Supplemental Appendix:
The Aggregate Green Elasticity of Substitution

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A Data preparation

A.1 Non-combustible Consumption

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

A.2 Electricity Trade

To account for electricity trade, I compute the electrical generating sector's energy mix for each US state. I 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

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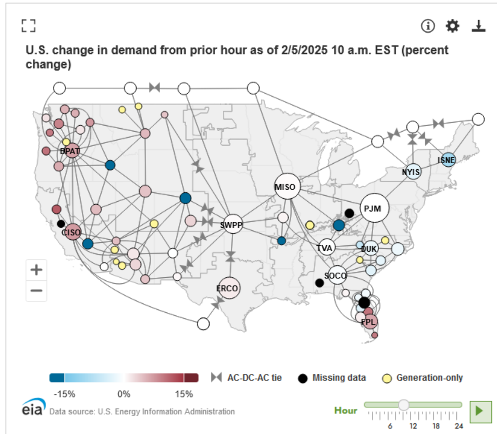


Figure A.1: Snapshot of American Electrical Grid

sources. I undertake a similar exercise for Canada and Mexico. I obtain their electricity sources' shares from EMBER (2024). Because I do not have information on their fossil fuel energy efficiency, nor on their respective expenditure, I 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, I combine the information on US's energy imports (Administration, 2024) with Canada's energy exports (Canada Energy Regulator, 2025)[1] to compute the share of net electricity imported into the US from Canada and/or Mexico.

In a second step, I consider three American major grid regions, the Eastern, Western and Texas grids[2], 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 I 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 I would still not be able to surpass the lack of knowledge of the origin (source) of electricity transmitted.

Using the previous regional delineations I 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, I assign proportionally to net importing states the average

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

[2] 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.

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.

primary energy used to generate the imported electricity in each pool. To determine this pool, I first compute the net imported electricity for each grid. Having only 3 US grids and knowing imports and exports allows me to determine the origins (destinations) of imported (exported) electricity. I 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, I add to every net importing state the respective proportion of primary energy imported through the grid's pool.

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

B The price of Clean Energy

I 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, t, respectively. Notice that the values of β_2 are expected to be negative, whereas I get a positive value, reflecting the underlying endogeneity. Nonetheless, the implied relationship is strong — as demonstrated by the high explanatory powers.

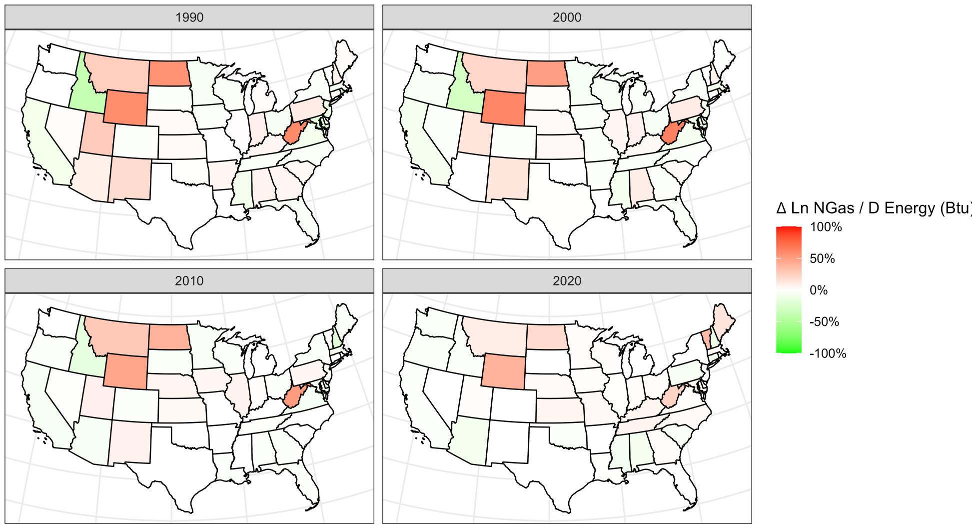


Figure A.3: Effect of Adjustment on Natural Gas

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.

Table B.1: Electricity FOC Regression

	$\widehat{P^D_t}$	
	(1)	(2)
Constant	0.0202	-0.0695*
	(0.0259)	(0.0391)
$\widehat{P^e_t}$	3.078***	2.564***
	(0.6496)	(0.6079)
$\widehat{\frac{E^{D,e}_t}{E^e_t}}$	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.,

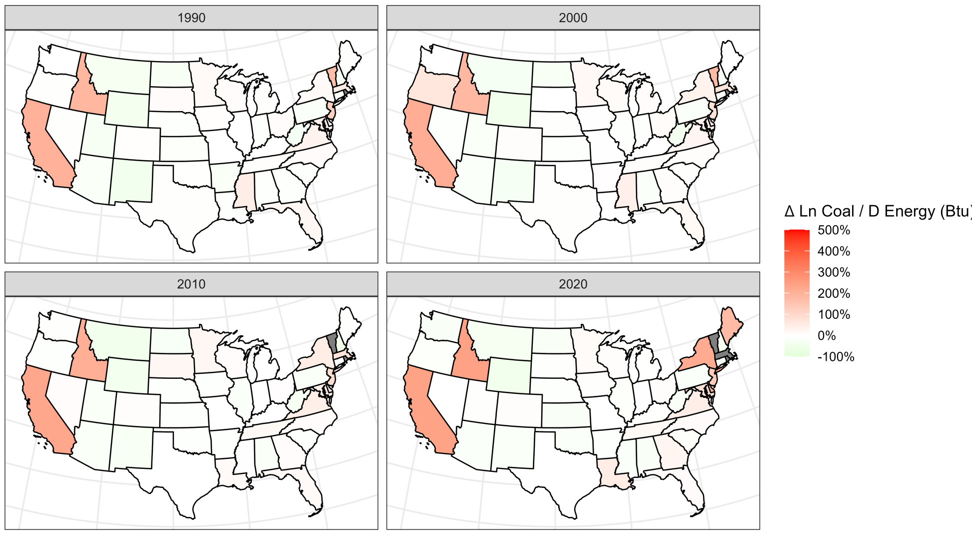


Figure A.4: Effect of Adjustment on Coal

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.

Papageorgiou et al. (2017)). This choice is driven by data limitations: installed net summer capacity[3] series in the SEDS database only begin in 2008, and account for all installed capacity, not just the electricity generating sector's (which remains its biggest contributor). Nevertheless, I demonstrate that the dynamics of total installed capacity and clean electricity production are closely aligned over the available period. Specifically, figure B.1 compares the logarithmic growth rates of installed net summer capacity across all clean energy sources with states' clean electricity production[4], 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 I relied on installed capacity figures.

[3]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.

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

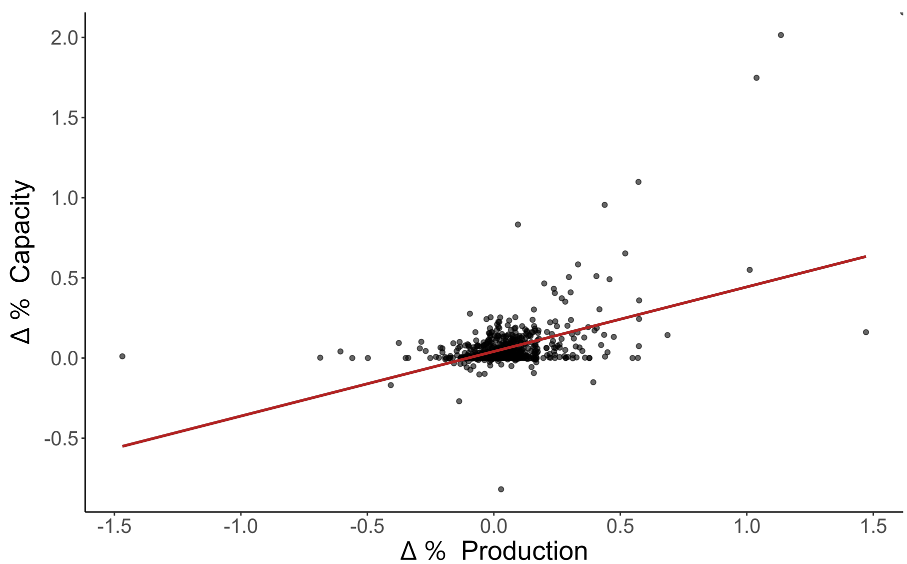


Figure B.1: Clean Energy Capacity vs Production

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).

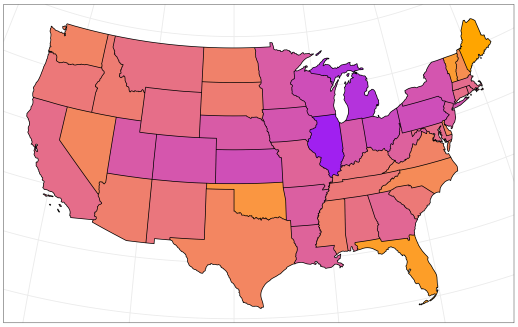
C Identification

C.1 Shift-share instrument

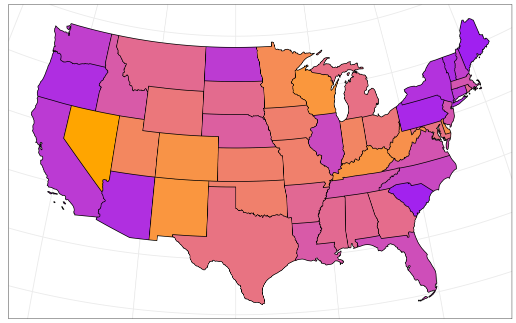
Shift-share Weights. In figure C.1 I present the geographical distribution of shift-share weights for each sub-type of energy. Petroleum and natural gas tend to have a higher relative preponderance in other uses apart from electricity generation. In turn, coal's expenditure share is usually higher in 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 my shift-share instrument are presented in figure C.3. Although they are very correlated across time, there is relevant orthogonal variation.

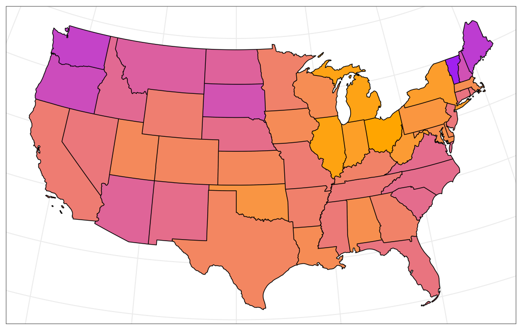
Crude Oil and Petroleum Prices. I begin by computing the principal components of annual state-level petroleum prices across the US throughout my sample. I present the corresponding scree plot in figure C.4. After computing the first principal component, I regress it on the the price of crude oil, using the West Texas Intermediate. I present the results in table C.1.



(a) Natural Gas



(b) Coal



(c) Petroleum

Figure C.1: 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.

Determinants of the SSIV Shares. Table C.2 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

I propose two alternative instruments for the electricity shares. The first refines the partition of my 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. I use the third instead of the second lag of the shares because I have included a lag of the shift-share instrument. I present the results in that order in table C.3. This also allows me to test for endogeneity. With that in mind I conduct a Sargan test by including the three instruments in the same IV regression. The corresponding test statistic is 2.07, and so I do not have statistical evidence to contradict the hypothesis of exogeneity for any of the instruments.

Table C.2: 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.

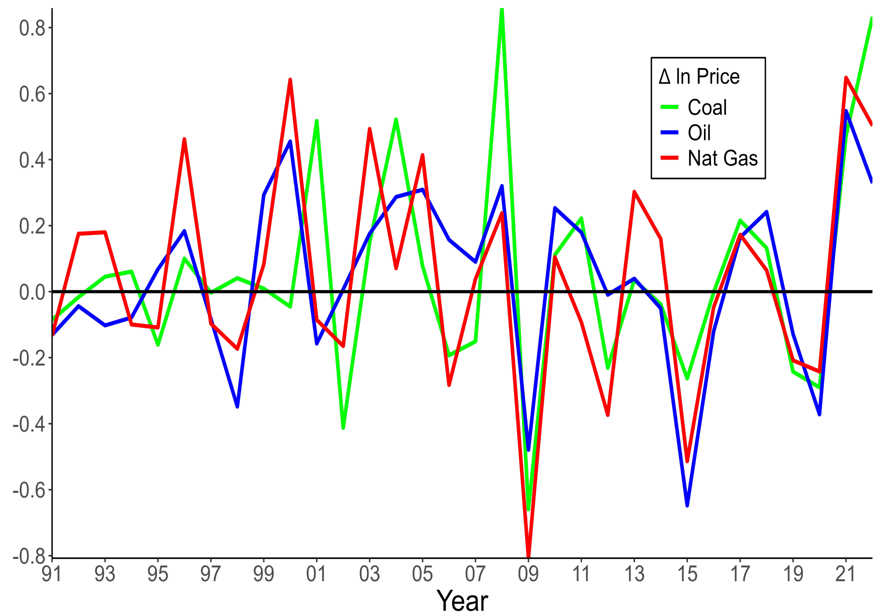


Figure C.3: Commodity Price Variation

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).

D Results

Complements to Discussion. To complement my discussion, I plot the actual price evolution for clean and dirty energy, as well as total consumption, in figure D.1. This shows that the trends in generation costs for wind and solar energy evolved very similarly. In figure D.2 I replicate figure 6 using the raw data instead. Figure D.3 uses photovoltaic LCOE estimates in place of wind's.

The full results from estimating equation (17) are provided in table D.1.

D.1 Further Robustness Checks

Alternative Samples. In order to show that my main policy conclusions are not driven by the sample of shocks, I 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 my main sample. I present the results in table D.2. Ending in 2019 slightly increases my point estimate to 0.54. Excluding either 2008 or 2009, the years with the highest swings in fossil fuel prices in my 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-

Figure C.4: Petroleum Price's Scree Plot

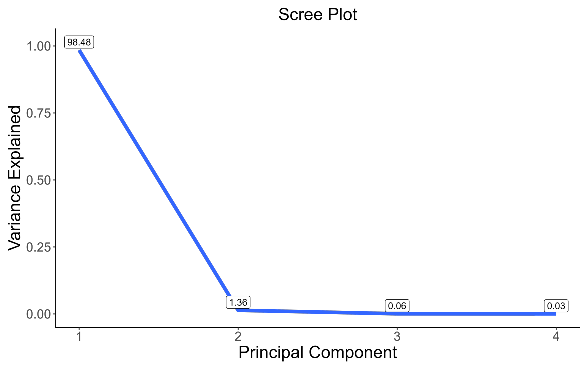


Table C.1: Petroleum Regression on wti

	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.3: 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
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.

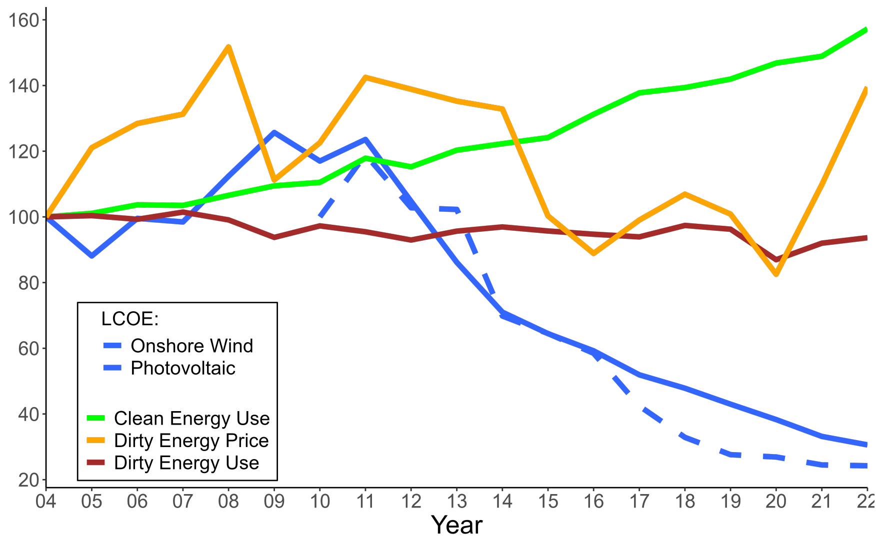


Figure D.1: Energy Consumption and Prices.

Notes: Plot of pollutant and non-pollutant energy consumption and prices. Values normalized to 100 in 2004, except for photovoltaic LCOE estimates whose series starts in 2010. LCOE estimates are from International Renewable Energy Agency (2024). All prices account for inflation.

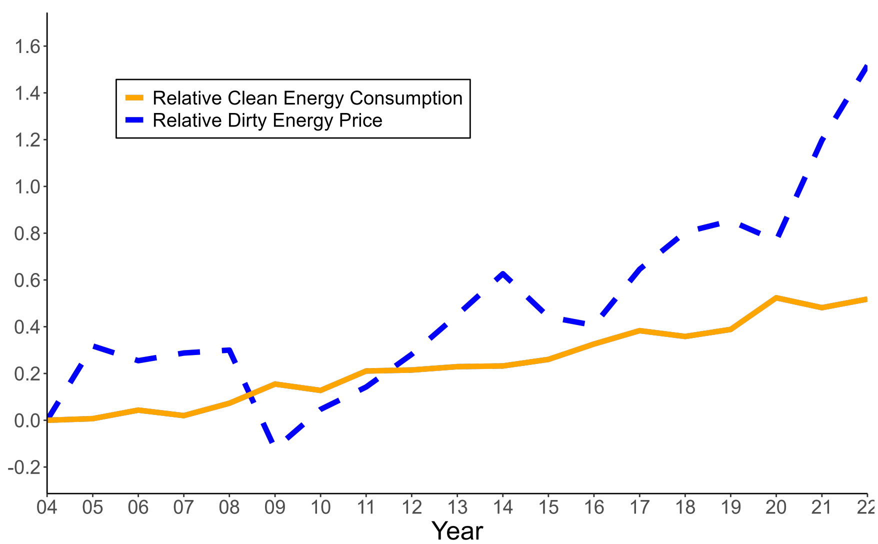


Figure D.2: Relative Clean Energy Consumption and Relative Dirty Energy Prices.

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 2004 prior to the log transformation. As a proxy for clean energy prices, I use onshore wind LCOE estimates from International Renewable Energy Agency (2024). All prices are adjusted for inflation.

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

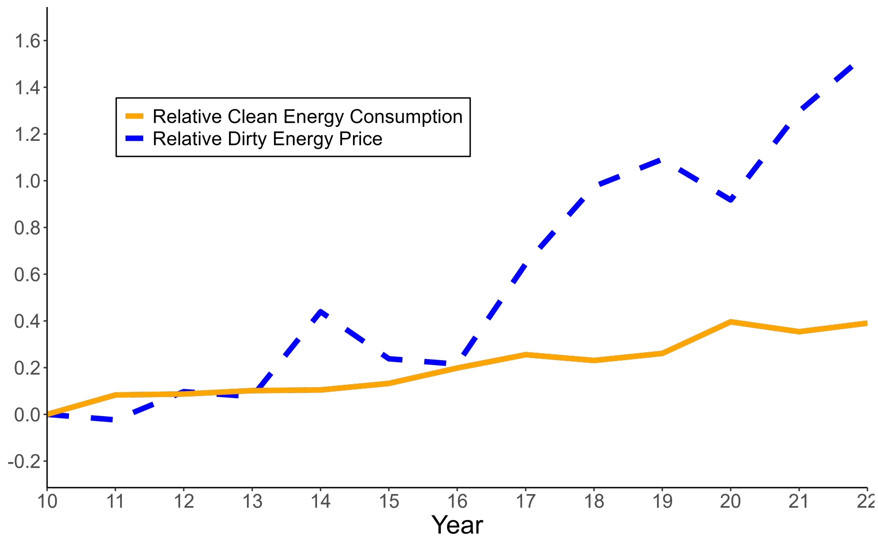


Figure D.3: Relative Clean Energy Consumption and Relative Dirty Energy Prices.

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, I use photovoltaic LCOE estimates from International Renewable Energy Agency (2024). All prices are adjusted for inflation.

as it includes cases such as Vermont who in 2015 decommissioned a nuclear power 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's 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 $\nu\%$ 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

Table D.1: Kmenta Approximation

	Levels	First-differences
	(1)	(2)
$\ln \frac{E^C_{i,t}}{E^D_{i,t}}$	0.2201***	
	(0.0575)	
$\left(\ln \frac{E^C_{i,t}}{E^D_{i,t}}\right)^2$	0.0204***	
	(0.0061)	
t	0.0394***	
	(0.0008)	
Intercept		0.0393***
		(0.0007)
$\Delta_t \ln \frac{E^C_{i,t}}{E^D_{i,t}}$		0.3699***
		(0.0384)
$\Delta_t\left(\ln \frac{E^C_{i,t}}{E^D_{i,t}}\right)^2$		0.0348***
		(0.0050)
σ	1.313	1.426
Observations	1,424	1,424
Adjusted R^2	0.98466	0.24687
F-statistic	1,043.0	7.7469
State fixed effects	✓	

Notes: Results of estimating equation (17). The headers indicate if the regression was estimated in levels or in first-differences. The implied point estimates for the aggregate elasticity are displayed in the σ row. The sample is the same as in my main specification. The standard errors are clustered at the state level and are presented in parenthesis below the estimate. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

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

Table D.2: 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
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 my 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.

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, $\varepsilon^{P^e_j}_{P^D} = \frac{d \ln P^e_j / P^C}{d \ln P^D / P^C}$. Naturally both of these effects matter more the higher is the share of energy in costs, s^E_j. 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 subsection 6.3 I trim the tails of each window individually. Here I repeat the rolling regressions using instead the estimation sample from my main specification - presented in subsection 5.1. A caveat is that I must use the observations excluded from the sample before 2008 in order to define the SSIV weights - otherwise I would lose those states. These observations, nonetheless, remain excluded from the estimation sample. I display the results in figure E.1.

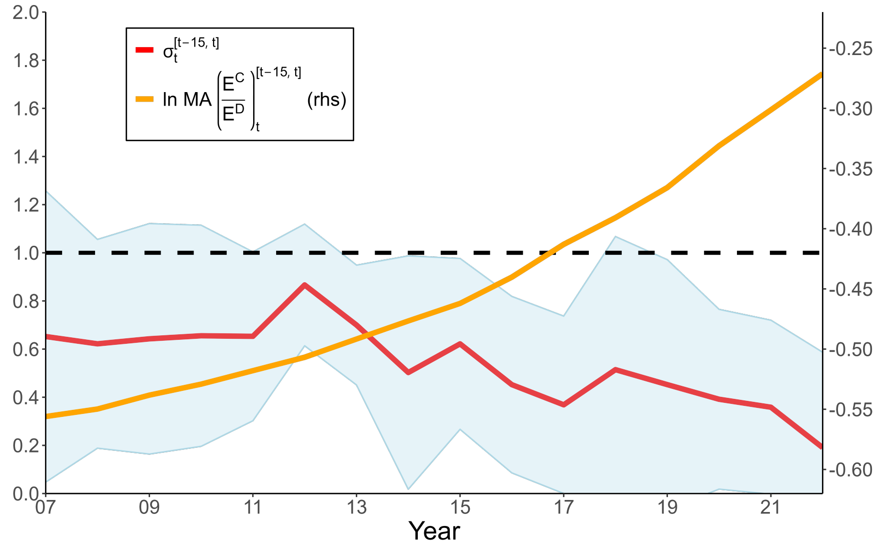


Figure E.1: Rolling Regressions of equation (15)

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

E.3 Calibration Exercise

I now provide the details of the calibration exercise laid out in table 5. I 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[5] I 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 BEA's National Income and Product Accounts' table 6.2D[6], I 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 me to compute all end-use expenditure shares. I am left with assigning the share of electricity spending to clean or dirty sources. To do this, I first take LCOE prices for renewables from U.S. Energy Information Administration (2018) for 2022, my main year of analysis. I choose to use the forecasted prices in 2018 to allow for a lag between planning and implementation. To extend the LCOEs back to 2007, I 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 I have the actual se-

[5]See here.
[6]See here.

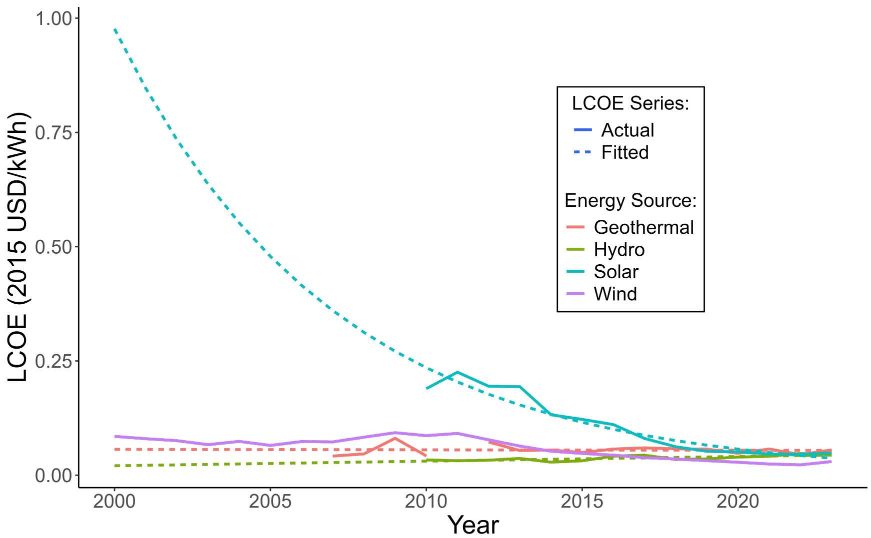


Figure E.2: Renewables' LCOE Dynamics

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.

ries available. For the remaining one I lack the data. As a result, I linearly regress the data and predict the missing values. For solar I use an exponential fit. For geothermal and hydropower I use instead a linear fit. I present the series and fitted values in figure E.2.

For nuclear generation in 2022 I 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, I opt to maintain this assumption. The drawback is that the price of clean electricity is actually lower in 2007 because most clean electricity originates from this source. I linearly interpolate the prices for missing years.

Finally, I 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 I am able to compute the average price per kwh and Btu for clean and dirty energy, respectively. I 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 I can split the end-use expenditure shares in electricity into clean and dirty generation.

Because my model does not foresee market power nor other fixed costs, I opt to compute a virtual price of electricity. I 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, I compute the virtual price of electricity. I need this to compute $\varepsilon_{P^D}^{P_j^E}$.

Together, this information allows me to compute the aggregate elasticity of substitution, σ, using equation (18), if I 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, I need that $d\ln P^D = d\ln P^e = 0$. Taking the price index for electricity, I 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,

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

Moreover, to increase the share of clean energy by approximately 10%, I 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 I can solve for $d \ln a^e$ and $d \ln P^C$ which are equal to

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

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, I have that

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

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

References

Administration, U.S. Energy Information, “International Energy Statistics,” 2024.

Canada Energy Regulator, “Electricity Trade Summary,” January 2025.

EMBER, “Statistical Review of World Energy,” 2024.

International Renewable Energy Agency, “Renewable Power Generation Costs in 2023 - with minor processing by Our World in Data,” 2024.

Nuclear Energy Institute, “Nuclear Costs in Context 2025,” February 2025.

Papageorgiou, Chris, Marianne Saam, and Patrick Schulte, "Substitution between Clean and Dirty Energy Inputs: A Macroeconomic Perspective," *The Review of Economics and Statistics*, May 2017, *99* (2), 281–290.

U.S. Energy Information Administration, "Annual Energy Outlook 2018," Technical Report, U.S. Department of Energy, Washington, DC 2018.

— , "Monthly Energy Review – March 2024," Technical Report DOE/EIA-0035(2025/3), U.S. Energy Information Administration March 2025.

U.S. Environmental Protection Agency, "U.S. Grid Regions," December 2024.