How much does increasing non-fossil fuels in electricity generation reduce carbon dioxide emissions?

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Abstract

Many international organizations have called for an increased usage of renewable energy as a means to reduce CO_2 emissions and address climate change. This paper uses a large panel data set of 117 countries and recently developed panel estimation techniques to answer the question by how much does increasing non-fossil fuels in electricity generation reduce the subsequent carbon dioxide emissions. For the full sample, we find long-run displacement elasticities for non-fossil fuel consumption per capita of approximately -0.33; however, for the *share* of non-fossil fuels used in electricity generation, those long-run displacement elasticities are -0.75. Thus, a one percent increase of the share of non-fossil fuel electricity generation reduces CO_2 emissions per capita from electricity generation by about 0.75%. Long-run share displacement elasticities for non-OECD are substantially higher than those for OECD countries (approximately -0.90 to -0.53). These results have a number of policy implications.

Keywords: Carbon dioxide emissions; fossil-fuel displacement; renewable electricity; time-series, cross-section methods

Highlights

- We investigate how much increasing non-fossil fuels in electricity reduces CO_2 emissions
- By considering a large panel data set of 117 countries
- Long-run displacement elasticities for non-fossil fuel consumption per capita are -0.33
- But are -0.75 for the share of non-fossil fuels in electricity generation
- A 1% increase in non-fossil fuel electricity generation reduces CO_2 emissions by 0.75%.

1. Introduction

This paper addresses the question by how much does increasing non-fossil fuels in electricity generation reduce the subsequent carbon dioxide emissions, and does so by empirically examining cross-sectional time-series data. This question is a timely one: (i) increasing the use of renewable energy sources is a popular policy goal, e.g., the UN's "Sustainable Energy For All" goal of doubling the share of renewable energy in the global energy mix by 2030[1], and the Asia-Pacific Economic Cooperation (APEC) economies' goal of doubling the 2010 share of renewables in the energy supplies across APEC members by 2030[2]; and (ii) certainly, one of the motivations of such goals is the reduction of carbon dioxide emissions. It is also important to determine the extent to which non-fossil fuels replaced fossil fuels historically since projection models often assume that non-fossil fuels perfectly offset fossil fuels in assessing carbon reduction policies/alternative scenarios. Yet, recent estimates of how much increasing non-fossil fuels lowered the *consumption* of fossil fuels ranged from surprisingly low [1] to substantially and significantly below unity [2]. Such low displacement elasticities might suggest that policies to encourage switching to non-fossil fuels have not been very effective.

York [1] analyzed by how much each unit of electricity generated by non-fossil fuels displaced units of fossil fuel-generated electricity. York considered an unbalanced dataset comprised of 132 countries, covering 1960-2009, and used a fixed-effects model with the Prais-Winsten correction for first-order autocorrelation. York estimated particularly small non-fossil fuel displacement elasticities: -0.09 for all non-fossil fuels, and -0.22 and -0.10 for nuclear energy and hydropower, respectively, when those sources were analyzed separately.

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1 http://www.se4all.org
2 http://www.apec.org/Press/News-Releases/2014/1121_renewables.aspx

Liddle and Sadorsky [2] revisited York's question by considering a balanced dataset from the World Bank (63 countries, spanning 1971-2010), and using a lagged dependent variable model, and by employing OLS-based estimators that are robust to cross sectional dependence and stationarity, in addition to serial correlation. The short-run elasticities of displacement were negative, statistically significant and ranged from -0.30 to -0.24. The long-run elasticities of displacement were negative, statistically significant and ranged from -0.52 to -0.50. These displacement elasticities were considerably larger than those found by York, indicating that non-fossil fuel sources of electricity generation do displace fossil fuel sources of electricity generation and that in the long-run a 1% increase in non-fossil fuel electricity generation reduces fossil fuel electricity generation by about -0.50%. Again, since a major motivation for reducing the use of fossil fuels is lowering carbon dioxide emissions, this paper examines the extent to which shifting toward non-fossil fuels in electricity generation reduces the resulting carbon emissions.

There is an extensive literature looking at the determinants of carbon dioxide (CO_2) emissions at the macro level [3–13]. Most of this research shows that affluence, population, energy consumption, and energy intensity increases CO_2 emissions. Modernization (measured using variables for industrialization and urbanization) has different effects on carbon dioxide emissions, with industrialization generally leading to lower CO_2 emissions while the impact of urbanization on CO_2 emissions is mixed. Shafiei and Salem [10] presented evidence showing that non-renewable energy consumption increases CO_2 emissions while renewable energy consumption decreases CO_2 emissions. None of these papers, however, specifically addressed the question of by how much does increasing the share of non-fossil fuels in electricity generation reduce the subsequent carbon dioxide emissions from electricity generation. Some recent work [14,15] has estimated the emissions offset from wind generated electricity by analyzing US generator-based data; however, we wish to consider a wide range of countries, including developing ones; hence, we must take a macro-data approach. Our empirical approach uses recently developed panel regression techniques that take into account cross sectional dependence between the countries. Results are presented for the world data set as well as two sub-panels of OECD and non-OECD countries.

This paper is organized as follows. The next sections set out the literature review, model and methods, and data. This is followed by sections on the results, policy implications and conclusions.

2. Literature Review

The impact of energy use on carbon dioxide emissions at the country level is an active area of research. Research has been conducted for individual countries and for groups of countries (either regional groups or income groups). Since approximately 2/3 of carbon dioxide emissions come from the production, transportation and consumption of fossil fuels, and since fossil fuels account for the vast majority of global energy consumed, it is reasonable to expect a strong positive correlation between CO_2 emissions and energy consumption. Renewable energy (biomass, geothermal, solar, tide, wave, wind) is not carbon intensive, and so increasing the amount of renewable energy consumed relative to fossil fuel consumption should help to reduce carbon dioxide emissions.

Ang [16] used vector error correction model (VECM) techniques to examine the dynamic causal relationship among income, energy consumption, and CO_2 emissions for France over the period 1960 to 2000. A long run equilibrium relationship exists among these variables with increases in energy consumption increasing CO_2 emissions. Soytas et al [17] used the Toda and

Yamamoto [18] approach to model the dynamic relationship among income, energy consumption, and CO_2 emissions in the United States for the period 1960 to 2004. They found that energy use Granger causes carbon dioxide emissions.

Apergis and Payne [19] used panel cointegration techniques to study the dynamic relationship among income, energy consumption, and CO_2 emissions for six Central American countries over the period 1971 – 2004. They found that in the short run causality runs from energy consumption and income to carbon emissions. In the long run there is bi-directional causality between carbon emissions and energy consumption. Halicioglu [20] studied the dynamic causal relationship among income, energy consumption, CO_2 emissions, and foreign trade for Turkey over the years 1960 to 2005 using autoregressive distributed lag (ARDL) techniques. He found two long run cointegration relationships. The first long run cointegration relationship showed how carbon dioxide emissions are explained by income, energy consumption, and foreign trade. The second cointegration relationship showed how income is determined by energy consumption, carbon dioxide emissions, and foreign trade. The long run and short run elasticities of CO_2 emissions with respect to energy consumption were approximately 0.75 and 0.57, respectively. There is also evidence of bi-directional Granger causality between energy consumption and carbon dioxide emissions. Soytas and Sari [21] studied the long run relationship among income, energy consumption, and carbon dioxide emissions in Turkey over the years 1960 to 2000. They found that carbon dioxide emissions Granger causes energy consumption. Zhang and Cheng [22] studied the direction of Granger causality among income, energy use, and carbon dioxide emissions in China for the period 1960 to 2007. They found evidence of causality running from energy consumption to carbon dioxide emissions in the long run.

Apergis et al. [23] investigated the dynamic relationship among nuclear energy consumption, renewable energy consumption and carbon emissions for a panel of 19 developed and developing countries over the years 1984 to 2007. They found that nuclear energy consumption has a significant negative impact on CO_2 emissions. Unfortunately, renewable energy has the opposite effect. Chang [24] looked at the dynamic relationship among CO_2 emissions, income, oil consumption, natural gas consumption, coal consumption, and electricity consumption for China. Granger causality is found running from energy to CO_2 emissions. Lean and Smyth [25] used panel regression techniques to study the dynamic relationship among CO_2 emissions, electricity consumption and income for five ASEAN countries over the period 1980 to 2006. In the long run there is unidirectional Granger causality running from electricity consumption and CO_2 emissions to economic growth. In the short run, there is evidence of unidirectional Granger causality running from CO_2 emissions to electricity consumption. Menyah and Wolde-Rufael [26] used vector autoregression (VAR) techniques to investigate the dynamic relationship among CO_2 emissions, nuclear energy consumption, renewable energy consumption, and income in the United States for the period 1960 to 2007. They found Granger causality running from nuclear energy consumption to CO_2 emissions and conclude that greater usage of nuclear energy could reduce CO_2 emissions. They did not, however, find any evidence of causality from renewable energy consumption to CO_2 emissions.

Sharma [11] used dynamic panel data methods to study the determinants of CO_2 emissions for 69 countries. The data set covered the period 1985 to 2005. Two measures of energy use were studied: 1) per capita total primary energy consumption and 2) per capita electric power consumption. In addition to analyzing the determinants of carbon dioxide emissions for all 69 countries (the global panel), three additional sub-panels were also analyzed (high income countries, middle income countries, and low income countries). Per capita electric power consumption had a positive and statistically significant impact on CO_2 emissions for the high income panel of countries. So, too, was the case with per capita total primary energy consumption. Tiwari [27] was unable to find a long run cointegration relationship among CO_2 emissions, real income and renewable energy consumption for India. Impulse response function analysis revealed that a shock to renewable energy consumption had a positive initial impact on CO_2 emissions followed by a gradual reduction. Chen et al. [28] used panel cointegration and vector error correction models to study the dynamic relationship among income, energy consumption and carbon emissions for 188 countries over the period 1993 to 2010. Analysis was conducted for the whole world and two sub-groups of countries (developed and developing). They found evidence of a long run cointegration relationship among income, energy consumption and carbon emissions. They found unidirectional causality from energy consumption to CO_2 emissions for both developed and developing countries.

Baek [29] conducted a panel cointegration analysis of CO_2 emissions and nuclear energy consumption in 12 major nuclear energy consuming countries that account for nearly 80% of the world's nuclear energy generation. Panel cointegration techniques were applied to a data set covering the period 1980-2009. He found that nuclear energy reduces CO_2 emissions. Jaforullah and King [30] studied the usefulness of using renewable energy to mitigate CO_2 emissions in the United States. They modeled CO_2 emissions as a function of nuclear energy consumption, renewable energy consumption, income, and a price variable. VECMs were estimated on data covering 1965 to 2012. Cointegration and causality tests showed that CO_2 emissions are negatively related to renewable energy consumption but unrelated to nuclear energy consumption. These research results are different from other research that found a negative relationship between carbon emissions and nuclear energy [31–35].

In summary, most research finds a positive relationship between fossil fuel energy consumption and CO_2 emissions. While there is growing evidence that renewable energy consumption and nuclear energy consumption help to reduce carbon dioxide emissions, none of these papers, however, examined the extent to which shifting toward non-fossil fuels in electricity generation reduces the resulting carbon dioxide emissions.

3. Model and methods

First, we analyse the carbon emissions displacement from increasing the amount of non-fossil fuels:

$$\ln CO2E_{it} = \alpha_i + a_i \ln CO2E_{it-1} + b_i \ln GDP_{it} + c_i \ln RE_{it} + u_{it} \qquad (1)$$

where subscripts *it* denote the *i*th cross-section and *t*th time period, and *CO2E*, *GDP*, and *RE* are carbon dioxide emissions from electricity production, real GDP per capita, and electricity consumption from nuclear and renewable sources per capita, respectively.

Since renewable energy sources are often subsidized [14,15], increasing their consumption will not necessarily offset fossil fuel consumption. Also, renewable energy goals are often stated in terms of the share of fuel consumption (see Footnotes 1 and 2). Hence, we analyse the carbon emissions reduction from increasing the share of non-fossil fuels used in electricity, too:

$$\ln CO2E_{it} = \alpha_i + a_i \ln CO2E_{it-1} + b_i \ln GDP_{it} + c_i \ln shRE_{it} + u_{it} \qquad (2)$$

Where *shRE* is the share of electricity production from non-fossil fuel sources.

Lastly, for OECD countries, we consider the impact of fossil fuel prices by adding, separately, a real index of natural gas and steam coal to Equations 1-2. The IEA reports a real index of natural gas and coal prices for industry and households for OECD countries beginning in 1978. Employing data from Baade [36], we extend these real price indices for some OECD countries to 1971. Ultimately, we construct unbalanced natural gas and coal price data for 23 and 16 OECD countries, respectively. Furthermore, because the price series are indices, we analyze natural gas and coal in separate regressions.

For the macro-level variables we consider, cross-sectional correlation/dependence is expected because of, for example, regional and macroeconomic linkages that manifest themselves through (i) common global shocks, like the oil crises in the 1970s; (ii) institutional memberships like the OECD and IEA; or (iii) local spillover effects between countries or regions. Table 1 displays the results of the Pesaran [37] CD test[3], which employs the correlation coefficients among the time-series for each panel member to test for cross-sectional dependence (the null hypothesis of the test is cross-sectional independence). The mean absolute value correlation coefficient (rho) is also reported in the table (with values ranging between 0.43 and 0.66). For all the variables, cross-sectional independence was rejected.

Table 1

The variables analyzed are also highly trending, stock-based variables, and thus, may be nonstationary—in other words, their mean, variance, and/or covariance with other variables changes over time. We employ a so-called second-generation panel unit root test that relaxes the cross-sectional independence assumption: the Pesaran [38] CIPS test[4] allows for cross-sectional dependence to be caused by a single (unobserved) common factor, and has the advantages of being valid for unbalanced panels and for panels in which the cross-sectional dimension is large. The null hypothesis for this test is that the data series contains a unit root. Since the results of

[3] This test is implemented via the STATA command xtcd, which was developed by Markus Eberhardt.
[4] This test is implemented via the STATA command pescadf, which was developed by Piotr Lewandowski.

unit root tests can be sensitive to the lag order, we report the results of unit root tests estimated with lags from 0-3. The results in Table 2 suggest that Log GDP p.c. is indeed nonstationary while the results for the other variables are mixed—but for no variable could the null of a unit root be consistently rejected.

Table 2

Given that the data exhibit both cross-sectional correlation and nonstationarity, we employ two heterogeneous panel estimators: the Pesaran [39] common correlated effects mean group estimator (CMG) and augmented mean group (AMG) estimator by Eberhardt and Teal [40].[5] The CMG estimator accounts for the presence of unobserved common factors by including in the regression cross-sectional averages of the dependent and independent variables. The AMG estimator accounts for cross-sectional dependence by including in the regression a common dynamic process—which is extracted from year dummy coefficients of a pooled regression in first differences. Both estimators are robust to nonstationarity, cointegration, structural breaks, and serial correlation, and at least mitigate, if not fully address, cross-sectional correlation. In addition to capturing omitted variables, the lagged dependent variable model allows for the estimation of short-run and long-run coefficients (the confidence intervals for the long-run coefficients are based on the delta method). For diagnostics we run on the residuals and report (in Tables 3-5) (i) the Pesaran CD test to determine/measure the extent of cross-sectional dependence and (ii) the Pesaran CIPS test to demonstrate that the residuals are stationary. Results are presented for the full sample of countries as well as two sub-samples consisting of OECD and non-OECD countries, respectively.

[5] These estimators are implemented via the STATA command suite xtmg, which was developed by Markus Eberhardt.

4. Data

The dataset is from the International Energy Agency and contains observations from 117 countries, spanning 1971-2011. The dataset is not balanced—rather, all countries with at least 20 observations are included (for several countries—particularly ex-Soviet and Yugoslav ones—data begin in 1990). The variables considered are: carbon emissions per capita from electricity and heat generation, real GDP per capita (converted at PPP), electricity consumption from nuclear and renewable sources (e.g., hydro, geothermal, solar, wind, tide, wave, and biofuels) per capita, and the share of electricity output generated from nuclear and renewable sources (i.e., non-fossil fuel sources). All variables are in natural logs. We use a lagged dependent variable model to capture some missing variables and help account for the variables' stock-nature. Since each variable is measured in natural logarithms, the estimated coefficients can be interpreted as elasticities.

5. Results, discussion, and policy implications

5.1 Non-fossil fuel consumption per capita (Equation 1)

The estimated coefficient on the lagged CO_2 emissions variable ranges from 0.49 to 0.63[6], indicating a moderate amount of persistence in CO_2 emissions from electricity generation. The RMSE values between the two estimators are very similar, indicating that based on this measure there is not much to choose between the CMG or AMG specification. Also, the regression diagnostics are good—the residuals are stationary, and, while cross-sectional independence could be rejected, the resulting absolute correlation coefficient is small (0.15 to 0.17).

Table 3

[6] Estimated coefficients are calculated using a weighted average method robust to outliers. The practical implication of this method is that outliers receive less weight in the calculation of sample averages.

As Table 3 reports, we estimate long-run elasticities for non-fossil fuel consumption of between -0.26 and -0.35. So in the long-run, a 1% increase in non-fossil fuel-generated electricity consumption reduces carbon emissions from electricity generation by only a quarter to a third of one percent. While we split our sample into OECD and non-OECD countries, the elasticities for the two sub-samples do not appear to be significantly different.

Of course, there are several reasons why one might not expect full, one-to-one displacement of CO_2 emissions. First, while nuclear energy does displace coal-based electricity, many renewable fuels (e.g., solar, wind) are used to improve peak load coverage instead of base load generation, and thus, may not displace any energy. Second, there might not be unitary CO_2 reduction; since gas and oil are more expensive than coal, non-fossil fuels would displace gas and oil first (before coal), and the resulting lowering of CO_2 would be less (since coal is more carbon-intensive than gas and oil). Also, it matters how renewables are encouraged: if renewables increase because of subsidies, then energy demand has been stimulated, and fossil fuels may not decline much.

5.2 Share of non-fossil fuels used in electricity generation (Equation 2)

Table 4 presents the share of non-fossil fuel reduction short-run and long-run elasticities for per capita carbon dioxide emissions from electricity generation. By contrast to the results of two earlier studies [1-2] and our results in Table 3, the displacement/reduction elasticities for carbon dioxide emissions estimated here from the full sample are substantially larger—particularly the long-run elasticity. Indeed, the long-run estimations suggest that a shift toward non-fossil fuel sources lowers carbon emissions from electricity production by about 75% (the elasticities were -0.73 and -0.76 for the CMG and AMG specifications, respectively), i.e., a one percent increase in the fuel mix toward non-fossil fuel sources lowers carbon emissions by 3/4 of one percent. Hence, policies that shift the electricity generation fuel mix toward non-fossil fuel sources are an effective way to lower carbon emissions from electricity in the long-run. Notice that the long-run displacement elasticities are approximately twice as large as the short-run displacement elasticities.

Table 4

For the OECD sub-sample, the long-run displacement elasticities range between -0.46 to -0.60. These elasticities are smaller in absolute value than the corresponding values for the full sample. The long-run displacement elasticities for the non-OECD sub-sample range in value between -0.84 to -0.95, which are larger than the corresponding values from the full sample. Furthermore, for both non-OECD sub-sample elasticity estimations, unity is within the 95% confidence interval. Comparing these results, the long-run displacement elasticity is largest, in absolute value, for the non-OECD panel. These results show that increasing the share of non-fossil fuels in electricity generation has a larger impact on the reduction of CO_2 emissions per capita from electricity generation in non-OECD countries than in OECD countries.

5.3 Coal and natural gas prices in OECD countries

Lastly, we consider the role of coal and natural gas prices. Again, these regressions include only OECD countries, and for many of those countries price data was not available. Table 5 shows that when the share of non-fossil fuels was considered, the price elasticities were relatively small and usually insignificant. Whereas, when non-fossil fuel consumption per capita was included, the price elasticities were similarly small, but mostly significant-to-marginally significant. Rather than suggest a lack of importance of fossil fuel prices, we believe the relatively unimpactful results reflect the limited coverage of price data. Indeed, the relatively weaker price results when the share of non-fossil fuels was included, implies a potential endogeneity between fossil fuel prices and the share of non-fossil fuels. In other words, one way to ensure that when the share of non-fossil fuels increased, the amount of fossil fuels—and thus carbon emissions—would decrease, would be to raise fossil fuel prices.

Table 5

6. Conclusions

There is a large literature looking at the relationship between energy consumption and carbon dioxide emissions, and most of this research finds that energy consumption is positively correlated with CO_2 emissions. There is a smaller body of research showing that renewable energy consumption and nuclear energy consumption are each negatively correlated with CO_2 emissions. There is little research that specifically addresses the question of by how much does increasing the share of non-fossil fuels in electricity generation reduce the subsequent carbon dioxide emissions from electricity generation. In this paper, we estimate the carbon dioxide emissions displacement from increasing the amount of non-fossil fuels in electricity generation. Our data set consists of an unbalanced panel of 117 countries covering the period 1971 to 2011. We estimate models using recently developed panel regression techniques that take into account cross-sectional dependence. We present results for the full data set as well as two sub-panels of countries (OECD, non-OECD).

Our results demonstrate that merely increasing the consumption of non-fossil fuels has only a moderate impact on reducing carbon emissions. However, increasing the *share* of non-fossil fuels used in electricity generation—and thereby ensuring that at least some of the increase in non-fossil fuels comes at the expense of fossil fuels—has a substantial impact on lowering carbon emissions. Indeed, for non-OECD countries, increasing the share of non-fossil fuels by one percent has a potentially unitary impact on lowering carbon emissions. Such share-based targets have gained popularity/importance (e.g., Footnotes 1-2). Hence, our results imply an important role for policy—particularly policies like carbon-based taxes (even though our results for natural gas and coal prices were modest to insignificant).

Our results also show the displacement effect is larger in non-OECD countries than in OECD countries, indicating that increasing the share of non-fossil fuels in electricity generation has a bigger impact on the reduction of CO_2 emissions per capita from electricity generation in non-OECD countries. One possible explanation for this difference is that OECD countries are experiencing carbon lock-in. This condition occurs when the economic activities of a country are so heavily dependent upon the burning of fossil fuels (due to socio-economic, political, or technological factors) that substitution to non-fossil fuels becomes very difficult. OECD countries are typically a group of countries that have industrialized much earlier and are more dependent upon fossil fuels. A tax on carbon is one possible way to lessen these carbon lock-in effects.

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Table 1. Cross-sectional dependence: Absolute value mean correlation coefficients and Pesaran (2004) CD test. IEA data, 117 countries, 1971-2011, unbalanced.

Variables	**CD-test**	**Abs corr. coeff.**
Log CO2 emissions pc	50.3*	0.53
Log GDP pc	234.7*	0.66
Log non-fossil fuels pc	151.4*	0.49
Log Sh non-fossil fuels	6.6*	0.43
Log Coal price	19.4*	0.47
Log Nat. Gas price	46.4*	0.52

Note: * p-value 0.001. Data for coal and natural gas prices are for only 16 and 23 OECD countries, respectively.

Table 2. Pesaran (2007) CIPS panel unit root test results. IEA data, 117 countries, 1971-2011, unbalanced.

	Constant w/o trend				**Constant w/ trend**			
	Number of lags							
	0	1	2	3	0	1	2	3
Log CO2 emissions p.c.	0.000	0.000	0.003	0.002	0.143	0.552	0.997	1.000
Log GDP p.c.	1.000	0.819	1.000	1.000	1.000	0.995	1.000	1.000
Log non-fossil fuels pc	0.000	0.000	0.000	0.142	0.000	0.000	0.199	0.976
Log Sh non-fossil fuels	0.000	0.000	0.000	0.272	0.004	0.009	0.115	0.973
Log Coal price	0.068	0.169	0.076	0.003	0.078	0.135	0.090	0.021
Log Nat. Gas price	0.031	0.029	0.083	0.076	0.434	0.208	0.260	0.083

Notes: P-values shown. Null hypothesis is the series is I(1). Data for coal and natural gas prices are for only 16 and 23 OECD countries, respectively.

Table 3. Non-fossil fuel consumption displacement elasticities for CO_2 emissions from electricity generation. Natural log of CO_2 emissions from electricity generation per capita is dependent variable.

	Full sample		OECD		Non-OECD	
	CMG	AMG	CMG	AMG	CMG	AMG
	Short-run elasticities					
Log CO_2 emissions p.c. (-1)	0.49***	0.63***	0.59***	0.62***	0.49***	0.62***
	[0.45 0.54]	[0.58 0.68]	[0.51 0.67]	[0.53 0.70]	[0.44 0.54]	[0.56 0.67]
Log GDP p.c.	0.51***	0.24***	0.30*	0.31***	0.27***	0.17***
	[0.39 0.63]	[0.14 0.33]	[0.09 0.6]	[0.14 0.48]	[0.16 0.38]	[0.05 0.29]
Log non-fossil fuels p.c.	-0.17***	-0.12***	-0.11**	-0.11***	-0.13***	-0.44***
	[-0.23 -0.12]	[-0.17 -0.07]	[-0.18 -0.03]	[-0.17 -0.05]	[-0.20 -0.06]	[-0.58 -0.31]
	Long-run elasticities					
Log GDP p.c.	1.01***	0.64***	0.72***	0.80***	0.94***	0.70***
	[0.75 1.27]	[0.37 0.91]	[0.07 1.37]	[0.32 1.29]	[0.65 1.23]	[0.40 1.00]
Log non-fossil fuels p.c.	-0.34***	-0.33***	-0.26***	-0.30***	-0.35***	-0.34***
	[-0.45 -0.23]	[-0.47 -0.19]	[-0.45 -0.06]	[-0.47 -0.13]	-0.50 -0.20]	[-0.52 -0.16]
Observations	4227	4227	1261	1261	2996	2996
x-sections	117	117	34	34	83	83
RMSE	0.23	0.25	0.12	0.13	0.26	0.29
Order of integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CD (p)	6.1(0.000)	9.3(0.000)	3.1(0.002)	3.6(0.000)	2.8(0.007)	3.5(0.000)
Mean rho	0.16	0.15	0.17	0.17	0.16	0.16

Notes: *** and ** indicate statistical significance at the 0.001 and 0.01 levels, respectively. 95% confidence intervals shown in brackets. Confidence intervals for the long-run elasticities are based on the delta method.

RMSE is the root mean squared error, and p.c. is per capita.

Diagnostics: Order of integration of the residuals is determined from the Pesaran (2007) CIPS test: I(0)=stationary. Mean rho is the mean absolute correlation coefficient of the residuals from the Pesaran (2004) CD test. CD is the test statistic from that test along with the corresponding p-value in parentheses. The null hypothesis is cross-sectional independence.

Table 4. Share of non-fossil fuel displacement elasticities for CO_2 emissions from electricity generation. Natural log of CO_2 emissions from electricity generation per capita is dependent variable.

	Full sample		OECD		Non-OECD	
	CMG	AMG	CMG	AMG	CMG	AMG
	Short-run elasticities					
Log CO_2 emissions p.c. (-1)	0.46***	0.55***	0.52***	0.55***	0.44***	0.53***
	[0.40 0.51]	[0.50 0.60]	[0.44 0.61]	[0.47 0.64]	[0.38 0.50]	[0.47 0.59]
Log GDP p.c.	0.39***	0.19***	0.31**	0.26***	0.37***	0.17**
	[0.26 0.51]	[0.11 0.27]	[0.09 0.53]	[0.13 0.39]	[0.20 0.53]	[0.05 0.29]
Log share non-fossil fuels	-0.40***	-0.34***	-0.22***	-0.27***	-0.47***	-0.44***
	[-0.50 -0.29]	[-0.43 -0.25]	[-0.33 -0.10]	[-0.40 -0.14]	[-0.63 -0.32]	[-0.58 -0.31]
	Long-run elasticities					
Log GDP p.c.	0.71***	0.42***	0.66***	0.58***	0.66***	0.37**
	[0.47 0.95]	[0.23 0.60]	[0.18 1.13]	[0.27 0.88]	[0.35 0.96]	[0.11 0.63]
Log share non-fossil fuels	-0.73***	-0.76***	-0.46***	-0.60***	-0.84***	-0.95***
	[-0.93 -0.53]	[-0.98 -0.55]	[-0.71 -0.20]	[-0.93 -0.29]	[-1.13 -0.55]	[-1.27 -0.63]
Observations	4227	4227	1261	1261	2966	2966
x-sections	117	117	34	34	83	83
RMSE	0.21	0.23	0.10	0.11	0.24	0.26
Order of integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CD (p)	6.70(0.000)	11.25(0.000)	4.67(0.000)	4.50(0.000)	1.27(0.203)	4.73(0.000)
Mean rho	0.16	0.15	0.17	0.17	0.16	0.15

Notes: *** and ** indicate statistical significance at the 0.001 and 0.01 levels, respectively. 95% confidence intervals shown in brackets. Confidence intervals for the long-run elasticities are based on the delta method.

RMSE is the root mean squared error, and p.c. is per capita.

Diagnostics: Order of integration of the residuals is determined from the Pesaran (2007) CIPS test: I(0)=stationary. Mean rho is the mean absolute correlation coefficient of the residuals from the Pesaran (2004) CD test. CD is the test statistic from that test along with the corresponding p-value in parentheses. The null hypothesis is cross-sectional independence.

Table 5. Dynamic heterogeneous parameter estimates considering coal and natural gas prices. Short-run elasticities shown. OECD countries only. Natural log of CO_2 emissions from electricity generation per capita is dependent variable.

	CMG	**AMG**	**CMG**	**AMG**	**CMG**	**AMG**	**CMG**	**AMG**
Log CO_2 p.c. (-1)	0.25***	0.44***	0.35***	0.49***	0.30***	0.49***	0.41***	0.58***
	[0.11 0.40]	[0.31 0.57]	[0.24 0.46]	[0.38 0.60]	[0.16 0.44]	[0.36 0.61]	[0.30 0.53]	[0.48 0.69]
Log GDP p.c.	0.42***	0.39***	0.37**	0.26**	0.52***	0.59***	0.27*	0.54***
	[0.17 0.68]	[0.10 0.68]	[0.03 0.70]	[0.03 0.48]	[0.18 0.85]	[0.24 0.94]	[-0.02 0.57]	[0.19 0.89]
Log share non-fossil fuels	-0.29***	-0.24***	-0.30***	-0.29***				
	[-0.43 -0.16]	[-0.39 -0.08]	[-0.46 -0.14]	[-0.44 -0.13]				
Log non-fossil fuels p.c.					-0.30***	-0.22***	-0.21***	-0.14**
					[-0.44 -0.15]	[-0.38 -0.08]	[-0.36 -0.06]	[-0.27 -0.02]
Log Coal price	0.01	-0.03			-0.04	-0.05**		
	[-0.04 0.06]	[-0.08 0.02]			[-0.11 0.04]	[-0.10 -0.00]		
Log Natural Gas price			-0.05	-0.04***			-0.07*	-0.07***
			[-0.12 0.01]	[-0.08 -0.01]			[-0.16 0.01]	[-0.12 -0.02]
Observations	600	600	841	841	600	600	841	841
x-sections	16	16	23	23	16	16	23	23
RMSE	0.06	0.07	0.06	0.08	0.07	0.08	0.08	0.09
Order of integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CD (p)	-1.0(0.31)	1.1(0.27)	2.9(0.00)	3.0(0.00)	-1.0(0.33)	1.8(0.08)	2.4(0.02)	3.2(0.00)
Mean rho	0.18	0.15	0.16	0.16	0.17	0.15	0.16	0.17

Notes: ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. 95% confidence intervals shown in brackets. RMSE is the root mean squared error, and p.c. is per capita.

Diagnostics: Order of integration of the residuals is determined from the Pesaran (2007) CIPS test: I(0)=stationary. Mean rho is the mean absolute correlation coefficient of the residuals from the Pesaran (2004) CD test. CD is the test statistic from that test along with the corresponding p-value in parentheses. The null hypothesis is cross-sectional independence.