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# To What Extent Do Alternative Energy Sources Displace Coal and Oil in Electricity Generation? A Mean-Group Panel Analysis

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**Abstract:** This paper determines by how much alternative electricity generation sources—natural gas, nuclear, hydro, and renewables—displace electricity generation from coal and oil. It does so by employing a first-difference model and a mean-group estimator applied to a panel that spans 1985–2019 for 27 high- and 13 middle-income countries. As such, our approach avoids/addresses several statistical issues common in long-macro panel analyses—heterogeneity, nonstationarity, and cross-sectional dependence—that have largely been ignored/unaddressed in previous displacement studies. Ultimately, we find that the displacement effect is small and only marginally significant for nuclear, and is significant though less than unity for natural gas and hydro, whereas intermittent renewables (solar and wind) have unitary displacement effect. These results suggest a substantially greater displacement potential for alternative generation sources than typically found by the previous literature. In other words, increasing hydro and wind and solar are all impactful ways to decarbonize the electricity system.

**Keywords:** electricity generation; displacement; energy transition; renewables; carbon mitigation; nonfossil fuels

## 1. Introduction

One of the clearest routes to lower carbon emissions is to reduce the carbon intensity of electricity generation. Electricity generated from natural gas emits considerably less carbon than does electricity generated from coal and oil. (Energy security is another motivation to reduce electricity generation from oil.) Electricity generation sources like nuclear, hydro, solar, wind, and geothermal are essentially carbon-free at the margins. Yet, empirical analyses on the displacement impact of low- and zero-carbon energy sources often have yielded disappointing results (e.g., [1–6]); other analyses have calculated only a modest displacement effect that was less than one-to-one/unitary (e.g., [7,8]). The current paper revisits this displacement question and finds a substantial and much larger impact than did those previous papers for nonfossil fuels—particularly solar and wind—in displacing coal and oil used in electricity generation.

The displacement literature comes in two flavors: (1) the dependent variable is in energy consumption terms (e.g., [1,3–6] and the present paper), and (2) the dependent variable is in carbon emissions terms (e.g., [2,7–9]). It is important to note that when displacement papers consider carbon emissions, the focus is necessarily on carbon emissions from electricity generation since these are the emissions that electricity from nuclear or renewable sources would displace. (Energy from nuclear or renewable sources is almost never directly consumed; rather, such sources are used to generate electricity.) Hence, the displacement literature is distinct from the larger literature that analyzes general, economy-wide carbon emissions.

York [1] determined that increasing nonfossil fuels used to generate electricity by one unit resulted in a lowering of fossil fuels used in such generation by less than one-tenth of the same unit. Greiner et al. [3] estimated that an increase in kWh per capita generated from nonhydro renewable sources lowered fossil-fuel-generated electricity by

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only 0.2 kWh per capita. However, renewable-generated electricity offset nuclear-generated electricity by a factor greater than one. Sikirica [4] determined that core nations—primarily the same countries considered here—would need 2.6 megawatts per capita of alternative fuel generation to displace one megawatt per capita of fossil fuel generation. Rather et al. [5] found nearly identical results for a panel of seven (of the 20) Asia Pacific Economic Cooperation economies (for slightly different energy aggregations, i.e., renewable electricity displacing non-renewables). Considering 73 economies, Rather and Mahalik [6] estimated an even lower displacement coefficient, suggesting that six units of renewable energy are necessary to displace one unit of fossil fuel energy.

Liddle and Sadorsky [9] found that merely increasing the consumption of nonfossil fuels has only a moderate impact on reducing carbon emissions, i.e., a displacement elasticity around 0.4. However, increasing the *share* of nonfossil fuels used in electricity generation—and thereby ensuring that at least some of the increase in nonfossil fuels comes at the expense of fossil fuels—had a near unitary impact on lowering carbon emissions. Greiner et al. [2] found that increased $CO_2$ emissions from natural-gas-generated electricity did not suppress $CO_2$ emissions from coal-generated electricity—the emissions displacement coefficient for natural gas was always statistically insignificant. Lastly, Sovacool et al. [7] estimated that the share of electricity from nuclear production had a statistically insignificant impact on per capita carbon emissions from electricity, heat, and industry, whereas the share of electricity from renewable (including hydro) production had a negative, statistically significant coefficient of between $-0.3$ to $-0.4$. By contrast, Fell et al. [8], considering the Sovacool et al. [7] data but using fixed effects to measure a cotemporaneous effect rather than the lagged effect that [7] measured, estimated (particularly) large, statistically significant offset impacts for both nuclear and renewables of around $-1.0$ and $-1.6$, respectively.

All these papers used models with the variables in levels and they included on the right-hand side (RHS) GDP per capita along with either additional aggregations of energy consumption or additional aggregations of carbon emissions from fossil fuels, which are necessarily defined by the same aggregation of energy consumption. (In addition, some models included other variables that are often used to determine energy demand such as urbanization and manufacturing share of GDP.) Since energy consumption/demand is a function of GDP per capita (or income) and energy prices (see, e.g., [10]), these models have substantial RHS endogeneity; and it is not clear that the models actually are measuring displacement. Hence, we think a displacement model should be focused on change and have variables in first differences rather than in levels (unlike most other papers, Liddle and Sadorsky [9] included a lagged dependent variable and so an element of a difference-based model). Also, it seems best not to include GDP per capita in order to not confound a displacement model with a demand one.

Further, even though the variables analyzed can have different units, some papers did not log-transform or otherwise center the variables (e.g., [1–4]). Further still, despite considering datasets containing many time and country observations, most/several of these analyses (e.g., [1,2,4,7,8]) ignored statistical issues that are important for long-macro panels—nonstationarity, cross-sectional dependence, and heterogeneity (i.e., coefficients are not the same for each country).

Our contributions to the displacement literature are several: (1) we consider data that allow renewable energy to be disaggregated into solar, wind, and geothermal—unlike the previously discussed papers; (2) we use an improved model with the variables in first differences and with GDP excluded, and we demonstrate that the first-differencing and GDP exclusion produce stationary and weakly cross-sectionally dependent residuals; and (3) we employ a mean-group estimator that allows the country coefficients to differ. As a result of these innovations, and in contrast to much of the earlier displacement literature, we find coal and oil displacement effects that are significant for natural gas and hydro (but less than unitary) and that are unitary for renewables (solar, wind, and geothermal) and for intermittent renewables (solar and wind).

## 2. Materials and Methods

We wanted to use data sources that are available without cost, are subject to review, and allow for the disaggregation of renewable energy. So, the main source was the BP Statistical Review of World Energy (July 2021). We collected data on electricity generation in terawatt-hours for coal, oil, natural gas, nuclear, hydro, solar, wind, and geothermal. Observations ran from 1985 to 2019 for 23 countries. The data were balanced, but the entries for some countries in some years for some generation sources were zero. We collected data for an additional 17 European countries from Eurostat. These data ran from 1990 to 2019. The panel consisted of 27 high- and 13 middle-income countries. Appendix A Table A1 lists the panel countries by income-group classification and indicates their data source.

Figure 1 shows how the *panel average* for each of five electricity generation technology shares has changed over 1990–2019. Hydro and nuclear have been effectively constant at around 20–17% each. The share of coal and oil has been cut nearly in half, having been displaced by increases in natural gas and, more recently, renewables (solar, wind, and geothermal).

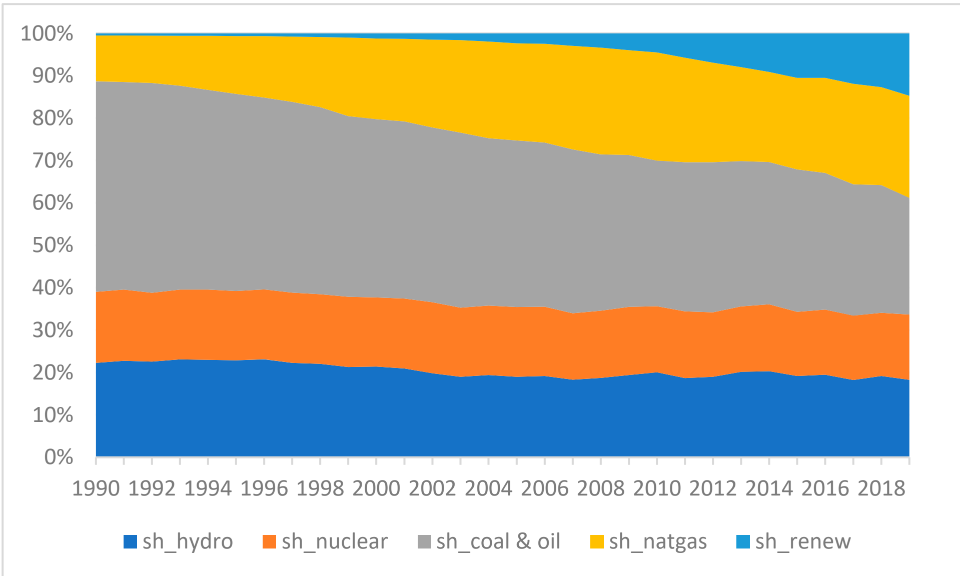


**Figure 1.** Yearly panel average shares of electricity generation technologies over 1990–2019. Natgas = natural gas; renew = wind + solar + geothermal.

Table 1 indicates the substantial variance within the 40-country panel of those technology shares. Over time and across countries, the average share for renewables was low. Denmark was the country that (recently) reached 75% of electricity generation from renewables (predominately from wind).

**Table 1.** Summary statistics for shares of electricity generation sources, 40 countries, 1985–2019.

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Share coal and oil | 1315 | 0.41 | 0.26 | 0.00 | 0.99 |
| Share natural gas | 1315 | 0.19 | 0.18 | 0.00 | 0.79 |
| Share nuclear | 1315 | 0.16 | 0.20 | 0.00 | 0.80 |
| Share hydro | 1315 | 0.20 | 0.24 | 0.00 | 1.00 |
| Share renewables | 1315 | 0.04 | 0.07 | 0.00 | 0.75 |

Note: renewables = wind + solar + geothermal.

Figure 2 demonstrates in another way the diversity among the countries in generation technologies. The figure displays the average share over the sample for each country. All countries but Norway used coal and oil in electricity generation, but those fossil fuels' prominence varied substantially. All countries used some renewables, but their average share was small. Nearly all countries employed both natural gas and hydro, but those technologies' relative importance differed considerably. Lastly, many countries used nuclear, but its share too had a large variance.

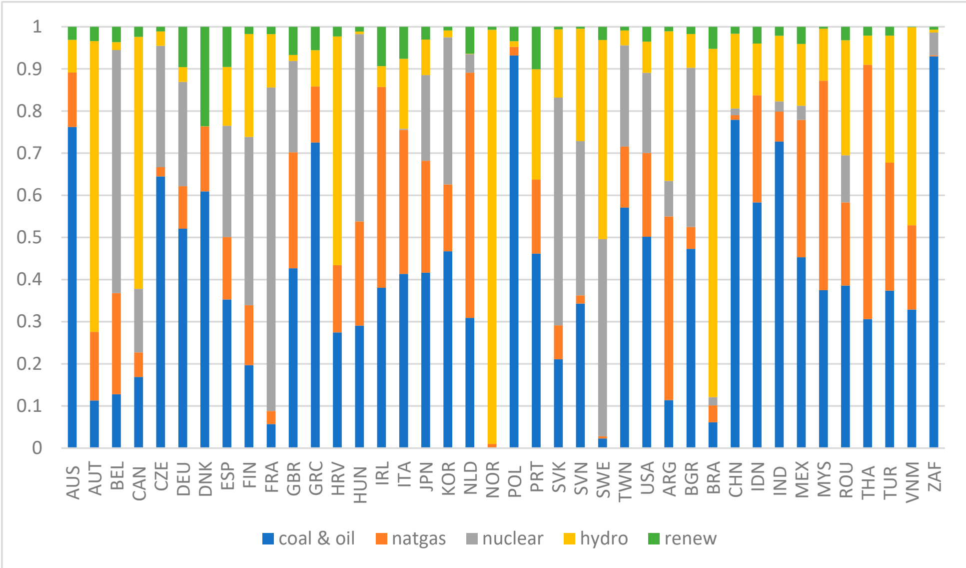


**Figure 2.** Average shares of electricity generation for each country (over the sample). Natgas = natural gas; renew = wind + solar + geothermal.

Since we wanted to know by how much coal and oil use in electricity generation declines when the use of an alternative source increases, and since all the generation-based variables were in the same units, we used a first difference in levels model. In addition, first-differencing in levels rather than in logs meant that we did not have to adjust observations that were zero. Table 2 displays the correlation matrix for the first-differenced independent variables. The nonfossil-fuel-based sources were more (positively) correlated in the all-country panel than in the high-income-only panel, perhaps because all forms of electricity continued to increase in middle-income countries, whereas electricity consumption had mostly leveled in high-income countries (see, e.g., [11]). The main concern for multicollinearity was between wind and solar; however, first-differencing substantially reduced the correlations among the variables (e.g., compare Table 2 to Appendix A Table A2).

**Table 2.** Independent variable correlation matrix.

| | All Countries (40) | | | | |
|---|---|---|---|---|---|
| | **ΔNatural Gas** | **ΔNuclear** | **ΔHydro** | **ΔWind** | **ΔSolar** |
| Δnatural gas | 1 | | | | |
| Δnuclear | −0.0659 | 1 | | | |
| Δhydro | −0.0952 | 0.0643 | 1 | | |
| Δwind | 0.2007 | 0.1959 | 0.317 | 1 | |
| Δsolar | 0.1232 | 0.2334 | 0.2124 | 0.7694 | 1 |
| Δgeo | 0.0488 | 0.2244 | 0.2961 | 0.5747 | 0.6196 |
| | **High-Income Countries (27)** | | | | |
| Δnatural gas | 1 | | | | |
| Δnuclear | −0.0989 | 1 | | | |
| Δhydro | −0.1809 | −0.0954 | 1 | | |
| Δwind | 0.2483 | −0.039 | 0.0792 | 1 | |
| Δsolar | 0.1732 | −0.0172 | 0.0171 | 0.5564 | 1 |
| Δgeo | −0.017 | 0.0415 | 0.0203 | 0.1243 | 0.165 |

Because we had sufficient observations for each country and because we believed that countries would have different coefficients, we used a mean-group estimator (MG) that first estimated country-specific regressions and then averaged those individual-country coefficients to arrive at panel coefficients. When averaging those individual coefficients, we followed the standard practice of robust regressions (see [12]), in which outliers are weighted down in the calculation of the panel coefficient. For each regression, we confirmed that the country-specific coefficients were not homogenous via a test based on [13]. This test compares the difference between coefficients obtained from a fixed-effects regression and the (averaged) coefficients obtained from an MG-based regression. So, while we were interested in and reported coefficients drawn from a group of countries (as opposed to being interested in a particular country's coefficients), a fixed-effects-based estimator would be biased.

Again, the dependent variable was based on the amount of electricity generated from coal and oil. We included the amount of electricity generated from natural gas as an independent variable, even though switching to natural gas cannot lead to decarbonization *per se*, but because natural gas is the least carbon-intensive fossil fuel, its use marks an improvement over coal-generated electricity. We implemented a nested modeling approach, whereby the first equation considers the impact of natural gas and all nonfossil fuels taken together:

$$\Delta CoalOil_{it} = \alpha_i + \beta_i^1 \Delta natgas_{it} + \beta_i^2 \Delta nonFossilfuels_{it} + \varepsilon_{it} \tag{1}$$

where $t$ represents the time dimension and $i$ the country dimension; $\Delta$ is the first-difference operator; $\alpha$ is a cross-sectional specific constant; the $\beta$s are cross-sectional specific coefficients to be estimated; *CoalOil* is the amount of electricity generated from coal and oil; *natgas* is the amount of electricity generated from natural gas; *nonFossilfuels* is the amount of electricity generated from the sum of nuclear, hydro, solar, wind, and geothermal; and $\varepsilon_{it}$ is the error term. The second equation further breaks down nonfossil fuel sources:

$$\Delta CoalOil_{it} = \alpha_i + \beta_i^1 \Delta natgas_{it} + \beta_i^2 \Delta nuclear_{it} \beta_i^3 \Delta hydro_{it} + \beta_i^4 \Delta renewables_{it} + \varepsilon_{it} \tag{2}$$

where *nuclear* is the amount of electricity generated from nuclear; *hydro* is the amount of electricity generated from hydro; and *renewables* is the amount of electricity generated from the sum of wind, solar, and geothermal. The last equation explicitly separates solar, wind, and geothermal (*geo*):

$$\Delta CoalOil_{it} = \alpha_i + \beta_i^1 \Delta natgas_{it} + \beta_i^2 \Delta nuclear_{it} + \beta_i^3 \Delta hydro_{it} + \beta_i^4 \Delta solar_{it} + \beta_i^5 \Delta wind_{it} + \beta_i^6 \Delta geo_{it} + \varepsilon_{it} \tag{3}$$

Since we first-difference the variables, nonstationarity should not be an issue; however, for each regression, we demonstrated via the Pesaran panel unit root (CIPS) test [14] that the residuals were stationary. Cross-sectional dependence is another concern common to macro panels; so, we performed another diagnostic test—a version of the Pesaran cross-sectional dependence (CDw) test [15]—to show that a null hypothesis of weak cross-sectional dependence cannot be rejected for the residuals. (Appendix B contains a detailed discussion of these issues: heterogeneity, nonstationarity, and cross-sectional dependence.)

## 3. Results and Discussion

Table 3 contains the regression results for the various equations for both the all-country and high-income-only country panels. As expected for first-difference models, the CIPS test confirmed that all regression residuals were stationary. The CDw test could not reject weak cross-sectional dependence in all the residuals, likely, at least in part, because GDP was excluded from the models. (GDP is a particularly cross-sectionally correlated variable among high-income countries, and its inclusion in models can make avoiding cross-sectionally dependent residuals challenging; see, e.g., [10].) Lastly, the Pesaran and Yamagata [13] test demonstrated that the country-specific coefficients were not homogenous for each regression (at the highest levels of significance); thus, fixed-effects estimators would be biased and inconsistent. (Appendix B Table A3 contains a demonstration of the extent of this bias in using fixed effects on Equation (4).)

**Table 3.** Regression results. Dependent variable change in electricity generated from coal and oil. All variables are in level first differences. 1985–2019 (unbalanced).

| | High-Income 27 Countries | | | | High- and Middle-Income 40 Countries | | | |
|---|---|---|---|---|---|---|---|---|
| | **Equation (1)** | **Equation (2)** | **Equation (3)** | **Equation (4)** | **Equation (1)** | **Equation (2)** | **Equation (3)** | **Equation (4)** |
| Δnatgas | −0.344 **** (0.0870) | −0.341 **** (0.0875) | −0.315 **** (0.0796) | −0.341 **** (0.0879) | −0.358 **** (0.0749) | −0.336 **** (0.0765) | −0.296 **** (0.0723) | −0.342 **** (0.0761) |
| ΔnonFossilfuels | −0.556 **** (0.0918) | | | | −0.509 **** (0.0674) | | | |
| Δnuclear | | −0.0771 (0.0472) | −0.0700 ** (0.0304) | −0.0757 * (0.0409) | | −0.0678 * (0.0380) | −0.0495 (0.0324) | −0.0666 * (0.0378) |
| Δhydro | | −0.527 **** (0.130) | −0.559 **** (0.1435) | −0.553 **** (0.142) | | −0.470 **** (0.0843) | −0.512 **** (0.0874) | −0.505 **** (0.0897) |
| Δrenewables | | −1.027 **** (0.176) | | | | −0.945 **** (0.194) | | |
| Δsolar | | | −1.725 *** (0.609) | | | | −1.624 *** (0.573) | |
| Δwind | | | −0.808 *** (0.288) | | | | −0.801 * (0.411) | |
| Δgeo | | | −0.180 (0.366) | −0.230 (0.446) | | | −0.0447 (0.324) | −0.154 (0.346) |
| Δ(solar + wind) | | | | −0.854 **** (0.152) | | | | −1.126 **** (0.245) |
| Obs | 843 | 843 | 843 | 843 | 1275 | 1275 | 1275 | 1275 |
| RMSE | 18.04 | 15.94 | 14.93 | 15.2 | 24.9 | 22.8 | 22.1 | 22.5 |
| CDw | −0.9 | −0.2 | −0.5 | −0.1 | 1.5 | −0.3 | 1.2 | 0.5 |
| CIPS | I(0) | I(0) | I(0) | I(0) | I(0) | I(0) | I(0) | I(0) |
| P-Y adj. delta | 12.7 **** | 6.5 **** | 4.4 **** | 5.3 **** | 20.4 **** | 9.9 **** | 5.5 **** | 6.4 **** |

Notes: ****, ***, **, and * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. Standard errors are in parentheses (constructed nonparametrically as described in [16]). Diagnostics: RMSE = root mean squared error. CDw = Juodis and Reese weighted CD test [17] on residuals. The null hypothesis is weak cross-sectional dependence. CIPS = Pesaran CIPS test [14] on residuals. The null hypothesis is nonstationary. I(0) = stationary. P-Y adj. delta = Pesaran and Yamagata test [13] for slope homogeneity. The null hypothesis is mean-group average coefficients are the same as fixed-effects coefficients.

For Equation (1), the two variables (change in natural gas and change in nonfossil fuels) were significant and had the expected signs. The fact that the coefficients were less than one suggested that to some extent increases in natural gas or nonfossil fuel use accommodate higher electricity demand (rather than just offset coal and oil use). For Equation (2), natural gas, hydro, and renewables were all significant and negative. The coefficient for natural gas was similar to that for Equation (1); the coefficient for hydro was similar to that for nonfossil fuel in the previous regression. The coefficient for renewables was negative one (or nearly so for the larger panel); so, renewables offset coal and oil entirely at the margin. The coefficient for nuclear was small and marginally significant; but many countries did not use nuclear, and Germany and Japan reduced their use substantially after the March 2011 earthquake and tsunami in Tohoku, Japan.

Equation (3) breaks out other renewables. The coefficients for natural gas, nuclear, and hydro were similar to Equation (2)'s results. The coefficients for solar and wind were large—near unity or higher in the case of solar—and negative, suggesting that these technologies have potential to substantially offset the use of coal and oil, and similarly, to lower carbon emissions. The coefficient for geothermal was small and insignificant (while negative), but its use is mostly limited to countries near the Pacific Ring of Fire.

As discussed earlier, there was substantial correlation among solar, wind, and geothermal (for the high-income panel, only solar and wind were very correlated). So, there was a multicollinearity concern for the Equation (3) regressions. But there was no clear way to deal with this collinearity between solar and wind. Centering the variables did not appear to help, and neither did logging and then differencing them. Ultimately, since we had no strong a priori reason to believe that solar and wind would be much different, we summed the two intermittent renewables to create a combined variable and Equation (4):

$$\Delta CoalOil_{it} = \alpha_i + \beta_i^1 \Delta natgas_{it} + \beta_i^2 \Delta nuclear_{it} + \beta_i^3 \Delta hydro_{it} + \beta_i^4 \Delta(solar + wind)_{it} + \beta_i^5 \Delta geo_{it} + \varepsilon_{it} \quad (4)$$

The other variables (natural gas, nuclear, hydro, and geothermal) had very similar coefficients in Equation (4) as in Equation (3), suggesting that the multicollinearity primarily manifested itself between solar and wind. The coefficient for the intermittent renewable variables (solar plus wind) was highly significant, negative and, depending on the panel, a little larger than one or slightly below one (but unity was well within the 95% confidence interval for that regression).

While the displacement factor was well under unity, the coefficients for natural gas and hydro were robustly statistically significant, negative, and not negligible (i.e., they were between $-0.3$ and $-0.5$). A significant displacement effect for natural gas runs in contrast to Greiner et al. [2], which focused on carbon emissions. Of course, increasing natural gas at the expense of coal-generated electricity only reduces carbon emissions relatively—it is not a course for zero emissions. A small and only sometimes significant effect for nuclear is in concert with Sovacool et al. [7], who found an insignificant impact for nuclear in mitigating carbon emissions.

The most substantial finding here was the roughly one-to-one coal and oil displacement effect for renewables (solar, wind, and geothermal) and for intermittent renewables (solar and wind). Sovacool et al. [7] determined that renewables lowered carbon emissions, but it is not clear that the impact they measured was as large as the one measured here. A unitary displacement impact for renewables and a significant (but less than a unitary impact) for hydro is in strong contrast to the early paper of York [1] that calculated an effect of an order of magnitude smaller than unity. Greiner et al. [3] did find a fossil fuel displacement effect for renewables when they restricted their sample to nuclear producing nations. Greiner et al. [3] argued that the existence of several (e.g., nuclear plus renewables) possible electricity-generation-displacement sources was important. However, they also demonstrated that nuclear-producing nations had disproportionately higher incomes than their whole sample.

While our all-country sample contained only 13 middle-income countries, it did include many of the most important ones (e.g., Brazil, China, India, Indonesia, South Africa). Our results were effectively the same for the 27-country high-income panel and the 40-country panel. Yet, it is possible that adding more non-high-income countries could impact the results. Indeed, the previous papers that uncovered little displacement effect considered panels with many more middle- and low-income countries (likely because they used sources that did not disaggregate renewables).

As mentioned before, electricity consumption has stagnated in most high-income countries; thus, measuring displacement is more likely there than in countries for which electricity consumption is still increasing. For countries with increasing electricity consumption, different generation sources are more likely to be positively correlated (because they are all increasing). But that does not mean there is no displacement outside high-income countries. The displacement effect could be occurring in future growth—new renewables are displacing the growth of fossil fuel generation rather than leading to the decommissioning of still-viable plants.

There is one caveat for the finding of unitary displacement from intermittent renewables (i.e., wind and solar). It is well understood that having a particularly high percentage (e.g., over 50%) of intermittent renewables in an electricity system poses substantial challenges (see, e.g., [18,19]); but, except for Denmark, no country in our panel had a share of wind and solar in their generation mix above 40%. So, were intermittent renewables to become the primary generation source, their displacement coefficient might be expected to decline at the margin.

## 4. Summary and Conclusions

Again, in contrast to much of the earlier displacement literature (e.g., [1,3–6]), we find electricity-generation coal- and oil-displacement effects that are unitary for solar and wind, and that are significant but less than unitary for hydro. It would be useful for future research to focus on the policies that encourage this substitution of nonfossil fuels for fossil fuels in electricity generation.

Further, we argue that the model and methods used here mark an important improvement over (most) previous displacement papers. First-differencing the variables and not including GDP (on the RHS) is a better strategy for several reasons. A first-difference or change model more closely approximates the displacement question than does a levels model; if the (RHS) generation sources change, how does the generation source of interest (LHS) change? And, first-differencing variables that are (likely) trending reduces the risk that regression residuals will be nonstationary (i.e., that the regression will be spurious). Including GDP along with various aggregations of energy consumption/generation creates an obvious RHS endogeneity issue since GDP/income is the most important explainer of all energy sources (services). In addition to avoiding RHS endogeneity, excluding GDP makes it more probable that regression residuals will be only weakly cross-sectionally dependent (and discards another highly trending/possibly nonstationary RHS variable). Lastly, when one has sufficient time observations (say 25 or more for five or so independent variables), allowing the country coefficients to be different (i.e., using a mean-group estimator) eliminates the homogeneity bias of the fixed-effects estimator. Again, these statistical issues, common in long-macro panel analyses—heterogeneity, nonstationarity, and cross-sectional dependence—have largely been ignored/unaddressed in previous displacement studies.

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**Informed Consent Statement:** Not relevant.

**Data Availability Statement:** The data are freely available via: http://www.bp.com/statisticalreview and https://ec.europa.eu/eurostat/data/database. The empirical part of this paper used Stata. Specifically, the following routines were employed: xtmg and multipurt, which were developed by Markus Eberhardt; xthst, which was developed by Tore Bersvendsen and Jan Ditzen; and xtcd2, which was developed by Jan Ditzen.

**Conflicts of Interest:** The author declares no conflicts of interest.

## Appendix A. Additional Tables

**Table A1.** Countries in the dataset by income classification and data source.

| High-Income | | Middle-Income |
|---|---|---|
| Australia | Japan | Argentina |
| Austria [a] | Netherlands | Brazil |
| Belgium [a] | Norway [a] | Bulgaria [a] |
| Canada | Poland | China |
| Croatia [a] | Portugal [a] | India |
| Czechia [a] | Slovakia [a] | Indonesia |
| Denmark [a] | Slovenia [a] | Malaysia |
| Finland [a] | South Korea | Mexico |
| France [a] | Spain | Romania [a] |
| Germany | Sweden [a] | South Africa |
| Greece [a] | Taiwan | Thailand |
| Hungary [a] | United Kingdom | Turkey |
| Ireland [a] | US | Vietnam |
| Italy | | |

Note: data are from the BP Statistical Review of World Energy except for those countries indicated with [a], for which the data are from Eurostat.

**Table A2.** Correlation matrix for the independent variables in level terms.

| | All Countries (40) | | | | |
|---|---|---|---|---|---|
| | natural gas | nuclear | hydro | wind | solar |
| natural gas | 1 | | | | |
| nuclear | 0.7831 | 1 | | | |
| hydro | 0.3026 | 0.3588 | 1 | | |
| wind | 0.5614 | 0.4179 | 0.5747 | 1 | |
| solar | 0.3892 | 0.2518 | 0.4535 | 0.8487 | 1 |
| geo | 0.7931 | 0.7117 | 0.597 | 0.6873 | 0.5681 |
| | **High-Income Countries (27)** | | | | |
| natural gas | 1 | | | | |
| nuclear | 0.7962 | 1 | | | |
| hydro | 0.49 | 0.5645 | 1 | | |
| wind | 0.7314 | 0.4883 | 0.2812 | 1 | |
| solar | 0.5516 | 0.2725 | 0.1612 | 0.7647 | 1 |
| geo | 0.8794 | 0.7844 | 0.5484 | 0.6445 | 0.5305 |

## Appendix B. Nonstationarity, Cross-Sectional Dependence, and Heterogeneity in Long-Macro Panel Data Models

Highly trending variables may have nonconstant means, i.e., be nonstationary. Such variables are often made stationary by taking first differences; in such a case, they are I(1) variables. Socio-economic variables (e.g., GDP, population) often have I(1) properties, or at least they have nonconstant means. If these trending, possibly I(1) variables are included in regressions without being treated (e.g., first-differenced), the resulting residuals likely will/may have nonconstant means, too. When regression residuals are not stationary or not I(0), the regression is referred to as spurious [20].

Dependence among units/countries violates a basic OLS assumption. Cross sectional dependence (CSD) occurs in panel variables because of phenomena like international trade and shared institutions (e.g., EU, IEA membership). CSD is measured by calculating the correlation between units/countries. High cross-correlation is particularly prominent in variables like GDP.

While adding time dummies to a regression can pick up global shocks, the country-level dependence of variables like GDP is more pervasive, e.g., OECD country GDP growth rates tend to be highly similar. CSD can be addressed/mitigated by adding cross-sectional averages of the dependent and independent variables (see, e.g., [21]). CSD in the regression residuals suggests omitted variable bias and endogeneity, and thus can indicate biased and inconsistent estimates. In other words, merely adjusting the standard errors (via, e.g., the Driscoll–Kraay method) is not sufficient.

Fixed-effects (FEs) estimators remove the unit/country means from the variables, and so, like mean-group (MG) estimators, analyze over-time variance (as opposed to cross-country variance). However, FEs estimators assume that the coefficients are the same for all units/countries. On the other hand, MG estimators relax the homogeneity assumption by calculating coefficients for each country and then averaging those heterogeneous/country-specific coefficients to arrive at the panel coefficients. The assumption of homogeneous coefficients is testable, and when such tests are administered, the typical results are rejection in favor of heterogenous coefficients—for example, the present analysis and [11,22]. When coefficient homogeneity is rejected, FEs estimators will be biased and inconsistent (if homogeneity is not rejected, heterogenous/MG estimators would still be unbiased and consistent, but they would be inefficient).

Appendix B Table A3 compares the previous results (Table 3) for Equation (4) (when wind and solar are combined) to results from a two-way (country and time) fixed-effects regression. Again, the assumption of homogenous coefficients was rejected. Because all variables have been first-differenced, the fixed-effects residuals are stationary; however, weak cross-sectional dependence in the residuals could be rejected (in favor of strong dependence). For most variables (the exception being hydro), the fixed-effects coefficients are substantially different from the MG coefficients for both panels. For solar plus wind and geothermal, the fixed-effects coefficients resulted in an even greater difference from the mean-group coefficients and are, arguably, implausible.

**Table A3.** Regression results from two-way fixed effects compared to original (mean group) results. Dependent variable change in electricity generated from coal and oil. All variables are in level first differences. 1985–2019 (unbalanced). Equation (4) variables considered.

| Estimator | Mean Group (Table 3) | | Country and Time Fixed Effects | |
|---|---|---|---|---|
| | All Countries | High-Income | All Countries | High-Income |
| Δnatgas | −0.342 ****<br>(0.0761) | −0.341 ****<br>(0.0879) | −0.60 ***<br>(0.18) | −0.74 ****<br>(0.17) |
| Δnuclear | −0.0666 *<br>(0.0378) | −0.0757 *<br>(0.0409) | −0.24<br>(0.20) | −0.51 ****<br>(0.12) |
| Δhydro | −0.505 ****<br>(0.0897) | −0.553 ****<br>(0.142) | −0.41 *<br>(0.22) | −0.55 **<br>(0.23) |
| Δ(solar + wind) | −1.126 ****<br>(0.245) | −0.854 ****<br>(0.152) | −0.10<br>(0.50) | −2.52 ****<br>(0.45) |
| Δgeo | −0.154<br>(0.346) | −0.230<br>(0.446) | 6.33 ***<br>(1.82) | 2.49<br>(1.70) |
| Obs | 1275 | 843 | 1275 | 843 |
| RMSE | 22.5 | 15.2 | 26.5 | 16.5 |
| CIPS | I(0) | I(0) | I(0) | I(0) |
| CDw | 0.5 | −0.1 | −2.1 ** | −2.3 ** |

Notes: ****, ***, **, and * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. Standard errors are in parentheses. Diagnostics: RMSE = root mean squared error. CDw = Juodis and Reese weighted CD test [17] on residuals. The null hypothesis is weak cross-sectional dependence. CIPS = Pesaran CIPS test [14] on residuals. The null hypothesis is nonstationary. I(0) = stationary.

Thus, the table demonstrates the extent of the bias (or assumption of homogenous coefficients) from using fixed-effects estimators on long-macro panel data. (The coefficients could have been biased because of residual cross-sectional dependence, too.) Because the variables were first-differenced, nonstationary residuals were not a problem. However, when similar variables (i.e., energy consumption, carbon emissions, GDP) enter an FEs regression in level terms—as many of the previously discussed papers appear to have done (e.g., [1–3,8])—nonstationary residuals or a spurious regression are additional perils along with allowing insufficient heterogeneity and residual cross-sectional dependence (see [10,22,23]).

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