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Does aid for renewable energy reduce the consumption of fossil energy?

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Abstract

This study investigates whether official development assistance (ODA) for renewable energy reduces fossil fuel consumption in recipient countries. In doing so, it addresses a critical policy question regarding the effectiveness of aid in supporting energy transitions and climate goals in low- and middle-income countries. To examine this question, we use two panel datasets covering up to 31 countries between 2002 and 2022. The first is a time-series cross-sectional panel analyzed with panel cointegration techniques, while the second is a cross-sectionally dominated dataset with averaged values, analyzed using the system GMM estimator. This dual-method approach accounts for different data characteristics and ensures the robustness of the results. These consistently show that ODA for renewable energy reduces fossil energy consumption. We also find that ODA for renewable energy increases renewable energy consumption and reduces CO2 emissions. These results suggest that targeted renewable energy aid effectively supports decarbonization efforts in developing countries. This study is the first to provide systematic evidence on the impact of foreign aid for renewable energy on fossil fuel use in recipient countries. It is also novel in that it examines the effect of foreign aid for renewable energy on both renewable energy consumption and CO2 emissions.

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1. Introduction

While high-income countries have managed to reduce their greenhouse gas emissions since 2007, emissions in low- and middle-income countries have shown a strong upward trend since 2002.[1] For these countries, achieving a shift from fossil fuels to renewable energy is especially important to reverse this trend and mitigate climate change without nuclear power. Low- and middle-income countries, however, often lack sufficient domestic resources for financing this shift. Therefore, high-income countries provide official development assistance (ODA) for renewable energy projects to poorer nations. However, there are several reasons why such aid may fail to achieve its intended outcome of reducing fossil fuel consumption in recipient countries.

First, in countries with extensive oil, gas, and coal resources, shifting from fossil fuels to renewables may be difficult due to both the economic interests of the fossil fuel industry and the availability of relatively cheap fossil fuel energy. *Second*, renewable energy projects may not be well-integrated into existing energy infrastructure if there are no efficient grids to distribute renewable energy. *Third*, the technical expertise required to implement, manage, and sustain renewable energy technologies can be scarce in recipient countries. *Fourth*, aid may be ineffective due to factors such as corruption and poor planning. *Fifth*, when high-income countries provide aid for renewable energy projects, the recipient governments might reallocate their own budgeted funds from renewable energy initiatives to other uses.

In addition to these arguments, which question the effectiveness of aid for renewable energy in reducing fossil fuel consumption, there is a substantial body of research that casts doubt on the effectiveness of development aid in various areas. This includes studies, inter alia, on the impact of aggregated development aid on economic growth (e.g., Rajan and Subramanian, 2008; Herzer et al., 2014) and studies on the effects of health aid on public health outcomes (e.g., Williamson, 2008; Wilson, 2011).

Given these concerns, and to potentially avoid an enormous waste of public money, it is important to know whether or not ODA for renewable energy reduces fossil energy consumption in recipient countries. Surprisingly, however, there are no studies on this important question; hence, the answer is still unknown. This gap motivates the present study, which aims to examine the impact of foreign aid for renewable energy on fossil energy consumption.

By investigating this impact, this study complements the small but growing literature on the impact of foreign aid on CO_2 emissions in recipient countries. Overall, this literature does not provide strong evidence that foreign aid reduces CO_2 emissions in recipient countries (see Pinar, 2023, for a review of this literature). While some studies find evidence that 'green' aid reduces CO_2 emissions, others question its effectiveness (similar to several studies on the impact of development aid on economic growth or on the effects of health aid on public health outcomes, as mentioned above).

For example, Bhattacharyya et al.'s (2018) results suggest that aid for renewable energy, lagged by five years (to address potential endogeneity problems), tends to have no significant effect on CO_2 emissions. Unfortunately, this result provides no information about the contemporaneous effects of development aid, nor about the effects of using a shorter lag. Li et al. (2021) find that green aid alone does not significantly contribute to reductions in CO_2 emissions; however, when green aid is interacted with the quality of institutions, aid has a conditional negative effect on CO_2 emissions. Unfortunately, the authors do not report the results of overidentification restriction tests for their GMM models, which raises some doubt on the validity of their findings. Finally, Mahalik et al. (2021) find that, in India, energy aid increases CO_2 emissions. However, this finding does not necessarily imply that aid for renewable energy has a positive effect on CO_2 emissions.[2]

[1] This statement is based on data from the World Development Indicators (available at https://databank.worldbank.org/source/world-development-indicators).

[2] Energy aid includes, in addition to support for renewable energy, aid directed toward fossil energy. In the study by Mahalik et al. (2021), the overall positive effect of energy aid on CO_2 emissions may therefore be driven (in part) by the positive impact of fossil-energy aid on emissions. Mahalik et al. (2021, p. 7) argue that 'foreign energy finance will worsen the quality of the environment if it is invested more in the extraction of mining and metal resources required for enhancing economic growth.'

Moreover, most studies on green aid and CO_2 emissions, including the one by Li et al. (2021), suffer in particular from at least one of the following two methodological problems. The first is the use of foreign aid commitments, which often differ significantly from actual disbursements (due to certain donors promising more than they actually give or due to certain recipients absorbing less aid than donors expect). The second is the use of 'financial aid to mitigate climate change' (sometimes referred to as 'climate aid' or 'green aid') as the variable of interest—a 'black box' variable that collapses all financial aid intended to promote efforts to reduce or limit GHG emissions, such as aid to improve the energy efficiency of school buildings and hospitals, aid to support clean public transport, aid to promote research in satellite information for climate modeling purposes, aid for flood protection measures, and aid for renewable energy (OECD, 2023). In this paper, we avoid these two problems by using a more accurate and concrete measure of actual aid activity: ODA disbursements for renewable energy.

While our focus is on examining the impact of foreign aid for renewable energy on fossil energy consumption, we also check the plausibility of our results by performing regressions of both CO_2 emissions and the consumption of renewable energy on ODA disbursements for renewable energy. Thus, we also directly contribute to the literature on aid and CO_2 emissions. In addition, our study is novel in that the impact of ODA for renewable energy on renewable energy consumption has not been previously examined.[3]

Thus, we make the following contributions to the literature: *First*, we examine whether aid for renewable energy is effective in reducing fossil energy consumption, which is the main focus of this paper. *Second*, if aid for renewable energy reduces fossil energy consumption in recipient countries by shifting from fossil fuels to renewable energy, we should observe a positive effect of this aid on renewable energy consumption. To check the plausibility of our results, we also examine this effect. *Third*, we not only examine the impact of aid for renewable energy on fossil energy consumption and on renewable energy consumption, but also its impact on CO_2 emissions (using ODA disbursements for renewable energy). If aid for renewable energy reduces fossil energy consumption and increases renewable energy consumption, we should observe a negative effect of aid for renewable energy on CO_2 emissions. Our analysis can thus be interpreted as the first study on

[3] Two related studies should be mentioned: Wang et al. (2021) and Guo et al. (2024). Both examine the impact of overall ODA (as a percentage of gross national income), not ODA specifically for renewable energy, on 'renewable energy development,' measured as the ratio of renewable energy consumption to total final energy consumption. Wang et al. find a non-linear relationship in Sub-Saharan African (SSA) countries: ODA promotes renewable energy development when carbon dioxide intensity and urbanization are below certain thresholds, but hinders it beyond these thresholds. Guo et al. report that ODA positively influences renewable energy development in SSA, with stronger effects in countries with sound management and transparent policy environments. However, neither study provides information on how aid specifically for renewable energy affects the absolute consumption of renewable energy. Instead, the results may reflect composition effects: if an increase in ODA is driven by aid in less energy-intensive areas such as policy support, institutional development, education, or technical assistance, while aid for energy-intensive industrial products or fossil energy declines, total energy consumption may decrease with increasing aid, which in turn may raise the ratio of renewable to total energy consumption. To our knowledge, no study has directly examined the impact of aid specifically targeted at renewable energy on renewable energy consumption. For completeness, however, a finding from a further related study should be noted: Jaina and Bardhan (2024) find that aid for renewable energy generation increases the share of renewable electricity in total installed electricity capacity.

the impact of aid for renewable energy on CO_2 emissions and the main channel (fossil energy consumption) through which aid for renewable energy reduces CO_2 emissions.[4]

Finally, a methodological contribution of this paper is the use of two datasets. The first dataset is an unbalanced cross-sectional time-series panel dataset with annual time-series observations for 24 countries between 2002 and 2022. This dataset allows us to employ panel cointegration methods, which are designed both to test whether two or more non-stationary variables exhibit a long-run relationship and to estimate relationships involving such variables. If non-stationary variables are not cointegrated, the results from regressions involving these variables may be spurious in panels with a large time dimension. If non-stationary variables are cointegrated, conventional statistical inference may also be invalid in large T panels.

The second dataset is an unbalanced cross-sectionally dominated panel dataset covering 31 countries between 2002 and 2022, with data averaged over three-year and five-year periods. Due to the reduced number of time series observations per country in this dataset, there is no risk of spurious regressions or invalid statistical inference, which allows us to use conventional panel estimators for small T and large N, such as GMM.

In both datasets, using panel cointegration methods and the system GMM estimator, we find that ODA for renewable energy reduces fossil fuel consumption. Our results also suggest that aid for renewable energy has a positive effect on the consumption of renewable energy and a negative effect on CO_2 emissions.

2. Models and data

The basic model we use for our panel cointegration analysis is represented by the equation

$$\log FEC_{it} = \beta \log RENAID_{it} + c_i + \mu_{it}$$
$$\mu_{it} = \rho f_t + \varepsilon_{it} \tag{1}$$

where $\log FEC_{it}$ is the natural logarithm of the per capita consumption of fossil energy across countries i in periods t, $\log RENAID_{it}$ is the natural logarithm of ODA disbursements per capita for renewable energy across the same countries and periods, β is the elasticity of fossil energy consumption with respect to renewable energy aid, c_i represents country-specific fixed effects, and μ_{it} is the error term, which is composed of idiosyncratic stochastic shocks ε_i and the effects ρ of unobserved common factors f_t. Failing to control for these factors can result in cross-sectional dependence in the errors, potentially leading to biased parameter estimates.

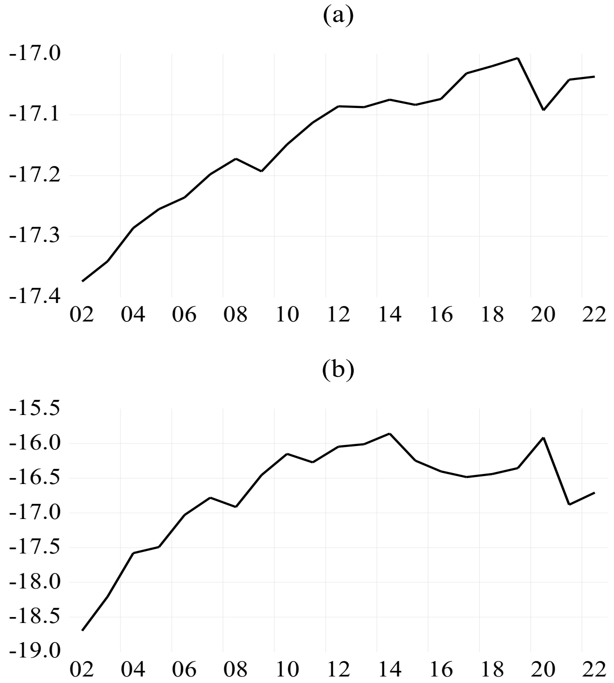
We control for unobserved common factors by demeaning our variables, which involves subtracting the average value of each variable from the same variable in each period. This approach is equivalent to using the residuals from regressions of each variable on time dummies. While demeaning allows us to extract common stochastic trends from our data, we also explicitly control for a common deterministic trend by including country-specific time trends, thereby allowing the effects of this deterministic trend to vary across countries. Additionally, we ensure that our estimates are not biased by error cross-sectional dependence stemming from unobserved common factors by

[4] With one exception—Wu et al. (2021)—previous studies that find evidence suggesting that green (or climate) aid reduces CO_2 emissions do not investigate the underlying mechanisms. It is therefore not entirely clear whether the observed reduction in emissions reported in these studies is driven by a decrease in fossil energy consumption. Green aid can free up resources in recipient countries that are then reallocated to other purposes. These resources could lead to increased but less carbon-intensive consumption of fossil energy in other sectors, or they could be used to finance technologies that improve the carbon intensity of fossil energy. As a result, CO_2 emissions may decline even without a reduction in overall fossil fuel consumption. Wu et al. (2021), however, find that climate aid has a direct negative effect on CO_2 emissions and an indirect negative effect on CO_2 emissions via its negative impact on the share of traditional fossil energy consumption in total energy consumption. The main differences between this study and that by Wu et al. are that we use aid for renewable energy rather than climate aid (which includes not only aid for renewable energy), that we use disbursements rather than commitments, and that we examine total rather than relative fossil energy consumption. Moreover, while the focus of Wu et al. is on CO_2 emissions, our focus is on the consumption of fossil energy.

applying the bias-corrected cross-sectional dependence test developed by Pesaran and Xie (2023) to the residuals from equation (1).[5]

Equation (1) implicitly assumes that if $\log FEC_{it}$ and $\log RENAID_{it}$ can be characterized as non-stationary processes with stochastic trends, these two variables are cointegrated. Figure 1, which displays the cross-country averages of both variables over the sample period for our 24-country dataset, reveals that both variables exhibit trends that may be stochastic. Cointegration implies the existence of a long-run relationship between variables that exhibit stochastic trends and share the same order of integration. If variables are 'integrated' but not cointegrated, there is no long-run relationship between them. Using such variables in conventional OLS fixed-effects regressions may lead to spurious results (Kao, 1999), as noted in the Introduction. Therefore, it is necessary to examine the time series properties of the variables and to test whether they are cointegrated.

Figure 1. Cross-country averages of (a) $\log FEC_{it}$ and (b) $\log RENAID_{it}$



Note: The figure shows the averages of the main variables in the annual panel dataset of 24 countries.

However, even if non-stationary variables are cointegrated, conventional OLS-based statistical inference is invalid due to a second-order asymptotic bias caused by autocorrelation and endogeneity. Therefore, we employ the panel fully modified ordinary least squares (P-FMOLS) estimator proposed by Pedroni (2001), which permits valid inference even in the presence of autocorrelated errors and endogenous regressors.[6] As a robustness check, we also estimate β using the pooled mean group (PMG) estimator of Pesaran et al. (1999). A potential disadvantage of this

[5] We use the Pesaran and Xie (2023) test instead of the commonly used Pesaran (2004) test because the latter lacks power to detect error cross-sectional dependence in models that include time dummies or cross-sectional averages, or are based on demeaned data. The Pesaran and Xie (2023) test is a modified version of the Pesaran (2004) test that corrects for the bias inherent in the original Pesaran (2004) test.

[6] The fully modified ordinary least squares estimator corrects for endogeneity and autocorrelation semi-parametrically by utilizing the OLS residuals and the first differences of the regressors. Another method for estimating cointegrating relationships is the dynamic ordinary least squares (DOLS) method, which addresses endogeneity and serial correlation parametrically using lead, lag, and current values of differenced regressors. However, DOLS reduces the number of observations per cross-sectional unit due to the use of leads and lags, which may lead to a substantial loss of observations. Therefore, to minimize the problem of low statistical power associated with the use of small sample sizes, we prefer the FMOLS estimator.

estimator, which is based on an autoregressive distributed lag (ARDL) model, is that it requires weakly exogenous regressors, like any ARDL model.

The existence of a cointegrating relationship between two or more integrated variables is robust to the inclusion of additional variables, implying that there is no need to include additional variables in an existing cointegrating relationship. Nevertheless, to examine the robustness of our results, we estimate equation (1) both with and without additional variables.

Based on the literature on the determinants of aid flows and energy consumption (per capita), we include the following variables: the log of real GDP per capita (log$GDPPC_{it}$), the log of the gross secondary school enrollment rate (log$SCHOOL_{it}$), the log of the trade-to-GDP ratio (log$TRADE_{it}$), and the log of the GDP deflator (log$PRICE_{it}$), which serves as a rough proxy for the overall energy price.[7]

Moreover, to check the plausibility of our results, we replace log$RENAID_{it}$ with the log of overall ODA disbursements per capita, excluding ODA disbursements for renewable energy per capita (log$NONRENAID_{it}$), and logFEC_{it} with the log of per capita consumption of renewable energy (log$RENC_{it}$) and the log of per capita CO_2 emissions from energy consumption (log$CO2_{it}$). The definitions of the variables and the sources of the data are detailed in Table A1 in the appendix.

While cointegration indicates that long-run Granger causality is present in at least one direction, it does not specify the direction of this causality.[8] To determine the direction of long-run causality in the cointegrating relationship, we use a standard two-step approach. The first step is to use the P-FMOLS estimate of β to compute the error-correction term. The second step involves incorporating this error-correction term into error-correction models for ΔlogFEC_{it} and Δlog$RENAID_{it}$. If the coefficient of the error-correction term (α_1) in the ΔlogFEC_{it} equation is significant while the coefficient of the error-correction term (α_2) in the Δlog$RENAID_{it}$ equation is not, it suggests that long-run causality flows from $RENAID_{it}$ *to* FEC_{it}. Conversely, if α_2 is significant and α_1 is not, it indicates causality from FEC_{it} to $RENAID_{it}$. When both α_1 and α_2 are significant, it implies bidirectional long-run causality.

Data on fossil energy consumption and ODA disbursements for renewable energy are available for 31 countries from 2002 to 2022. Since panel cointegration techniques require uninterrupted time series data over sufficiently long periods, we include all countries that have continuous time series data with at least 15 consecutive observations for both variables. The resulting dataset comprises an unbalanced panel of 24 countries, which are listed in Table A2 in the appendix. We note here that the lack of sufficient time-series data forces us to exclude two countries (Iraq and Sri Lanka) from the analysis involving control variables.

A concern might be that we exclude seven or nine countries with available data from the raw dataset, which contains annual data for 31 countries. The problem with the raw dataset is its large time dimension, which may not only lead to spurious regressions but also results in too many instruments in the system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). As is well-known, too many instruments can lead to biased estimates and weaken the Hansen test of overidentifying restrictions. As a rule of thumb, the number of instruments should be smaller than the number of cross-sectional units (e.g., countries).

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[7] We apply the natural logarithm to the gross secondary school enrollment rate and the trade-to-GDP ratio for two reasons. First, for consistency, since all other variables in the model are log-transformed, allowing the coefficients to be interpreted uniformly as elasticities. Second, for econometric reasons: when these variables are included in levels rather than in logarithms, the Arellano and Bond (1991) test for second-order serial correlation becomes significant in the GMM estimations. The estimated coefficients on log$RENAID_{it}$ (available upon request) remain qualitatively unchanged when $SCHOOL_{it}$ and $TRADE_{it}$ are used instead of log$SCHOOL_{it}$ and log$TRADE_{it}$.

[8] The direction of causality may be unclear due to the potential endogeneity of aid for renewable energy, given that the consumption of fossil energy could have both positive and negative effects on foreign aid for renewable energy. On the one hand, high fossil fuel consumption leads to environmental degradation and climate change, which may raise awareness and urgency for the transition to renewable energy. This heightened awareness can motivate donor countries to increase foreign aid for renewable energy projects. On the other hand, political and economic interests could result in less support for renewable energy initiatives, as countries benefiting from cheap fossil fuel exports may have less incentive to fund renewable energy projects abroad.

We use the system GMM estimator in addition to the estimators mentioned above. As is well-known, this estimator is a dynamic panel estimator designed to address endogeneity through the use of internal instruments, while also circumventing the 'Nickell bias' that arises when applying a fixed effects estimator to a lagged dependent variable model in panels with a small time dimension. We apply the system GMM estimator to a dynamic version of equation (1) that includes the control variables mentioned above, along with time dummies.[9] We treat the lagged dependent variables as weakly exogenous (as is common practice), the time dummies as strictly exogenous (as is common practice), and all other variables as endogenous.

To eliminate the risk of spurious regressions and ensure that the number of instruments in our GMM regressions does not exceed the number of cross-sectional units, we construct a second, cross-sectionally dominated dataset for all 31 countries with available data by averaging the data over three-year or five-year periods: 2002–2004, 2005–2009, 2010–2014, 2015–2019, and 2020–2022. It should be added that, to avoid too many instruments, we are forced not only to reduce the time series dimension of our panel but also to limit the lags in GMM-style instruments to three and collapse the instruments. The countries in the second dataset are also listed in Table A2. Descriptive statistics for the main variables are provided in Table A3.

Table 1. Estimates of the long-run relationship between foreign aid for renewable energy and the consumption of fossil energy

	(1) P-FMOLS	(2) PMG
Error-correction term		-0.5761***
		(0.0537)
log$RENAID_{it}$	-0.0043**	-0.0098***
	(0.0022)	(0.0021)
CD (*p*-value)	0.394	0.618
Number of observations	456	456

Notes: P-FMOLS = panel fully modified ordinary least squares estimator developed by Pedroni (2001); PMG = pooled mean group estimator developed by Pesaran et al. (1999). In applying the P-FMOLS estimator, we allowed for heterogeneous first-stage coefficients and used the sandwich estimator, which allows for heterogeneous variances. The dependent variable in the P-FMOLS regression is logFEC_{it}. The dependent variable in the PMG regression is ΔlogFEC_{it}. Both regressions include individual fixed effects and individual time trends. Both regressions are based on demeaned data to control for error cross-sectional dependence caused by common factors. The PMG results are based on an ARDL(1, 1) model; the lag order was chosen using the Schwarz information criterion, with a maximum of three lags. CD denotes the bias-corrected cross-sectional dependence test developed by Pesaran and Xie (2023) (applied to the regression residuals). The numbers in parentheses are standard errors. The P-FMOLS standard errors were calculated using a heteroscedasticity-and-autocorrelation-consistent covariance matrix. *** (**) indicates significance at the 1% (5%) level.

3. Results

Table A4 and Table A5 in the appendix present several pre-tests for unit roots and cointegration, respectively. Overall, these tests suggest that log$RENAID_{it}$ and logFEC_{it} are non-stationary and cointegrated, implying that a non-spurious long-run relationship exists between these variables.

Column (1) of Table 1 presents the P-FMOLS estimate of β. This estimate is significant at the 5% level and implies, if viewed causally, that an increase in aid for renewable energy per capita by one percent reduces the consumption of fossil energy per capita by 0.0043 percent. To evaluate the magnitude and plausibility of this estimate, we multiply the estimated coefficient on log$RENAID_{it}$ by the ratio of the average growth rate of $RENAID_{it}$ (0.093502) to the average growth rate of FEC_{it} (0.029062). The resulting value implies that the average increase in aid for renewable energy (per capita) in our sample was responsible for a reduction in fossil energy consumption (per capita) that corresponds in absolute value to about 1.39% of the average increase in fossil fuel energy

[9] We use the forward orthogonal deviations transformation proposed by Arellano and Bover (1995), which subtracts the average of all remaining future periods from the level in period *t*. Since the two-step estimator is more efficient than the one-step estimator, we use the former. However, a well-known issue with the two-step estimator is that its standard errors may be significantly biased downward in small samples. Following common practice, we account for this issue by applying the Windmeijer (2005) finite sample correction to the standard errors.

consumption. In other words, without aid for renewable energy, the increase in fossil energy consumption would have been about 1.39% higher.

At first sight, this effect appears to be small. However, the percentage share of ODA for renewable energy in total ODA is only about 2.96% on average in our sample, and ODA for renewable energy makes up only 0.0146% of GDP on average in our sample. For comparison, the average share of gross capital formation in GDP in our sample during is about 24.77%. Thus, our estimate is not only plausible but also suggests that doubling ODA for renewable energy could contribute to reversing the trend of increasing consumption of fossil energy (shown in Figure 1).

In column (2) of Table 1, we check the robustness of the negative effect of aid for renewable energy on fossil energy consumption using an alternative estimator, the PMG estimator. The coefficient on the lagged error correction term is negative and highly significant, which can be interpreted as confirmatory evidence of cointegration. Additionally, the PMG estimate of β remains negative and statistically significant.

For completeness, we note that the bias-corrected cross-sectional dependence test developed by Pesaran and Xie (2023), denoted in the table as CD, does not suggest that the results in Table 1 are biased by the presence of error cross-sectional dependence stemming from unobserved common factors.

Table 2. P-FMOLS estimates of the long-run relationship between aid for renewable energy and the consumption of fossil energy, with additional variables, and P-FMOLS estimates with ODA net of renewable energy aid instead of aid for renewable energy

	(1)	(2)
log$RENAID_{it}$	-0.0048***	
	(0.0009)	
log$NONRENAID_{it}$		-0.0021
		(0.0044)
log$GDPPC_{it}$	0.6991***	0.9720***
	(0.0496)	(0.0178)
log$SCHOOL_{it}$	0.1579***	0.20578***
	(0.0314)	(0.0187)
log$TRADE_{it}$	0.1194***	0.0885***
	(0.0162)	(0.0122)
log$PRICE_{it}$	-0.0869***	-0.0064
	(0.0201)	(0.0043)
Number of observations	339	323

Notes: The dependent variable is logFEC_{it}. We allowed for heterogeneous first-stage coefficients and used the sandwich estimator, which allows for heterogeneous variances. Both regressions include individual fixed effects and individual time trends. Both regressions are based on demeaned data to control for error cross-sectional dependence caused by common factors. Since the data on the control variables are not available for all countries and years for which the data on our main variables are available, we were forced to exclude two countries, Iraq and Sri Lanka, from the sample. The results in Table 1 are based on more observations than those in Table 2 because the latter includes additional variables. Since data for all variables are not available for every country in every year of the observation period, the regressions with control variables are based on a smaller number of observations than those without controls. Moreover, the dataset with the control variables has some gaps, preventing us from applying cross-sectional dependence tests, which require complete time series over a sufficiently long period. The numbers in parentheses are heteroscedasticity-and-autocorrelation-consistent standard errors. *** indicates significance at the 1% level.

In column (1) of Table 2, we check the robustness of our results to the inclusion of the variables described in the previous section.[10] The estimated coefficients on these variables are largely consistent with the findings of previous studies. The only exception is the coefficient on the gross secondary school enrollment rate. A possible explanation for the positive coefficient is that educated individuals often have higher disposable incomes and may spend more on luxury goods and services,

[10] It should be noted that, due to gaps in the dataset with control variables, it is not possible to apply cross-sectional dependence tests, which require complete time series over a sufficiently long period for a sufficient number of countries.

which can be energy-intensive. For example, more frequent international travel or larger homes may result in increased fossil fuel use.[11]

In column (2), we replace aid for renewable energy with ODA excluding aid for renewable energy. As expected, the coefficient on log$NONRENAID_{it}$ is statistically insignificant. This provides further support that the significant negative coefficient on log$RENAID_{it}$ is not a spurious regression phenomenon.

Table 3. P-FMOLS estimates of the relationships between aid for renewable energy and the consumption of renewable energy, as well as P-FMOLS estimates of the relationship between aid for renewable energy and CO_2 emissions

	(1) Dependent variable: log$RENC_{it}$	(2) Dependent variable: log$CO2_{it}$
log$RENAID_{it}$	0.0155***	-0.0044***
	(0.0032)	(0.0010)
log$GDPPC_{it}$	-0.3442***	0.6950***
	(0.0747)	(0.0480)
log$SCHOOL_{it}$	0.9463***	0.1423***
	(0.0630)	(0.0292)
log$TRADE_{it}$	-0.25933***	0.1299***
	(0.0396)	(0.01613)
log$PRICE_{it}$	-0.3088***	-0.0920***
	(0.0132)	(0.0198)
Number of observations	339	323

Notes: We allowed for heterogeneous first-stage coefficients and used the sandwich estimator, which allows for heterogeneous variances. Both regressions include individual fixed effects and individual time trends. Both regressions are based on demeaned data to control for error cross-sectional dependence caused by common factors. Since the data on the control variables are not available for all countries and years for which the data on our main variables are available, we were forced to exclude two countries, Iraq and Sri Lanka, from the sample. Moreover, the dataset with the control variables has some gaps, preventing us from applying cross-sectional dependence tests, which require complete time series over a sufficiently long period. The numbers in parentheses are heteroscedasticity-and-autocorrelation-consistent standard errors. *** indicates significance at the 1% level.

In Table 3, we present additional plausibility checks. If aid for renewable energy reduces fossil energy consumption in recipient countries, we should observe both a positive effect of aid for renewable energy on renewable energy consumption and a negative effect of aid for renewable energy on CO_2 emissions. The results in Table 3 are consistent with these expectations: the coefficient on log$RENAID_{it}$ is positive and statistically significant in the P-FMOLS regression with log$RENC_{it}$ as the dependent variable, and negative and statistically significant in the P-FMOLS regression with log$CO2_{it}$ as the dependent variable.

Table 4. Long-run causality tests

	ΔlogFEC_{it} equation	Δlog$RENAID_{it}$ equation
Coefficient of the error-correction term, α_1	-0.5910***	
	(0.0535)	
Coefficient of the error-correction term, α_2		-0.6589
		(0.6110)
Number of observations	434	434

Notes: The results are based on demeaned data to account for error cross-sectional dependence. Both regressions include individual fixed effects and individual time trends. Numbers in parentheses are heteroskedasticity- and autocorrelation-consistent standard errors. *** indicates significance at the 1% level.

Table 4 reports the results of our causality tests. While the coefficient of the error-correction term in the ΔlogFEC_{it} equation is significant, the coefficient of the error-correction term in the Δlog$RENAID_{it}$ equation is insignificant. Thus, we find evidence that long-run causality in the

[11] This effect is not necessarily excluded by including GDP per capita, since GDP per capita is an average value that may remain approximately constant if some incomes (of individuals with higher education) increase while other incomes (of lower-educated individuals) decrease.

estimated relationship between the variables is unidirectional, with causality running from aid for renewable energy to fossil energy consumption.

Table 5. System GMM estimates

	(1) Dependent variable: logFEC_{ii}	(2) Dependent variable: log$RENC_{it}$	(3) Dependent variable: log$CO2_{it}$
logFEC_{it-1}	0.8372***		
	(0.1194)		
log$RENC_{it-1}$		0.8067***	
		(0.0868)	
log$CO2_{it-1}$			0.7896***
			(0.1660)
log$RENAID_{it}$	-0.0374**	0.0483**	-0.0370**
	(0.0144)	(0.0213)	(0.0135)
log$GDPPC_{it}$	-0.0876	0.1902	-0.0679
	(0.1837)	(0.1945)	(0.2583)
log$SCHOOL_{it}$	0.4688*	0.1813	0.5435**
	(0.2745)	(0.4571)	(0.2532)
log$TRADE_{it}$	0.0863	-0.0146	0.0766
	(0.1501)	(0.1644)	(0.1384)
log$PRICE_{it}$	-0.0282	-0.0440	-0.0243
	(0.0497)	(0.1014)	(0.0503)
AR2 (*p*-value)	0.134	0.637	0.102
HANSEN (*p*-value)	0.490	0.242	0.486
Difference-in-Hansen (*p*-value)	0.417	0.548	0.556
No. of instruments	29	29	29
No. of countries	31	31	31
No. of obs.	129	129	129

Notes: The dependent variable is logFEC_{it}. All specifications control for both country and time fixed effects. All estimates are based on period averages. AR2 is the Arellano-Bond test for second-order autocorrelation in differenced residuals. HANSEN is the Hansen test of overidentifying restrictions. The Difference-in-Hansen is the difference-in-Hansen test for the validity of GMM instruments in the levels equation. The number of instruments should be less than the number of countries. To ensure this, and to avoid the problems associated with instrument proliferation, we limited the lags in GMM-style instruments to three and collapsed the instruments. While the time dummies were treated as strictly exogenous, the lagged dependent variables were treated as weakly exogenous, and all other explanatory variables were treated as endogenous. The results are based on the two-step system GMM estimator, using the forward orthogonal deviations transformation. Robust standard errors, based on the small sample correction proposed by Windmeijer (2005), are shown in parentheses. *** (**) [*] indicates significance at the 1% (5%) [*] level

Finally, in Table 5, we present the results from system GMM regressions. As described in Section 2, these regressions are based on a sample that includes all (31) countries with available data, averaged to reduce the number of time-series observations (to avoid possible spurious regressions and the problem of too many instruments).

Following common practice, we also report the *p*-values of the Arellano and Bond (1991) test for second-order serial correlation (AR2), the *p*-values of the Hansen test for overidentifying restrictions (HANSEN), the difference-in-Hansen test for the validity of GMM instruments in the levels equation, and the number of instruments. The AR2 test indicates that the errors exhibit no second-order serial correlation, while the Hansen test and the difference-in-Hansen test suggest that the instruments are valid. Additionally, the number of instruments is always less than the number of cross-sectional units. We therefore conclude that the models presented in Table 5 are correctly specified.

The coefficient on log$RENAID_{it}$ is negative and statistically significant in the GMM regression with logFEC_{it} as the dependent variable. Since we instrument log$RENAID_{it}$, the results in column (1) suggest that ODA for renewable energy has a causal negative effect on fossil energy consumption. The results in columns (2) and (3) suggest that ODA for renewable energy has a causal positive effect on renewable energy consumption and a causal negative effect on CO_2 emissions. Thus, our previous findings are corroborated by the GMM results.[12]

4. Policy implications and conclusion

Several policy implications can be drawn from our findings. *First*, the findings from this study imply that aid for renewable energy can make an important contribution to reducing fossil fuel consumption and supporting a transition to clean energy without relying on nuclear power. *Second*, given that the amount of ODA for renewable energy is relatively small, donors can substantially increase the magnitude of the aid-induced reduction in fossil energy consumption by significantly increasing their budgets for ODA for renewable energy. *Third*, given the urgent need to mitigate climate change and reduce dependence on fossil energy, and considering that the share of ODA for renewable energy in total ODA is very small, donors should consider reallocating funds from other, non-green aid programs to renewable energy aid programs.

The overall conclusion from our study is that targeted foreign aid for renewable energy projects is effective in promoting the transition from fossil to renewable energy sources and thus in reducing CO_2 emissions.

Finally, a limitation of this study should be noted. It is reasonable to assume that the effects of aid for renewable energy on fossil energy consumption vary across countries and are therefore contingent on country-specific socio-economic factors. This study does not identify which of these factors enhance the effectiveness of aid for renewable energy. Addressing this question lies beyond the scope of the present paper but represents a fruitful avenue for future research.

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[12] As an additional plausibility check, we estimated a system of three equations using a three-stage least squares (3SLS) estimator. In the first equation, CO_2 emissions are explained by fossil energy consumption (along with our control variables). In the second equation, fossil energy consumption is explained by renewable energy consumption (along with our control variables). In the third equation, we explain renewable energy consumption by aid for renewable energy (using a one-period lag of this variable to control for its potential endogeneity in the renewable-energy equation and to account for the fact that the effect of renewable energy aid typically materializes only with some delay). The estimation of this three-equation system serves to test the hypothesis that aid for renewable energy reduces CO_2 emissions by promoting the substitution of fossil fuels with renewable energy sources. The results of this 3SLS estimation are presented in Table A6 in the Appendix and confirm this hypothesis.

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Appendix

Table A1. Variable definitions and data sources

Variable	Sources
FEC: Per capita consumption of fossil energy (in exajoules), measured as the sum of oil, gas, and coal consumption	The data on oil, gas, and coal consumption are from the 2024 Energy Institute Statistical Review of World Energy (available at https://www.energyinst.org/statistical-review/resources-and-data-downloads). The sum of oil, gas, and coal consumption has been divided by the population size from the World Development Indicators (available at https://databank.worldbank.org/source/world-development-indicators).
RENAID: ODA per capita for renewable energy, measured in constant millions of 2022 dollars	The data on ODA disbursements for renewable energy are from the OECD Creditor Reporting System (accessible via the OECD Data Explorer at https://data-explorer.oecd.org/) and have been divided by the population size from the World Development Indicators (available at https://databank.worldbank.org/source/world-development-indicators).
GDPPC: Real GDP per capita, measured in PPP and constant 2021 international dollars.	World Development Indicators (available at https://databank.worldbank.org/source/world-development-indicators)
SCHOOL: Gross secondary school enrollment rate	World Development Indicators (available at https://databank.worldbank.org/source/world-development-indicators)
TRADE: Imports plus exports as a percentage of GDP	World Development Indicators (available at https://databank.worldbank.org/source/world-development-indicators)
PRICE: GDP deflator (linked series)	World Development Indicators (available at https://databank.worldbank.org/source/world-development-indicators)
NONRENAID: Overall ODA per capita minus ODA per capita for renewable energy, measured in constant 2022 dollars.	The data on ODA for renewable energy and overall ODA disbursements are from the OECD Creditor Reporting System (accessible via the OECD Data Explorer at https://data-explorer.oecd.org/) and have been divided by the population size from the World Development Indicators (available at https://databank.worldbank.org/source/world-development-indicators).
RENC: Per capita consumption of renewable energy (in exajoules)	The data on renewable consumption are from the 2024 Energy Institute Statistical Review of World Energy (available at https://www.energyinst.org/statistical-review/resources-and-data-downloads) and have been divided by the population size from the World Development Indicators (available at https://databank.worldbank.org/source/world-development-indicators).
CO2: Per capita carbon dioxide emissions from energy consumption, measured in million metric tons	The data on carbon dioxide emissions from energy consumption are from the 2024 Energy Institute Statistical Review of World Energy (available at https://www.energyinst.org/statistical-review/resources-and-data-downloads) and have been divided by the population size from the World Development Indicators (available at https://databank.worldbank.org/source/world-development-indicators).

Table A2. Countries in the datasets

Countries in the annual dataset		Countries in the averaged dataset	
Argentina	Malaysia	Algeria	Iraq
Bangladesh	Mexico	Argentina	Kazakhstan
Brazil	Morocco	Azerbaijan	Malaysia
Chile	North Macedonia	Bangladesh	Mexico
China	Pakistan	Belarus	Morocco
Colombia	Philippines	Brazil	North Macedonia
Ecuador	South Africa	Chile	Pakistan
Egypt	Sri Lanka	China	Peru
India	Thailand	Colombia	Philippines
Indonesia	Türkiye	Croatia	South Africa
Iraq	Ukraine	Ecuador	Sri Lanka
Kazakhstan	Vietnam	Egypt	Thailand
		India	Türkiye
		Indonesia	Ukraine
		Iran	Uzbekistan
			Vietnam

Table A3. Descriptive statistics

	logFEC_{it}	log$RENC_{it}$	log$CO2_{it}$	log$RENAID_{it}$	log$GDPPC_{it}$	log$SCHOOL_{it}$	log$TRADE_{it}$	log$PRICE_{it}$
Annual dataset								
Mean	-17.122	-19.694	-12.869	-16.814	9.471	4.387	4.068	4.615
Median	-17.125	-19.597	-12.827	-16.783	9.574	4.440	4.008	4.592
Maximum	-15.677	-17.556	-11.281	-10.677	10.450	4.875	5.349	8.810
Minimum	-19.305	-24.208	-15.329	-23.282	7.996	2.991	3.113	2.443
Std. Dev.	0.794	1.334	0.828	2.336	0.595	0.298	0.500	0.677
Dataset with 5-year averages								
Mean	-17.037	-19.805	-12.815	-16.730	9.487	4.406	4.087	4.597
Median	-16.832	-19.771	-12.670	-16.599	9.587	4.456	4.029	4.592
Maximum	-15.745	-17.511	-11.331	-11.493	10.428	4.798	5.326	8.919
Minimum	-19.265	-23.814	-15.321	-23.646	8.001	3.040	3.158	2.378
Std. Dev.	0.787	1.418	0.792	2.267	0.577	0.281	0.474	0.831

Table A4. Panel unit root tests

	Im et al. (2003)	Pesaran (2007)
Levels		
logFEC_{it}	0.227	0.996
log$RENAID_{it}$	0.207	0.254
First differences		
ΔlogFEC_{it}	0.000	0.024
Δlog$RENAID_{it}$	0.000	0.000

Notes: The reported values are *p*-values. The unit root tests for the variables in levels are based on specifications that include country-specific intercepts and country-specific time trends, while the tests for the first differences of the variables are based on specifications that include only country-specific intercepts. The Im et al. (2003) test implicitly assumes error cross-sectional independence and can be biased if the errors are cross-sectionally dependent. To account for error cross-sectional dependence caused by unobserved common factors in the panel unit root test developed by Im et al. (2003), we used demeaned data. The panel unit root tests developed by Pesaran (2007) explicitly control for error cross-sectional dependence caused by unobserved common factors by incorporating weighted cross-sectional averages of the variables and are therefore applied to the original, untransformed data. Two lags of the first differences were used in the tests, which are ADF-type tests.

Table A5. Panel cointegration tests

Pedroni (1999)		
Panel variance ratio statistic	1.252	
Panel rho-statistic	-1.281*	
Panel PP-statistic	-4.510***	
Panel ADF-statistic	-6.610***	
Group rho-statistic	1.113	
Group PP-statistic	-3.563***	
Group ADF-statistic	-5.890***	
Larsson et al. (2001)	Cointegration rank	
	$r = 0$	$r = 1$
Standardized panel trace statistics without small sample correction	6.616***	0.263
Standardized panel trace statistics with small sample correction	4.224***	-0.789
Gengenbach et al. (2016)		
ECM *t*-statistic		
Banerjee and Carrion-i-Silvestre (2017)		
CIPS statistic	-3.352**	

Notes: The dependent variable in the tests developed by Pedroni (1999) and Banerjee and Carrion-i-Silvestre (2017) is $\log FEC_{it}$; the dependent variable in the Gengenbach et al. (2016) test is $\Delta\log FEC_{it}$; the Larsson et al. (2001) test treats all variables as potentially endogenous and is based on a vector error-correction specification with $\Delta\log FEC_{it}$. and $\Delta\log RENAID_{it}$ as dependent and independent variables. All tests are based on specifications that include country-specific intercepts and individual time trends. For the Pedroni (1999) (PP and ADF) tests, the number of lags was determined by the Schwarz criterion, with a maximum of three lags. Similarly, for the Banerjee and Carrion-i-Silvestre (2017) test, the lag length was selected using the general-to-specific method, with a maximum of three lags. One lag of the first differences was included in the Gengenbach et al. (2016) test. Similarly, we used one lag in the Larsson et al. (2001) test. The standardized panel trace statistics from the Larsson et al. (2001) approach are based on country-specific trace statistics from the Johansen (1988) time series approach. A well-known problem is that the Johansen trace statistics tend to over-reject the null hypothesis in small samples. To avoid the Larsson et al. test also overestimating the cointegrating rank, we present the standardized panel trace statistics not only in their original form, i.e., without small-sample correction, but also based on small-sample corrected country-specific trace statistics using the correction factor suggested by Reinsel and Ahn (1992). We used the mean and variance provided by Breitung (2005) to calculate the standardized panel trace statistics. Since the Banerjee and Carrion-i-Silvestre (2017) test requires a balanced panel, we constructed such a panel by including only those countries with complete time series for the period 2003-2022 (19 countries). Since the Gengenbach et al. (2016) test also implicitly assumes a balanced panel with sufficiently long time series, this test has also been applied to this panel. The relevant 1% (5%) [10%] critical value for the Gengenbach et al. (2016) t-test (for $N = 20$) is -3.212 (-3.060) [-2.980] with an intercept and a linear trend. The critical values are from the online appendix of Gengenbach et al. (2016) (available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/jae.2475). The relevant 5% (10%) critical value for the Banerjee and Carrion-i-Silvestre (2017) test (for $T = 20$ and $N = 20$) is -3.04 (-2.94) with an intercept and a linear trend. These values are from Banerjee and Carrion-i-Silvestre (2011), the working paper version of the article by Banerjee and Carrion-i-Silvestre (2017). Banerjee and Carrion-i-Silvestre (2011) do not tabulate 1% critical values. The Pedroni (1999) and Larsson et al. (2001) statistics are distributed as standard normal. The variance ratio test, as well as the standardized panel trace statistic, has a one-sided rejection region consisting of large positive values, whereas the other Pedroni tests reject for large negative values. We used demeaned data for the Pedroni (1999) and Larsson et al. (2001) tests to account for error cross-sectional dependence caused by common factors. The Gengenbach et al. (2016) and Banerjee and Carrion-i-Silvestre (2017) tests account for error cross-sectional dependence due to unobserved common factors via the use of (weighted) cross-sectional averages. *** (**) [*] indicates rejection of the null hypothesis of no cointegration at the 1% (5%) [10%] level.

Table A6. 3SLS estimates

	(1) Dependent variable: log$CO2_{it}$	(2) Dependent variable: logFEC_{it}	(3) Dependent variable: log$RENC_{it}$
logFEC_{it}	0.7870***		
	(0.0653)		
log$RENC_{it}$		-0.3779***	
		(0.0719)	
log$GDPPC_{it}$	0.1987***	0.4639***	
	(0.0483)	(0.1145)	
log$SCHOOL_{it}$	0.2364***	0.6387***	
	(0.0424)	(0.1334)	
log$TRADE_{it}$	-0.0378**	0.0271	
	(0.0189)	(0.0696)	
log$PRICE_{it}$	0.0022	-0.0846***	
	(0.0065)	(0.0318)	
log$RENAID_{it-1}$			0.0502***
			(0.2811)
log$GDPPC_{it-1}$			-0.1905
			(0.2583)
log$SCHOOL_{it-1}$			0.4229*
			(0.2419)
log$TRADE_{it-1}$			-0.1792
			(0.1678)
log$PRICE_{it-1}$			-0.0719
			(0.0830)

Notes: The number of countries is 31, and the number of observations is 129. The results are based on 5-year averages. We estimated the system of simultaneous equations (1), (2), and (3) using a three-stage least squares (3SLS) estimator, which accounts for correlations between the error terms across equations. 3SLS treats logFEC_{it} and log$RENC_{it}$ as endogenous. To control for the potential endogeneity of log$RENAID_{it}$ in the log$RENC_{it}$ equation, and to account for the fact that the effect of renewable energy aid on renewable energy consumption usually materializes only after a certain time lag, we used a one-period lag of log$RENAID_{it}$ in the log$RENC_{it}$ equation. All equations include country and period fixed effects. Standard errors are in parentheses. *** (**) [*] indicates significance at the 1% (5%) [*] level. The results in the table suggest that aid for renewable energy increases the consumption of renewable energy, thereby inducing a substitution of fossil energy with renewable energy. Since fossil energy consumption is a major determinant of CO_2 emissions, this implies that aid for renewable energy reduces CO_2 emissions through its effect on fossil energy consumption.