The Aggregate Green Elasticity of Substitution*

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Abstract

We introduce a new strategy to estimate the aggregate elasticity of substitution between polluting and non-polluting energy. Exploiting variation in US states' energy mixes, we obtain an elasticity of 0.50 — significantly lower than prior studies. This challenges the notion that the energy transition can occur without compromising economic growth. A bottom-up model links aggregate to sectoral elasticities, highlighting transportation as a key constraint. Crucially, aggregate elasticity dynamics depend more on micro-level substitution patterns than on the distribution of the energy mix. Consistent with this, we find no evidence of rising substitutability over the past decade despite rapid clean energy adoption.

1 Introduction

Many assessments of the feasibility, pace, and cost of the energy transition hinge on the concept of an aggregate elasticity of substitution — that is, the economy-wide capacity to substitute polluting energy sources with cleaner alternatives. Despite its centrality, our understanding of this concept remains limited. This paper advances this literature in two key ways. First, it introduces a novel empirical strategy to estimate an aggregate elasticity of 0.50 for the United

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States (US), the world's second-largest emitter of carbon dioxide in the world (Climate Watch, 2021). Second, it develops a theoretical framework that links sectoral energy use to aggregate energy consumption, connecting our macro-level estimates to micro-level mechanisms. These contributions offer new insights into the sources and dynamics of the aggregate elasticity, with implications for the effectiveness of policy tools like subsidies.

Estimating aggregate elasticities of substitution is notoriously difficult, as the dynamics of the factor inputs reflect both the evolution of relative prices and of unobserved determinants, such as technological progress and productivity shocks (Grossman and Oberfield, 2022). To address the subsequent endogeneity concerns, we exploit the cross-sectional variation in energy mixes across US states and implement a shift-share design in the spirit of Bartik (1991). Specifically, we leverage on the differences in polluting energy expenditure shares between the overall economy and the electric power sector. 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. This allows us to identify the elasticity of substitution, yielding a point estimate of 0.50.

Our finding carries significant policy implications. Through the lens of the canonical model of Acemoglu et al. (2012), such a low elasticity implies that subsidies alone are insufficient to promote the transition to net-zero emissions – rendering the most important climate policy tool in the US ineffective. In addition, it raises concerns regarding the compatibility of the transition to carbon neutrality and continued economic growth. Other quantitative assessments suggest that such an inflexible energy mix can more than double the optimal carbon tax relative to previous estimates in the literature (Hochmuth et al., 2025). As a result, not only can the overall burden be much higher than previously expected, but it could also be significantly more unequally distributed.

A core challenge in estimating substitution elasticities in the context of energy lies in measuring clean energy prices. Prior work has often proxied clean energy with electricity, but this would not only be misleading in the US, where a substantial share of electricity remains carbon-intensive — reaching 58% as recently as 2022, but would also not fit our goal of studying the full spectrum of energy consumption. We address this challenge by tracing the composition of electricity generation across energy sources. This approach allows us to infer prevailing clean energy prices without relying on source-specific cost data. In doing so, we account for shifts in the US's clean energy mix — from a reliance on nuclear to a frontier increasingly shaped by wind and solar — in a data-driven manner.

Our methodology also captures total energy use across the entire economy, rather than focusing solely on business or manufacturing activity. This broader scope is important for two reasons. First, transportation and residential use together account for a larger share of US energy consumption than the industrial and commercial sectors combined. Second, the composition of energy use varies dramatically across sectors. Electrification in transportation remains extremely limited, with more than 99% of its energy expenditures still attributable to fossil fuels as of 2022. This sector alone accounts for over 53% of total energy expenditures. These patterns imply that transportation plays a disproportionately large role in determining the aggregate elasticity — a point we reinforce through our model.

A potential criticism of our approach is that it abstracts from cross-border energy substitution via trade (Moll et al., 2023). However, 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. We therefore believe that our estimates capture the dominant forces shaping aggregate substitutability.

To interpret our estimates, following Oberfield and Raval (2021), we introduce a bottom-up model that makes the determinants of the aggregate elasticity explicit. This framework connects sectoral elasticities to the macro-level response and aligns our findings with microeconomic evidence. For instance, we show that energy end-using sectors must exhibit average elasticities of around 0.81 for our aggregate estimate to hold. This implies that the supply side is more flexible than the aggregate elasticity would suggest — displaying an average technological elasticity of 0.56, given a value of 0.52 for the electricity-generating sector. The gap between this supply-side elasticity and the aggregate response reflects the limited ability of final consumption to reallocate demand across goods and services in response to relative price changes.

We also use the model to explore how changes in the energy mix affect substitutability. Notably, we find that increasing the share of clean energy has little effect on the economy's capacity to substitute away from dirty energy unless it is accompanied by greater sectoral flexibility. Unfortunately, considering the last two decades, we do not find evidence of an increase in the US's aggregate elasticity.

Beyond its methodological contributions, this paper also seeks to shed light on the US energy context. Given the substantial differences in energy composition, policy frameworks, and consumption patterns across countries, we caution against extrapolating estimates from other regions. In this sense, our US-focused analysis provides not only novel evidence but also insight that is essential for designing effective, context-specific energy policy.

Related Literature. The integration of energy and climate considerations into macroeconomic models has become increasingly vital for understanding the dynamics of the energy transition. Central to these frameworks is the elasticity of substitution between clean and dirty energy sources, which governs how readily an economy can shift away from fossil fuels.

Acemoglu et al. (2012) is a seminal contribution to this field. They develop a model in which directed technical change plays a pivotal role in the energy transition. Their findings show that if the elasticity of substitution is below a critical threshold, neither market forces nor subsidies alone can trigger the transition to net-zero carbon emissions. They suggest a threshold value of 1.5, which is substantially higher than our estimated value of 0.50. Only when the elasticity exceeds this threshold do subsidies become effective as a standalone policy tool; otherwise, a combination of carbon taxes and green subsidies is necessary. Furthermore, at very low elasticities — below unity, as our estimate indicates — economic growth itself may be at odds with climate goals.

Casey et al. (2023) also analyse the effectiveness of clean energy subsidies, emphasizing their interaction with the substitution possibilities between energy sources. They show that subsidies reduce emissions only if they lower the marginal product of dirty energy, which requires sufficiently high substitutability between clean and dirty inputs. In standard settings with low substitution elasticity and inelastic energy demand, subsidies can perversely increase emissions and reduce welfare relative to laissez-faire. These findings further challenge the view that subsidies are a universally effective climate policy and underscore the importance of estimating the elasticity of substitution to evaluate their potential benefits.

In contrast, Golusov et al. (2014) present a dynamic stochastic general equilibrium model where the optimal carbon tax is derived from a simple formula that depends only on current GDP, the discount rate, and the expected damage elasticity. Notably, their formulation implies that the optimal tax is independent of the elasticity of substitution between energy sources. Their conclusions though, rely on the assumption of path-independence in energy production.

A parallel literature examines the relationship between economic activity and finite energy resources. For instance, Hassler et al. (2021), using a quantitative model, and Känzig and Williamson (2024), employing time-series methods, both emphasize the crucial role of energy-saving technologies in sustaining economic growth despite the near absence of substitutability between energy and other factors of production. The capability to replace fossil fuels with clean energy sources represents one such technological innovation. Our analysis suggests that this source of energy efficiency has played a minor role, thus further emphasizing the importance of advancements in overall energy-saving technologies.

Complementing the theoretical macroeconomic literature, broader empirical work has sought to pin down substitution elasticities across different fuels. Stern (2012) conducts a meta-analysis of interfuel elasticities — reporting a wide interval of estimates ranging from 0.3 to 2.5. Notwithstanding, the literature studying specifically the elasticity of substitution between polluting and non-polluting energy sources still remains scarce. Our work aims precisely to deepen our understanding of this concept. Papageorgiou et al. (2017) is, to our knowledge, the first study with this same objective. Using sectoral OECD data on energy-using businesses and the electricity generation sector, they estimate a parametric CES specification via non-linear least squares, finding elasticities of 3 and 1.8, respectively. However, they do not account for technological progress, leaving endogeneity concerns unaddressed. In addition, their analysis excludes air transport, residential energy use, and private vehicle consumption — omitting a substantial share of total energy demand.

Jo (2024) addresses the endogeneity problem by focusing on manufacturing plants in France and employing an instrumental variables strategy. They report elasticities between 1.4 and 3, depending on the instrument used. As we argue in this paper, however, manufacturing is not representative of aggregate energy consumption. Moreover, while it may be reasonable to treat electricity as a clean energy source in France, this assumption does not hold in the US context. Using the same French manufacturing data, Jo and Miftakhova (2024) further show that substitution elasticities increase with electricity use. They suggest that, if this relationship holds at the aggregate level, the energy transition could be faster and less costly. We find no evidence of this at the aggregate level in the US over the past two decades.

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 our empirical exercise. Section 4 details the empirical strategy employed to measure 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. Finally, section 7 concludes.

2 The Aggregate Elasticity of Substitution

We begin by outlining the theoretical framework underpinning our empirical analysis. Following the literature in environmental macroeconomics (Hassler et al., 2016; Lemoine, 2024) we posit that state-level output is a function of an energy composite, and other inputs, such as labor and capital. We 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[1], $E_{i,t}^C$

[1]We use interchangeably the nomenclature dirty and polluting, and clean and non-polluting.

and $E^D_{i,t}$, respectively, so that

$$E_{i,t} = \left((A^D_{i,t} E^D_{i,t})^{\frac{\sigma-1}{\sigma}} + (A^C_{i,t} E^C_{i,t})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

$A^D_{i,t}$ 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. Our 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 aggregate polluting and non-polluting energy consumption. Implicitly this nested CES formulation assumes that energy is separable from the other factors of production. Advantageously for us, to study σ, we need not specify $H_{i,t}$ further nor do we need to know the value of η.

We 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[2] (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 our 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[3].

Discussion About Modelling Assumptions. We 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 capacities 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. 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, our framework does not explicitly model for other important considerations such as tail-risk or the role expectations

[2]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.

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

play in the build up of energy infrastructure capacity (Kellogg, 2014), especially for clean energy.

Moreover, our formulation assumes perfect substitution within energy aggregates. Although this is the case physically — since fuel based energy generation always involves combustion, and fuel-conversion technologies do exist[4], this does not necessarily hold economically[5]. 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[6]. 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, we choose to maintain the literature's formulation for comparability and practicality — we avoid having to estimate two latent parameters[7]. In addition, this formulation guarantees that we do not underestimate the elasticity in the case of high substitutability between clean energy and only a subset of the fuels considered.

Finally, we also 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).

Equilibrium Conditions. We assume that the economy-wide demand for energy is perfectly competitive, so that the aggregate demand for dirty fuels is represented by the following first-

[4]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).

[5]Although conceptually different from the constant elasticity formulation we 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.

[6]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.

[7]Even if we chose not to estimate the inner elasticities and instead used values from the literature, we would not be able to capture the productivity parameters. On top of this, to the best of our knowledge, there is no counterpart to the work of Stern (2012) for clean energy.

order conditions

$$E^D_{i,t} = (A^D_{i,t})^{\sigma-1}\left(\frac{P^D_{i,t}}{P^E_{i,t}}\right)^{-\sigma} E_{i,t}, \tag{3a}$$

$$E^C_{i,t} = (A^C_{i,t})^{\sigma-1}\left(\frac{P^C_{i,t}}{P^E_{i,t}}\right)^{-\sigma} E_{i,t}, \tag{3b}$$

where $P^C_{i,t}$ and $P^D_{i,t}$ are the prices of clean and dirty energy sources, respectively, and $P^E_{i,t}$ 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, we find that

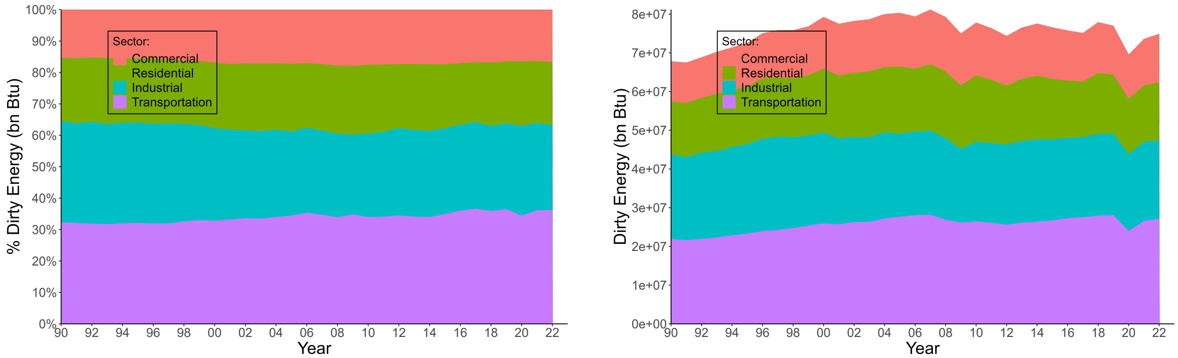
$$\widehat{\frac{E^D_{i,t}}{E^C_{i,t}}} = -\sigma \widehat{\frac{P^D_{i,t}}{P^C_{i,t}}} + (\sigma - 1)\widehat{\frac{A^D_{i,t}}{A^C_{i,t}}}, \tag{4}$$

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

We 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, $A^D_{i,t}$ and $A^C_{i,t}$. We propose solutions to each of these problems in section 4.1 and section 4.2, respectively. Lastly, by using log-differences instead of levels, we bypass the problem of unit conversion.

2.1 Accounting for The Full Energy Spectrum

Unlike some of the empirical macroeconomics literature, our framework includes all energy use, not just stationary non-residential energy. To motivate this choice, figure 1 plots the evolution of dirty energy consumption across end-using sectors for the US from 1990 to 2022. We 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 has edged down while transportation's fuel consumption has tended to rise. These contrasting dynamics point to the inadequacy of using industrial-specific energy elasticities in frameworks studying overall energy consumption dynamics, as in most macroeconomic models, further motivating our comprehensive framework.



(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.

3 Data

We 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. Our 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, we 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[8]. Accordingly, we 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; our focus on petroleum products therefore aligns with both the data and the conceptual framework presented in section 2.

We 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, lubricants, or asphalt. Thus, our measures of energy use capture only consumption for heat and power generation[9]. 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

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

[9] Further details on variable construction are provided in section A.1 of the appendix.

between fuel use and emissions.

Following standard practice in the macroeconomic literature (Hassler et al., 2016), we express all energy in British thermal units (Btu). For polluting energy, we 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, we 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 our empirical exercises uses log growth rates, conversion factors matter only within energy categories. We define the price of dirty energy as the consumption-weighted average of the subcomponents' prices.

3.1 Accounting for Electricity Trade

Our 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, we implement a two-step procedure. First, we 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, we 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[10]. We account 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 A.2 of the appendix.

Descriptive statistics of the final dataset and of the primary energy consumption changes

[10]For a depiction of the grid infrastructure as of 2025, see figure A.1 in the 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.

induced by our procedure are reported in table 1[11]. We further document the impact of our adjustments in section A.2 of the 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 our 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 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, we incorporate primary energy indirectly imported from other states, thereby internalizing trade's effect on the energy consumption mix.

[11] 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.

4 Empirical Approach

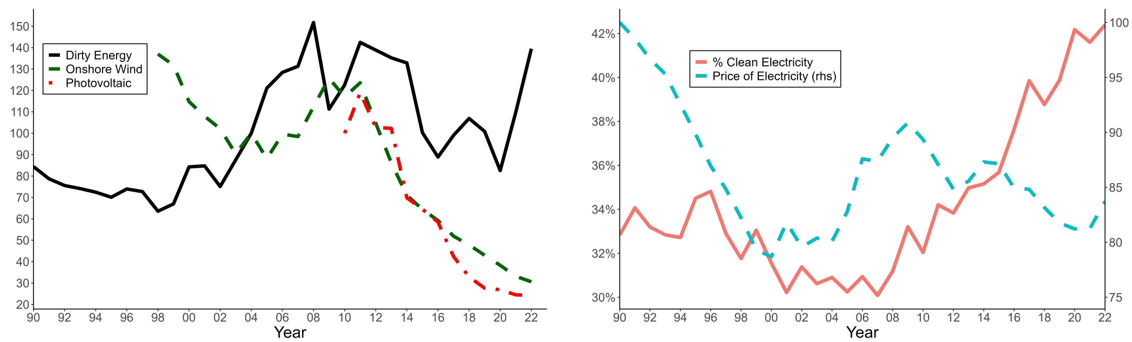
This section shows how we account for the price of clean energy and presents our identification strategy.

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, we 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 our 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 our 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, 2025). 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% in 2006 to 37% in 2022. Accordingly, our measurement of clean energy prices must consider the evolution of the clean energy frontier, adding further complexity to the task.

Rather than attempting to directly measure clean energy costs, we adopt an indirect approach to estimating the price of non-polluting energy. Specifically, we 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. We 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, a sharp fall in wind and solar LCOEs during the 2010s coincides with a significant increase in the clean electricity share from 32% to 42%.



(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).

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, we adopt a variant of the framework used by Papageorgiou et al. (2017)[12] and assume that 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

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

[12]Unlike their approach, we use actual energy consumption rather than installed capacity, because the SEDS only records the latter's from 2008 onward. Notwithstanding, the dynamics of clean installed capacity and clean electricity production are very similar as we show in section B.1 of the appendix.

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

$$\widehat{P_{i,t}^C} = \widehat{P_{i,t}^e} - \frac{1}{\nu}\widehat{\frac{E_{i,t}^{e,C}}{E_{i,t}^e}} + \frac{\nu-1}{\nu}\widehat{A_{i,t}^{e,C}}. \tag{6}$$

While we do not attempt to measure this proxy directly, we exploit the implied relationship in our empirical strategy. As such, we briefly assess the relevance of equation (6). Using the symmetric first-order condition for dirty energy, we 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 B.1 in section B of the appendix. For our 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 we acknowledge that equation (6) does not capture all of the complexities of electricity market operations, and that this simple exercise has notable limitations[13], we interpret the high explanatory power as supportive evidence of its usefulness to capture the evolution of clean energy prices, which is our primary objective.

Finally, two additional considerations are pertinent to our 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 we abstracted from in our derivation (Borenstein and Bushnell, 2015). Because our identification strategy relies on exogenous shifts in supply costs, this issue does not pose a problem for our analysis; we can subsume any mark-up term into the unobserved productivity parameter, $A_{i,t}^{e,C}$[14]. Second, as in equation (4), the productivity parameters are unobservable. To address this, we instrument for prices and shares in our estimation procedure.

4.2 Identification Strategy

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

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

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

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

[14] $A_{i,t}^{e,C} \equiv \mu_{i,t}^{\frac{1}{\nu-1}}\widetilde{A_{i,t}^{e,C}}$, 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.

The empirical counterpart of equation (7) is

$$\widehat{\frac{E^C_{i,t}}{E^D_{i,t}}} = \beta \widehat{\frac{P^D_{i,t}}{P^e_{i,t}}} + \gamma \widehat{\frac{E^{e,C}_{i,t}}{E^e_{i,t}}} + e_{i,t}. \tag{8}$$

We can quantify σ if we are able to consistently estimate β in equation (8). Direct OLS estimation is biased due to endogeneity stemming from the unobserved variables, $\sigma\frac{(1-\nu)}{\nu}\widehat{A^{e,C}_{i,t}} + (\sigma-1)\widehat{\frac{A^D_{i,t}}{A^C_{i,t}}}$, 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, we instrument for both $\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$ and $\widehat{\frac{E^{e,C}_{i,t}}{E^e_{i,t}}}$. Although γ is not our 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 $\mathbb{E}(\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}} \cdot \widehat{\frac{E^{e,C}_{i,t}}{E^e_{i,t}}} | X_{i,t}) \neq 0$. Consequently, relying solely on an instrument for the relative prices risks biasing our estimates through a bad control problem, since the clean energy share itself correlates with the error term[15] (Angrist and Pischke, 2009).

4.2.1 Instrumenting for the Relative Prices

We 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 our 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 $t-1$, we 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), we have that electricity prices

[15] We thank Jaeeun Seo for highlighting and clarifying this issue.

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), we 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, we 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. We 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 we explore to build our 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 we consider the total revenue in electricity sales, motivated theoretically above. In our exercise we also only consider petroleum, coal and natural gas when building the instrument. We exclude biomass because of its comparatively hyper-localized nature. Our instrument thus takes the following form

$$\left(\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}\right)^{IV} = \sum_k \omega^k_i \cdot \widehat{P^k_t}, \tag{12}$$

where $\widehat{P^k_t}$ are the common price shifters, and ω^k_i are the time-invariant state-specific shares.

As our shares we fix the weights in equation (11) to their 1990 values, $\omega^k_i \equiv \omega^k_{i,1990}$, the first year of our sample which we exclude from the estimation exercise. We present the geographical variation of each weight in figure C.6 of the appendix. As price shifters we use the annual log growth rates in US relevant commodity price indices. Specifically, we 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[16]. We plot the time series of the log growth rates for all three commodity prices in figure C.8 of the appendix.

Our 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 implies that we 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 our 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 (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 we show that excluding them from our sample does not change the results. Finally, the inclusion of time and state fixed effects means that we require exogeneity relative only to the changes in state-specific energy demand shifters.

Control Variables and Threats to Identification. In our baseline specification, we include a lag of the dependent variable to account for possible auto-correlation in the error-term. Following Borusyak et al. (2024), we include state fixed-effects to capture the heterogeneous SSIV weights, $\sum_k \omega_i^k \neq 1$, and control for other potential non-observables. We 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 our set-up this does not seem necessary since both oil and gas behave as random walks[17]. In comparison, coal is third-order integrated. We show later that including another lag of the instrument does not change our results.

[16]Using principal component analysis, we 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, we get an $R^2 = 98.8\%$. Multiplying the two we reach our value. See section C.1 in appendix for more details.

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

Because we 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 our setting. The relevant margin of variation in our case is not just the number of shifters, but also the number of times we observe them since we are working with panel data. Notwithstanding, we 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 we 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[18]. Additionally, we include a lag for the state-specific average generating power plant's vintage for each dirty energy source[19]. This ensures that we 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[20]. Lastly, to control for changes in the energy composition, we 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[21]. In table C.3 of the appendix we show that our 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[22] 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 we use the average of the growth rates for states located outside of the electrical grid to which i belongs:

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

where $\mathcal{P}$ 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 our 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

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

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

[20]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).

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

[22]Petroleum Administration for Defense Districts.

evolution has largely been driven by common factors, justifying our instrument's relevance. In the beginning of our sample, the political curtailment of new nuclear power plants lead 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.

We 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. We present their results in section C.2 of the appendix. While the first-stage F-statistic is weak for the first instrument, neither estimate challenges our main conclusions. Furthermore, this allows us to conduct a Sargan test for exogeneity. Importantly, we cannot reject the null hypothesis for any of the proposed instruments.

4.3 Regression Model

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

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

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. We can then identify σ from $\beta = -\sigma$, our main object of interest, and ν indirectly through $\gamma = \beta/\nu$.

5 Results

This section presents the results from our main exercise and the robustness checks undertaken. We draw some policy implications from the estimates.

5.1 Baseline Results

We 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). Our sample spans 1991 to 2022 with the exclusion of the pandemic period[23] and contains all contiguous US states[24]. To reduce the influence of extreme values, we trim observations at the 1st and 99th percentiles of the dependent variable or the two main explanatory variables[25].

[23]Including 2020 further decreases our point estimates, but affects statistical precision significantly. This may reflect the extreme behaviour of commodity prices during this year. Ending the sample in 2019 instead does not meaningfully change our results. A full analysis of the sample period selection is provided in section D.1 in the appendix.

[24]We combine the District of Columbia with Maryland.

[25]This excludes 64 of the 1440 observations comprising our original sample.

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
F-statistic	105.70	27.967	2.6854	0.77695
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.

We 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. We cluster standard errors at the year and state level.[26]. 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), we do not weight the regressions. Weighting the regressions produces similar results, which we report in table 4.

The point estimates of our 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 value increases slightly to 0.52 for the electricity generation 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 we would expect symmetrically induced biases due to the opposing correlations between the clean electricity share and the relative dirty energy price, and the state-specific shifters. Finally, excluding the additional controls marginally increases our estimate to 0.53.

Discussion. Before comparing our results to the existing literature and drawing policy implications, it is worth noting that our relatively low elasticity estimates are consistent with recent US experience with wind and solar energy generation. Since 2010, clean energy consumption has risen markedly — by 42 percentage points. However, this expansion appears less dramatic when juxtaposed with the evolution of generation costs: wind LCOE estimates, for example, have declined by a remarkable 74 percentage points — a dynamic closely followed by photovoltaic technology (International Renewable Energy Agency, 2024). Over the same period dirty energy prices exhibited volatility but, on average, hovered around 94% of their 2010 level, while total dirty energy consumption decreased by only 4 percentage points.

To contextualize these developments, figure 5 plots the relative consumption of clean energy against the relative price of dirty energy, both computed as log-ratios and normalized to zero in 2010. Between 2010 and 2022, the relative price of dirty energy rose by 1.47 log-points, while the relative use of clean energy increased by only 0.39 log-points. These figures imply an "observed elasticity" of approximately 0.27. Ending instead in 2019, prior to the Covid-19 pandemic, yields a slightly higher value of 0.32. Alternatively, because the LCOE estimates are for new power plants, we can lag the clean energy prices by three years for example[27]. This would still increase the implied value, but marginally to 0.28. Notably, all figures are smaller than our estimate of

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

[27]Lagging by four years would yield a value of 0.30, by five 0.23.

0.50, supporting our findings. In addition, this exercise speaks to concerns regarding the time horizon of our elasticity estimate.

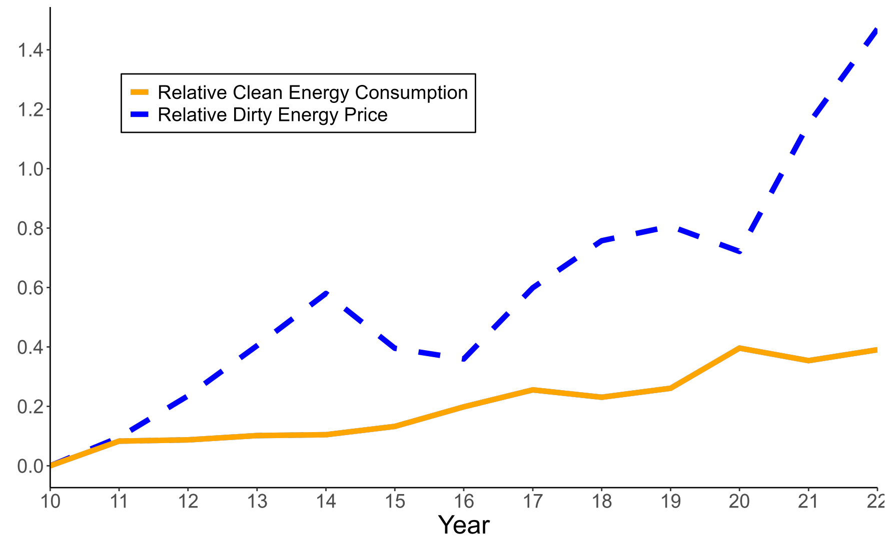


Figure 5: Clean Energy Consumption vs Dirty Energy Prices.

Notes: The figure plots two series for the US: the log-difference in average energy prices between polluting and non-polluting sources, and the log-difference in energy consumption between clean and dirty energy. Both series are normalized to 100 in 2010 prior to the log transformation. As a proxy for clean energy prices, we 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 D.11 in appendix. All prices are adjusted for inflation.

Our results for the elasticity of substitution are indeed much smaller than those implied by previous studies. The key reasons for this discrepancy are both the lower implicit electricity generation elasticity of 0.52 – compared to 1.8 in Papageorgiou et al. (2017), and the inclusion of all energy consumption, not just business energy. In section 6.2 we formalize this point and highlight specifically the importance of accounting for residential and non-stationary energy consumption.

5.2 Robustness Checks

We 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 our shift-share instrument. First, we want to ensure that our 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

[28]We present further checks in section D.1 of the appendix – specifically related to our sample's period. The results remain similar.

Table 3: Robustness Checks

	(1)	(2)	(3)	(4)	(5)
$\frac{\widehat{P^D_{i,t}}}{P^e_{i,t}}$	-0.4880**	-0.6081**	-0.4877**	-0.5702**	-0.4443***
	(0.2372)	(0.2765)	(0.2107)	(0.2712)	(0.1463)
$\frac{\widehat{E^{e,c}_{i,t}}}{E^e_{i,t}}$	-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
F-statistic	0.67431	0.78672	0.80514	0.10215	0.51799
1^{st} stage F-statistic, $\frac{\widehat{P^D_{i,t}}}{P^e_{i,t}}$	30.981	27.337	32.178	29.503	19.714
1^{st} stage F-statistic, $\frac{\widehat{E^{e,c}_{i,t}}}{E^e_{i,t}}$	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.

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) we present our results with two lags of the SSIV instrument instead of one. The estimate decreases marginally to 0.49.

A second concern is that our national price shifters for natural gas and coal are not 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 we replicate our exercise using instead foreign price indices as shifters. Specifically we 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 our baseline specification, and remains considerably below the previous literatures' values.

Another threat to our 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 our results, we repeat our 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) we 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 our main specification's statistical bounds.

Finally, to account for the potential inertia in energy adjustments not captured by yearly data, we aggregate our 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. We again trim the 1% tails. We provide the results in column (5). The elasticity level decreases further to 0.44 while the statistical precision increases.

Geographical Sensitivity. We do not weight our 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 our results. To assess this, we re-estimate our main specification, equation (15), sequentially excluding one state at a time. We map the difference between these estimates and our baseline value in figure 6. Our 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.

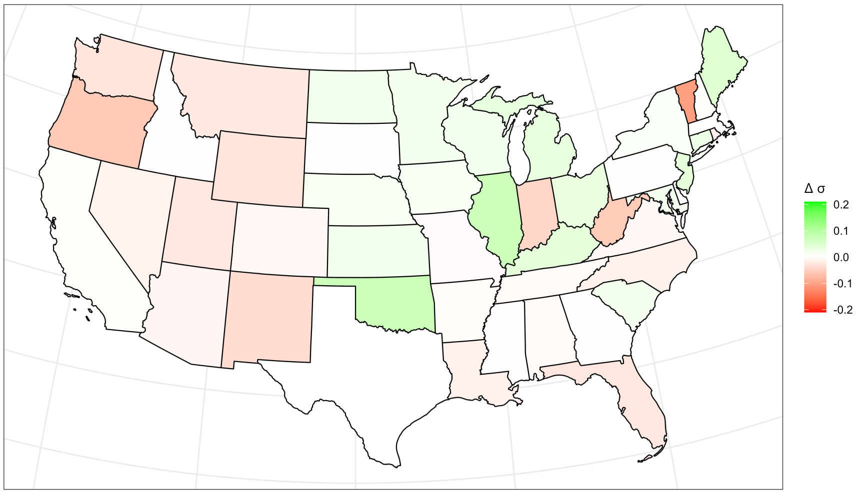


Figure 6: Geographical Sensitivity.

Notes: The map displays the difference between our 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.

To address potential concerns regarding outlier influence and national representativeness, we re-estimate our 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 our results. As shown in table 4, the resulting elasticity estimates remain close to the unweighted baseline and are generally smaller.

5.3 Policy And Welfare Implications

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

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
F-statistic	0.77378	0.76838	0.77678
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.

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 our preferred specification rejects the notion that clean and dirty energy types are gross substitutes in the United States. Although not all our robustness checks can reject this hypothesis, all specifications agree that the elasticity must be much closer to unity than previously thought.

Finally, recent work highlights the importance of the aggregate elasticity for understanding the distributional burden of the energy transition. Building on a large literature emphasizing the non-homotheticity of energy consumption[29] — particularly after the Russian invasion of Ukraine, Hochmuth et al. (2025) show that poorer households may be over 50% worse off than their richer counterparts as a result of the European energy transition. These outcomes are highly dependent on the elasticity of substitution between green and dark energy in final energy use. Although this parameter does not exactly match our concept of aggregate elasticity, we show in section 6 that it must be below unity. This low substitutability suggests even greater distributional disparities than those inferred by Hochmuth et al. (2025). Moreover, it has strong policy implications: for instance, the optimal carbon tax nearly doubles when the assumed elasticity falls from 3 to 2, so our findings should further amplify this value. In contrast, Cruz and Rossi-Hansberg (2024) find that σ has no impact on the projected regional variation in climate change-induced damages. However, they show that by the end of the next century, assuming an energy elasticity of 0.5 — exactly our point estimate — leads to average welfare losses that are 27% higher than under a scenario where the elasticity is 2.7.

6 From Macro to Micro

In this section we 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 our estimates reflect not a unique aggregate parameter, but the combination of several "lower-level" elasticities.

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

6.1 Bottom-up Model

Consider n distinct energy using sectors[30]. In line with the evidence provided in the literature (Hassler et al. (2022), Känzig and Williamson (2024)), similarly to Jo (2024), we 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[31], and E_j is the energy consumption bundle. Further, we 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,

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

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

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

We consider a unique electricity generation function. Notwithstanding, this set-up can also accommodate sector-specific electricity production functions — we 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, our framework can also accommodate this by adjusting the sectoral breakdown. In contrast, this model structure ignores the supply side's network structure. We 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, we 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

[30] We 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.

[31] We assume that their price does not depend on energy prices.

connection to our 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. We recast the elasticity in terms of expenditures, instead of quantities, because it helps when thinking about its determinants. Together with an in-depth analysis, in section E of the appendix we 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*

$$\sigma = \chi\tilde{\varepsilon} + (1-\chi)\tilde{\sigma}. \tag{16}$$

$\chi, \tilde{\varepsilon}$ 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 (16) is a convex combination[32] 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 we denote as the "aggregate technological elasticity". As a result of our 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. 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 Technological Elasticity

Equipped with equation (16), we 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, we 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, we 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. We focus on 2022, the latest available data, but also present 2007 which we will use in section 6.3. We present the full calibration of the expenditure shares in table 5. In section E.3 of the appendix we detail all the steps taken to compute these figures. In brief, we 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, we are 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 we assign the electricity expenditure of each end-use sector to clean or dirty

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

sources. Everything else is measured directly from the data. We 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 we consider.

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 E.3. $\theta_j = \frac{P_j^e E_j}{\sum_j P_j^e E_j}$ 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.

We 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, we would not expect a meaningful difference if we were able to account for at-home personal vehicle charging.

Together with our estimates for ν and σ, our 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, $\tilde{\sigma} = \alpha^{e,C}\sigma' + (1 - \alpha^{e,C}\nu') \approx 0.56$ — 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.

Connection to Previous Literature. To end this subsection we note that our aggregate elasticity estimate is significantly smaller than the values presented by previous studies. This is explained by the distinct scopes. We here account for all energy consumed in the economy — and thus estimate the aggregate elasticity, as opposed to the sectoral or plant-level elasticities like in Papageorgiou et al. (2017) and Jo (2024), respectively. The difference is made clear by proposition 1.

Notwithstanding, note that our aggregate elasticity value does not necessarily contradict the business and industrial elasticities reported in these studies. To illustrate this, we consider an alternative calibration. We assign an elasticity of 3 to the goods and services sector, consistent with Jo (2024). For the transportation and residential sectors, we use values of 0.3 and 0.1, respectively — reflecting the price elasticity of gasoline and residential heating reported in Kilian and Zhou (2024) and Davis and Kilian (2011). Keeping our initial calibration for the electricity sector's elasticity, equation (16) yields an aggregate elasticity of approximately 0.62 — within the relevant confidence bounds provided by our main specification in table 2.

6.3 Variable Elasticity of substitution

We 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 our context. Recent work by Jo and Miftakhova (2024) demonstrates that, at the aggregate level, this mechanism could significantly accelerate the energy transition, thereby reducing its costs. Notably, it might overturn the "de-growth" prediction implied by Acemoglu et al. (2012), when starting out with an aggregate elasticity below unity — in accordance with our point estimate of 0.50.

To test the VES hypothesis, we examine both the time-series and cross-sectional variation in clean energy use in the US throughout our sample period. We begin by analyzing the time-series variation, re-estimating the regression model specified in equation (15) on a rolling basis. We 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. Our 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.

In a second exercise, we examine the cross-sectional heterogeneity in the aggregate elasticity across US states. To do so, we 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 our sample period. If the elasticity increases with the state's share of clean energy, this coefficient should be negative[33]. The results, presented in table 6, do not provide clear evidence of this. Both estimates are statistically indistinguishable from zero. In addition, the lagged interaction term is positively signed.

Neither exercise provides definitive evidence supporting the VES hypothesis. From the perspective of our 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, we recalculate the aggregate elasticity using the 2007 expenditure shares — the first year in our window, as shown in table 5, while keeping the baseline elasticity parameters unchanged.

[33] Higher share decreases are 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
F-statistic	0.71228	0.73333
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 our 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.

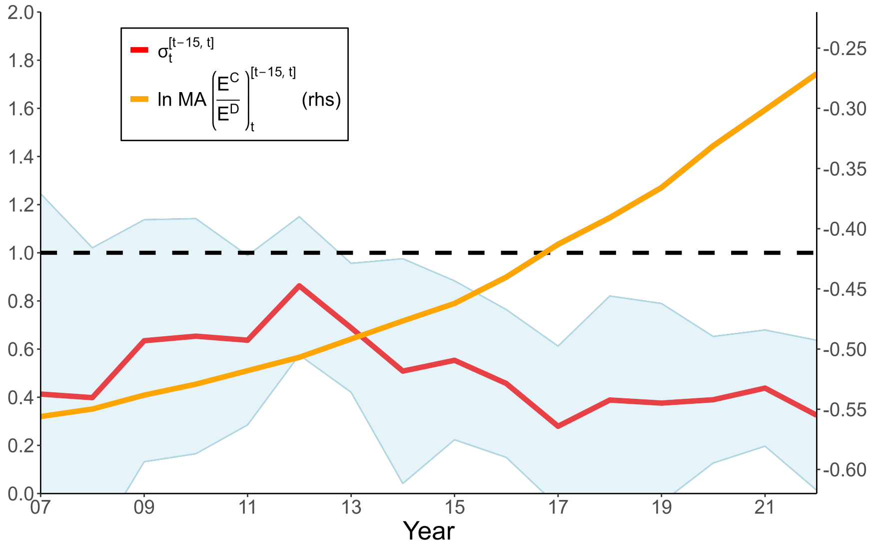


Figure 7: Rolling Regressions of equation (15)

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.

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 unchanged for the transportation and production sectors. Similarly, energy's share of residential services' total costs was 3.93 higher, remaining unchanged for the other two sectors. In contrast, the share of clean energy expenditure increased significantly in goods and services production, and residential use, by 9.89 and 12.16 percentage points, respectively. No noticeable change existed in transportation. Lastly, the weight of the latter sector's in the economy's energy expenditures increased 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 our baseline estimate of 0.50, but not significantly different — in agreement with our empirical findings. Thus, we conclude that no significant changes could have occurred in the sectoral elasticities.

The Importance of Micro Elasticities Our 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 (16) 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, we 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. We demonstrate that the impact in the aggregate elasticity crucially relies on the source of the increase.

In the first scenario, we analyse the effect of increasing the clean electricity share by 10%, while maintaining the other expenditure shares and sectoral elasticities from our baseline calibration[34]. Using equation (16), we find that the aggregate elasticity would basically remain unchanged at 0.50.

In a second scenario, we examine the impact of replacing 10% of the transportation sector's primary dirty energy consumption[35] (measured in Btus) with an equivalent amount of electricity[36]. 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) find that increasing charging infrastructure in the US would likely promote electric vehicle adoption. Since infrastructure availability naturally scales with rising EV demand, a positive feedback between elasticity 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

[34] 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 appendix's section E.4.

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

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

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 in the US. 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

We 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 our empirical strategy involves inferring the price of clean energy from the behaviour of the electricity-generating sector. Our central estimate, around 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, our results underscore the potentially high and unevenly distributed costs of decarbonizing the economy.

To support our empirical approach, we 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 our 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 our calibration suggests must be around 0.81 on average. As a result, the overall "technological elasticity of substitution" for the economy is approximately 0.56. Second, the combination of a low elasticity of demand with limited use of clean energy in transportation leads to further under-adjustment in the energy mix. Consumption's under-reaction to relative price changes explains the remaining difference between the aggregate and technological elasticities. These findings highlight the importance of adopting a comprehensive perspective on energy consumption — an angle that much of the existing literature neglects.

We 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 our 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 understanding the distinct roles individual energy sources can play in decarbonizing the economy — a point especially relevant when microfounding individual's energy choices, as in Acemoglu et al. (2016).

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Online Appendix

A Data preparation

A.1 Non-combustible Consumption

In order to account for non-combustible energy, we closely follow note 3 of the EIA's Monthly Energy Review's section 1 (U.S. Energy Information Administration, 2025). We exclude entirely from petroleum consumption the industrial use of miscellaneous petroleum products, waxes, special naphthas, petrochemical feedstock, residual and distilate fuel oil. We also remove the entire consumption of lubricants, and asphalt and roal oil. Lastly, we remove a proportion of non-combustile use petroleum coke and hydrocarbon gas liquids following the MER's national estimates for the year. For coal consumption, we again use the national estimated proportion of non-combustible use of coal coke in manufacturing for the adjustment. Finally, we follow the same national average procedure to remove a proportion of the natural gas consumed by the industrial sector. We follow the same methodology for expenditures.

A.2 Electricity Trade

To account for electricity trade, we compute the electrical generating sector's energy mix for each US state. We then identify the net exporting states and remove the amount of primary energy used to produce their exported electricity. Note that this assumes no consignment. In reality it is possible that the exporting electricity comes from a specific subset of power plants and energy sources. We undertake a similar exercise for Canada and Mexico. We obtain their electricity sources' shares from EMBER (2024). Because we do not have information on their fossil fuel energy efficiency, nor on their respective expenditure, we use the US's yearly averages to input for these. This procedure is needed to back-out the amount of primary dirty energy consumed in electricity production and the respective expenditure. Finally, we combine the information on US's energy imports (Administration, 2024) with Canada's energy exports (Canada Energy Regulator, 2025)[37] to compute the share of net electricity imported into the US from Canada and/or Mexico.

In a second step, we consider three American major grid regions, the Eastern, Western and Texas grids[38], following U.S. Environmental Protection Agency (2024). Their delineation is determined by the electrical distribution infrastructure which is minimally connected between the three regions. For expository purposes we display a snapshot of the American electricty grid in figure A.1. In turn, the interconnection within the three grids is high. In practice, even within these grids further distinctions based on infrastructure, market access or legal oversight are warranted. Specifically, different sub-regions have different electricity transmission organizations that regulate the access and distribution of electricity. This alternative nonetheless is infeasible for two reasons. The first is that multiple organizations operate in some states, especially in the Midwest and Northwest of the US. The second is that we would still not be able to surpass the lack of knowledge of the origin (source) of electricity transmitted.

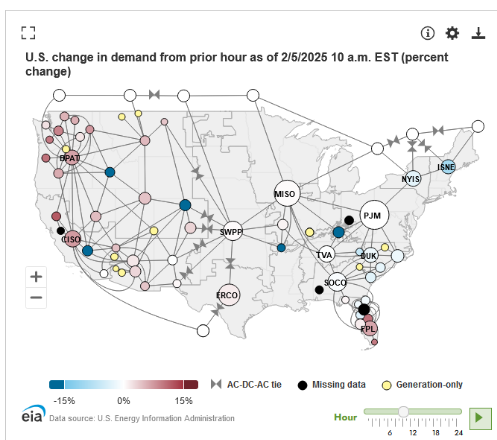


Figure A.1: Snapshot of American Electrical Grid

Using the previous regional delineations we assume that each grid constitutes a unique pool of electricity trade so that any electricity is exported into the pool and then imported proportionally across net importing states. As a result, we assign proportionally to net importing states

[37]We use the national trade values and not the state-to-state trade statistics because we do not have information on the energy mixes of Canadian states. Moreover, given our pooling approach, the SEDS provides sufficient information to understand the source of imports/exports.

[38]The western grid is made up of Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, Wyoming. The remaining states apart from Texas are assigned to the eastern grid.

the average primary energy used to generate the imported electricity in each pool. To determine this pool, we first compute the net imported electricity for each grid. Having only 3 US grids and knowing imports and exports allows us to determine the origins (destinations) of imported (exported) electricity. We then aggregate the imported electricity's energy mix in each net importing grid together with that from net exporting states located within the grid. Using these values, we add to every net importing state the respective proportion of primary energy imported through the grid's pool.

We plot some relevant metrics to assess the impact of accounting for electricity trade in figure A.2, figure A.3, and figure A.4.

Figure A.2: Clean-to-dirty Energy Adjustment

Notes: The map plots the log-point change in the ratio between Non-Pollutant and Pollutant Energy Consumption due to the electricity trade adjustment.

B The price of Clean Energy

We present the results from regressing the dirty energy first-order condition in table B.1. The equation estimated takes the form $\widehat{P_t^D} = \beta_0 + \beta_1 \widehat{P_t^e} + \beta_2 \widehat{\frac{E_t^{e,D}}{E_t^e}} + \varepsilon$, excluding and including a time-trend, $\gamma_0 t$,respectively. Notice that the values of β_2 are expected to be negative, whereas we get a positive value. This reflects the underlying endogeneity. Nonetheless it does not contradict our point that the implied relationship is strong — as demonstrated by the high explanatory powers.

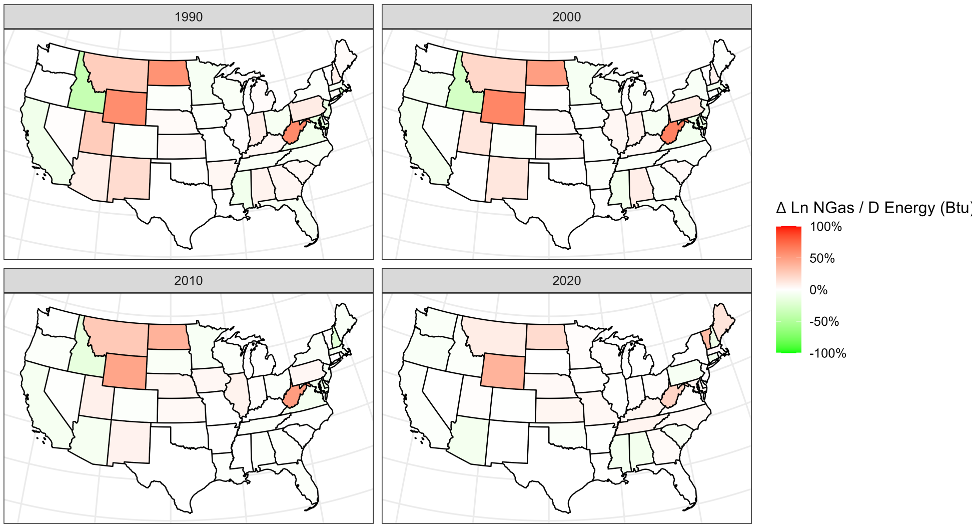


Figure A.3: Effect of Adjustment on Natural Gas

Notes: The map plots the log-point change in the share of Natural Gas on Dirty Energy Consumption as a result of the electricity trade adjustment.

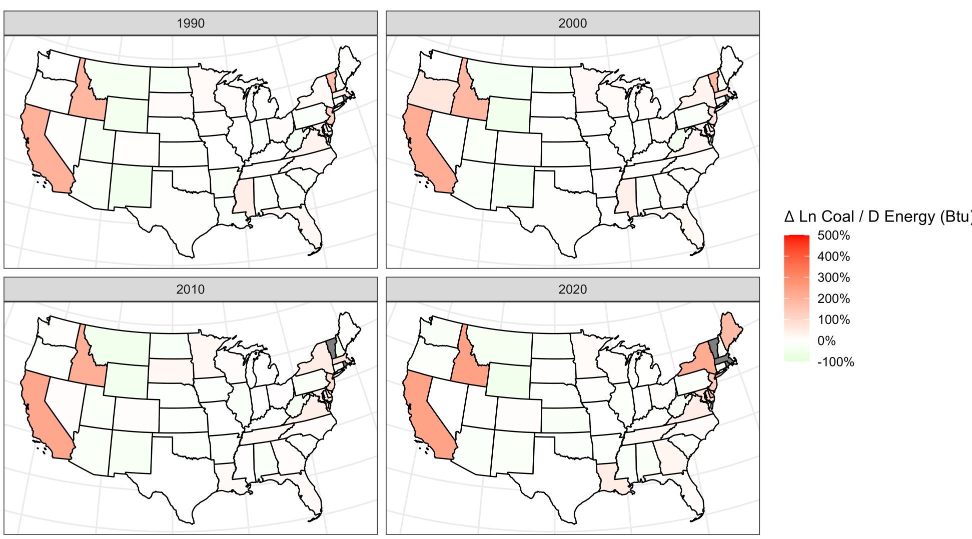


Figure A.4: Effect of Adjustment on Coal

Notes: The map plots the log-point change in the share of Coal on Dirty Energy Consumption as a result of the electricity trade adjustment. The grey shaded states for 2020 are Vermont and Massachusetts who did not use coal directly. Their actual values after the electricity trade adjustment are 7813 and 79134, which represent 7.58% and 6.92% of total dirty energy consumed, respectively. They net imported 65% and 70% of their total electricity consumption, respectively.

Table B.1: Electricity FOC Regression

	$\widehat{P_t^D}$	
	(1)	(2)
Constant	0.0202	-0.0695*
	(0.0259)	(0.0391)
$\widehat{P_t^e}$	3.078***	2.564***
	(0.6496)	(0.6079)
$\frac{\widehat{E_t^{D,e}}}{E_t^e}$	4.072***	5.758***
	(1.034)	(1.098)
t		0.0069***
		(0.0024)
Observations	31	31
R^2	0.58379	0.67966

B.1 Capacity vs Consumption

Equation (6), which serves as a proxy for clean energy prices to generate the regression model described in equation (15), uses the growth rate of clean electricity consumption instead of specific production inputs — such as installed capital — commonly employed in the literature (e.g., Papageorgiou et al. (2017)). This choice is driven by data limitations: installed net summer capacity[39] series in the SEDS database only begin in 2008. Nevertheless, we demonstrate that the dynamics of installed capacity and clean electricity production are closely aligned over the available period. Specifically, figure B.5 compares the logarithmic growth rates of installed net summer capacity across all clean energy sources with states' clean electricity production[40], revealing a strong linear relationship. Meaningful changes in capacity, are typically accompanied by equivalent variations in production. At the same time, variations in production can occur even when capacity remains constant. This can happen due to unexpected annual climacteric conditions for example. On top of practicality, using consumption data facilitates accounting for electricity trade, a task that would be substantially more complicated if we relied on installed capacity figures.

[39]The maximum output that a generating unit, plant, or system can supply to the grid under normal summer conditions, net of the electricity used onsite.

[40]Contrarily to the empirical procedure, we here use state production of clean electricity. This compares directly with the installed capacity — measured within the state.

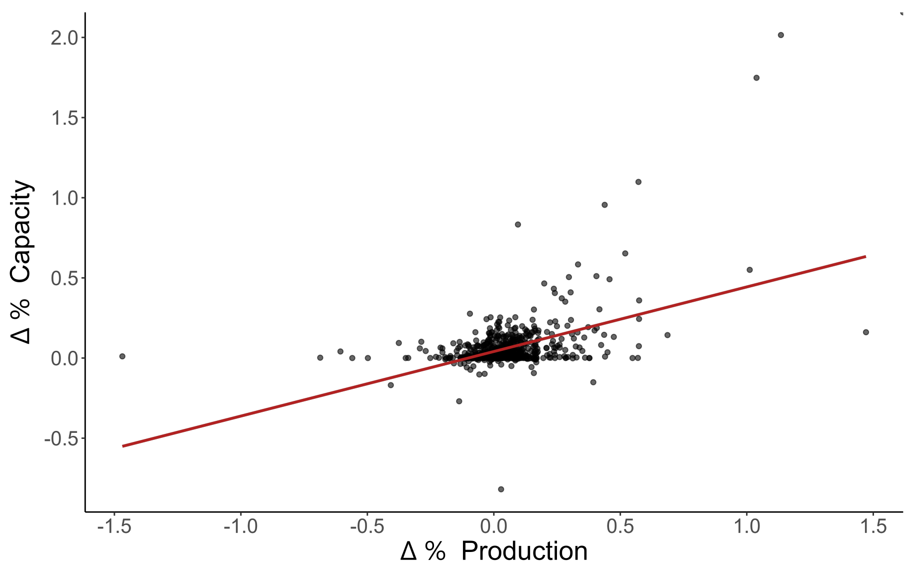


Figure B.5: Clean Energy Capacity vs Production

Notes: The scatterplot compares states' annual logarithmic growth rates in clean electricity production to net installed summer capacity, all measured in kwh. The line is a fitted regression line. Series spans 2009 to 2022. It excludes Delaware until 2011 because its power generating sector did not produce any clean electricity before that (but the residential sector, as defined by the EIA, did).

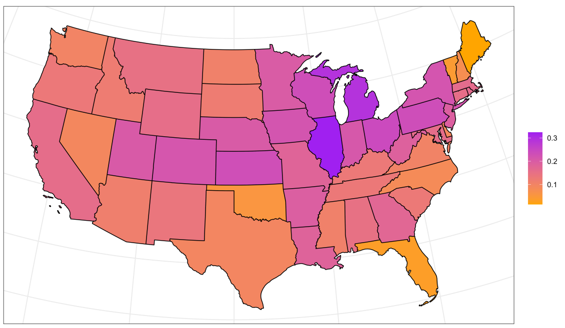
C Identification

C.1 Shift-share instrument

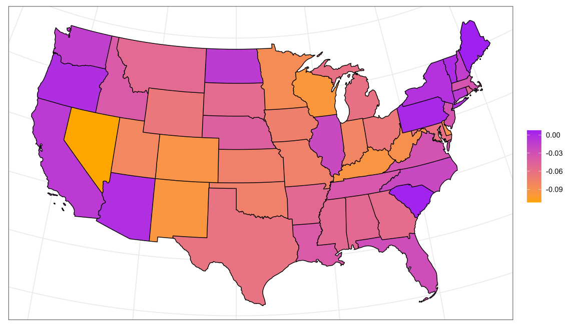
Shift-share Weights. In figure C.6 we present the geographical distribution of shift-share weights for each sub-type of energy. Petroleum and natural gas tend to have a higher relative preponderance in other uses apart from electricity generation. In turn, coal's expenditure share is usually higher in electricity generation, hence the negative values. Although the scales are different, in absolute value, the variation is similar across petroleum and natural gas, and smaller in coal. The distribution across the US is typically symmetric, especially between coal and natural gas. Places where coal has a relatively more preponderant role, have lower weights for gas and vice-versa.

The commodity price time-series used as shifters to construct our shift-share instrument are presented in figure C.8. Although they are very correlated across time, there is relevant orthogonal variation.

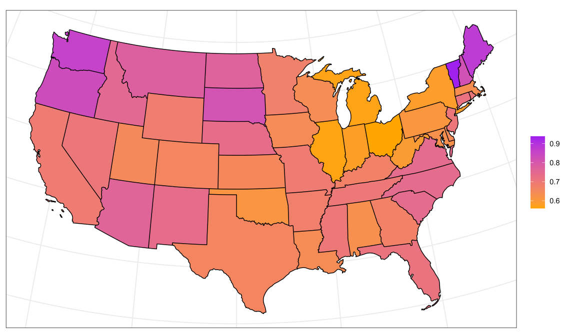
Crude Oil and Petroleum Prices. We begin by computing the principal components of annual state-level petroleum prices across the US throughout our sample. We present the corresponding scree plot in figure C.9. After computing the first principal component, we regress it on the the



(a) Natural Gas



(b) Coal



(c) Petroleum

Figure C.6: Shift-share Weights

Notes: The maps present the US variation in expenditure share differences for commodity j between the overall economy and electricity generation, $\omega_i^j \equiv \omega_{i,1990}^{D,j} - \omega_{i,1990}^{e,j}$, for each of the three energy sub-types considered, natural gas, petroleum and coal, in 1990. The scales are different across the maps.

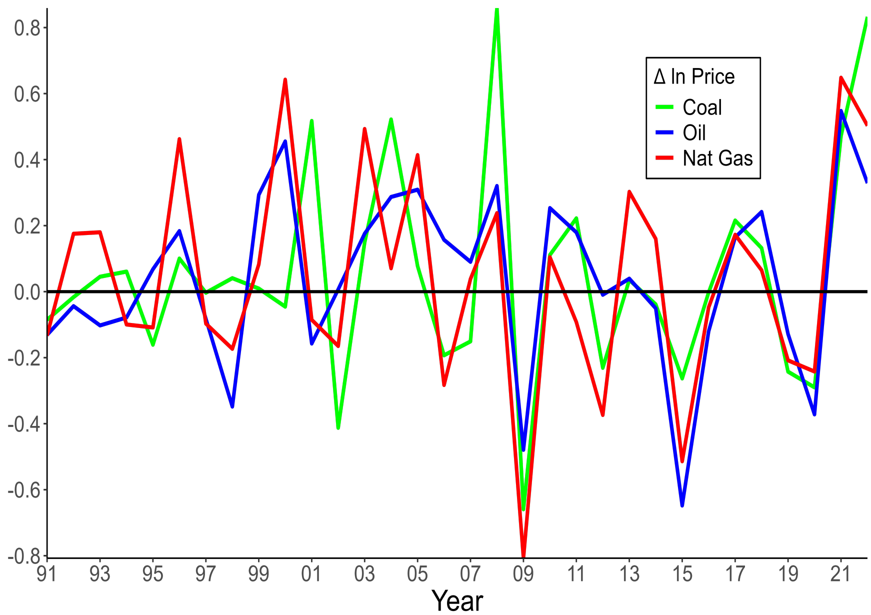


Figure C.8: Commodity Price Variation

Notes: Time-series plot of log growth rates in the three commodity prices considered: the West Texas Intermediate for Petroleum (Oil), the US's Central Appalachian coal spot price (Coal), and the Henry Hub's natural gas spot price (Nat Gas).

price of crude oil, using the West Texas Intermediate. We present the results in table C.2.

Determinants of the SSIV Shares. Table C.3 presents the results from regressing the SSIV shares - the difference expenditure weights in 1990 - on different exogenous state-specific factors.

C.2 Alternative Instruments for Electricity Shares

We propose two alternative instruments for the electricity shares. The first increases the partition of our main instrument, now computing the growth rate average of states outside of state i's regional electricity grid determined by its RTO/ISO or other market form. The second instead uses the third lag of the log of relative clean energy shares. We use the third instead of the second lag of the shares because we have included a lag of the shift-share instrument. We present the results in that order in table C.4. This also allows us to test for endogeneity. With that in mind we conduct a Sargan test by including the three instruments in the same IV regression. The corresponding test statistic is 1.82, and so we do not have statistical evidence to contradict the hypothesis of exogeneity for any of the instruments.

Table C.3: Exogenous determinants of Relative Weights (1990)

	ω_i^{petr}		ω_i^{ngas}		ω_i^{coal}	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.70		1.6***		-0.57**	
	(0.42)		(0.38)		(0.23)	
ln Population (89)	-0.02	-0.001	0.03***	0.005	0.009	0.02***
	(0.01)	(0.01)	(0.008)	(0.01)	(0.006)	(0.006)
ln Person per Sq. mile (89)	-0.06***	-0.08***	0.03***	0.06***	-0.01**	-0.03***
	(0.01)	(0.02)	(0.009)	(0.01)	(0.005)	(0.007)
ln Avg Precipitation (80-89)	0.09**	0.10**	-0.06**	-0.06**	0.04*	0.04*
	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)
ln Avg Temperature (80-89)	0.15*	0.20	-0.32***	-0.37***	0.02	0.06
	(0.08)	(0.15)	(0.08)	(0.12)	(0.06)	(0.07)
ln Distance to LA	0.07**	0.04	-0.06**	-0.04**	0.01	-0.002
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
ln Distance to Cushing, OK	0.04***	0.04**	-0.01	-0.008	0.02**	0.02**
	(0.01)	(0.02)	(0.03)	(0.04)	(0.009)	(0.009)
ln Distance to WY	0.03**	0.008	-0.02	-0.010	0.002	-0.008
	(0.01)	(0.02)	(0.01)	(0.009)	(0.007)	(0.007)
Observations	48	48	48	48	48	48
R^2	0.59244	0.71986	0.50842	0.63664	0.31585	0.52385
PADD$^+$ fixed effects		✓		✓		✓

Notes: Results from regressing the SSIV weights on pre-determined variables. The sample includes the 48 contiguous US states. The standard errors are Heteroskedasticity-robust and are presented in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Figure C.9: Petroleum Price's Scree Plot

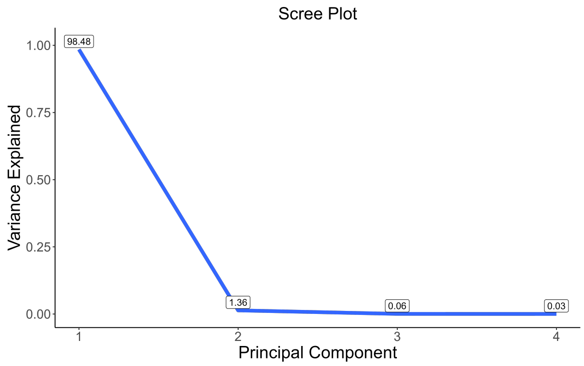


Table C.2: Petroleum Regression on wti

	1^{st} PC
	(1)
Constant	-16.67***
	(0.3852)
WTI	0.3367***
	(0.0068)
Observations	33
R^2	0.98767

Notes: The figures on the scree plot represent each principal component's variance share. The regression table presents the results from regressing the main principal component on the West Texas Intermediate annual average price. The sample spans 1990 to 2022.

Table C.4: Alternative Instruments for Clean Electricity Share

	(1)	(2)	(3)
$\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$	-0.4989**	-0.5673**	-0.5297**
	(0.2258)	(0.2294)	(0.2179)
$\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$	-0.9529***	-0.7820**	-0.9385***
	(0.0592)	(0.2952)	(0.0716)
Observations	1,376	1,329	1,329
Adjusted R^2	0.90457	0.87852	0.89989
F-statistic	0.59969	0.42485	0.75909
1^{st} stage F-statistic, $\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$	23.999	17.021	16.000
1^{st} stage F-statistic, $\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$	39.353	4.6515	38.579
Sargan Test-statistic			2.0685
State fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Extra Controls	Yes	Yes	Yes

Notes: Results when using alternative instruments for $\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$. Column (1) uses an alternative grid region delineation. Column (2) uses the third lag of $\frac{E^{e,c}_{i,t}}{E^e_{i,t}}$. Column (3) includes both instruments to conduct a Sargan Test. The sample includes the 48 contiguous US states and spans 1991 to 2022, excluding 2020. 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.

D Results

Complements to Discussion. To complement our discussion, we plot the actual price evolution for clean and dirty energy, as well as total consumption, in figure D.10. This shows that the trends in generation costs for wind and solar energy evolved very similarly. We replicate figure 5 using photovoltaic LCOE estimates in figure D.11.

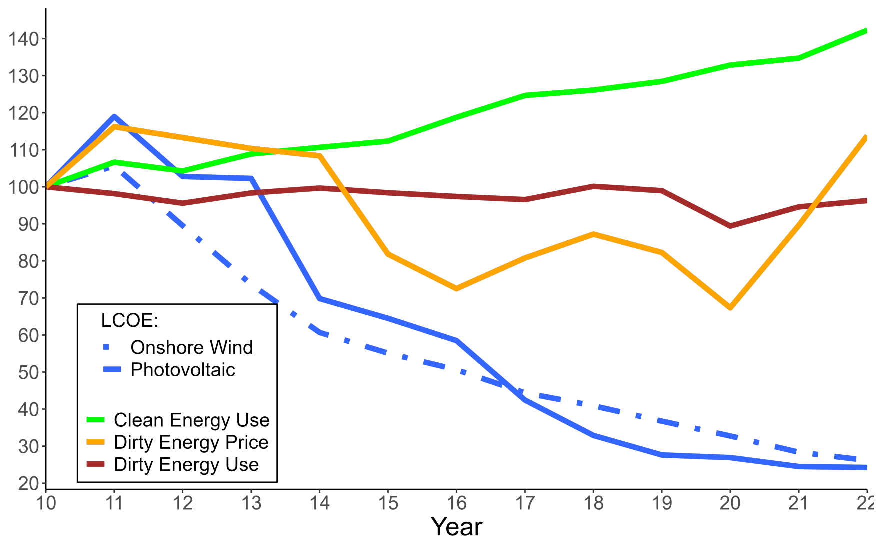


Figure D.10: Energy Consumption and Prices.

Notes: Plot of pollutant and non-pollutant energy consumption and prices. Values normalized to 100 in 2010. LCOE estimates are from International Renewable Energy Agency (2024). All prices account for inflation.

D.1 Further Robustness Checks

Alternative Samples. In order to show that our main policy conclusions are not driven by the sample of shocks, we repeat the estimation of equation (15) with a sample now: *i)* ending before the Covid-19 pandemic, in 2019; *ii)* including 2020, again trimming the 1% tails; *iii)* including 2020 but now using two-year windows; *iv)* excluding 2008; *v)* excluding 2009; and *vi)* not trimming our main sample. We present the results in table D.5. Ending in 2019 slightly increases our point estimate to 0.54. Excluding either 2008 or 2009, the years with the highest swings in fossil fuel prices in our sample, decreases the point estimate to 0.47 and 0.46, respectively. Including covid significantly decreases the point estimate to 0.38 and increases the standard errors. When using 2-year buckets instead precision increases significantly. The estimate remains lower at 0.38. Finally, using the untrimmed sample increases the point estimate to 0.59. Doing so may be problematic as it includes cases such as Vermont in 2015 who decommissioned a nuclear power

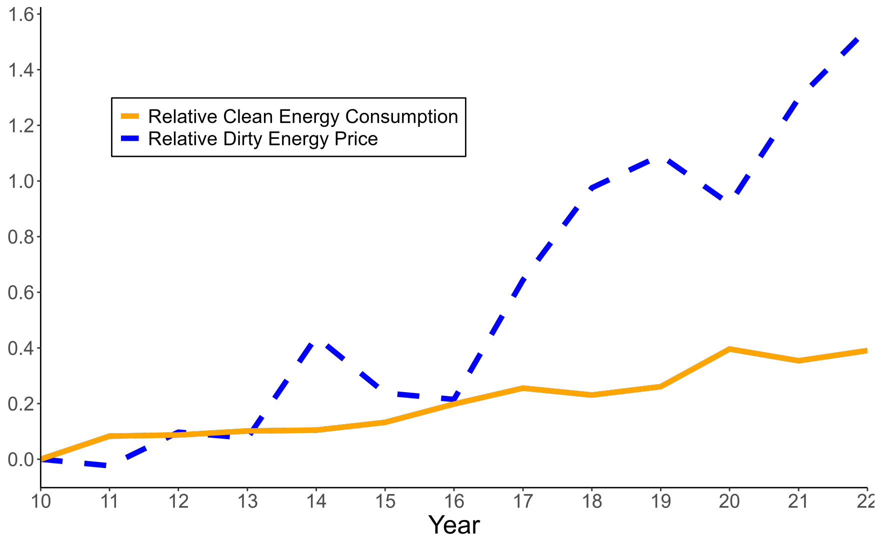


Figure D.11: Relative Clean Energy Consumption and Relative Dirty Energy Prices.

Notes: The figure plots two series for the U.S.: the log-difference in average energy prices between pollutant and non-pollutant sources, and the log-difference in energy consumption between clean and dirty energy. Both series are normalized to 100 in 2010 prior to the log transformation. As a proxy for clean energy prices, we use photovoltaic LCOE estimates from International Renewable Energy Agency (2024). All prices are adjusted for inflation.

plant at the end of 2014, thus observing a massive decline in clean energy consumption — totally unrelated to contemporaneous commodity price fluctuations.

E From Macro to Micro

E.1 Model

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 $\alpha_j = \frac{P^C E^C_j}{P^C E^C_j + P^d E^D_j}$ to be the energy expenditure share of clean energy, where

$$E^D_j = E^d_j + E^e_j \times \frac{E^{e,D}_j}{E^e_j} \tag{17}$$

Table D.5: Alternative Samples

	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$	-0.5438**	-0.3777	-0.3792**	-0.4715*	-0.4615*	-0.5871**
	(0.2440)	(0.2625)	(0.1600)	(0.2548)	(0.2490)	(0.2787)
$\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$	-0.9477***	-0.9779***	-0.9659***	-0.9599***	-0.9629***	-0.8801***
	(0.0809)	(0.0830)	(0.0697)	(0.0827)	(0.0768)	(0.0834)
Observations	1,292	1,421	687	1,328	1,340	1,440
Adjusted R^2	0.90188	0.90677	0.90449	0.90542	0.90402	0.91210
F-statistic	0.70664	0.86305	0.57408	0.75453	0.72805	0.38809
1^{st} stage F-statistic, $\widehat{\frac{P^D_{i,t}}{P^e_{i,t}}}$	30.755	30.632	20.706	29.776	28.684	35.109
1^{st} stage F-statistic, $\widehat{\frac{E^{e,c}_{i,t}}{E^e_{i,t}}}$	73.337	78.561	31.299	78.415	76.244	31.420
State fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓
Extra Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Results when changing the sample. Column (1)'s data ends in 2019. Column (2)'s includes covid. Column (3)'s includes covid but uses 2 year buckets instead. Column (4) excludes 2008. Column (5) excludes 2009. Column (6) does not trim our main sample. The sample includes the 48 contiguous US states and starts in 1991. All except column (5)'s data exclude the 1% tails. All regressions are unweighted. 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.

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

$$E_j^C = E_j^e \times \frac{E_j^{e,C}}{E_j^e} \tag{18}$$

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, we 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 $\frac{d\theta_j}{d \ln \frac{P^D}{P^C}}$, we 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, we 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

$$\frac{d \ln \frac{s_j^E}{s^j}}{d \ln \frac{P^D}{P^C}} = \varepsilon_{P^D}^{P_j^E} (1 - s_j^E) \tag{19}$$

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 we 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, we 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, we 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 we can conclude that

$$\frac{d\ln\frac{TC_j}{TC}}{d\ln\frac{P^D}{P^C}} = (1-\varepsilon)s_j^E \cdot \varepsilon_{P^D}^{P_j^E}. \tag{20}$$

Finally, combining equation (19) with equation (20), we have that

$$\sum_j \alpha_j\frac{d\theta_j}{d\ln\frac{P^D}{P^C}} = \sum_j(\alpha_j - \alpha)\theta_j\varepsilon_{P^D}^{P_j^E}(1-\varepsilon s_j^E). \tag{21}$$

Turning to $\frac{d\alpha_j}{d\ln\frac{P^D}{P^C}}$ we 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 $\frac{d\ln\frac{\alpha_j}{1-\alpha_j}}{d\ln\frac{P^D}{P^C}}$, we find that

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

Using the definitions in equation (17) and equation (18) together with the fact that we have assumed a unique electricity production function,

$$\frac{d\ln\frac{P^C E_j^C}{P^C}}{d\ln\frac{P^D}{P^C}} = \frac{d\ln\frac{P^e E_j^e}{P^C}}{d\ln\frac{P^D}{P^C}} + \frac{d\ln(\frac{P^C E^{e,C}}{P^e E^e}/P^C)}{d\ln\frac{P^D}{P^C}}$$

and

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

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

$$\frac{d\ln\frac{\alpha_j}{1-\alpha_j}}{d\ln\frac{P^D}{P^C}} = \alpha_j^d \frac{d\ln\frac{P^e E_j^e}{P^D E_j^d}}{d\ln\frac{P^D}{P^C}} + \frac{d\ln\alpha^{e,C}}{d\ln\frac{P^D}{P^C}} - (1-\alpha_j^d)\frac{d\ln(1-\alpha^{e,C})}{d\ln\frac{P^D}{P^C}}. \tag{22}$$

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, we have that

$$\frac{d\ln\alpha^{e,C}}{d\ln\frac{P^D}{P^C}} = (1-\nu)\cdot -(1-\alpha^{e,C}) = (\nu-1)(1-\alpha^{e,C}). \tag{23}$$

Symmetrically, we 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,

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

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, we 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,

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

[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 we have that $\frac{dP^e}{dP^C} = (\frac{P^C}{P^e})^{-\nu}a^{e,C}$. Finally, from the FOC, we know that $(\frac{P^C}{P^e})^{1-\nu}a^{e,C} = \alpha^{e,C}$. Together with the chain rule of logarithms, we have our result.

Replacing equations (23) to (25) into equation (22), yields

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

Combining equation (21) and equation (26), we prove that

$$\begin{aligned}\sigma = 1 &+ \sum_j \frac{\theta_j(\alpha_j-\alpha)}{\alpha(1-\alpha)}\varepsilon_{P^D}^{P_j^E}(1-\varepsilon s_j^E)\\ &+ \sum_j \frac{\theta_j(1-\alpha_j)\alpha_j}{\alpha(1-\alpha)}\left[\alpha_j^d(\sigma_j-1)\alpha^{e,C} + (\nu-1)(1-\alpha^{e,C})\left(1+(1-\alpha_j^d)\frac{\alpha^{e,C}}{1-\alpha^{e,C}}\right)\right]\end{aligned} \tag{27}$$

Now we 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

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

Rearranging equation (27), we reach equation (16)

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

and prove proposition 1.

□

Detailed Interpretation. The aggregate elasticity depends on two effects, one depicting the consumption reshuffling and another the energy reallocation. Starting with the latter, the energy mix adjustment depends on two sources, specific to the nature of energy consumption and the layered structure of energy production. The first is the adjustment in the electricity's energy mix ν. Since every sector j's electricity originates from the same source, everyone's electricity becomes ν% greener in response to an increase in the relative price of dirty energy. The second source of adjustment is sector j's own adjustment away from dirty energy into electricity, determined by σ_j. This generates a reshuffling effect as the diversion away from primary dirty energy consumption will now be fulfilled by both dirty and clean-based electricity. The benefit of each effect evolves symmetrically, and is determined both by the clean energy expenditure share in electricity generation, $\alpha_j^{e,C} = \frac{P^C E_j^{e,C}}{P^C E_j^{e,C} + P^D E_j^{e,D}}$, and by sector j's dirty expenditure share $\delta_j^D = \frac{P^D E_j^D}{P^D E_j^D + P^D E_j^{e,D}}$. As the share of clean electricity increases, moving away from primary dirty energy has a higher effect on the energy mix because it is fulfilled by proportionally more clean energy. Similarly, the higher the primary dirty energy consumption, the more sector j's elasticity matters, as it diverts away from more dirty energy. In addition, note that the energy redirected towards electricity also benefits from the reshuffling towards cleaner electricity sources - reflected in the additional terms in the ν'. In contrast, these two forces attenuate the electricity's elasticity since either the electricity adjustment does not have a big impact due to the already high share of clean energy or because its share of total end-use energy is low. Finally, sector j's energy mix balance, $\frac{\alpha_j(1-\alpha_j)}{\alpha(1-\alpha)}\theta_j$, determines its contribution to the overall energy adjustment.

The consumption reallocation effects is a result of the differentiated sectoral sensitivities to relative energy prices and to consumers' sensitivity to changes in relative prices, embodied by the elasticity of demand ε. Sector j's sensitivity to energy prices is captured by its marginal cost's elasticity to the relative price of dirty energy, $\varepsilon_{P^D}^{P_j^e} = \frac{d \ln P_j^e / P^C}{d \ln P^D / P^C}$. Naturally both of these effects matter more the higher is the share of energy in costs, s_j^E. Moreover, the reallocation away or into sector j is determined by its higher or lower relative consumption of clean energy, determined by the size and sign of $\frac{\alpha_j(\alpha_j - \alpha)}{\alpha(1-\alpha)}\theta_j$. Hence, $\frac{\alpha_j(\alpha_j - \alpha)}{\alpha(1-\alpha)}\theta_j$ can be either negative or non-negative.

E.2 Rolling Regressions of Original Sample

In section 6.3 we trim the tails of each window individually. Here we repeat the rolling regressions using instead the estimation sample from our main specification - presented in section 5.1. A caveat is that we must use the observations excluded from the sample before 2008 in order to define the SSIV weights - otherwise we would lose those states. These observations, nonetheless, remain excluded from the estimation sample. We display the results in figure E.12.

E.3 Calibration Exercise

We now provide the details of the calibration exercise laid out in table 5. We aggregate all the EIA data by sector and year. Quantities and expenditures are summed, and prices are the ratio of expenditures to quantities. From the BEA's Fixed Assets Accounts' table 2.7[42] we assign items 18, 62, 89, and 90 to transportation, 34 and 67 to the residential sector, and 4, 11, 26, 37, 48, 53, 58, 59, 60, 61, 65, 66, 85, 86, 87, 88, 91, 95, and 98 to goods and services. Similarly, from the

[42]See here.

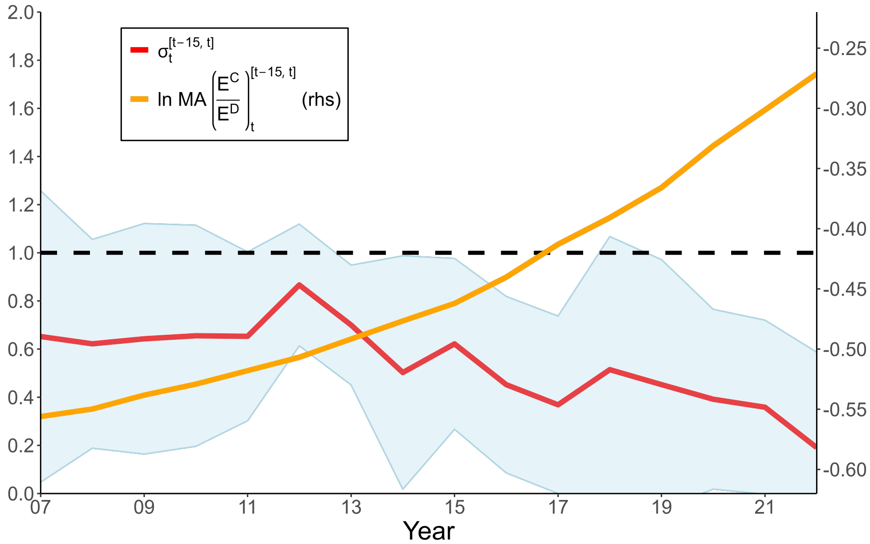


Figure E.12: Rolling Regressions of equation (15)

Notes: Rolling regressions of equation (15) with 15 year windows. The sample used matches our main exercise's - presented in section 5.1. 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.

BEA's National Income and Product Accounts' table 6.2D[43], we assign items 22, 23, 39, and 43 to transportation, 12 and 63 to the residential sector, and 4, 15, 16, 17, 18, 19, 20, 21, 24, 25, 26, 35, 40, 41, 42, 52, 57, 64, 65, 69, 73, 74, 79, 82, and 85 to the production sector.

The previous step allows us to compute all end-use expenditure shares. We are left with assigning the share of electricity spending to clean or dirty sources. To do this, we first take LCOE prices for renewables from U.S. Energy Information Administration (2018) for 2022, our main year of analysis. We choose to use the forecasted prices in 2018 to allow for a lag between planning and implementation. To extend the LCOESs back to 2007, we rely on the LCOE price dynamics for onshore wind and photovoltaic for the U.S., and the world average geothermal and hydroelectric LCOEs from International Renewable Energy Agency (2024). Specifically, for wind we have the actual series available. For the remaining one we lack the data. As a result, we linearly regress the data and predict the missing values. For solar we use an exponential fit. For geothermal and hydropower we use instead a linear fit. We present the series and fitted values in figure E.13.

For nuclear generation in 2022 we use instead the marginal costs provided in Nuclear Energy Institute (2025). This choice is based on the idea that nuclear in 2022 is not the marginal generation source. Although this may not be the case in 2007, for consistency, we opt to maintain this

[43]See here.

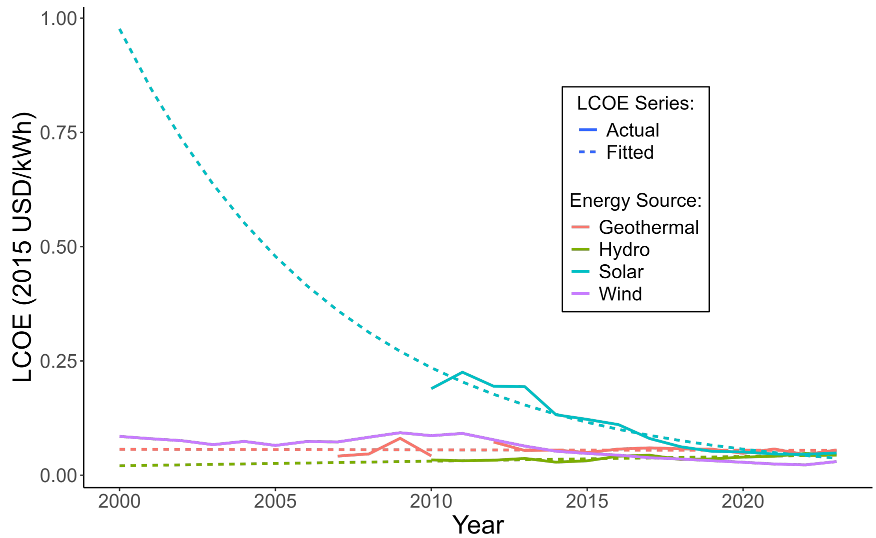


Figure E.13: Renewables' LCOE Dynamics

Notes: Original data from International Renewable Energy Agency (2024). The fitted values are obtained by regressing the available series on a constant and the year, or the logarithm of the year for solar generation.

assumption. The drawback is that the price of clean electricity is actually lower in 2007 because most clean electricity originates from this source. We linearly interpolate the prices for missing years.

Finally, we use the expenditures in fossil fuels and biomass in the electric power sector from the SEDS to compute prices for each pollutant energy source. The point here is that most of the costs for electricity generation from dirty sources are determined by fuel prices and not by infrastructure costs.

Using these figures we are able to compute the average price per kwh and Btu for clean and dirty energy, respectively. We multiply these prices by the quantities of electricity produced or dirty energy consumed in electricity generation - retrieving an estimate for the expenditure shares in each energy aggregate. Equipped with these we can split the end-use expenditure shares in electricity into clean and dirty generation.

Because our model does not foresee market power nor other fixed costs, we opt to compute a virtual price of electricity. We first take the first-order conditions implied by profit maximization with a CES function, and compute the implied a^e from the prices and expenditure shares. Then, using the CES price index, we compute the virtual price of electricity. We need this to compute $\varepsilon_{PD}^{P_j^E}$.

Together, this information allows us to compute the aggregate elasticity of substitution, σ, using equation (16), if we know the sectoral and consumption elasticities.

E.4 Counterfactual Exercises

Electricity Counterfactual. Note that in order for the share of electricity not to change across energy end-use sectors, we need that $d\ln P^D = d\ln P^e = 0$. Taking the price index for electricity, we have that

$$d\ln P^e = \frac{d\ln a^e}{d\ln P^e} d\ln a^e + \frac{d\ln P^C}{d\ln P^e} d\ln P^C.$$

where $\frac{d\ln a^e}{d\ln P^e} = \frac{da^e}{dP^e}\frac{a^e}{P^C}$. Using the expressions,

$$\frac{da^e}{dP^e} = \frac{1}{1-\nu}(P^e)^\nu[(P^C)^{1-\nu} - (P^D)^{1-\nu}]$$

and

$$\frac{dP^C}{dP^e} = \frac{1}{1-\nu}(P^e)^\nu(1-\nu)(P^C)^\nu a^e.$$

Hence,

$$d\ln P^e = \frac{1}{1-\nu} a^e \left[\left(\frac{P^C}{P^e}\right)^{1-\nu} - \left(\frac{P^D}{P^e}\right)^{1-\nu}\right] d\ln a^e + a^e \left(\frac{P^C}{P^e}\right)^{1-\nu} d\ln P^C.$$

Finally, note that from the FOC, $a^e \left(\frac{P^C}{P^e}\right)^{1-\nu} = \alpha^{e,C}$. As a result,

$$\begin{aligned} & d\ln P^e = 0 \\ \iff \; & d\ln P^C = -\frac{1}{\alpha^{e,C}(1-\nu)}\left(1 - \frac{1-\alpha^{e,C}}{1-a^e}\right) d\ln a^e. \end{aligned}$$

Moreover, to increase the share of clean energy by approximately 10%, we need that

$$d\ln\frac{E^{e,C}}{E^e} = -\nu d\ln P^C + d\ln a^e = 0.1$$

Hence,

$$d\ln P^C = \frac{d\ln a^e - 0.1}{\nu}.$$

Now we can solve for $d\ln a^e$ and $d\ln P^C$ which are equal to

$$\begin{aligned} d\ln a^e &= \frac{0.1}{1-\nu A} \\ d\ln P^C &= \frac{A0.1}{1-\nu A} \end{aligned}$$

where $A \equiv -\frac{1}{\alpha^{e,C}(1-\nu)}(1-\frac{1-\alpha^{e,C}}{1-a^e})$. As a result of this change, $d\ln\alpha^{e,C} \neq 0$ and $d\ln\alpha_j \neq 0 \forall j$ unless $d\ln P^C = -0.1$, in which case, the aggregate elasticity remains the same. In particular, we have that

$$\begin{aligned} d\ln\alpha^{e,C} &= \frac{d\ln\alpha^{e,C}}{d\ln P^C E^{e,C}} d\ln P^C E^{e,C} + \frac{d\ln\alpha^{e,C}}{d\ln P^D E^{e,D}} d\ln P^D E^{e,D} \\ &= (1-\alpha^{e,C}) d\ln P^C E^{e,C} - (1-\alpha^{e,C}) d\ln P^D E^{e,D} \\ &= (1-\alpha^{e,C})(d\ln a^e + (1-\nu) d\ln P^C + \frac{a^e}{1-a^e} d\ln a^e). \end{aligned}$$

We can then use the chain rule to find the effect on $\alpha^{e,C}$,

$$d\alpha^{e,C} = \alpha^{e,C} d\ln\alpha^{e,C}$$

and α_j,

$$\begin{aligned} d\alpha_j^d &= \frac{d\alpha_j^d}{d\alpha^{e,C}} d\alpha^{e,C} \\ &= (1-\alpha_j^d) d\alpha^{e,C}, \end{aligned}$$

since $\alpha_j = \alpha^{e,C}(1-\alpha_j^d)$. We can then recompute the aggregate elasticity.