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Does Foreign Aid Reduce Energy and Carbon Intensities in Developing Countries? *

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Abstract: Advanced OECD countries are widely held responsible to contain global carbon emissions by providing financial and technical support to developing economies, where emissions are increasing most rapidly. It is open to question, however, whether more generous official development assistance would help fight climate change effectively. Empirical evidence on the effects of foreign aid on energy and emission intensities in recipient countries hardly exists. We contribute to closing this gap by considering energy use and carbon emissions as dependent climate-related variables, and the volume and structure of aid as possible determinants. In particular, we assess the impact of aid that donors classify to be specifically related to energy issues. In addition to OLS estimations, we perform dynamic panel GMM and LSDVC (corrected least squared dummy variables) estimations. We find that aid tends to be effective in reducing the energy intensity of GDP in recipient countries. All the same, the carbon intensity of energy use is hardly affected. Scaling up aid efforts would thus be insufficient to fight climate change beyond improving energy efficiency.

Keywords: Energy intensity, CO_2 emissions, foreign aid, developing countries

JEL classification: F35; Q41; Q55

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1 Introduction

Carbon emissions have increased most strongly in developing countries, particularly in China (Raupach et al. 2007). The International Energy Agency forecasts future emission growth rates of more than three per cent per annum in China and other non-OECD countries in Asia, and more than two per cent in Latin America - compared to about 0.1 per cent in OECD countries (IEA 2008). Starting at a similar magnitude of carbon (CO_2) emissions in 2006, the considerable gap in emissions growth implies that non-OECD emissions would be about twice the OECD emissions in 2030 (Table 1). Emissions grow at a lower rate than total primary energy demand in OECD countries due to an increasing share of modern low-carbon technologies. On the contrary, emissions tend to grow at a higher rate than total primary energy demand in non-OECD countries where such technologies are often lacking.

Table 1: IEA projections of CO_2 emissions and energy growth, 2006-2030

Region or country	Emissions 2006	Emissions 2030	Emissions growth	Energy growth
OECD	12 791	13 166	0.1	0.5
Non-OECD	14 119	26 021	2.6	2.4
Non-OECD Asia	8 363	17 299	3.1	2.8
Latin America	972	1 598	2.1	2.0
Africa	845	1 170	1.4	1.4
USA	5 670	5 804	0.1	0.4
China	5 648	11 706	3.1	3.0

Note: Yearly CO_2 emissions in Mt and average yearly percentage growth rates of CO_2 emissions and of total primary energy demand between 2006 and 2030 in the IEA (2008) reference scenario.

It is widely agreed that OECD countries bear major responsibility for future emissions in developing countries. The Bali Road Map requires the former to provide technical and financial support to the latter, e.g., through financing the Climate Investment Fund governed by the World Bank (World Bank 2009). While OECD countries have pledged contributions to such funds, developing countries consider current transfers to be insufficient. For instance, in their preparations for the Copenhagen summit on climate change in December 2009, the African Union demanded from OECD countries (additional) financial transfers in the order of US-$67 billion per annum (The Economist, September 3rd, 2009). The World Bank (2010: 245) calls for “a new multilateral effort” “to scale up public finance in support of developing countries."

It is open to question, however, whether more generous funding of developing countries would help fight climate change effectively. On the one hand, it is often in developing countries where emission reductions can be realized most efficiently, which provides the justification of policy instruments such as the Clean Development Mechanism (CDM). On the other hand, the available evidence for the diffusion of climate friendly technologies through international (financial and knowledge) transfers is highly ambiguous. As for market-related transmission mechanisms, some country-specific evidence suggests that foreign direct investment(FDI) by multinational companies helps economize on energy use in developing and emerging host economies through technology transfers. However, Perkins and Neumayer (2009) caution against the optimistic view of FDI inflows improving the domestic pollution efficiency. Likewise, Hübler and Keller (2010) cannot generally confirm energy efficiency gains in developing countries via FDI inflows and imports.

The role of foreign aid, i.e. official financial and technical cooperation granted by governments, in achieving energy and climate-related goals has received only scant attention in previous empirical literature. Hübler and Keller (2010) find energy efficiency to be associated with foreign aid, but possible endogeneity of aid is not addressed systematically. Arvin et al. (2006: 83) attribute the absence of a consistent causal pattern "to the heterogeneity among developing countries and to the multifaceted nature of the relationship between aid and the environment." Indeed, it is through various - direct and indirect - channels that foreign aid may affect energy use and carbon emissions in recipient countries. Financial and technical support for specific projects in the energy sector of recipient countries could have direct effects, even though foreign aid tends to be fungible. Indirect effects may work through aid-induced increases in per-capita income in the recipient countries. However, it remains heavily disputed whether aid has been effective in stimulating economic growth, with even recent surveys of the relevant literature coming to sharply opposing conclusions (McGillivray et al. 2006; Doucouliagos and Paldam 2009).

In the light of the elusive aid-growth nexus, it has been argued that a more disaggregated view on aid effectiveness is warranted (e.g., Harms and Lutz 2005; Mavrotas and Ouattara 2006; Dreher et al. 2008). Donors have stressed repeatedly that they pursue multiple objectives when granting aid (e.g., Isenman and Ehrenpreis 2003), among which climate-related objectives figure prominently. At the same time, focusing on specific outcome variables requires taking the composition of aid into account. The traditional approach of employing data on total aid inflows disregards the heterogeneity of aid. Aid effectiveness is likely to differ across specific outcome variables as well as specific types of aid. It is against this backdrop that we empirically assess the impact of foreign aid on climate-related variables.

Higher aid inflows provide the recipient country with more financial resources and technical expertise that should help improve energy efficiency and contain climate change. Apart from increasing the overall amount of aid, donors may shape the energy and emission intensities in recipient countries by trying to tie the recipients' hands on how to use aid. Chao and Yu (1999) present a theoretical model showing that aid earmarked specifically for pollution abatement can lead to a win-win situation for both donor and recipient countries. Likewise, Rübbelke (2004: 104) argues that, compared to unconditional transfers, "making transfer payments conditional on specific purposes" could reduce "dispersion losses of transfers" and, thus, enhance aid effects on containing energy-related global externalities.

Tying aid to clearly defined projects in particular sectors in the recipient countries appears to be a particularly strict form of earmarking. In the present context of energy intensity and emission intensity, we account for aid in the energy sector and the industrial sector. However, aid is fungible so that recipients may effectively (mis-)use tied aid by redirecting domestic resources from projects and sectors that donors wish to promote.

We do not attempt to account for all possible indirect channels through which aid may affect energy and emissions intensities. Yet it is in several ways that we extend the existing literature. First, in contrast to earlier studies, we consider both energy use and carbon emissions as dependent climate-related variables. In this way, we take into account that the increase in global emissions since 2000 was largely due to "a cessation or reversal of earlier declining trends in the energy intensity of gross domestic product (energy use divided by GDP) and the carbon intensity of energy (emissions divided by energy use)" (Raupach et al. 2007). Second, we consider both the volume and the structure of foreign aid as possible determinants. Third, we account for the possible endogeneity of aid and employ dynamic panel GMM estimations covering close to 80 developing countries and the period 1973-2005.

2 Analytical background and hypotheses

As a starting point of our analysis, we examine the Kaya identity which disentangles the different drivers of carbon emissions (Raupach et al. 2007):

$$C = P\frac{G}{P}\frac{E}{G}\frac{C}{E} = Pgec, \quad \forall\{r,t\} \tag{1}$$

The equation refers to country r in year t, with C standing for carbon (CO_2) emissions, P for population, G for gross domestic product (GDP) and E for energy consumption. The identity is reformulated in intensity form, where g denotes per-capita GDP; e and c denote the energy intensity of production and, respectively, the emission intensity of energy use. Our analysis focuses on the effect of foreign aid on e and c. As already indicated in the introduction, we do not attempt to resolve the persistent aid-growth debate in this paper; nor do we attempt to isolate any indirect effects of aid working through population growth.[1]

Following the model of Antweiler et al. (2001) on the impact of trade on pollution, foreign aid could have a scale, composition and technique effect on carbon emissions. Our setup above captures the scale effect by the joint effect of population and income $Pg = G$. Given a Leontief type technology where inputs and outputs stay in constant proportion, scaling up production ceteris paribus increases G, E and C to the same extent so that e and c stay constant. Hence, we do not consider the scale effect $Pg = G$ in our analysis of e and c.

The composition effect on e is due to production shifts towards sectors that are more (or less) energy intensive. Similar to Hübler and Keller (2010), we capture the composition effect by controlling for the share of industrial value added in GDP, denoted by s^{ind}. We expect that a rising s^{ind} leads to a rising economy-wide e, since industrial production is on average more energy intensive than agriculture and services. In addition,

[1] The recent aid literature has paid little attention to the possibly opposing effects aid may have on population growth. An exception is Azarnert (2008) who argues that the decline in fertility has been relatively slow in the aid-dependent sub-Saharan region.

we considered the share of energy intensive exports in total industrial exports as a proxy of the relative importance of energy intensive production within the industrial sector.[2]

Foreign aid might lead to an increase in e through the composition effect if it were concentrated on industrial projects and, thus, contributed to the expansion of the industrial sector. However, the share in total aid by all donors allocated to the industrial sector (including mining and construction) of all recipient countries is fairly low (about 1.8 per cent in 1995-2007; OECD 2009b). Moreover, aid in industries that are clearly energy intensive (such as chemicals, metals, coal mining, oil and gas, refineries, etc.) played a minor role compared to aid for the promotion of small and medium-sized enterprises. Hence, it appears unlikely that aid reinforces the composition effect on energy intensity. In any case, it is hardly possible to isolate the impact of aid on the composition effect captured by s^{ind}.

Turning to the technique effect, determinants of general productivity potentially also affect e and c by improving energy efficiency and reducing carbon intensity. Such determinants include R&D and product and process imitation. Since we cannot explicitly capture all determinants of technological progress, we interpret g as a general productivity measure so that e is supposed to fall with rising g. Furthermore, we interpret gross capital formation, denoted by investment I, as a specific driver of technological progress. We expect that investment involves the replacement of old facilities by new ones and introduces more efficient technologies. Recalling the composition effect, however, investment can be directed into more or less energy intensive sectors, so that its overall effect on e is ambiguous. More specifically, we define investment i in intensity form relative to G.

Aid may affect e through the technique effect by adding to investment, transferring relevant know-how, and influencing the supply and consumption of energy in recipient countries. Similar to the composition effect, we do not attempt to isolate aid-induced investment effects. They are most likely to be small. Doucouliagos and Paldam (2006: 239) conclude from their meta study that "there is no evidence of statistically significant aid-investment effect." It may also be noted that all donors classified just 22 per cent of their overall aid in 1995-2007 to be clearly related to an investment project.[3]

[2]Results are not reported as this indicator remained insignificant throughout.

[3]The Creditor Reporting System (CRS) database (OECD 2009b) differentiates between types of aid,

Aid can reasonably be expected to reduce e to the extent that it involves transfers of relevant know-how. According to OECD guidelines, technical cooperation is meant to augment the level of knowledge and technical skills of the population in recipient countries, thereby increasing their capacity to make effective use of existing factor endowments. In addition, so-called investment-related technical cooperation could provide expertise required by local firms for an efficient implementation of investment projects. Yet it is open to question how large the aid-induced technique effect could be. The CRS database lists technical cooperation as one of the major types of aid, but this type accounted for only 19 per cent of all donors' commitments in 1995-2007 (OECD 2009b).

Taken together these considerations suggest the following equation for energy intensity e:

$$e = f(a, i, g, s^{Aind}, s^{Aene}, s^{ind}), \quad \forall\{r, t\} \tag{2}$$

with i, g, s^{ind} representing the controlling variables explained before.[4] Our focus is on a, expecting transfers of technical knowledge stemming from total aid inflows. Such transfers are written in intensity form relative to GDP, i.e., $a = \frac{A}{G}$.

Apart from total aid a, we assess the possible impact of sector-specific aid items s^{Asec}. More specifically, we include aid directed to industry, mining and construction, as a share in total aid denoted by s^{Aind}, and the share of aid for energy-related projects, denoted by s^{Aene}. As an alternative to specifications in which total aid inflows are augmented by these aid shares, we will present estimations in which total aid inflows are replaced by inflows of sector-specific aid, i.e., aid for industry and aid for energy, a^{ind} and a^{ene}. s^{Aind} and, respectively, a^{ind} may capture production-related technique effects that other aid items, notably aid in social sectors such as health and education, are unlikely to have.

among which "only investment project" is one of the major categories. The contribution of this type to aid in the industrial sector is considerably higher, however (48 per cent).

[4] In the empirical specification, we will add two-way fixed effects in order to capture other relevant determinants of e that we cannot explicitly include for reasons of data availability. We thus account for unobserved heterogeneity across countries as well as common time trends. For instance, there is a lack of energy price data, especially for developing countries such as sub-Saharan African countries. Energy price effects might be captured by both time dummies (changing world market prices for energy products) and country dummies (e.g. energy-importing landlocked countries typically being exposed to higher energy prices). Econometric reasoning further underpins the importance of including times dummies. As pointed out by Roodman (2006) their inclusion makes the assumption of no contemporaneous correlation across individuals more likely to hold, which is necessary for the validity of Arellano-Bond autocorrelation tests and the estimation of robust standard errors in GMM estimation.

s^{Aene} and, respectively, a^{ene} can have countervailing effects on e. On the one hand, aid for more effective energy policy and administration as well as for training, education and research in energy should reduce e. On the other hand, the energy intensity - as captured by official statistics - could rather increase if the focus of aid is on expanding private access to energy, for example through expanding the electricity grid to remote areas. This could result in higher reported energy intensity until better access to reliable energy sufficiently raises GDP by inducing additional income generating activities.

Policy statements and strategy papers of donors stress both access to energy by the poor and more efficient use of energy as important objectives.[5] However, access considerations appear to have dominated donor efforts in the past, notably in the poorest recipient countries where large parts of the population lacked access.[6] Indeed, the distribution of energy aid across so-called purpose codes indicates that items which could have reduced e directly played a minor role even in the recent past. Taken together, energy policy and administration, energy education and training, and energy research accounted for 19 per cent of total commitments in the energy sector by all donors in 1995-2007 (OECD 2009b).[7]

Similar considerations apply to the emission intensity c, which depends on the share of fossil fuels in all energy sources.[8] Again, investment can be directed into more or less emission intensive facilities so that the impact of i on c is ambiguous. Investment would reduce c to the extent that it is used for installing modern renewable energy sources

[5]For instance, when outlining its medium-term aid policy in 1999, the Japanese Ministry of Foreign Affairs rated energy problems to "constitute a global-scale policy issue that is closely related to the response to global environmental problems and the achievement of sustainable development. Moreover, in many developing countries, securing access to adequate energy supplies constitutes to be a vital challenge in the realization of economic development" (`http://www.mofa.go.jp/policy/oda/summary/1999/ref2_02.html`). For a recent strategy paper, see BMZ (2007).

[6]The World Bank estimates that 1.6 billion people in developing countries still have no access to electricity (`http://web.worldbank.org/WBSITE/EXTERNAL/NEWS/0,,print:Y~isCURL:Y~contentMDK:21513875~menuPK:34480~pagePK:64257043~piPK:437376~theSitePK:4607,00.html`http://web.worldbank.org/WBSITE/EXTERNAL/NEWS/0,,print:Y isCURL:Y contentMDK:21513875 menuPK:34480 pagePK:64257043 piPK:437376 theSitePK:4607,00.html).

[7]See Auer (2006) for a case study of a small-scale, knowledge-oriented aid project in Mexico that aimed at improved energy efficiency in local companies through donor-sponsored educational seminars.

[8]Note that emissions from the traditional use of biomass for cooking and heating, which is of major importance in developing countries amounting to around 80 per cent of global bioenergy use, are not included in available emissions data. The WDI's CO_2 emission series covers only those emissions "stemming from the burning of fossil fuels and the manufacture of cement" (World Bank 2008). This is reasonable considering that the pure burning of biomass is climate-neutral (neglecting emissions from land use change and the release of soil carbon) as the carbon dioxide released during combustion was previously captured by the plants.

such as hydro, wind and solar power. On the other hand, investment in inefficient, conventional coal power plants would cause c to rise. Likewise, the impact of g on c is ambiguous. In earlier stages of economic development, countries may satisfy their rapidly growing energy demand by employing any low-cost energy technologies. Coal power in China represents a case in point. In later stages, countries may shift to "clean" technologies.

Aid may help reduce c. Advanced donor countries are capable of developing and applying efficient technologies. At the same time, various donors consider aid to be a means of fostering the spread of "climate friendly", low-carbon technologies such as hydro, wind and solar power. Indeed, recent donor funding of renewable energy and energy efficiency has increased considerably. According to the project-based classification of Hicks et al. (2008), multilateral and bilateral donors granted US-$ 7.5 billion for renewable energy and energy efficiency in the 1990s, compared to just US-$ 2.3 billion in the 1980s.

Yet there are several reasons to expect rather small effects of past aid efforts on the emission intensity c. As concerns aid for energy, critics suspect that major donors have hardly changed course. Yamaguchi (2005: 421) concludes from reviewing Japanese aid that "energy-related ODA has changed little despite pledges since the late 1980s to increase environmentally friendly projects." The World Resources Institute finds that more than 80 per cent of the World Bank's lending in the energy sector in 2000-2004 did not consider climate change issues in project appraisals (Sohn et al. 2005). The CRS database reveals that aid for power generation from renewable sources was only a fraction (38 per cent) of aid for power generation from non-renewable sources in 1995-2007 (OECD 2009b). At the same time, so-called new renewable energy (geothermal, solar, wind, ocean, and biomass) accounted for just 4.3 per cent of total energy aid by all donors (OECD 2009b).

Furthermore, some donors such as the German Ministry for Economic Cooperation and Development (BMZ) admit that the overall results of technical cooperation in the 1980s and 1990s meant to promote renewable energy and adapted technologies were "mostly sobering" (BMZ 2007: 16), partly because financial cooperation was still concentrated on conventional energy systems. This implies that the effects of past aid efforts on the emission intensity in recipient countries largely depend on efficiency gains through aid financing of conventional energy sources.

Against this background, the equation for c is similar to that for e:

$$c = f(a, i, g, s^{Aind}, s^{Aene}, s^{ind}), \quad \forall\{r, t\} \tag{3}$$

3 Econometric model and data

We derive econometric formulations from equations (2) and (3) in order to quantify the effect of aid intensity $a = \frac{A}{G}$ on energy intensity $e = \frac{E}{G}$ and emission intensity $c = \frac{C}{E}$. We carry out dynamic panel regressions by applying OLS, GMM as well as LSDVC estimators (see below for details). In the baseline estimation, we only include total aid intensity as a regressor plus the controlling variables introduced in the previous section:

$$
\begin{aligned}
e_{rt} &= \beta_1 e_{rt-1} + \beta_2 a_{rt} + \beta_3 g_{rt} + \beta_4 i_{rt} + \beta_5 s^{ind}_{rt} + \varsigma_r + \tau_t + \epsilon_{rt} && (4)\\
c_{rt} &= \beta_1 c_{rt-1} + \beta_2 a_{rt} + \beta_3 g_{rt} + \beta_4 i_{rt} + \beta_5 s^{ind}_{rt} + \varsigma_r + \tau_t + \epsilon_{rt} && (5)
\end{aligned}
$$

These formulations imply that the current energy and emission intensities are determined by the corresponding intensities in the last period, total aid inflows relative to GDP, per-capita income, investment, and the share of industrial production in GDP. ς_r denotes country specific fixed effects, τ_t denotes year specific fixed effects;[9] country fixed effects are included in OLS estimations, but drop out when differencing in GMM estimations. ϵ_{rt} is the error term. All variables (dependent and lagged dependent variable and regressors) except share variables are in logs throughout the paper.

In the next step, we extend the baseline specifications by accounting for the structural composition of aid. More precisely, we include the share of aid for energy and, alternatively, the share of aid for industry as an additional regressor on both e and c,

[9]F-tests of joint significance justified the inclusion of time period fixed effects in most cases. An exception are the LSDVC estimations, where time FE were nevertheless retained for the sake of consistency.

denoted as s^{Asec} for sectoral aid share:

$$\begin{aligned} e_{rt} &= \beta_1 e_{rt-1} + \beta_2 a_{rt} + \beta_3 s^{Asec}_{rt} + \beta_4 g_{rt} + \beta_5 i_{rt} + \beta_6 s^{ind}_{rt} + \varsigma_r + \tau_t + \epsilon_{rt} \quad (6) \\ c_{rt} &= \beta_1 c_{rt-1} + \beta_2 a_{rt} + \beta_3 s^{Asec}_{rt} + \beta_4 g_{rt} + \beta_5 i_{rt} + \beta_6 s^{ind}_{rt} + \varsigma_r + \tau_t + \epsilon_{rt} \quad (7) \end{aligned}$$

Finally, we modify the baseline specification by substituting total aid inflows by sector-specific inflows of aid, a^{sec}, i.e. aid for energy or aid for industry.

$$\begin{aligned} e_{rt} &= \beta_1 e_{rt-1} + \beta_2 a^{sec}_{rt} + \beta_3 g_{rt} + \beta_4 i_{rt} + \beta_5 s^{ind}_{rt} + \varsigma_r + \tau_t + \epsilon_{rt} \quad (8) \\ c_{rt} &= \beta_1 c_{rt-1} + \beta_2 a^{sec}_{rt} + \beta_3 g_{rt} + \beta_4 i_{rt} + \beta_5 s^{ind}_{rt} + \varsigma_r + \tau_t + \epsilon_{rt} \quad (9) \end{aligned}$$

Data on CO_2 emissions, energy consumption, GDP (total and per capita) and industry value added as a percentage of GDP are taken from the World Development Indicators (World Bank 2008). Our panel covers almost 80 countries for which the relevant data are available and which are classified by the World Bank as *low income*, *lower middle income* and *upper middle income* countries.[10] The time frame is 1973-2005.

The aid data come from two OECD sources. The International Development Statistics (IDS, available at: `http://www.oecd.org/dac/stats/qwids`) provide time series for disbursements of total aid by members of the OECD's Development Assistance Committee to low and middle income recipient countries.[11] Studies on aid effectiveness such as the present one should preferably use aid disbursements, rather than aid commitments (Michaelowa and Weber 2007; Dreher et al. 2008). Commitments often do not lead to actual resource flows to the recipient country, or the actual flow may be considerably delayed. When it comes to sector-specific aid for energy and industry, however, sufficiently long time series are available only for aid commitments. Sector-specific commitments are reported in the second OECD source, the Creditor Reporting System (CRS, available at: `http://stats.oecd.org/Index.aspx?DatasetCode=CRSNEW`). CRS statistics for earlier years suffer from underreporting, but this problem can reasonably be assumed to affect all sector-specific aid items to essentially the same extent (Michaelowa and Weber

[10] See Appendix B for our country sample.

[11] We use aid series in constant prices. Comparable data are missing for non-DAC donors, e.g., Arab countries, and private aid from non-government organizations and corporations.

2007; Aldasoro et al. 2010).[12] Consequently, the share of, say, aid for energy in overall aid commitments to one particular recipient country is unlikely to be misreported in the CRS. Missing entries for sector-specific aid in the CRS are set to zero.[13]

Finally, we combine the sector-specific shares in committed aid with total aid disbursements when performing the estimations with sector-specific amounts of aid, instead of total aid, as explanatory variables, where sector-specific *sec* encompasses energy-specific *ene* and industry-specific *ind*. More precisely, we mitigate measurement problems by multiplying total aid disbursements from IDS, A_{rt}^{IDSdis}, with sector-specific aid shares based on commitments from CRS. Put differently, aid committed in one particular sector, A_{rjt}^{CRScom}, is adjusted by multiplying with the ratio of total IDS disbursements over total CRS commitments as in the equation below, where the subscript j refers to sectors.

$$A_{rjt} = A_{rjt}^{CRScom} \frac{A_{rt}^{IDSdis}}{\sum_j A_{rjt}^{CRScom}} \tag{10}$$

This yields sectoral aid $a_{rt}^{sec} = \frac{A_{rjt}}{G_{rt}}$ as a substitute for total aid and sectoral aid shares $s_{rt}^{Asec} = \frac{A_{rt}^{IDSdis}}{\sum_j A_{rjt}^{CRScom}}$ required for the estimations.

All aid data enter the regressions as three-year moving averages. This is standard practice in the aid literature: Annual aid flows, in particular sector-specific aid, tend to be volatile so that it is advisable to smooth the data (Gupta et al. 2006).

Our dataset extends over a thirty-year period though the average number of time periods per country actually available for estimation ranges around 20 due to the unbalancedness of our sample. Descriptive statistics and bivariate correlations are provided in Appendix A.

[12]It is difficult to conceive that donors underreported aid only in some sectors.

[13]This follows logically from the assumption that underreporting is not sector-specific; as long as there is at least one positive entry for any sector in the CRS database for a particular donor and year, it can then be ruled out that positive commitments go unreported for the sectors of interest here, i.e., energy and industry.

4 Estimation

4.1 Methodological remarks

Given the time dimension of our sample, a discussion about the appropriateness of OLS (ordinary least squares) versus GMM (generalized method of moments) techniques is warranted. We start out with OLS regressions, including country and period fixed effects. However, including the lagged dependent variable as a regressor in a model with a fixed time dimension T leads the OLS fixed effects estimator to be biased. This bias is serious for small T as pointed out by Nickell (1981).

Given the time dimension of our sample, a discussion about the appropriateness of OLS versus generalized method of moments (GMM) techniques is warranted. We start out with OLS regressions, including country and period fixed effects. However, including the lagged dependent variable as a regressor in a model with a fixed time dimension T leads the OLS fixed effects estimator to be biased. This bias is serious for small T as pointed out by Nickell (1981). The endogeneity of the lagged dependent variable that induces the bias can be addressed by a variety of IV/GMM techniques. Arellano and Bond (1991) have developed an instrumental variable technique that first-differences the data and uses lags of the dependent variable in levels in order to instrument for the differenced lagged dependent variable included as a regressor.

The lagged-dependent-variable bias becomes less serious when T grows larger. Yet, Judson and Owen (1999), following the work of Kiviet (1995), find that even with $T = 30$, the LSDV (least squares dummy variable) estimator displays a bias of 3-20 per cent. Comparing different GMM estimators, they find evidence for the one-step GMM estimator outperforming two-step estimation and that a "restricted GMM procedure" – using less instruments than available – does not significantly hamper the performance of GMM estimation (Judson and Owen 1999:13). They conclude that the LSDVC (corrected least squares dummy variable estimator) consistently outperforms other techniques based on a RMSE (root mean square error) criterion. The LSDVC estimator has been made available for unbalanced panels by Bruno (2005a/b).

Attanasio et al. (2000) examine the appropriateness of different estimation techniques in a study on saving, growth and investment linkages for panels with a cross-sectional range of 38 to 123 countries and a time dimension range of 24 to 34 years.

They argue that with the data dimensions at hand one should resort to estimation techniques that make use of T asymptotics, rather than using estimators that have been developed for micro panels exploiting N asymptotics. Attanasio et al. run both OLS and GMM regressions for the different data sets and find GMM estimates to be less precise. They conclude that "when T is big enough, the bias that comes with an OLS estimator of a dynamic model is to be preferred to the loss of precision that follows the implementation of an instrumental-variable procedure" (Attanasio et al. 2000:200).

Bruno (2005a) builds upon previous Monte Carlo studies and introduces a bias corrected LSDV estimator for unbalanced panels. Bruno (2005b) develops the STATA routine xtlsdvc that implements the newly developed estimator and allows the estimation of a bootstrap variance-covariance matrix for this estimator. Monte Carlo evidence is provided that compares three different LSDVC estimators to the uncorrected LSDV, Anderson and Hsiao (1982), Arellano and Bond (1991) and Blundell and Bond (1998) estimators. According to both bias and RMSE criteria, the LSDVC estimator outperforms the others for samples with a comparatively small cross section. Bruno (2005b) thus provides strong evidence favouring the use of the LSDVC estimator over IV/GMM methods for the samples constructed as part of his Monte Carlo study$(N, \bar{T}) = (20, 20)$ and $(N, \bar{T}) = (10, 40)$.

All in all, these methodological contributions strongly suggest to perform OLS and LSDVC estimations, rather than exclusively relying on GMM estimations in a macro panel such as the one we use. We therefore provide results from all three estimation techniques in the subsection to follow.

4.2 Results

Table 2 presents results for various model specifications estimated by OLS including country fixed effects. In panel A of the table, energy intensity represents the dependent variable. The base specifications reported in column (1) includes the lagged dependent variable, total aid GDP per capita, and the investment share as regressors. The lagged dependent variable is highly significant, indicating that the energy intensity of production is strongly path dependent. A higher level of economic development lowers energy intensity as expected: An increase in per-capita income by 1 per cent is associated with a decline in e by almost 0.1 per cent. Similarly, investment is negatively correlated with energy intensity, though only at the 10 per cent level of significance in the base specification.

Turning to our variable of principal interest, total aid intensity enters highly significant at the one per cent level and negative in column (1). The negative correlation between total aid and energy intensity corroborates Hübler and Keller (2010). However, the quantitative impact of aid on energy intensity appears to be small. Taken at face value, the coefficient suggests that it would require a permanent doubling of annual aid efforts in order to reduce the energy intensity by about 1.5 per cent.[14] The long-run impact of aid is considerably higher, however. Taking the coefficient of the lagged dependent variable into account to assess long-run effects, a doubling of aid would reduce the energy intensity by more than 9 per cent.[15]

In column (2), we include the industry share as an additional controlling variable.[16] However, this variable remains insignificant and hardly affects previous results.[17] The same applies to the extended specifications reported in columns (3) and (4) where we enter the sectoral aid share variables, in addition to total aid intensity. The significance and size of the coefficient of total aid decline just slightly, compared to columns (1) and (2), while the coefficients of both share variables are far from conventional significance levels. Likewise, we do not find significant aid effects on the energy intensity when replacing total aid by the amounts of sector-specific aid in columns (5) and (6). Unless more reliable data on sector-specific aid become available, it is hard to decide whether the poor results on these variables are mainly due to deficient data and underreporting. Alternatively, our results may indicate that the fungibility of project-related aid undermines donor attempts to tie the recipients' hands.

As for the results on emission intensity as the dependent variable, panel B of Table 2 resembles panel A in that the specifications with total aid in columns (1) and (2)

[14]Note that G8 leaders promised to double aid to Africa at the summit in Gleneagles, Scotland, in 2005. Climate change and aid to Africa represented major topics of discussion in Gleneagles; for details, see: `http://www.unmillenniumproject.org/press/g8overview.htm`.

[15]Referring to equations (4)-(9), the long-run effect of aid on the dependent variable is given by $\frac{\beta_2}{1-\beta_1}$.

[16]As mentioned earlier, we also performed estimations with the share of energy-intensive exports in total exports as an additional controlling variable. These estimations are not shown in the tables as this variable turned out to be insignificant throughout.

[17]Nevertheless, we retain s^{ind} as it does turn out significant with emission intensity on the left-hand side.

offer the most relevant findings. Furthermore, emission intensity is almost as path dependent as energy intensity, indicated by the size and significance of the coefficient of the lagged dependent variable. Nonetheless, the effects on emission intensity contrast sharply with those on energy intensity. The coefficient of per-capita GDP switches sign, i.e., rising income leads to higher emission intensity at the five per cent level of significance. The same happens to the investment share which is robustly positively correlated with emission intensity. This also holds for the industry share, which was insignificant before.

All this reveals a shift towards a "dirtier" fuel mix in the course of economic development in our sample of developing countries and emerging economies. Rising income leads to more fossil fuel use. The switch from traditional biomass use to the use of more "advanced", but also more CO_2 emitting fossil fuels is reinforced by more investment and a higher industry share. The burning of biomass is commonly considered to be carbon-neutral so that there are no related emissions which would show up in the statistics (see footnote 8). Hence, the replacement of biomass by fossil fuels has an unambiguously positive effect on the overall amount of emissions. Energy statistics, by contrast, cover all primary sources of energy, including (traditional) biomass use so that the effect of the shift from biomass to fossil fuel on energy use measures is not as clear cut.

Most interestingly in the present context, foreign aid does not work against this shift towards a "dirtier" fuel mix. In other words, according to our results the effectiveness of aid in reducing the energy intensity in recipient countries does not carry over to emissions. The coefficient of the aid variable even turns positive in panel B of Table 2, though failing to pass conventional significance levels.[18] This invites the tentative conclusion that aid is unlikely to help fight climate change beyond reducing the energy intensity in recipient countries.

– *Table 2 about here* –

As a matter of fact, all important OLS results hold for the LSDVC estimations reported

[18]It may be noted that in unreported specifications without the investment share as a controlling variable, aid and emission intensity did display a significantly positive correlation.

in Table 3. We have chosen the Anderson and Hsiao estimator as an initial estimator and opted for a bias correction up to order $O(1/NT^2)$. In order to calculate the bootstrap variance-covariance matrix, 100 repetitions were used.

Comparing the uncorrected OLS results with the corrected estimations reveals a considerable degree of robustness. OLS might actually be the appropriate estimator given the panel dimensions at hand, considering that accounting for the potential bias induced by the inclusion of the lagged dependent variable hardly alters our results. One thing to point out is that time dummies are insignificant in most LSDVC estimations. We retained them nevertheless for the sake of consistency with the uncorrected OLS and the GMM estimations where time dummies prove to be significant.

As concerns our principal interest in the effectiveness of foreign aid, the contrast between the results with energy intensity and, respectively, emission intensity as the dependent variable is as striking as before. Again, total aid is strongly and negatively correlated with energy intensity in panel A. The short-term impact, as given by the coefficients of the aid variable, is almost the same as in Table 2. The long-run effect increases somewhat, when comparing columns (1) of panels A in Tables 3 and 2 (11.7 versus 9.3 per cent if donors doubled aid). At the same time, aid once again appears to be ineffective in reducing the emission intensity.

– *Table 3 about here* –

We finally report results for GMM estimations following Arellano and Bond (1991) in Table 4 in order to account for the potential bias introduced by having the lagged dependent variable on the right-hand side. Furthermore, we account for possible endogeneity of aid. We use the STATA device *xtabond2* introduced by Roodman (2006). This package offers Windmeijer corrected standard errors in two-step estimation.[19]

A critical issue when estimating macro panels with GMM methods is the number of instruments included, which increases quadratically in T. Roodman (2009) challenges as too liberal the rule of thumb according to which it is sufficient to keep the number of instruments below N, the number of cross sections. Another issue is that precisely the

[19]According to Roodman (2006), this renders two-step estimation somewhat superior to one-step estimation leading to lower bias and standard errors.

Sargan and Hansen J-tests used for testing specification and more specifically instrument validity become weak with too many instruments.[20] In order to reduce the instrument count, Roodman (2009) proposes to collapse the instrument matrix and/or to reduce the lag depth used as instruments. We opt for the combination of both measures. We thus instrument for the lagged dependent variable and the aid variables using available lags 1 to 20.[21] As can be seen in Table 4, the Hansen statistics approve of our chosen specification. We also report the p-value associated with the Difference-in-Hansen statistic that tests for the validity of the assumption of regressors being exogenous. We do not reject the null and therefore conclude that our specification is accepted.

As discussed above, there are reasons to consider LSCDV estimations superior to GMM estimations in the present panel context. Nevertheless, it is reassuring that major results do hold in Table 4. This is even though some of our controlling variables are no longer significant. This refers to the investment share in particular, which turns out to be completely insignificant in both panels of Table 4. The picture on per-capita GDP is ambiguous: Its negative effect on energy intensity strengthens considerably, while its positive effect on emission intensity is no longer significant at conventional levels (except for the base specification in column 1).

As for the aid variables, the negative impact of total aid on energy intensity is generally maintained. While the significance level declines to the 10 per cent level in columns (1) and (2) in panel A, the size of the coefficients increases considerably. The short-run impact of total aid on energy intensity would still be small, with a doubling of aid leading to a 3-4 per cent decrease in energy intensity. The long-run effect would increase further to 16 per cent according to the coefficients of the aid variable and the lagged dependent variable in the base specification in column (1).

It is interesting to note that the GMM estimations also provide some evidence that sector-specific aid may be effective in reducing the energy intensity in recipient countries. More precisely, aid related to energy projects enters significantly negative, at the five per cent or better, when additionally included as a share in total aid (column

[20] According to Roodman (2009), the Sargan test is less sensitive to too many instruments, but this apparent advantage comes at the expense that errors need to be homoskedastic for consistency, which is rarely the case. We therefore only report the Hansen J-test.

[21] This essentially means y_{t-2} to y_{t-21} for y being the dependent variable and aid_{t-1} to aid_{t-20} for the aid variables. In the specifications including a sectoral aid share, which is also treated as endogenous, the number of lags per endogenous variable is reduced further to 15.

3) or when energy-specific aid flows replace total aid flows (column 5). However, the quantitative impact of aid for energy appears to be very small in column (5), even in the log run (just two per cent if donors doubled aid for energy). Furthermore, we caution against reading too much into this GMM result, recalling the insignificance of sector-specific aid in previous OLS and LSCDV estimations. The same applies to the significantly positive correlation between aid in the industrial sector and the emission intensity in column (6) on panel B. It deserves to be stressed, however, that the GMM estimations with emission intensity as the dependent variable underscore our previous finding according to which aid does not help fight climate change beyond improving energy efficiency.

– Table 4 about here –

5 Summary and conclusions

Global carbon emissions cannot be contained effectively without reducing the strong growth in emissions in various developing countries and emerging economies. At the same time, the so-called Bali Road Map requires advanced OECD countries to provide substantial financial and technical assistance to strengthen the incentives and capability of relatively poor economies to take part in fighting climate change. Calls for scaling up foreign assistance, e.g. in form of internationally financed technology funds, have attracted most attention in the context of the Copenhagen summit on climate change in December 2009. Surprisingly, empirical evidence is largely lacking on whether more generous aid funding would be sufficient to achieve energy and climate-related goals.

It is through various channels that foreign aid may affect energy use and carbon emissions in the recipient countries. In this paper, we focus on the direct effects of the overall amount as well as the composition of aid on specific outcome variables, i.e., the energy intensity of production and the emission intensity of energy use. By accounting for specific aid items such as aid for energy projects, we address the proposition that donors may improve the effectiveness of aid by tying the recipients' hands. Another contribution to the existing literature is that we perform dynamic panel GMM and

LSDVC estimations, in addition to OLS regressions, for a large panel covering almost 80 developing countries and the period 1973-2005.

We find that the total inflow of aid tends to be effective in reducing the energy intensity of production in recipient countries. The effect of total aid on energy intensity proves to be robust to changes in the specification and also holds across different estimation strategies. The quantitative effect is rather small, however. For instance, the basic LSDVC estimation reveals a reduction in energy intensity by about 12 per cent in the long run if donors kept their promise to double annual aid efforts. Substantial improvements in energy intensity would thus require huge financial transfers. Consequently, our results suggest targeting aid better to where energy savings can be achieved effectively. Another implication is that aid can at best complement local policies for improving energy efficiency and preventing wasteful use of energy, notably by discontinuing the subsidization of fossil fuel consumption in many countries.

In contrast to energy intensity, the carbon intensity of energy use is hardly affected by total aid, possibly because of lacking incentives to reduce emissions in the recipient countries. Again, this result is strikingly robust across OLS, LSDVC and GMM estimations. Scaling up aid efforts would thus be insufficient to fight climate change beyond improving energy efficiency. The incentives for emission savings could be strengthened through a carbon price or through targeted financial and technological assistance. The issue of carbon prices could be addressed in a future CDM (clean development mechanism), while a technology fund might help target foreign assistance.

Our estimations with sector-specific aid offer surprisingly few additional insights. In particular, aid for energy-related projects typically fails to reduce either energy intensity or emission intensity. This holds not only when we extend the basic specification by sectoral aid shares, but also when we replace total aid flows by flows of aid for energy or aid for industry. High fungibility of sector-specific aid may explain these findings. For instance, by redirecting local funds to purposes disliked by foreign donors, the recipients could render ineffective the donors' attempts to tie the recipients' hands by project-related funding in the energy sector. On the other hand, the responsibility for limited effectiveness of sector-specific aid may rest with the donors themselves. The effectiveness of aid in the energy sector could be improved if donors redirected aid from funding of power generation and non-renewable energy sources to funding of energy efficiency improvements and renewable energy sources. This may also occur indirectly through aid for energy policy, research and education. This issue shall be addressed in future research once a detailed breakdown of aid data will be available for a sufficiently long time period.

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Appendices

A Descriptive statistics

Table A.2: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
energy intensity (kg oil equivalent / constant 2000 US$)	2491	0.895	0.838	0	6.220
emission intensity (kg / kg oil equivalent)	2282	1.977	1.374	0.021	24.997
total aid /GDP	3247	0.129	0.160	-0.001	1.362
sectoral aid energy / GDP	3109	0.006	0.022	-0.001	0.940
sectoral aid industry / GDP	3109	0.005	0.012	0.000	0.173
aid-for-energy share	3529	0.057	0.086	0	0.751
aid-for-industry share	3529	0.041	0.071	0	0.600
GDP per capita (constant 2000 US$)	3845	1554.9	1615.6	56.5	9929.9
Industry, value added (% of GDP / 100)	3505	0.217	0.092	-0.238	1.136
Gross fixed capital formation, (% of GDP / 100)	3601	0.287	0.127	0.019	0.942

Table A.3: Correlation matrix

	$log(e_{t-1})$	$log(c_{t-1})$	$log(a)$	$log(a^{ene})$	$log(a^{ind})$	s^{Aene}	s^{Aind}	$log(g)$	s^{ind}	i
lagged log(energy intensity)	1									
lagged log(emission intensity)	-0.47	1								
log(total aid / GDP)	0.45	-0.53	1							
log(sectoral aid energy / GDP)	0.31	-0.34	0.62	1						
log(sectoral aid industry / GDP)	0.26	-0.36	0.68	0.56	1					
aid-for-energy share	-0.02	0.07	-0.15	0.44	0.03	1				
aid-for-industry share	-0.15	0.10	-0.14	0.02	0.42	0.17	1			
log(GDP per capita)	-0.78	0.65	-0.69	-0.49	-0.45	0.02	0.14	1		
industry share	-0.23	0.45	-0.35	-0.22	-0.18	0.05	0.17	0.45	1	
investment share	-0.13	0.34	-0.17	0.05	-0.04	0.23	0.14	0.27	0.42	1

B Sample of countries

Table B.1: Sample of countries included in estimations

Albania	Croatia	Lebanon	Sri Lanka
Algeria	Dominican Republic	Libya	Sudan
Angola	Ecuador	Macedonia	Syria
Argentina	Egypt	Malaysia	Tajikistan
Armenia	El Salvador	Mexico	Tanzania
Azerbaijan	Ethiopia	Moldova	Thailand
Bangladesh	Gabon	Morocco	Togo
Benin	Georgia	Mozambique	Tunisia
Bolivia	Ghana	Namibia	Turkey
Bosnia	Guatemala	Nepal	Turkmenistan
Botswana	Haiti	Nicaragua	Uruguay
Brazil	Honduras	Nigeria	Uzbekistan
Cameroon	India	Oman	Venezuela
Chile	Indonesia	Pakistan	Vietnam
China	Iran	Panama	Yemen
Colombia	Jamaica	Paraguay	Zambia
Congo, Dem. Rep.	Jordan	Peru	Zimbabwe
Congo, Rep.	Kazakhstan	Philippines	
Costa Rica	Kenya	Senegal	
Cote d'Ivoire	Kyrgyz Republic	South Africa	

Tables to be inserted in the text

Table 2: OLS regressions

dependent variable	*Panel A: log(energy intensity)* (1)	(2)	(3)	(4)	(5)	(6)	*Panel B: log(emission intensity)* (1)	(2)	(3)	(4)	(5)	(6)
log(lagged dependent)	0.841***	0.838***	0.814***	0.815***	0.813***	0.822***	0.777***	0.766***	0.756***	0.755***	0.727***	0.753***
	(58.52)	(57.80)	(32.90)	(33.14)	(27.99)	(28.16)	(29.49)	(31.15)	(27.44)	(27.70)	(23.58)	(25.82)
log(total aid)	-0.0148***	-0.0156***	-0.0123**	-0.0123**			0.0139	0.0121	0.00956	0.0101		
	(-3.23)	(-3.05)	(-2.54)	(-2.55)			(1.52)	(1.26)	(0.94)	(0.99)		
log(sectoral aid energy)					-0.00192						0.00165	
					(-1.54)						(0.80)	
log(sectoral aid industry)						-0.00235						0.00266
						(-1.52)						(1.08)
aid-for-energy share			-0.0177						0.0162			
			(-0.82)						(0.47)			
aid-for-industry share				-0.00625						-0.0648		
				(-0.12)						(-1.24)		
log(GDP per capita)	-0.0878***	-0.0816***	-0.0859***	-0.0857***	-0.0626**	-0.0709***	0.100**	0.0892**	0.105**	0.107**	0.0777*	0.0996**
	(-4.50)	(-3.96)	(-3.42)	(-3.42)	(-2.64)	(-2.81)	(2.40)	(2.00)	(2.21)	(2.28)	(1.84)	(2.43)
investment share	-0.0661*	-0.0991***	-0.0900**	-0.0921**	-0.100**	-0.106***	0.318***	0.274***	0.231***	0.236***	0.336***	0.213**
	(-1.84)	(-2.74)	(-2.28)	(-2.32)	(-2.45)	(-2.66)	(3.23)	(3.06)	(2.84)	(2.88)	(3.26)	(2.54)
industry share		-0.0197	-0.0243	-0.0231	0.0276	-0.0159		0.352***	0.297**	0.297**	0.287**	0.393**
		(-0.48)	(-0.48)	(-0.46)	(0.63)	(-0.31)		(2.93)	(2.18)	(2.18)	(2.13)	(2.44)
constant term	-0.626***	-0.678***	-0.812***	-0.809***	-0.950***	-0.831***	0.917***	0.975***	0.945***	0.944***	1.292***	0.955***
	(-4.97)	(-4.89)	(-4.47)	(-4.46)	(-4.90)	(-4.48)	(2.98)	(3.07)	(2.82)	(2.84)	(4.92)	(3.04)
Number of observations	1890	1779	1713	1713	1397	1540	1886	1775	1713	1713	1397	1540
Number of countries	77	77	77	77	76	76	77	77	77	77	76	76
Average time periods per country	24.55	23.10	22.25	22.25	18.38	20.26	24.49	23.05	22.25	22.25	18.38	20.26
R^2 (adjusted)	0.882	0.884	0.859	0.859	0.835	0.858	0.694	0.702	0.678	0.678	0.650	0.683
F test time dummies (p-value)	0.000	0.001	0.001	0.001	0.001	0.000	0.001	0.003	0.003	0.002	0.002	0.012

t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: LSDVC regressions

dependent variable	*Panel A: log(energy intensity)*						*Panel B: log(emission intensity)*					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
log(lagged dependent)	0.873***	0.885***	0.845***	0.846***	0.855***	0.859***	0.841***	0.830***	0.827***	0.828***	0.854***	0.835***
	(35.66)	(22.77)	(26.52)	(24.86)	(11.67)	(15.04)	(42.88)	(46.70)	(41.12)	(41.36)	(27.73)	(31.80)
log(total aid)	-0.0149***	-0.0163***	-0.0131***	-0.0133***			0.0136	0.0117	0.00913	0.0100		
	(-3.39)	(-3.14)	(-2.59)	(-2.64)			(1.51)	(1.20)	(0.90)	(1.01)		
log(sectoral aid energy)					-0.00175						0.00312	
					(-0.77)						(0.69)	
log(sectoral aid industry)						-0.00254						0.00363
						(-1.09)						(0.73)
aid-for-energy share			-0.0196						0.0223			
			(-0.66)						(0.38)			
aid-for-industry share				-0.00603						-0.0575		
				(-0.18)						(-0.87)		
log(GDP per capita)	-0.0652***	-0.0782***	-0.0447**	-0.0447*	-0.0172	-0.0314	0.0643*	0.0565*	0.0723**	0.0724**	0.0587	0.0613
	(-3.23)	(-2.99)	(-2.04)	(-1.91)	(-0.38)	(-0.80)	(1.77)	(1.71)	(2.22)	(2.22)	(1.11)	(1.47)
investment share	-0.109**	-0.150**	-0.132***	-0.136***	-0.156*	-0.164**	0.311***	0.274***	0.225**	0.236**	0.367**	0.237*
	(-1.97)	(-2.53)	(-2.62)	(-2.68)	(-1.88)	(-2.58)	(3.48)	(2.84)	(2.26)	(2.37)	(2.09)	(1.74)
industry share		0.00799	-0.0289	-0.0275	0.0336	-0.0194		0.276***	0.233**	0.236**	0.237	0.322**
		(0.14)	(-0.57)	(-0.52)	(0.39)	(-0.24)		(2.96)	(2.29)	(2.31)	(1.20)	(2.01)
Number of observations	1890	1779	1397	1540	1713	1713	1886	1775	1397	1540	1713	1713
Number of countries	77	77	76	76	77	77	77	77	76	76	77	77
Average time periods per country	24.5	23.1	18.4	20.3	22.2	22.2	24.5	23.1	18.4	20.3	22.2	22.2
F test time dummies (p-value)	0.788	0.926	0.968	0.280	0.498	0.536	0.292	0.249	0.867	0.317	0.056	0.080

t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: GMM regressions

dependent variable	*Panel A: log(energy intensity)*						*Panel B: log(emission intensity)*					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
log(lagged dependent)	0.778***	0.771***	0.470***	0.516***	0.563***	0.600***	0.786***	0.771***	0.837***	0.653***	0.892***	0.861***
	(8.67)	(9.45)	(4.96)	(4.34)	(5.05)	(4.43)	(10.75)	(9.16)	(8.33)	(7.30)	(8.16)	(6.87)
log(total aid)	-0.0359*	-0.0422*	-0.0543**	-0.0296			0.0257	0.0612	0.0288	0.0863		
	(-1.67)	(-1.98)	(-2.51)	(-1.32)			(0.61)	(1.23)	(0.61)	(1.29)		
log(sectoral aid energy)					-0.00878**						0.00202	
					(-2.40)						(0.30)	
log(sectoral aid industry)						-0.000887						0.00803*
						(-0.31)						(1.78)
aid-for-energy share			-0.142***						0.107			
			(-3.18)						(1.64)			
aid-for-industry share				0.00399						-0.116		
				(0.07)						(-0.76)		
log(GDP per capita)	-0.409***	-0.414***	-0.538***	-0.513***	-0.487***	-0.367***	0.145*	0.133	0.106	0.161	0.00331	0.0215
	(-5.45)	(-5.57)	(-6.84)	(-6.58)	(-7.10)	(-3.82)	(1.80)	(1.34)	(1.10)	(1.44)	(0.03)	(0.29)
investment share	0.0758	0.0516	0.0497	0.0425	0.121	0.00389	0.0675	0.0388	0.00255	0.0137	0.158	-0.0370
	(0.98)	(0.61)	(0.63)	(0.60)	(1.52)	(0.05)	(0.27)	(0.16)	(0.01)	(0.07)	(0.67)	(-0.23)
industry share		0.0766	0.0686	0.0577	0.0970	-0.00278		0.305*	0.410**	0.247	0.288	0.450*
		(0.85)	(0.74)	(0.79)	(1.37)	(-0.03)		(1.73)	(2.15)	(1.15)	(1.46)	(1.85)
Number of observations	1806	1693	1625	1625	1266	1418	1802	1689	1625	1625	1266	1418
Number of countries	77	77	77	77	76	76	77	77	77	77	76	76
Average time periods per country	23.5	22.0	21.1	21.1	16.7	18.7	23.4	21.9	21.1	21.1	16.7	18.7
F test time dummies (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.009	0.106	0.006	0.080	0.009
AR(2) ($prob > chi^2$)	0.16	0.060	0.45	0.46	0.35	0.12	1.00	0.80	0.74	0.74	0.51	0.39
Number of instruments	72	73	78	78	73	73	72	73	78	78	73	73
Hansen test ($prob > chi^2$)	0.26	0.29	0.68	0.61	0.88	0.28	0.37	0.41	0.23	0.63	0.21	0.70
Difference-in-Hansen ($prob > chi^2$)	0.23	0.23	0.55	0.56	0.80	0.22	0.27	0.32	0.25	0.68	0.15	0.49

t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$