reflects not only capital and fuel expenditures but also variable costs tied to output adjustments, such as depreciation and retrofitting (International Atomic Energy Agency, 2018). This distinction is especially relevant in the first half of my sample, when nuclear accounted for over 66% of clean electricity on average, and in practice functioned as the only scalable clean energy source. Between 1990 and 2010, its capacity factor rose dramatically, from 66% to 91.1%, while its annual electricity output increased by roughly 40%, from 576,862 to 806,968 million kWh (U.S. Energy Information Administration, 2025a). Thereafter, the sharp decline in aeolic — and later solar — power generation costs fuelled the rise in clean energy consumption, with their share increasing from 3% of total clean energy use in 2006 to 37% in 2022. Accordingly, my measurement of clean energy prices must consider the evolution of the clean energy frontier, adding further complexity to the task.



(a) LCOEs and Dirty Energy Prices (b) Electricity Prices and Clean Energy Share

Figure 3: Electricity Generation and the Price of Clean Energy.

Notes: The price of electricity is normalized relative to 1990. The price of dirty energy and the wind LCOE estimates are normalized relative to 2004, when wind's electricity share started to rise. Photovoltaic's LCOE estimates are normalized to 2010 when the series starts. All prices are adjusted for inflation. LCOE prices are directly taken from International Renewable Energy Agency (2024).

Rather than attempting to directly measure clean energy costs, I adopt an indirect approach to estimating the price of non-polluting energy. Specifically, I exploit the dynamics of the power generating sector's electricity composition — the main source of electricity production — and end-use electricity prices, as these trends primarily reflect shifts in the relative prices of different energy sources. Figure 3 illustrates this relationship. Figure 3a overlays normalized LCOE estimates for wind and solar for new power plants from International Renewable Energy Agency (2024) with dirty energy prices. Figure 3b compares electricity prices with the share of clean electricity. I can observe that electricity prices broadly follow polluting energy prices, the main source of electricity in the US. In turn, shifts in electricity source shares match changes in relative prices. For instance, the sharp fall in wind and solar LCOEs during the 2010s coincides with the significant increase in the clean electricity share from 32% to 42%.

Taken together, these observations highlight the relationship between electricity prices, the composition of energy inputs in electricity generation, and the relative prices of clean and dirty energy sources. More importantly, they underscore the potential to leverage electricity market dynamics to estimate the implicit price of clean energy. To formalize this idea, I adopt a variant of the framework used by Papageorgiou et al. (2017)[13] and assume that

[13]Unlike their approach, I use actual energy consumption rather than installed capacity, because the SEDS only records the latter's from 2008 onward. Notwithstanding, the dynamics of total clean installed capacity and clean electricity production are very similar as I show in section 2.1 of the online appendix.

electricity is produced using a CES function that combines clean and dirty energy sources,

$$E^e_{i,t} = \left((A^{e,D}_{i,t} E^{e,D}_{i,t})^{\frac{\nu-1}{\nu}} + (A^{e,C}_{i,t} E^{e,C}_{i,t})^{\frac{\nu-1}{\nu}} \right)^{\frac{\nu}{\nu-1}}$$

where $E^e_{i,t}$ is total electricity produced, $E^{e,D}_{i,t}$ is the amount of dirty energy consumed by electricity generation, and $E^{e,C}_{i,t}$ the amount of electricity produced by clean sources. $A^{e,D}_{i,t}$ and $A^{e,C}_{i,t}$ are the respective unobservable share parameters, again dependent on time to allow for varying technological adaptability. Under competitive markets, the first order condition for clean energy is

$$E^{e,C}_{i,t} = \left(\frac{P^C_{i,t}}{P^e_{i,t}} \right)^{-\nu} (A^{e,C}_{i,t})^{\nu-1} E^e_{i,t}. \tag{5}$$

Taking log-differences and rearranging yields my clean energy price proxy

$$\widehat{P^C_{i,t}} = \widehat{P^e_{i,t}} - \frac{1}{\nu} \widehat{\frac{E^{e,C}_{i,t}}{E^e_{i,t}}} + \frac{\nu-1}{\nu} \widehat{A^{e,C}_{i,t}}. \tag{6}$$

While I do not attempt to measure this proxy directly, I exploit the implied relationship in my empirical strategy. As such, I briefly assess the relevance of equation (6). Using the symmetric first-order condition for dirty energy, I regress the average electricity-specific dirty energy price in the United States on the average price of electricity and the national share of dirty electricity, all expressed in log-differences. The full estimation results are reported in table 1 in section 2 of the supplemental appendix. For my purposes, it suffices to note that the statistical association is substantial, with an R^2 of 58%, which rises to 68% when a time trend is included. Although I acknowledge that equation (6) does not capture all of the complexities of electricity market operations, and that this simple exercise has notable limitations[14], I interpret the high explanatory power as supportive evidence of its usefulness to capture the evolution of clean energy prices, which is my primary objective.

Finally, two additional considerations are pertinent to my empirical exercise. First, electricity markets in the United States have not always been characterized by competitive access to the electricity grid or by fully competitive supply of electricity, a feature I abstracted from in my derivation (Borenstein and Bushnell, 2015). Because my identification strategy relies on exogenous shifts in supply costs, this issue does not pose a problem for my analysis; I can

[14] In particular, the embedded endogeneity suggested by the sign of $\widehat{\frac{E^{e,C}_{i,t}}{E^e_{i,t}}}$'s coefficient.

subsume any mark-up term into the unobserved productivity parameter, $A_{i,t}^{e,C}$[15]. Second, as in equation (4), the productivity parameters are unobservable. To address this, I instrument for prices and shares in my estimation procedure.

4.2 Identification Strategy

Equipped with equation (6) I can replace $P_{i,t}^{C}$ in equation (4) to obtain

$$\widehat{\frac{E_{i,t}^{D}}{E_{i,t}^{C}}} = -\sigma \widehat{\frac{P_{i,t}^{D}}{P_{i,t}^{e}}} - \frac{\sigma}{\nu} \widehat{\frac{E_{i,t}^{e,C}}{E_{i,t}^{e}}} + \sigma \frac{\nu - 1}{\nu} \widehat{A_{i,t}^{e,C}} + (\sigma - 1) \widehat{\frac{A_{i,t}^{D}}{A_{i,t}^{C}}}. \tag{7}$$

Equation (7) still pins down σ and, although the share parameters remain unobserved, all the other variables are measurable in the data.

The empirical counterpart of equation (7) is

$$\widehat{\frac{E_{i,t}^{C}}{E_{i,t}^{D}}} = \beta \widehat{\frac{P_{i,t}^{D}}{P_{i,t}^{e}}} + \gamma \widehat{\frac{E_{i,t}^{e,C}}{E_{i,t}^{e}}} + e_{i,t}. \tag{8}$$

I can quantify σ if I am able to consistently estimate β in equation (8). Direct OLS estimation is biased due to endogeneity stemming from the unobserved variables, $\sigma \frac{(1-\nu)}{\nu} \widehat{A_{i,t}^{e,C}} + (\sigma - 1) \widehat{\frac{A_{i,t}^{D}}{A_{i,t}^{C}}}$, captured by the error term, $e_{i,t}$. Notably, the environmental macroeconomics literature has documented the relationship between aggregate energy efficiency and fluctuations in dirty energy prices (Hassler et al., 2022; Känzig and Williamson, 2024). Even after controlling for such country-wide trends through time fixed effects, residual state-specific price variation may remain correlated with local demand shifters.

To address these concerns, I instrument for both $\widehat{\frac{P_{i,t}^{D}}{P_{i,t}^{e}}}$ and $\widehat{\frac{E_{i,t}^{e,C}}{E_{i,t}^{e}}}$. Although γ is not my primary parameter of interest, both variables must be instrumented to consistently estimate β. This is because the relative price of dirty energy and electricity are jointly determined with the clean energy share, implying that $\mathbb{E}(\widehat{\frac{P_{i,t}^{D}}{P_{i,t}^{e}}} \cdot \widehat{\frac{E_{i,t}^{e,C}}{E_{i,t}^{e}}} | X_{i,t}) \neq 0$. Consequently, relying solely on an instrument for the relative prices risks biasing my estimates through a bad control problem, since the clean energy share itself correlates with the error term[16] (Angrist and Pischke, 2009).

[15] $A_{i,t}^{e,C} \equiv \mu_{i,t}^{\frac{1}{\nu-1}} \widetilde{A_{i,t}^{e,C}}$, where $\mu_{i,t}$ is the mark-up, which may depend on prices and quantities, and $\widetilde{A_{i,t}^{e,C}}$ is the actual unobserved productivity parameter. The mark-up may also capture fixed costs, such as those related to electricity distribution infrastructure, which are not explicitly modelled here.

[16] I thank Jaeeun Seo for highlighting and clarifying this issue.

4.2.1 Instrumenting for Relative Energy Prices

I leverage the US states' cross-sectional variation in energy mixes to instrument for the relative price of dirty energy vis-à-vis electricity. To motivate my approach, note that the price of dirty energy is a consumption-weighted average of the prices of fossil fuels and biomass, so that $P^D_{i,t} = \sum_k \frac{E^k_{i,t}}{E^D_{i,t}} P^k_{i,t}$. As such, taking a first-order approximation around time $t-1$, I have that

$$\widehat{P^D_{i,t}} = \sum_k \omega^{D,k}_{i,t-1} \cdot \widehat{P^k_{i,t}} \tag{9}$$

where the weights, $\omega^{D,k}_{i,t-1} \equiv \frac{E^k_{i,t-1}}{E^D_{i,t-1}} \frac{P^k_{i,t-1}}{P^D_{i,t-1}}$, are the relative expenditure shares of each input. Similarly, due to the CES assumption the price of electricity is defined by the usual aggregator, $P^e_{i,t} = (\sum_{X \in \{C,D\}} (A^{e,X}_{i,t})^{\nu-1} (P^{e,X}_{i,t})^{1-\nu})^{1/(1-\nu)}$. Taking its first-order approximation around time $t-1$, and using the symmetric first-order condition of equation (5), I have that electricity prices change according to

$$\widehat{P^e_{i,t}} = \frac{E^{e,D}_{i,t-1}}{E^e_{i,t-1}} \frac{P^D_{i,t-1}}{P^{e,D}_{i,t-1}} \widehat{P^{e,D}_{i,t}}$$

in response to fluctuations in dirty energy prices. Plugging in the first-order approximation of $\widehat{P^{e,D}_{i,t}}$, equation (9), I have that

$$\widehat{P^e_{i,t}} = \sum_k \omega^{e,k}_{i,t-1} \cdot \widehat{P^{e,k}_{i,t}}, \tag{10}$$

where the weights, $\omega^{e,k}_{i,t-1} \equiv \frac{E^{e,D}_{i,t-1}}{E^e_{i,t-1}} \frac{E^{e,D,k}_{i,t-1}}{E^{e,D}_{i,t-1}} \frac{P^l_{i,t-1}}{P^{e,D}_{i,t-1}} \frac{P^{e,D}_{i,t-1}}{P^e_{i,t-1}} = \frac{E^{e,D,l}_{i,t-1}}{E^e_{i,t-1}} \frac{P^l_{i,t-1}}{P^e_{i,t-1}}$, are the expenditures shares of each dirty energy input in electricity production. As such, I can combine equation (9) and equation (10), to conclude that the ratio of dirty energy to electricity prices should, to a first order, move according to

$$\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}} = \sum_k \omega^k_{i,t-1} \cdot \widehat{P^k_{i,t}}, \tag{11}$$

where the weights, $\omega^k_{i,t-1} \equiv \omega^{D,k}_{i,t-1} - \omega^{e,k}_{i,t-1}$, are the differences in dirty expenditure shares between the overall economy and the electricity generating sector. I assume that input prices move in tandem, so that $\widehat{P^k_{i,t}} = \widehat{P^{e,k}_{i,t}}$.

Equation (11) provides a similar set-up to the standard shift-share instrumental variables (SSIV) formulation introduced in Bartik (1991) which I explore to build my instrument. The

use of distinct energy mixes as a source of variation is not unprecedented. Ganapati et al. (2020) and Jo (2024) have used similar approaches to instrument for energy cost changes at the industrial plant level. The main methodological difference lies on the denominator of the electricity price weight: they consider the total expenditure in fuels for electricity generation whereas I consider the total revenue in electricity sales, motivated theoretically above. In my exercise I also only consider petroleum, coal and natural gas when building the instrument. I exclude biomass because of its comparatively hyper-localized nature. My instrument thus takes the following form

$$\left(\frac{\widehat{P^D_{i,t}}}{P^e_{i,t}}\right)^{IV} = \sum_k \omega_i^k \cdot \widehat{P_t^k}, \tag{12}$$

where $\widehat{P_t^k}$ are the common price shifters, and ω_i^k are the time-invariant state-specific shares.

As my shares I fix the weights in equation (11) to their 1990 values, $\omega_i^k \equiv \omega_{i,1990}^k$, the first year of my sample which I exclude from the estimation exercise. I present the geographical variation of each weight in figure 6 of the supplemental appendix. As price shifters I use the annual log growth rates in US relevant commodity price indices. Specifically, I take log-differences of the annual averages of the West Texas Intermediate index for crude oil (wti), the US's Central Appalachian coal spot price, and the Henry Hub's natural gas spot price. While the latter two prices are literally the wholesale values of the corresponding commodities, the wti is the reference price for crude oil, and not for petroleum products per se. Nevertheless, it is by far the latter's main input, explaining more than 97% of state petroleum prices' time-series variation in the US[17]. I plot the time series of the log growth rates for all three commodity prices in figure 8 of the online appendix.

My identification assumption then takes the form:

$$\mathbb{E}(P_t^k \mathbb{E}(\omega_i^k e_{i,t} | X_{i,t}) | X_{i,t}) = 0, \forall k. \tag{13}$$

In words, condition 13 states that I do not expect states to systematically increase (decrease) their relative use of clean/dirty energy if not due to a decrease (increase) in the price of clean/dirty energy (Chodorow-Reich et al., 2021). The validity of my instrument relies then on the exogeneity of the commodity price fluctuations relative to state-specific energy demand. Since commodity markets are well integrated around the world, it is natural to think that states act as price takers and have a diminutive impact on price fluctuations

[17]Using principal component analysis, I find that the first common component explains around 98.5% of the variation in annual state-level petroleum prices across the US. Regressing the first principal component on annual wti changes, I get an $R^2 = 98.8\%$. Multiplying the two I reach my value. See section 3.1 of the online appendix for more details.

(Kilian and Zhou, 2024). A natural worry is that some US states play an outsized role as suppliers of oil and gas, and so may be differentially affected by their prices. In section 5.2 I show that excluding them from my sample does not change the results. Finally, the inclusion of time fixed effects implies that I require exogeneity relative to the changes in state-specific energy demand shifters only.

Control Variables and Threats to Identification. In my baseline specification, I include a lag of the dependent variable to account for possible auto-correlation in the error-term. Following Borusyak et al. (2024), I include state fixed effects to capture the heterogeneous SSIV weights, $\sum_k \omega_i^k \neq 1$, and control for other potential non-observables. I also insert one lag of the instrument so as to capture only the contemporaneous effects of commodity prices. This approach is akin to only using the innovations in the time series of prices, following the exclusion of the autoregressive component. In my set-up this does not seem necessary since both oil and gas behave as random walks[18]. In comparison, coal is third-order integrated. I show later that including another lag of the instrument does not change my results.

Because I only work with three commodity shifters, the concern may arise that the law of large numbers condition from Borusyak et al. (2022) does not apply to my setting. The relevant margin of variation in my case is not just the number of shifters, but also the number of times I observe them since I am working with panel data. Notwithstanding, I add additional controls to minimize the problem of potential endogeneity from ω_i^k — on top of fixing the weights before the estimation sample starts. As additional controls I include lagged weather patterns such as the logarithm of average precipitation and temperature in the region, important proxies for the suitability and effectiveness of renewable energy sources[19]. Additionally, I include a lag for the state-specific average generating power plant's vintage for each dirty energy source[20]. This ensures that I account for changes in energy infrastructure quality induced by commodity price fluctuations. This is especially relevant for coal reliant states where infrastructure is generally older[21].

Lastly, to control for changes in the energy composition, I include a lag for the share of manufacturing, and a lag for the share of energy related activities, such as mining and utilities, in states' gross domestic product[22]. In table 3 of the supplemental appendix I

[18] I use The Bayesian Information Criterion on a set of ARMA models to determine the optimal lag structure.

[19] These are computed using the National Center for Environmental Information's US Climate Divisional Database.

[20] These figures are computed using the EIA's form EIA-860M.

[21] As of 2021, the average American operating coal-fired generating unit was 45 years old, five years short of the average retirement age (U.S. Energy Information Administration, 2021).

[22] The data come from the BEA's regional accounts. Until 1997 I use the industrial classifications D for industry, and B and 49 for energy activities. After, I use classifications 31-33, and 21 and 22, respectively.

show that my instrument's shares are actually very related to exogenous state conditions. Climate, state's geographical characteristics — mediated by population density, and their location relative to oil and gas supply hubs can explain between 32% to 72% of total cross-sectional variation in relative fuel expenditure, depending on the inclusion of PADD[23] fixed effects.

4.2.2 Instrumenting for the Clean Electricity Share

To instrument for the growth rate in the clean electricity share in state i I use the average of the growth rates for states located outside of the electrical grid to which i belongs:

$$\left(\frac{\widehat{E^{e,C}_{i,t}}}{E^{e}_{i,t}}\right)^{IV} = \sum_{p\in\mathcal{P}_i} \frac{\widehat{E^{e,C}_{p,t}}}{E^{e}_{p,t}} \Big/ \sum_{p\in\mathcal{P}_i} 1 \tag{14}$$

where $\mathcal{P}_i$ is the set of states located outside i's electrical grid region. This selection, although conservative, ensures that state-specific developments in electricity markets, be it from electrical infrastructure development or changes in market structure, are not directly related to my instrument. This is justified by the electrical grids' partial isolation and distinctive regulatory and operational bodies, described in section 3. At the same time, the clean electricity share's long-run evolution has largely been driven by common factors, justifying my instrument's relevance. In the beginning of my sample, the political curtailment of new nuclear power plants led to a rise in the capacity factor of nuclear power. In the second half in turn, the global decrease in clean energy hard costs, starting in the mid to late 2000s, together with greener federal and state-level policies incentivized the installation of solar and wind energy infrastructure, raising the overall share of clean electricity.

I try alternative approaches as well, such as the internal instrument proposed by Arellano and Bond (1991) or a different delimitation based on states' electric power transmission system operators. I present their results in section 3.2 of the online appendix. While the first-stage F-statistic is weak for the first instrument, neither estimate challenges my main conclusions. Furthermore, this allows us to conduct a Sargan test for exogeneity. Importantly, I cannot reject the null hypothesis for any of the proposed instruments.

[23] Petroleum Administration for Defense Districts.

4.3 Regression Model

Following my identification strategy, my final regression model takes the form

$$\frac{\widehat{E^D_{i,t}}}{E^C_{i,t}} = \beta \frac{\widehat{P^D_{i,t}}}{P^e_{i,t}} + \gamma \frac{\widehat{E^{e,C}_{i,t}}}{E^e_{i,t}} + \Gamma' X_{i,t} + \alpha_i + \alpha_t + e_{i,t} \tag{15}$$

where $X_{i,t}$ are the additional controls discussed in section 4.2, and α_i and α_t are the state and year fixed effects. I can then identify σ from $\beta = -\sigma$, my main object of interest, and ν indirectly through $\gamma = \beta/\nu$.

5 Results

This section presents the results from my main estimation exercise and the robustness checks undertaken, and compares them to the previous literature. I also discuss the policy implications of gross complementarity between energy types, implied by my estimates.

5.1 Baseline Results

I use two-stage least squares with both instruments for $\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$ and $\widehat{\frac{E^{e,C}_{i,t}}{E^e_{i,t}}}$ to estimate equation (15). My sample spans 1991 to 2022 with the exclusion of the pandemic period[24] and contains all contiguous US states[25]. To reduce the influence of extreme values, I trim observations below the 1st and above the 99th percentiles of the dependent variable and/or the two main explanatory variables[26].

I report the results with and without the additional controls, together with the OLS estimates and the regression instrumenting only for the relative prices in table 2. I cluster standard errors at the year and state level.[27]. This is a more conservative approach than the recommendation by Borusyak et al. (2024) to cluster by year — the shifter level. Following Chodorow-Reich (2020), I do not weight the regressions. Weighting the regressions produces similar results, which I report in table 4.

The point estimates of my preferred specification, presented in column (4), indicate that the elasticity of substitution between primary clean and dirty energy consumption is approximately 0.50, while this object increases slightly to 0.52 for the electricity generation

[24]Including 2020 further decreases my point estimates, but affects statistical precision significantly. This may reflect the extreme behavior of commodity prices during this year. Ending the sample in 2019 instead does not meaningfully change my results. A full analysis of the sample period selection is provided in section 4.1 of the supplemental appendix.

[25]I combine the District of Columbia with Maryland.

[26]This excludes 64 of the 1440 observations comprising my original sample.

[27]A state- or year-clustered bootstrap yields very similar standard errors.

Table 2: Elasticity of Substitution Estimates

	OLS	Pseudo-IV	IV	
	(1)	(2)	(3)	(4)
$\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$	-0.2162***	-0.5768**	-0.5299**	-0.4969**
	(0.0649)	(0.2411)	(0.2529)	(0.2261)
$\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$	-0.9521***	-0.9296***	-0.9207***	-0.9571***
	(0.0311)	(0.0369)	(0.0809)	(0.0778)
Observations	1,376	1,376	1,376	1,376
Adjusted R^2	0.91110	0.90026	0.90148	0.90453
1^{st} stage F-statistic, $\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$		22.694	33.768	32.317
1^{st} stage F-statistic, $\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$			77.643	76.861
State fixed effects	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓
Extra Controls	No	Yes	No	Yes

Notes: Results of regressing equation (15). Column (1) presents the results under OLS estimation. Column (2) presents the results when only instrumenting for $\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$. Column (3) presents the results when instrumenting also for $\widehat{\frac{E^{C,e}_{i,t}}{E^e_{i,t}}}$. Column (4), in addition, includes the extra control variables. All regressions are unweighted and include a lag of the dependent variable. "Extra controls" refers to the annual lags of the states': average coal, natural gas and petroleum power plant vintages, the logarithm of the past 10 years' average precipitation and temperature, and the shares of energy activities, and of industry in gdp. The sample includes the 48 contiguous US states and spans 1991 to 2022, excluding 2020. The 1% tails are excluded. Standard errors are clustered at the year and state level. The standard errors are in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

sector. Focusing on the former figure, at the expense of lower precision, 0.50 is significantly higher than the point estimate of 0.22 implied by OLS, in column (1). In contrast, the full IV estimate is smaller than the Pseudo-IV figure, 0.58, presented in column (2), using only the instrument for relative prices. This is reassuring as the correlations between dirty energy prices and the state-specific shifters, and the latter and the share of clean electricity should have different signs, thus inducing opposing biases. Finally, excluding the additional controls marginally increases my estimate to 0.53.

Table 3: Robustness Checks

	(1)	(2)	(3)	(4)	(5)
$\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$	-0.4880**	-0.6081**	-0.4877**	-0.5702**	-0.4443***
	(0.2372)	(0.2765)	(0.2107)	(0.2712)	(0.1463)
$\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$	-0.9554***	-0.9419***	-0.9951***	-0.9497***	-0.9572***
	(0.0815)	(0.0806)	(0.0730)	(0.1019)	(0.0604)
Observations	1,329	1,376	1,292	1,376	639
Adjusted R^2	0.90189	0.89759	0.91346	0.89987	0.89864
1^{st} stage F-statistic, $\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$	30.981	27.337	32.178	29.503	19.714
1^{st} stage F-statistic, $\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$	70.092	77.733	80.590	75.837	29.697
State fixed effects	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓
Extra Controls	Yes	Yes	Yes	Yes	Yes

Notes: Results of robustness checks. Column (1) includes an extra lag of the SSIV instrument. Column (2) uses foreign commodity price indices. Column (3) excludes TX, NM and ND. Column (4) includes state-specific quadratic trends. Column (5) groups the observations in 2-year windows. All regressions are uneweighted. The sample includes the 48 contiguous US states and spans 1991 to 2022, excluding 2020 (and 2019 in column (5)). The 1% tails are excluded. Standard errors are clustered at the year and state level. The standard errors are in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5.2 Robustness Checks

I now present some of the robustness exercises conducted[28]. Each column of table 3 represents a separate exercise. The first three columns deal with concerns about the validity of my shift-share instrument.

First, I want to ensure that my results arise from contemporaneous variation in energy prices and not from the dynamic effect of past fluctuations. While this may not be a concern with natural gas and crude oil prices, which are essentially random walks, coal prices have been persistently decreasing and a BIC-based choice criterion would conclude that they are integrated of order 3. As such, in column (1) I present my results with two lags of the SSIV instrument instead of one. The estimate decreases marginally to 0.49.

A second concern is that my national price shifters for natural gas and coal are not

[28]I present further checks in section 4.1 of the online appendix — specifically related to my sample's period. The results remain similar.

entirely exogenous to states' energy demands since their markets may not be as integrated as crude oil's is at a global scale — due to transportation costs for example. To appease that concern I replicate my exercise using instead foreign price indices as shifters. Specifically I use the price of brent crude, the main European index for crude oil, the index for natural gas in Japan, and the coal index for Australian coal. The first is retrieved from FRED while the other two come from the World Bank's Commodity Markets Outlook. The results are provided in column (2). The point estimate increases to 0.61 but is still within the range admitted by my baseline specification, and remains considerably below the previous literatures' values.

Another threat to my identification strategy is the fact that some US states have an outsized influence in world energy markets, playing significant roles in the supply of natural oil and gas. The importance of this industry may skew their composition of energy and how they react to price fluctuations. To show that this bears no influence on my results, I repeat my regressions excluding Texas, New Mexico and North Dakota. The results are presented in column (3). The figures are again essentially unchanged with σ decreasing to 0.49.

On top of these, in column (4) I further try to account for the differential trends in energy composition across states by adding a state-specific quadratic time-trend. The point estimate of σ increases to 0.57, but is still within my main specification's statistical bounds.

Finally, to account for the potential inertia in energy adjustments not captured by yearly data, I aggregate my data to two-year buckets. Now, each observation represents a span of two years, instead of one. The SSIV weights are still set to the relative expenditure share of 1990 and the data span remains the same. I again trim the 1% tails. I provide the results in column (5). The elasticity level decreases further to 0.44 while the statistical precision increases.

Geographical Sensitivity. I do not weight my main regressions, following the recommendation of Chodorow-Reich (2020). At the state level, using weights may introduce bias in the estimated coefficients and affect the power of the first-stage regressions. Moreover, OLS and shift-share instrumental variables naturally weight observations according to their contribution to the variability of the regressors (Borusyak et al., 2022). However, it is important to understand which states drive my results. To assess this, I re-estimate my main specification, equation (15), sequentially excluding one state at a time. I map the difference between these estimates and my baseline value in figure 5. My results are largely insensitive to the exclusion of any single state. The most significant deviations arise from excluding Oklahoma and Vermont, resulting in estimates of 0.57 and 0.39, respectively.

To address potential concerns regarding outlier influence and national representativeness,

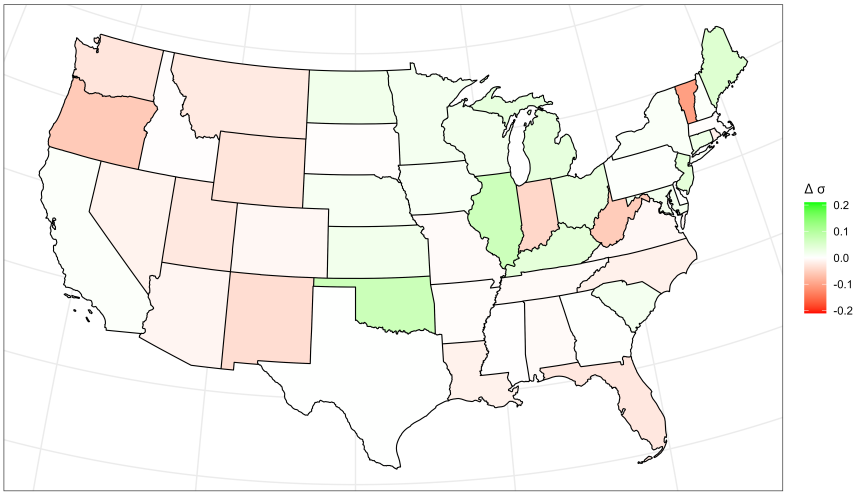


Figure 5: Geographical Sensitivity.

Notes: The map displays the difference between my baseline aggregate elasticity estimate, 0.50, and the result from re-estimating equation (15) when excluding the respective state. All re-estimated coefficients are significant at the 10% significance level.

I re-estimate my main regression using three proxy variables for state size as weights: the logarithm of population, real GDP, and total dirty energy consumption. These weighted specifications reduce the influence of smaller states on my results. As shown in table 4, the resulting elasticity estimates remain close to the unweighted baseline and are generally smaller.

5.3 Comparison to The Previous Literature

My results point to gross complementarity between different energy types, contradicting the general perception in the literature. As such, it is important to understand the sources of divergence, specifically in relation to the empirical paper of reference, Papageorgiou et al. (2017).

Many choices separate our studies. Firstly, we attempt to estimate related but conceptually different objects. I focus on the economy-wide elasticity, thus considering all energy consumed. Papageorgiou et al. (2017) instead attempt to estimate the elasticity separately for the electricity, and energy end-use business sectors. As a result, they ignore non-stationary and private energy use, which as of 2022 constituted 56% of total dirty energy consumption in the US. They find values of around 1.8 (higher than my estimate of 0.52), and 2.86 for each sector, respectively. While these are not directly comparable to my aggregate measure, in section 6 I derive a formula that translates sectoral estimates into an economy-wide value.

Table 4: Weighted Regressions

	Population (1)	Dirty Energy Consumption (2)	GDP (3)
$\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$	-0.4722*	-0.4665*	-0.4286*
	(0.2310)	(0.2340)	(0.2335)
$\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$	-0.9665***	-0.9643***	-0.9811***
	(0.0775)	(0.0772)	(0.0761)
Observations	1,376	1,376	1,376
Adjusted R^2	0.90622	0.90691	0.90907
1^{st} stage F-statistic, $\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$	31.264	30.736	29.916
1^{st} stage F-statistic, $\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$	75.831	75.142	74.703
State fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Extra Controls	Yes	Yes	Yes

Notes: Results from weighted instrumental variable estimation of equation (15). Column (1) weights by the logarithm of population. Column (2) weights by the logarithm of total dirty energy consumption. Column (3) weights by the logarithm of real gdp. The sample includes the 48 contiguous US states and spans 1991 to 2022, excluding 2020. The 1% tails are excluded. Standard errors are clustered at the year and state level. The standard errors are in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Using my calibration for the US in 2022 and the price elasticities[29] provided by Kilian and Zhou (2024) and Davis and Kilian (2011) for the transportation and residential sectors, respectively, I conclude that their estimates imply an aggregate elasticity of 1.51. This figure is much higher than my value of 0.50 but almost coincides with the 1.5 threshold provided by Acemoglu et al. (2012) — below which subsidies are not enough to incentivize the energy transition.

In addition to this, we opt for distinct methodological approaches. Broadly, empirical work studying elasticities of substitution has approached this task either indirectly, identifying the object of interest from the first-order conditions (FOC) of demand — as I do,

[29]I directly assign each sectors price elasticity to its corresponding CES parameter. Although the Marshallian and Hicksian price elasticities are not identical, Slutskys identity implies that the Hicksian elasticity — which excludes the income effect — is always less than or equal to the Marshallian one. This reinforces our point that the aggregate elasticity of substitution is lower than either of the estimates reported by Papageorgiou et al. (2017).

or directly, pinning down the parameters from a constant elasticity of substitution production function. Notwithstanding the identification choice, estimating this parameter requires overcoming the endogeneity problem generated, for example, from unobserved directed technological change (Grossman and Oberfield, 2022). Papageorgiou et al. (2017) acknowledge that they do not attempt to overcome this econometric hurdle. In contrast, I have proposed a strategy to address this problem through an instrumental variables approach. León-Ledesma et al. (2010) provide simulation evidence on the substitutability between capital and labour. Comparing the two methods, they find that using the FOC is superior to non-linear CES estimation if done using valid instrumental variables. Without instruments, the comparison depends on the variance of the error term. At lower variability, the former approach still dominates, reverting if this moment increases.

Finally, our geographical coverages differ: while they focus on OECD countries, my sample consists of the 48 contiguous US states. As I show in section 6, the composition of energy consumption across sectors matters for the aggregate elasticity, so this could also be the source of disagreement.

Replicating Papageorgiou et al. (2017). To shed light on the origins of the divergence, I attempt to apply their approach to my set-up: instead accounting for all energy consumption and applying it to all the contiguous US states. To fully replicate it I would identify σ from their CES-in-Cobb Douglas production function:

$$Y_{i,t} = H_{i,t}^{\alpha}\left((E_{i,t}^{D})^{\frac{\sigma-1}{\sigma}} + (E_{i,t}^{C})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}(1-\alpha)},$$

where $H_{i,t}$ is a Cobb-Douglas aggregator of capital, labour, and imported intermediate materials and services. Nevertheless, the lack of state-level capital data precludes the exact use of their econometric specifications. Recent literature has concluded for the near-perfect complementary nature between energy and other factors of production (Hassler et al., 2021). This means that a more suitable specification would consider a Leontief-in-CES function instead. Using this insight I am able to apply a very similar methodology, directly identifying σ from the fact that in equilibrium we must have that

$$Y_{i,t} \propto \left((E_{i,t}^{D})^{\frac{\sigma-1}{\sigma}} + (E_{i,t}^{C})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{16}$$

Following Papageorgiou et al. (2017), I use OLS to estimate the Kmenta approximation

of equation (16):

$$\ln \frac{Y_{i,t}}{E^D_{i,t}} = a_i + dt + \beta_1 \ln \frac{E^C_{i,t}}{E^D_{i,t}} + \beta_2 \left(\ln \frac{E^C_{i,t}}{E^D_{i,t}} \right)^2 + \varepsilon_{i,t}, \tag{17}$$

either in levels or in first-differences, where $Y_{i,t}$ is real state-level gdp, a_i are state fixed effects, and t represents the time-trend. I can identify $\sigma = \frac{\beta_1(1-\beta_1)}{\beta_1(1-\beta_1)-2\beta_2}$. The results imply an aggregate elasticity of approximately 1.37[30]. While the values are smaller than Papageorgiou et al. (2017)'s implied value of 1.51, they are not fundamentally different. As such, I conclude that the main source of diverge is methodological, not the distinct energetic and geographical scopes.

Recent US Experience with Renewables. I now turn to the American experience with renewable energy during the past two decades. This period offers compelling evidence of complementarity — rather than substitutability — between energy types, supporting my main findings.

In 2022, the end of my sample, the bulk of renewable energy in the US originated from wind, hydro and solar, while geothermal power played a diminutive role, representing 51%, 30%, 17%, and 2% of total renewable electricity, respectively. While hydropower's share has remained fairly stable, wind's importance has increased exponentially during this period, starting from only 5% in 2004 before becoming the main source of renewable energy. Solar's similarly stellar rise started later, around 2012 when it represented only 1% of total renewable electricity. As a result of these expansions, renewables surpassed nuclear to account for 56% of total clean electricity. In addition, clean sources' share of total electricity went from 31% in 2004 to 42% in 2022.

Together, renewables have been responsible for the rising trend in clean energy consumption which increased by 57 percentage points in the last two decades. In comparison, total dirty energy consumption has decreased by 6 percentage points. These diverging trends however appear less dramatic when juxtaposed with the evolution of generation costs: wind LCOE estimates, for example, have declined by 69.4 percentage points — a dynamic closely followed by photovoltaic technology (International Renewable Energy Agency, 2024). Over the same period in turn, dirty energy prices have exhibited significant volatility but, on average, hovered around 118% of their 2004 level.

To contextualize these developments with respect to my object of interest, figure 6 plots the four year moving averages of relative clean energy consumption against the relative price of dirty energy, both computed as log-ratios and normalized to zero at the beginning of the

[30] I provide the full results in table 5 of the online appendix.

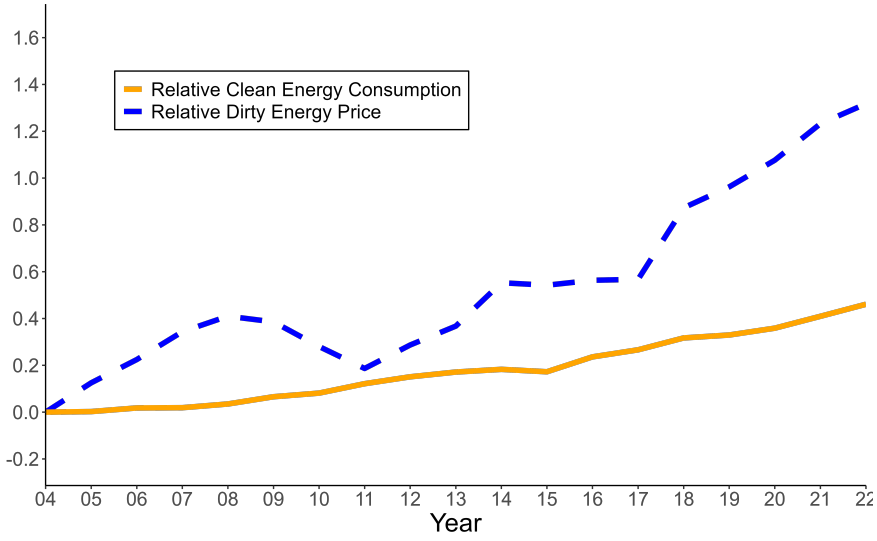


Figure 6: Clean Energy Consumption vs Dirty Energy Prices.

Notes: The figure plots the four-year moving average for two US time-series: the log-difference between average polluting and non-polluting energy prices, and the log-difference between total clean and dirty energy consumption. Both series are normalized to 0 in 2004. As a proxy for clean energy prices, I use onshore wind LCOE estimates for new power plants in the US from International Renewable Energy Agency (2024); analogous results using photovoltaic estimates are shown in figure 12 of the supplemental appendix. All prices are adjusted for inflation.

sample[31]. Between 2004 and 2022, the relative price of dirty energy rose by 1.52 log-points, while the relative use of clean energy increased by only 0.52 log-points. Together these figures imply an "observed elasticity" of approximately 0.34. Using 2019 as an end-point, prior to the post-pandemic boom, does not significantly change my conclusion, yielding a higher value of 0.46. Alternatively, because the LCOE estimates are for new power plants, one may think of past prices as the relevant benchmark for clean energy. If I instead lag the clean energy prices by three years for example[32], the observed elasticity would increase further to 0.5. Notably, all figures are below unit and close to my estimate of 0.50, supporting my findings. In addition, this exercise suggests that the long-run elasticity must not be significantly different from what I estimate for one and two-year horizons.

5.4 Policy And Welfare Implications

Taken at face value, my results have stark implications for energy policy. For example, through the lenses of the canonical model of Acemoglu et al. (2012), I would conclude,

[31]The moving average smooths the series. The plot with the raw data is presented in figure 11 of the supplemental appendix. Dirty energy price dynamics make the price series more volatile but the trends are very similar.

[32]Lagging instead by six years would yield a value of 0.54.

following proposition 3, that an economy-wide clean energy subsidy is not enough to enact the long-run transition away from dirty energy use. This conclusion thus renders ineffective the US's preferred approach to incentivize clean energy. At such a low elasticity of substitution level, it is impossible to counteract the incentives to use dirty energy alongside clean sources. The only way to ensure the transition away from fossil fuels in the long-run is to enact the optimal tax on ghg emissions, ensuring the necessary disincentive to accompany the clean energy increase with more fossil fuel usage. The logic is made clear in Casey et al. (2023). If energy as a whole is productive, increasing energy use, no matter its source, incentivizes more energy use. With low enough elasticity of substitution between energy sources, dirty energy consumption is thus promoted by an increase in clean energy availability. Consequently, at this elasticity level, Casey et al. (2023) argue that, all else equal, clean energy subsidies could increase ghg emissions in the short-run.

In addition to this, Acemoglu et al. (2012) conclude that under gross energy complementarity, $\sigma < 1$, the only way to attain the long-run energy transition is by halting economic growth. A generalized linear hypothesis test of my preferred specification rejects the notion that clean and dirty energy types are gross substitutes in the United States. Although not all my robustness checks can reject this hypothesis, all specifications agree that the elasticity must be much closer to unity than previously thought.

Their framework has recently been put in question, in particular the consideration of a constant elasticity of substitution. Jo and Miftakhova (2024) for example find a positive relationship between the electricity share of french industrial plants, and their adjustments to changes in relative prices. Extrapolating this to the overall economy, they consider instead a variable elasticity of substitution form for the energy aggregate. Consequently, the elasticity of substitution increases with the share of clean energy, accelerating the transition to carbon neutrality. Stöckl (2020) goes a step further and considers endogenous investment into the substitutability between energy sources, on top of energetic efficiency. This fully reverses the de-growth predictions of Acemoglu et al. (2012). Irrespectively, lower elasticities always imply more costly energy transitions and longer periods until net neutrality is achieved.

Finally, recent work has focused on the distributional consequences of the energy transition, underscoring the importance of the parameter studied here. Building on a large macroeconomic literature that accounts for the non-homotheticity of energy demand[33] — particularly following the Russian invasion of Ukraine — Hochmuth et al. (2025) find that poorer households experience 50% greater welfare losses than their richer counterparts as a

[33]See for example Kharroubi and Smets (2024), Känzig (2023) or Auclert et al. (2024) who emphasize the importance of non-homotheticity in energy consumption for the propagation and welfare effects of energy-related shocks.

result of the higher energy prices induced by European anti-carbon policies. These outcomes are highly dependent on the elasticity of substitution between green and dark energy in final consumption. Although this parameter does not exactly match my concept of aggregate elasticity, in section 6 I show that it must be below unity. This low substitutability suggests even greater distributional disparities than those inferred by the authors. Moreover, it has strong policy implications: for instance, the optimal carbon tax nearly doubles when the assumed elasticity falls from 3 to 2. This suggests that my findings should amplify even more the magnitude of this tax.

In contrast, Cruz and Rossi-Hansberg (2024) find that the aggregate elasticity has no impact on the projected regional variation in climate change-induced damages. Nevertheless, they show that by the end of the next century, assuming an energy elasticity of 0.5 — exactly my point estimate — leads to 27% higher average welfare losses than under their baseline scenario, where the elasticity is 2.7.

6 From Macro to Micro

In this section I lay out a model inspired by Oberfield and Raval (2021) that helps to dissect the concept of aggregate elasticity of substitution between polluting and non-polluting energy. In practice my estimates reflect not a unique aggregate parameter, but the combination of several "lower-level" elasticities.

6.1 Bottom-up Model

Consider n distinct energy using sectors[34]. In line with the evidence provided in the literature (Hassler et al. (2022), Känzig and Williamson (2024)), similarly to Jo (2024), I pose that their production functions take a Leontief form

$$Y_j = \min\{H_j/g_j, E_j\}$$

where, as in section 2, H_j is a combination of other factors of production[35], and E_j is the energy consumption bundle. Further, I assume that each sector j can consume directly either dirty energy or electricity, so that their energy bundle is a CES composite of both forms of energy,

$$E_j = \left((a_j^e)^{\frac{1}{\sigma_j}} (E_j^e)^{\frac{\sigma_j - 1}{\sigma_j}} + (1 - a_j^e)^{\frac{1}{\sigma_j}} (E_j^d)^{\frac{\sigma_j - 1}{\sigma_j}} \right)^{\frac{\sigma_j}{\sigma_j - 1}}.$$

[34] I denominate these sectors as energy-using because their output is directly provided to consumers. This can also include the direct provision of higher-order energy directly to consumers.

[35] I assume that their price does not depend on energy prices.

The electricity generation sector operates under full competition and produces electricity for the whole economy using either dirty or clean energy. Its production function also takes a CES form, so that

$$E^e = \sum_j E_j^e = \left((a^e)^{\frac{1}{\nu}} (E^{e,C})^{\frac{\nu-1}{\nu}} + (1-a^e)^{\frac{1}{\nu}} (E^{e,D})^{\frac{\nu-1}{\nu}} \right)^{\frac{\nu}{\nu-1}}.$$

I consider a unique electricity generation function. Notwithstanding, this set-up can also accommodate sector-specific electricity production functions — it would instead require distinct share and elasticity parameters. Some residential clean electricity for example is produced by households' own solar panels which are not connected to the electricity grid. Also, part of the industrial sector produces some of its own electricity from primary dirty energy consumed. In practice, my framework can also accommodate this by adjusting the sectoral breakdown. In contrast, this model structure ignores the supply side's network structure. I leave such a development for future work.

Finally, consumers consume a CES bundle of all sectors in the economy

$$C_j = \left(\sum_{j=1}^{n} D_j^{\frac{1}{\varepsilon}} Y_j^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}.$$

Because the elasticity of substitution is inherently a partial equilibrium concept, I assume that the prices of dirty and clean energy are unique, so that $P_j^d = P^{e,D} = P^D$, $P^{e,C} = P^C$. In connection to my empirical exercise, the aggregate elasticity of substitution is then the change in the overall economy's relative clean energy consumption when dirty energy's relative price changes, so that

$$\sigma \equiv \frac{d \ln \frac{E^C}{E^D}}{d \ln \frac{P^D}{P^C}} = \frac{d \ln \frac{E^C P^C}{E^D P^D}}{d \ln \frac{P^D}{P^C}} + 1$$

where $E^X = \sum_j E_j^X$, $X \in \{C, D\}$ is the total energy of type X consumed directly, or indirectly, by sector j. I recast the elasticity in terms of expenditures, instead of quantities, because it helps when thinking about its determinants. In section A of the in-paper appendix, I prove that σ takes the form laid out in proposition 1.

Proposition 1. In section 6.1's model, the aggregate elasticity of substitution between clean and dirty energy, $\sigma = d \ln \frac{E^C}{E^D} \Big/ d \ln \frac{P^D}{P^C}$, takes the form

$$\sigma = \chi \tilde{\varepsilon} + (1-\chi)\tilde{\sigma}. \tag{18}$$

$\chi, \tilde{\varepsilon}$ and $\tilde{\sigma}$ are defined as

$$\begin{aligned}
\chi &= \sum_j \theta_j \frac{(\alpha_j - \alpha)^2}{\alpha(1-\alpha)} \\
\tilde{\varepsilon} - 1 &= \sum_j \theta_j \frac{(\alpha_j - \alpha)}{\sum_j \theta_j (\alpha_j - \alpha)^2} \varepsilon_{P^D}^{P_j^e} (1 - \varepsilon s_j^E) \\
\tilde{\sigma} &= \alpha^{e,C} \sigma' + (1 - \alpha^{e,C}) \nu'
\end{aligned}$$

where

$$\sigma' - 1 = \sum_j \theta_j \frac{\alpha_j (1-\alpha_j)}{\sum_j \theta_j \alpha_j (1-\alpha_j)} \alpha_j^d (\sigma_j - 1)$$

is the average elasticity between electricity and primary dirty energy consumption adjusted for the latter's share in each sector, and

$$\nu' - 1 = \sum_j \theta_j \frac{\alpha_j (1-\alpha_j)}{\sum_j \theta_j \alpha_j (1-\alpha_j)} (1 + (1 - \alpha_j^d) \frac{\alpha^{e,C}}{1 - \alpha^{e,C}}) (\nu - 1)$$

is the electricity generation sector's elasticity accounting for higher order effects. $\theta_j = \frac{P_j^E E_j}{\sum_j P_j^E E_j}$ is sector j's share in the economy's total energy expenditure, where P_j^E are the sector-specific energy price indices. $s_j^E = \frac{P_j^H H_j}{P_j^E E_j + P_j^H H_j}$ is sector j's energy expenditure share, $\alpha_j^d = \frac{P^D E_j^d}{P^D E_j^d + P^e E_j^e}$ its share of primary dirty energy expenditure in total energy expenditure, and $\alpha_j = \frac{P^C E_j^C}{P^C E_j^C + P^D E_j^D}$ its share of (indirect) clean energy in total energy expenditure. $\varepsilon_{P^D}^{P_j^E} = \frac{d \ln P_j^E / P^C}{d \ln P^D / P^C}$ is sector j's energy bundle's price elasticity vis-a-vis the price of dirty energy. Lastly, $\alpha^{e,C} = \frac{P^C E^{e,C}}{P^C E^{e,C} + P^D E^{e,D}}$ is clean energy's share of total electricity generation costs.

Interpretation. As in Oberfield and Raval (2021), equation (18) is a convex combination[36] of two effects. The first, captured by $\tilde{\varepsilon}$, reflects the sectoral dispersion in sector-specific energy price sensitivities, and the associated reallocation of consumption. The second, captured by $\tilde{\sigma}$ reflects the economy's average capacity to replace dirty with clean energy — which I denote as the "aggregate technological elasticity". As a result of the layered energy production structure, this depends both on the energy end-using sectors' capacity to replace primary dirty energy with electricity, and on the electricity generation sector's own capability to replace dirty generation sources by clean ones. Intuitively, the first effect affects the consumption of clean energy by redirecting primary energy consumption towards electricity.

[36] $\chi \leq 1$ (Oberfield and Raval, 2021).

Table 5: Expenditure Shares Calibration

	Production		Residential		Transportation	
	2007	2022	2007	2022	2007	2022
θ_j	27.85%	25.71%	21.16%	21.05%	50.98%	53.24%
α_j	17.10%	26.99%	17.45%	29.61%	0.04%	0.04%
s_j^E	2.81%	2.12%	49.60%	45.67%	37.29%	36.65%
α_j^d	38.98%	37.77%	37.74%	31.72%	99.86%	99.91%
$\alpha^{C,e}$	28.02%	43.37%				

Notes: US expenditure shares derived from the EIA's SEDS, and BEA's FAA and NIPA. Full description of procedure in section 5.4. $\theta_j = \frac{P_j^e E_j}{\sum_j P_j^e E_j}$ is sector j's share in the economy's total energy expenditure. $s_j^E = \frac{P_j^E E_j}{P_j^E E_j + P_j^H H_j}$ is sector j's energy expenditure share, $\alpha_j^d = \frac{P^D E_j^d}{P^D E_j^d + P^e E_j^e}$ its share of primary dirty energy expenditure in total energy expenditure, and $\alpha_j = \frac{P^C E_j^C}{P^C E_j^C + P^C E_j^D}$ its share of (indirect) clean energy in total energy expenditure. $\alpha^{C,e} = \frac{P^C E^{C,e}}{P^C E^{C,e} + P^D E^{D,e}}$ is clean energy's share of total electricity generation costs and is common to all sectors.

Because only $\alpha^{e,C}$ of this electricity is clean, the amount of clean energy increases (relatively) by this share. In turn, when electricity turns to greener sources, only the dirty proportion, $(1 - \alpha^{e,C})$, can become greener. The higher order terms in turn capture this effect on the redirected primary energy consumption.

6.2 The Elasticity of Final Energy Use

Equipped with equation (18), I can back out the average elasticity of substitution for the energy end-use sectors, σ', from the estimates laid out in table 2. To do so, I follow the EIA's breakdown and consider only three sectors: residential, goods and services production, and transportation. While this breakdown differs from the typical economic delineations, it accommodates the use of the SEDS data. In addition, I use tables 2.7 and 6.2D from the Bureau of Economic Administration's (BEA) Fixed Assets, and National Income and Product Accounts to obtain the expenditure in other factors of production, namely capital goods — measured through investment, and labour — measured through employee compensation, respectively. I focus on 2022, the latest available data, but also present 2007 which I will use in section 6.3.

I present the full calibration of the expenditure shares in table 5. In section 5.4 of the appendix I detail all the steps taken to compute these figures. In brief, I use estimated LCOE prices for renewables, and marginal costs for nuclear and fossil fuels to derive the share of clean electricity expenditures for each year. Using the first-order conditions, I am able to

retrieve a^e which, through the CES price index, allows us to compute a virtual price for electricity. Based on the electricity expenditure shares I assign the electricity expenditure of each end-use sector to clean or dirty sources. Everything else is measured directly from the data.

I set the consumption elasticity parameter to 0.33, taken from column (6) in table I of Comin et al. (2021). Their methodology is preferred because the non-homothetic utility formulation allows for different income elasticities while maintaining a constant price elasticity of substitution. On top of this, their sectoral span is very large, covering a great part of households' expenditures in all the sectors I consider.

I attribute to clean energy sources 43.37% of total electricity generation expenditures. This is in line with the share of clean electricity, which in 2022 represented about 42% of total electricity generation. The bulk of the economy's energy spending comes from transportation, representing around 53% of total spending, followed by the productive and residential sectors, with approximately 26% and 21%, respectively. This disparity is explained by transportation's reliance on refined, and thus higher added-value, fuels such as gasoline and jetfuel, and its market structure — where most consumption is undertaken downstream of a long supply chain, in particular for road vehicles.

In contrast, clean energy is mostly consumed by the productive and residential sectors, with similar shares of around 27% and 30% of their total energy expenditures, respectively. Surprisingly, the clean expenditure share in transportation is almost inexistent. This is mostly explained by the dominance of road and air transportation in the US. Even then, the electrification share of rail transportation is very low, with diesel-powered trains prevailing. One caveat must be placed on this number: it is a lower bound of the real share of clean energy spending in transportation. This is the result of the SEDS's methodology which assigns all electricity consumed by houses to the residential sector. Since a great part of all electric vehicle (EV) charging is done at home, this naturally misses out on some of the transportation sector's electricity share. Notwithstanding, in 2022 EVs represented a tiny fraction of just 0.86% of total light-duty vehicles registered in the US, while plug-in hybrids and hybrid EVs together accounted for just 2.5% (U.S. Department of Energy, 2022). In addition, the SEDS already accounts for charging ports outside of homes. As such, I would not expect a meaningful difference if I were able to account for at-home personal vehicle charging.

Together with my estimates for ν and σ, my calibration implies that $\sigma' \approx 0.81$. This means that energy end-users' average elasticity between electricity and primary dirty fuels is considerably higher than the capability of the electricity sector to replace polluting energy sources by non-polluting ones, consistent with the findings in the previous literature. This

implies that the economy's technical ability to replace dirty by clean energy, $\tilde{\sigma} = \alpha^{e,C}\sigma' + (1 - \alpha^{e,C}\nu') \approx 0.56$, is slightly higher than the aggregate elasticity, σ. This difference is explained by the reallocative effect of demand, which counteracts the economy's technological ability to replace dirty by clean energy. This effect is determined both by the low elasticity of substitution of demand and by the dispersion in energy mixes.

Notice that consuming more goods and residential services has a positive effect on the energy mix, as these sectors spend indirectly a higher share of their energy expenditures on non-polluting source than the economy's average, α. In contrast, the transportation sector is very negatively skewed towards polluting energy, so its services have a negative impact on the economy's energy mix. Under complementarity across sectors, since $\varepsilon = 0.33 < 1$, consumer theory dictates that the share of goods whose prices go up increase their share in total spending (Matsuyama, 2023). In other words, the use of transportation decreases proportionally less than its price increases. This implies that an assessment of the economy's ability to change its energy mix based on the initial bundle of expenditures — the technological elasticity term, $\tilde{\sigma}$, is insufficient. Accounting for this adjustment on the consumption mix thus dampens it.

6.3 Variable Elasticity of Substitution

I conclude this section by examining whether the aggregate elasticity of substitution increases with the share of clean energy. This hypothesis follows from the general Variable Elasticity of Substitution (VES) theory, formalized by Revankar (1971), and adapted to my context. To test it, I examine both the time-series and cross-sectional variation in clean energy use in the US throughout my sample period.

I begin by analyzing the time-series variation, re-estimating the regression model specified in equation (15) on a rolling basis. I use 15-year windows, which effectively reduces the sample size for each regression by approximately half. The SSIV weights are fixed to the year preceding each window. The resulting estimates, alongside the moving average of the clean energy share, are presented in figure 7. My findings indicate that the estimates remain relatively stable over time, despite the clean energy share increasing substantially, particularly after 2008. Although statistical uncertainty is considerable, the point estimates do not suggest any upward trend. If anything, they agree with other findings of decreasing elasticities in more recent years (Kilian and Zhou, 2024).

In a second exercise, I examine the cross-sectional heterogeneity in the aggregate elasticity across US states. To do so, I interact the relative price of dirty energy vis-à-vis electricity with the logarithm of either the lagged or the median clean energy share for each state, calculated over my sample period. If the elasticity increases with the state's share of clean

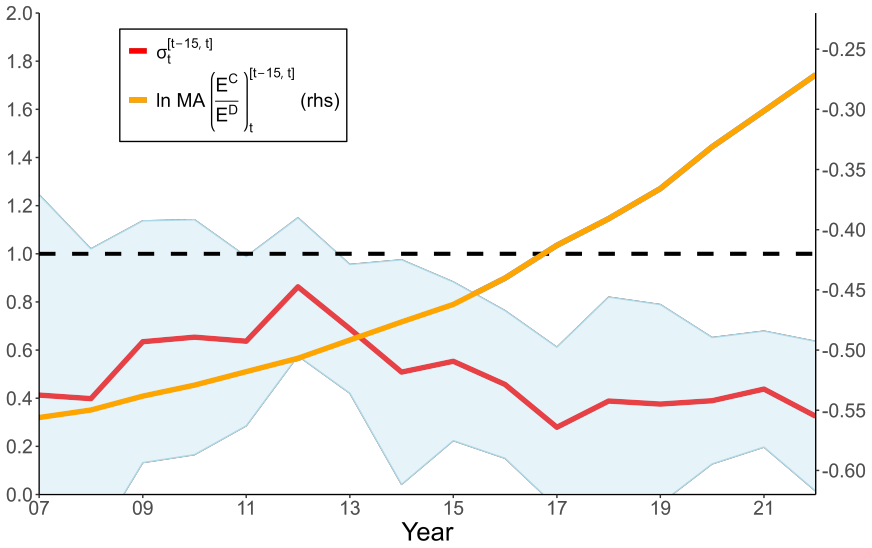


Figure 7: Rolling Regressions of equation (15)

Notes: Rolling regressions of equation (15) with 15 year windows. The windows are trimmed at the 1% level. SSIV weights are set to the year before the window starts. The shaded areas are the 90% confidence intervals. Standard errors are clustered at the state and year level. The yellow line represents the natural logarithm of the rolling average ratio of clean to dirty energy consumption measured in Btus.

energy, this coefficient should be negative[37]. The results, presented in table 6, do not provide clear evidence of this. Both estimates are statistically indistinguishable from zero. On top of this, the lagged interaction term is positively signed.

Neither exercise provides definitive evidence supporting the VES hypothesis. From the perspective of my model, these results further indicate that the economy's average ability to substitute away from dirty energy, $\tilde{\sigma}$, has likely remained stable. To investigate this, I recalculate the aggregate elasticity using the 2007 expenditure shares — the first year in my window, as shown in table 5, while keeping the baseline elasticity parameters unchanged.

Compared to 2022, the share of expenditure in clean electricity sources was 15.35 percentage points lower. This is explained by the lower clean electricity prices — a result of using the marginal cost for nuclear power which was the dominant source of clean energy in 2007, and by the CES assumption. In terms of end-use sectors, the expenditure share of primary dirty energy in 2007 was approximately 6.02 percentage points higher in the residential sector, while remaining roughly the same for the transportation and production sectors. Identically, energy's share of residential services' total costs was 3.93 percentage points higher, but unchanged for the other two sectors. In contrast, the share of clean energy expenditure increased significantly in goods and services production, and residential

[37]Higher shares should decrease the point estimate, which is the symmetric of the elasticity.

Table 6: Cross-Sectional Heterogeneity in σ

	(1)	(2)
$\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$	-0.4490*	-0.6175*
	(0.2529)	(0.3607)
$\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}} \times \text{Median}(\ln \frac{E^C_{i,t}}{E^D_{i,t}})$	-0.0083	
	(0.0157)	
$\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$	-0.9683***	-0.9334***
	(0.0870)	(0.1035)
$\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}} \times \ln \frac{E^C_{i,t-1}}{E^D_{i,t-1}}$		0.0217
		(0.0445)
$\ln \frac{E^C_{i,t-1}}{E^D_{i,t-1}}$		-0.0057
		(0.0088)
Observations	1,376	1,376
Adjusted R^2	0.90787	0.89043
1^{st} stage F-statistic, $\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$	21.598	21.498
1^{st} stage F-statistic, $\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}} \times \text{Median}(\ln \frac{E^C_{i,t}}{E^D_{i,t}})$	226.48	
1^{st} stage F-statistic, $\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$	51.210	47.493
1^{st} stage F-statistic, $\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}} \times \ln \frac{E^C_{i,t-1}}{E^D_{i,t-1}}$		165.53
Additional Controls	Yes	Yes

Notes: Results of interacting my main regressor with the states' sample-median or lagged share of clean energy. The sample includes the 48 contiguous US states and spans 1991 to 2022, excluding 2020. The 1% tails are excluded. Standard errors are clustered at the year and state level. The standard errors are in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

use, by 9.89 and 12.16 percentage points, respectively. No noticeable change happened in transportation. Lastly, the weight of the latter sector's in the economy's energy expenditures rose by 2.26 percentage points, in detriment of the production sector.

Despite the significant increase in the share of clean energy, recomputing the aggregate elasticity for 2007 yields a value of 0.54, slightly higher than my baseline estimate of 0.50, but not significantly different — in agreement with my empirical findings. Thus, I conclude that no significant changes could have occurred in the sectoral parameters for this to hold.

The Importance of Micro Elasticities My previous exercises suggest that an increase in the clean energy share may not necessarily be paired with growth in sectoral elasticities. In such a case, equation (18) implies that the aggregate elasticity is constrained by the lower-level elasticities. A key question arises then: how does the aggregate elasticity, holding all else equal, change as the clean energy share increases? To shed light on this, I conduct two distinct exercises, each reflecting credible scenarios for the US's medium horizon: i) an increase in the share of clean electricity, and ii) a rise in the electrification of the transportation sector. I demonstrate that the impact in the aggregate elasticity crucially depends on the source of the increase.

In the first scenario, I analyze the effect of increasing the clean electricity share by 10%, while maintaining the other expenditure shares and sectoral elasticities from my baseline calibration[38]. Using equation (18), I find that the aggregate elasticity would basically remain unchanged at 0.50.

In a second scenario, I examine the impact of replacing 10% of the transportation sector's primary dirty energy consumption[39] (measured in Btus) with an equivalent amount of electricity[40]. In this case, recomputing the elasticity of substitution reveals an increase of 0.04 in the aggregate elasticity, reaching 0.54. This rise in the elasticity is associated with the transition to cleaner energy, driven by substantial electrification within the transportation sector. Nevertheless, the change in the aggregate elasticity remains relatively modest.

These two thought experiments suggest that future developments in the American energy mix may or may not increase the elasticity of substitution. Whether the elasticity rises fundamentally depends on the source of the cleaner energy. Nonetheless, any changes are likely to remain modest unless there is a relationship — not modelled here — between the clean energy or electricity share, and the relevant micro elasticities of substitution.

Some literature points to a positive relationship between the two. For instance, Jo and Miftakhova (2024) identify such a mechanism among French manufacturing firms, where an increase in the electricity share correlates with a higher elasticity of substitution. This feedback loop could be particularly relevant for road transportation. Recent studies suggest that expanding charging infrastructure could strengthen the link between elasticity and the electricity share. For example, Cole et al. (2023) conclude that increasing charging infrastructure availability would likely promote electric vehicle adoption in the US. Since infrastructure accessibility naturally scales with rising EV demand, a positive feedback between the elasticity

[38]This can be achieved by a simultaneous increase in the price of clean energy, P^C, and in the ideal clean energy share, a^e. For details, see the supplemental appendix's section 5.5.

[39]This adjustment involves increasing the share of electricity parameter in transportation, a^e_j, while adjusting the D_j's to preserve sector sizes.

[40]Based on the EIA's electricity-to-Btu conversion factor of 3.412, as detailed in section 3.

and the electricity share in transportation appears plausible. Similarly, Fang et al. (2025) show that expanding electric high-speed rail in China fosters EV adoption. Implementing similar investments in parts of the US could have a substantial impact on the flexibility of transportation's energy use.

In contrast, the literature also highlights the decreasing ability to integrate additional clean electricity when its share is already significant. In particular, the intermittency of renewables can trigger a cannibalization effect where the correlated structure of electricity supply reduces the profitability of clean energy projects (Reichenberg et al., 2023). Potential solutions to mitigate this effect include increased battery storage, demand management, or improvements in the geographical interconnection of the electrical grid (López Prol et al., 2020). However, some of these solutions are still in their technological infancy or present significant implementation challenges. On the other hand, several studies have highlighted the potential effectiveness of carbon taxes in alleviating this issue (Brown and Reichenberg, 2021; Liebensteiner and Naumann, 2022).

7 Conclusion

I introduced a novel methodology to estimate the aggregate elasticity of substitution between polluting and non-polluting energy sources in the United States by leveraging cross-sectional variation in states' energy mixes. A key component of my empirical strategy involves inferring the price of clean energy from the behavior of the electricity-generating sector. My main estimate, 0.50, is substantially lower than commonly assumed in the literature. This has important policy implications: broad, untargeted subsidies may be insufficient on their own to drive a successful energy transition. Moreover, my results underscore the potentially high and unevenly distributed costs of decarbonizing the economy.

To support my empirical approach, I developed a bottom-up model in the spirit of Oberfield and Raval (2021), which clarifies the mechanisms driving the aggregate elasticity. Two main factors account for my relatively low estimates. First, the elasticity of substitution in electricity generation, estimated at approximately 0.52, constrains the economy's ability to integrate clean energy rapidly. This limitation dampens the higher elasticity in energy end-use sectors, which my calibration suggests must be around 0.81 on average. Second, the combination of a low elasticity of demand with limited use of clean energy in transportation leads to a further under-reactive energy mix.

I also find no evidence of an increase in the aggregate elasticity over the past two decades, despite substantial growth in clean energy consumption. This suggests that rising clean energy shares do not automatically translate into greater substitutability between energy types. The absence of such a positive feedback loop could hinder progress toward a cleaner

economy. As a result, policy should focus not only on incentivizing clean energy adoption through prices, but also on enhancing each sector's capacity to substitute between energy sources. The transportation sector, in particular, emerges as a critical target for intervention.

While this paper offers new insights into the elasticity of substitution between energy sources, many questions surrounding the economy's ability to adopt clean energy remain open. In particular, incorporating the complexities of electricity generation, as in Gowrisankaran et al. (2024), into dynamic equilibrium models is essential to understanding the dynamics of the energy transition (Desmet and Rossi-Hansberg, 2024). Abuin (2025) makes important progress in this direction. Additionally, a better grasp of the feedback between clean energy (or electricity) shares and sectoral energy elasticities of substitution could enhance the accuracy of long-term projections. Jo and Miftakhova (2024), for instance, provide compelling evidence of such mechanisms in the context of French manufacturing firms. Finally, while this paper has focused on the broad distinction between polluting and non-polluting energy, Acemoglu et al. (2023) underscore the importance of studying the roles individual energy sources can play in decarbonizing the economy — a point especially relevant when microfounding individuals' energy choices, as in Acemoglu et al. (2016).

Appendix

A Proof of Proposition 1

The proof follows very closely the steps detailed in Oberfield and Raval (2021).

Proof. First note that,

$$\sigma = \frac{d \ln \frac{E^C}{E^D}}{d \ln \frac{P^D}{P^C}} = 1 + \frac{d \ln \frac{E^C P^C}{E^D P^D}}{d \ln \frac{P^D}{P^C}}.$$

Define $\alpha_j = \frac{P^C E_j^C}{P^C E_j^C + P^d E_j^D}$ to be the energy expenditure share of clean energy, where

$$E_j^D = E_j^d + E_j^e \times \frac{E_j^{e,D}}{E_j^e} \tag{19}$$

is sector j's total dirty energy consumed directly and indirectly through electricity, and

$$E_j^C = E_j^e \times \frac{E_j^{e,C}}{E_j^e} \tag{20}$$

is its total consumption of clean energy indirectly through electricity. Moreover, define

$\alpha = \frac{P^C E^C}{P^C E^C + P^D E^D} = \sum_j \theta_j \alpha_j$ to be the economy's energy expenditure share of clean energy, where $\theta_j = \frac{P_j^e E_j}{\sum_j P_j^e E_j}$ is sector j's share in the economy's total energy expenditure. Notice that $\frac{E^C P^C}{E^D P^D} = \frac{\alpha}{1-\alpha}$. Hence,

$$\frac{d \ln \frac{E^C P^C}{E^D P^D}}{d \ln \frac{P^D}{P^C}} = \frac{d \ln \frac{\alpha}{1-\alpha}}{d \ln \frac{P^D}{P^C}}.$$

Using the chain rule and properties of logarithms, I have that

$$\frac{d \ln \frac{\alpha}{1-\alpha}}{d \ln \frac{P^D}{P^C}} = \frac{1}{\alpha(1-\alpha)} \sum_j \left(\theta_j \frac{d\alpha_j}{d \ln \frac{P^D}{P^C}} + \alpha_j \frac{d\theta_j}{d \ln \frac{P^D}{P^C}} \right).$$

Evaluating each term separately, and starting with $\frac{d\theta_j}{d \ln \frac{P^D}{P^C}}$, I note that $\theta_j = \frac{s_j^E}{s^E} \times \frac{TC_j}{TC}$, where $TC_j = P_j^E E^j + P_j^H H^j$ is sector j's total cost, with P_j^E and P_j^H its energy and H-factor price indices, respectively, and $s_j^E = \frac{P_j^E E^j}{TC_j}$ is the share of energy spending in total cost - mutatis mutandi for the whole economy when there is no subscript. Then,

$$\begin{aligned} \frac{d\theta_j}{d \ln \frac{P^D}{P^C}} &= \theta_j \frac{d \ln \theta_j}{d \ln \frac{P^D}{P^C}} \\ &= \theta_j \left(\frac{d \ln \frac{s_j^E}{s^E}}{d \ln \frac{P^D}{P^C}} + \frac{d \ln \frac{TC_j}{TC}}{d \ln \frac{P^D}{P^C}} \right). \end{aligned}$$

Again, evaluating each term separately, I have that $s_j^E = \frac{P_j^E E^j}{P_j^E E^j + P_j^H H^j} = \frac{P_j^E}{P_j^E + P_j^H g_j}$ from the Leontief assumption. Then

$$\frac{d \ln \frac{s_j^E}{s^j}}{d \ln \frac{P^D}{P^C}} = \varepsilon_{P^D}^{P_j^E} (1 - s_j^E) \tag{21}$$

where $\varepsilon_{P^D}^{P_j^E} = \frac{d \ln \frac{P_j^E}{P^C}}{d \ln \frac{P^D}{P^C}}$ is the elasticity of sector j's energy price index relative to dirty energy's price and I have used the fact that g_j and P_j^H are assumed constant.

In turn, note that $TC_j = \mu^{-1} P_j Y_j$ by the CES demand assumption and homogeneity of the CES production function, where μ is the mark-up, common to every sector. Moreover, note that $Y_j = Y \left(\frac{P_j}{P} \right)^{-\varepsilon} D_j$ is sector i's demand function. As such, $\frac{TC_j}{TC} =$

$\frac{\mu^{-1}P_jY\left(\frac{P_j}{P}\right)^{-\varepsilon}D_j}{\sum_j \mu^{-1}P_jY\left(\frac{P_j}{P}\right)^{-\varepsilon}D_j} = \frac{P_j^{1-\varepsilon}P^{\varepsilon}}{P^{1-\varepsilon}P^{\varepsilon}}D_j = \left(\frac{P_j}{P}\right)^{1-\varepsilon}D_j$ where P is the CES aggregate price index. Thus,

$$\frac{d\ln\frac{TC_j}{TC}}{d\ln\frac{P^D}{P^C}} = (1-\varepsilon)\frac{d\ln\frac{P_j}{P}}{d\ln\frac{P^D}{P^C}}$$

since D_j is a constant parameter. Note that $\sum\theta_j = 1 \implies \sum_j \frac{d\theta_j}{d\ln\frac{P^D}{P^C}} = 0$ so that $\sum_j \alpha_j\frac{d\theta_j}{d\ln\frac{P^D}{P^C}} = \sum_j(\alpha_j-\alpha)\frac{d\theta_j}{d\ln\frac{P^D}{P^C}}$ and any derivatives of aggregate variables disappear. As a result, I can disregard $\frac{d\ln\frac{P}{P^C}}{d\ln\frac{P^D}{P^C}}$ and only need to evaluate $\frac{d\ln\frac{P_j}{P^C}}{d\ln\frac{P^D}{P^C}}$. From the CES demand function, I have that $P_j = \mu MC_j$, where μ is constant. The Leontief production function implies that $MC_j = P_j^E + P_j^H g_j$ but because $P_j^H g_j$ are assumed constant, $\frac{d\ln\frac{P_j}{P^C}}{d\ln\frac{P^D}{P^C}} = \frac{P_j^E}{P_j^E+P_j^H g_j}\varepsilon_{P^D}^{P_j^E} = s_j^E\cdot\varepsilon_{P^D}^{P_j^E}$ and I can conclude that

$$\frac{d\ln\frac{TC_j}{TC}}{d\ln\frac{P^D}{P^C}} = (1-\varepsilon)s_j^E\cdot\varepsilon_{P^D}^{P_j^E}. \tag{22}$$

Finally, combining equation (21) with equation (22), I have that

$$\sum_j \alpha_j\frac{d\theta_j}{d\ln\frac{P^D}{P^C}} = \sum_j(\alpha_j-\alpha)\theta_j\varepsilon_{P^D}^{P_j^E}(1-\varepsilon s_j^E). \tag{23}$$

Turning to $\frac{d\alpha_j}{d\ln\frac{P^D}{P^C}}$ I have that $\frac{d\alpha_j}{d\ln\frac{P^D}{P^C}} = \alpha_j(1-\alpha_j)\frac{d\ln\frac{\alpha_j}{1-\alpha_j}}{d\ln\frac{P^D}{P^C}}$. Evaluating $\frac{d\ln\frac{\alpha_j}{1-\alpha_j}}{d\ln\frac{P^D}{P^C}}$, I find that

$$\frac{d\ln\frac{\alpha_j}{1-\alpha_j}}{d\ln\frac{P^D}{P^C}} = \frac{d\ln\frac{P^CE_j^C}{P^C}}{d\ln\frac{P^D}{P^C}} - \frac{d\ln\frac{P^DE_j^D}{P^C}}{d\ln\frac{P^D}{P^C}}.$$

Using the definitions in equation (19) and equation (20) together with the fact that I have assumed a unique electricity production function,

$$\frac{d\ln\frac{P^CE_j^C}{P^C}}{d\ln\frac{P^D}{P^C}} = \frac{d\ln\frac{P^eE_j^e}{P^C}}{d\ln\frac{P^D}{P^C}} + \frac{d\ln(\frac{P^CE^{e,C}}{P^eE^e}/P^C)}{d\ln\frac{P^D}{P^C}}$$

and

$$\frac{d\ln\frac{P^DE_j^D}{P^C}}{d\ln\frac{P^D}{P^C}} = \alpha_j^d\frac{d\ln\frac{P^dE_j^d}{P^C}}{d\ln\frac{P^D}{P^C}} + (1-\alpha_j^d)\left(\frac{d\ln\frac{P^eE_j^e}{P^C}}{d\ln\frac{P^D}{P^C}} + \frac{d\ln(\frac{P^{e,D}E^D}{P^eE^e}/P^C)}{d\ln\frac{P^D}{P^C}}\right).$$

where $\alpha_j^d = \frac{P^D E_j^d}{P_j^E E_j}$. Combining both terms and defining $\alpha^{e,C} = \frac{P^C E^C}{P^e E^e}$, I have that

$$\frac{d \ln \frac{\alpha_j}{1-\alpha_j}}{d \ln \frac{P^D}{P^C}} = \alpha_j^d \frac{d \ln \frac{P^e E_j^e}{P^D E_j^d}}{d \ln \frac{P^D}{P^C}} + \frac{d \ln \alpha^{e,C}}{d \ln \frac{P^D}{P^C}} - (1 - \alpha_j^d) \frac{d \ln (1 - \alpha^{e,C})}{d \ln \frac{P^D}{P^C}}. \tag{24}$$

By the chain rule $\frac{d \ln \alpha^{e,C}}{d \ln \frac{P^D}{P^C}} = \frac{d \ln \alpha^{e,C}}{d \ln \frac{P^C}{P^e}} \times \frac{d \ln \frac{P^C}{P^e}}{d \ln \frac{P^D}{P^C}}$. The first order conditions of electricity demand imply that

$$\frac{P^C E^{e,C}}{P^e E^e} = \left(\frac{P^C}{P^E} \right)^{1-\nu} a^{e,C} \equiv \alpha^{e,C}$$

Hence, $\frac{d \ln \alpha^{e,C}}{d \ln \frac{P^C}{P^e}} = (1 - \nu)$. Similarly, $\frac{d \ln \frac{P^e}{P^C}}{d \ln \frac{P^D}{P^C}} = (1 - \alpha^{e,C})$[41]. Combining the two, I have that

$$\frac{d \ln \alpha^{e,C}}{d \ln \frac{P^D}{P^C}} = (1 - \nu) \cdot -(1 - \alpha^{e,C}) = (\nu - 1)(1 - \alpha^{e,C}). \tag{25}$$

Symmetrically, I have that $\frac{d \ln (1-\alpha^{e,C})}{d \ln \frac{P^D}{P^C}} = \frac{d \ln (1-\alpha^{e,C})}{d \alpha^{e,C}} \frac{d \alpha^{e,C}}{d \ln \frac{P^D}{P^C}} = -\frac{1}{1-\alpha^{e,C}} \alpha^{e,C} \frac{d \ln \alpha^{e,C}}{d \ln \frac{P^D}{P^C}}$. As a result,

$$\frac{d \ln (1 - \alpha^{e,C})}{d \ln \frac{P^D}{P^C}} = -\frac{\alpha^{e,C}}{1 - \alpha^{e,C}} (\nu - 1)(1 - \alpha^{e,C}). \tag{26}$$

Lastly, $\frac{d \ln (\frac{P^e E_j^e}{P^D E_j^d})}{d \ln \frac{P^D}{P^C}} = \frac{d \ln (\frac{P^e E_j^e}{P^D E_j^d})}{d \ln \frac{P^D}{P^e}} \frac{d \ln (\frac{P^D}{P^e})}{d \ln \frac{P^D}{P^C}}$. From the FOC of primary energy demand, I have that $\frac{d \ln (\frac{P^e E_j^e}{P^D E_j^d})}{d \ln \frac{P^D}{P^e}} = \sigma_j - 1$. As before, $\frac{d \ln \frac{P^D}{P^e}}{d \ln \frac{P^D}{P^C}} = \frac{d \ln \frac{P^e}{P^D}}{d \ln \frac{P^C}{P^D}} = \alpha^{e,C}$. Hence,

$$\frac{d \ln (\frac{P^e E_j^e}{P^D E_j^d})}{d \ln \frac{P^D}{P^C}} = (\sigma_j - 1) \alpha^{e,C}. \tag{27}$$

Replacing equations (25) to (27) into equation (24), yields

$$\frac{d \ln \frac{\alpha_j}{1-\alpha_j}}{d \ln \frac{P^D}{P^C}} = \alpha_j^d (\sigma_j - 1) \alpha^{e,C} + (\nu - 1)(1 - \alpha^{e,C}) \left(1 + (1 - \alpha_j^d) \frac{\alpha^{e,C}}{1 - \alpha^{e,C}} \right). \tag{28}$$

[41] From the CES price index, $P^e = [(P^D)^{1-\nu} a^{e,D} + (P^C)^{1-\nu} a^{e,C}]^{1/(1-\nu)}$. Taking derivatives I have that $\frac{dP^e}{dP^C} = (\frac{P^C}{P^e})^{-\nu} a^{e,C}$. Finally, from the FOC, I know that $(\frac{P^C}{P^e})^{1-\nu} a^{e,C} = \alpha^{e,C}$. Together with the chain rule of logarithms, I have my result.

Combining equation (23) and equation (28), I prove that

$$\sigma = 1 + \sum_j \frac{\theta_j(\alpha_j - \alpha)}{\alpha(1-\alpha)} \varepsilon_{P^D}^{P_j^E}(1 - \varepsilon s_j^E) + \sum_j \frac{\theta_j(1-\alpha_j)\alpha_j}{\alpha(1-\alpha)} \left[\alpha_j^d(\sigma_j - 1)\alpha^{e,C} + (\nu - 1)(1 - \alpha^{e,C}) \left(1 + (1 - \alpha_j^d) \frac{\alpha^{e,C}}{1 - \alpha^{e,C}} \right) \right] \quad (29)$$

Now I can transform this into the aggregate quantities by defining $\chi = \sum_j \theta_j \frac{(\alpha_j - \alpha)^2}{\alpha(1-\alpha)} \leq 1$:

$$\tilde{\varepsilon} - 1 = \sum_j \theta_j \frac{(\alpha_j - \alpha)}{\sum_j \theta_j (\alpha_j - \alpha)^2} \varepsilon_{P^D}^{P_j^e}(1 - \varepsilon s_j^E),$$

and

$$\sigma' - 1 = \sum_j \theta_j \frac{\alpha_j(1-\alpha_j)}{\sum \theta_j \alpha_j (1-\alpha_j)} \alpha_j^d(\sigma_j - 1)$$

$$\nu' - 1 = \sum_j \theta_j \frac{\alpha_j(1-\alpha_j)}{\sum \theta_j \alpha_j (1-\alpha_j)} (1 + (1 - \alpha_j^d) \frac{\alpha^{e,C}}{1 - \alpha^{e,C}})(\nu - 1).$$

Rearranging equation (29), I reach equation (18)

$$\begin{aligned} \sigma &= 1 + \chi(\tilde{\varepsilon} - 1) + (1 - \chi)(\tilde{\sigma} - 1) \\ &= \chi\tilde{\varepsilon} + (1 - \chi)\tilde{\sigma}. \end{aligned}$$

and prove proposition 1.

□

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