Mitigating CO_2 emissions in developing countries: the role of foreign aid

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July 2017

Abstract

This paper empirically investigates the link between foreign aid and pollution, specifically CO_2 emissions in developing countries. We use a more complete and recent dataset to re-assess the environmental impact of foreign aid. Focusing on 112 aid recipient countries over the period 1980- 2013, we find that the effect of aid depends on the donor, with multilateral aid more likely to reduce pollution than bilateral aid for which we find no effect. However, when we more precisely look at the composition of bilateral aid, we find it has an effect when specifically targeted toward environment. This effect is non-linear, since we observe a pollution-reducing effect only for important amounts of bilateral environmental aid.

Keywords CO_2 emissions · Foreign aid · Environmental aid · Treshold effect

***JEL* Codes** E6 · F35 · O11 · Q53 · Q54

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1 Introduction

Aid is increasingly viewed as useful tool for shaping environmentally friendly policies, especially in developing countries. In 2009 in Copenhagen, developed countries pledged \$100billion per year as aid to developing countries for climate change mitigation and adaptation. In 2010, the climate conference held in Cancun set up the Green Climate Fund which role is to deal with the allocation of this amount. This highlights that aid is considered as an important instrument for shaping public policy, particularly environmentally friendly policies in this specific case.

Some empirical studies have paid attention to the effects of foreign aid on environmental protection in aid-recipient countries, but the literature is still inconclusive with mixed results (Arvin and Lew, 2009). Most recent studies (Lim et al., 2015) argue that the effect of aid is conditionned by other external flows such as trade or Foreign Direct Investments (FDI), and find a positive effect of aid on environmental protection which tends to be reversed for high values of these external flows. However, this finding relies on the "california effect" assumption (Prakash and Potoski, 2006) for which there is no real consensus in the literature. Moreover, the contrasted findings on aid seem to be associated to quality of aid data, as pointed out by Tierney et al. (2011), for who all aid studies have been driven by too little information because of incomplete data on foreign aid.

This paper empirically investigates the link between foreign aid and environmental degradation measured as CO_2 emissions in aid-recipient countries, using a more recent and more complete source of aid data. Compared to previous studies, we consider a much larger set of 112 countries over the 1980- 2013 period.

We find no statistically significant effect for total aid as previous studies (Lim et al., 2015); however, by disaggregating it, we find that the environmental impact of aid depends on the type of donor. In particular, multilateral aid turns out to be effective in reducing CO_2 emissions but not bilateral aid. Nevertheless, bilateral aid turns out to be effective if specifically targeted toward environment even though we find evidence of an inverted U-shape relationship between environmental bilateral aid and emissions, which implies that bilateral aid is only effective above the endogenously defined threshold of $10.57 per capita. This result highlights the need to increase environmental bilateral aid, because it is still insufficient for many countries in our study.

The rest of the paper is organized as follows. In section 2 we review the literature on the potential environmental impacts of foreign aid. The section 3 presents our data and empirical model, and the section 4 presents and discusses our results before we conclude in section 5.

2 Aid for environment: good or bad in fine?

The results of the literature concerning the environmental impact of foreign aid remain very mixed (Castro and Hammond, 2009). Some scholars suggest that aid can help to improve environmental quality. Tsakiris et al. (2005) mention that developed countries are increasingly involved in environmental protection during the recent years; therefore, they could use foreign aid as an incentive for recipient countries to provide public goods, in this case environmental protection, since developing countries take donor preferences into account in order to attract more aid (Hadjiyiannis et al., 2013): this competition for aid leads to efforts in terms of abatement in these countries. For others, environmental protection should be considered as a normal good; then, by promoting development and increasing citizens' incomes in developing countries, aid might indirectly lead to an increase in environmental protection in these countries as well, since the citizens' demand for this normal good will also increase (Arvin and Lew, 2009).

This last point is close to the Environmental Kuznets Curve theory (Grossman and Krueger, 1995) which suggests that there is an inverted U-shape relation between growth and environmental degradation. In fact, the underlying idea is that at the first stage of their development process, countries experience a high level of pollution due to a conflictual relation between growth and environmental protection; but beyond a certain level of development, because citizens' incomes increase, the demand for a cleaner environment becomes more important and we observe a decreasing level of pollution in the second stage of the process.

Also, according to Lim et al. (2015), this trade-off between growth and environmental protection is expected to be more pronounced in developing countries which are most in the first stage of the development process, and especially for governments which have no access to external resources and which are obliged to rely on domestic resources. This because such governments, given their low level of development coupled with a small tax base, participate in intensive resource plundering (Haber and Menaldo, 2011; Hamilton and Clemens, 1999), leading to environmental degradation. So, for such countries, aid could be considered as an additional "environmentally neutral"[1] revenue (Hicks et al., 2008) which allows them to partially relax this trade-off between economic growth and environmental protection. It could then be expected to be associated with an improvement of environmental quality.

However, it appears that considering aid as environmentally neutral could be in some sense risky to the extend that aid, even though it would have no direct effect on environment, could indirectly affect it through other channels. For instance, given the conflictual relation between economic growth and environmental protection (Grossman and Krueger, 1995), one could think that aid, which is first intended to promote development, is unlikely to enhance environmental protection while promoting economic growth. This because aid could reinforce this negative pressure growth has on environment: by stimulating economic growth, it may stimulate resource plunder or polluting industries.

[1] Hicks et al. (2008) suggest that aid has a neutral effect on environment since it is granted to recipient countries for different reasons(i.e natural disaster, democratization, economic development, etc.)

There are some studies which suggest that foreign aid creates bad incentives as it leads governments to delay important reforms (Ostrom et al., 2005), including environmental reforms. Also, it appears that aid mitigates the development of democratic institutions (Djankov et al., 2008) and works as a "resource curse" (Knack, 2001) because it frees governments from fiscal revenues and political support from their populations, leading them to under supply public goods, in this case environmental protection. Moreover, there is no guarantee that the aid granted for a specific sector will be totally dedicated to this sector because of fungibility. Several studies (Feyzioglu et al., 1998; Farag et al., 2009; Waddington, 2004) show that governments can reduce their spending in this sector and reallocate resources to others that seem to be of higher priority. Thus, all or part of the received aid is found to finance activities for which it was not intended for the base. Through this mechanism, aid can be granted for environmental protection but used by the recipient donor to finance other activities, including polluting ones. According to this, it might not be surprising to find a null or even a harmful effect of foreign aid on environment in some studies.

There are very few empirical studies that has been led on the link between foreign aid and environmental degradation. Most studies have just focused on specific environmental projects (Ross, 1996), a specific recipient country (Gutner, 2002) or a specific donor (Dauvergne et al., 1998). Indeed, the results remain inconclusive on the few existing ones that led analysis on a large set of countries. For instance, using a sample of developing countries, Arvin and Lew (2009) study the impact of foreign aid on three ecological indicators (CO_2 emissions, water pollution and deforestation) and find that while foreign aid helps reducing CO_2 emissions, it has an increasing effect on water pollution and deforestation. They conclude suggesting that "the economic and social conditions of individual recipient countries should be examined to understand such findings".

In the continuation of this, Lim et al. (2015) think such contradictory and inconclusive results are explained by the fact that the literature focuses on the average, unconditional, impact of aid. They suggest that other types resources flows from developed countries, such as trade and FDI inflows, might condition the effect of foreign aid. Using a sample of 88 countries over the 1980-2005 period, they find that aid is associated with superior environmental protection in the recipient country, at low levels of exports receipts and FDI inflows from developed countries, and that this positive effect tends to diminish or to be even reversed as these flows increase. This because aid frees these countries of their dependence to these flows and thus, of incentives for high environmental protection; this underlies on the somewhat heroic "california effect" hypothesis (Prakash and Potoski, 2006) and is totally challenged in the context of "pollution haven" hypothesis[2] (Eskeland and Harrison, 2003).

When it comes to the method of allocation, bilateral aid is much more criticized among scholars. Alesina and Dollar (2000) find that bilateral aid is more driven by political alliances or colonial past rather than the recipient country's performance. Following them, Dreher et al. (2008) use voting patterns at the United Nations to measure alignement between governements and show evidence that US aid is used to buy UN votes. Also using the voting patterns at the United Nations, Faye and Niehaus (2012) find that bilateral donors use aid to influence elections' results in recipient countries. Beyond these reasons, the exploitation of the recipient's market can also be a motivation for bilateral aid (Wagner, 2003). Thus, bilateral aid seems to be motivated by the personal interests of the donor country rather than by altruism; these results suggest that aid, including the one which is devoted to environmental protection, might have a weaker expected effect on the targeted goal if provided by a bilateral donor. Moreover, Michaelowa and Michaelowa (2011) find evidence that states often systematically miscode their aid, claiming it to contribute to climate change mitigation or adaptation

[2]The pollution haven hypothesis suggests that trade openess leads to an increase of pollution in developing countries through a relocation of dirty industries from the developed countries while the "california effect" suggests that trading with parters that have stringent environmental standards can lead to the transmission of these environmental preferences to the home country.

while in fact it does nothing related to that purpose. Their results help to understand why environmental effectiveness tests for aid sometimes produce either poor results or wrong interesting results.

Multilateral aid, on the other hand, appears to be less subject to criticism, this maybe because of two reasons according to Rodrik (1995): the first is due to information about recipients. Since the latter is a collective good, it might be underprovided by individual donors, while multilateral organisations are more likely to provide it, especially if it is necessary to monitor the recipient. The second argument is that the interaction between multilateral agencies and recipient countries is less politicized than those with bilateral donors. Multilateral assistance is also said to be more sensitive to recipients' interests and long-run development: it should then be expected to perform more than bilateral assistance (Lebovic and Voeten, 2009).

A final point, which seems to be not negligible in our view, was raised by Tierney et al. (2011) : it is "possible that aid debates have been driven by too little information" and that many results rely on very poor evidence because of very incomplete data on aid. It is therefore clear that environmental aid is no exception to this rule. They introduced a new dataset of foreign assistance, AidData, which they claim to cover more bilateral and multilateral donors and more types of aid than existing datasets[3]. They also claim it to improve project-level information about the activities funded by aid.

We contribute to this literature, using this dataset to assess the environmental effect of foreign aid according to the donor type. While the environmental effect of multilateral aid is not very surprising given its good reputation among scholars, we find that the relation between bilateral aid and CO_2 emissions is more complex.

[3]To provide an order of magnitude, they say in their article that "William Easterly, a contributor to this special issue, in his best-selling book *The White Man's Burden*(2006), pegged the sum of total aid since 1945 at $2.3 trillion, which is less than half of the total reported here".

3 Empirical framework

Our approach differs from earlier studies in different ways: First, we consider a much larger set of countries over the 1980- 2013 period because we use a more recent and more complete source of aid data, that helps to refine our understanding of aid. Second, we apply a rigourous coding scheme to disagregate our aid flows according to their environmental impact. This allows us to better assess its effect on pollution and not to make the trial of bilateral aid, since we show evidence of composition effects in its environmental impact. Finally, our econometric approach allows tackling endogeneity bias concerns, relative to the possible reverse causation link between pollution and environmental assistance.

3.1 Empirical model

Following Brock and Taylor (2010), we use the green Solow model, which predicts a convergence in per capita carbon dioxyde emissions. Their standard green Solow model is augmented here to take into account the role of Official Development Assistance (hereafter ODA) on environmental degradation which is measured by carbone dioxyde emissions per capita. The per capita CO_2 emissions process is modeled as:

$$Y_{it} = \phi_1 Y_{i,t-1} + \beta_1 ODA_{it} + X_{it}\beta_2 + \alpha_i + \tau_t + \epsilon_{it} \tag{1}$$

Where Y_{it} represents CO_2 emissions per capita in country i during period t. ϕ_1 is the coefficient of lagged per capita carbone dioxyde emissions. We are primarily interested in β_1 which is the coefficient of ODA and its subcomponents. X is the vector of control variables; these include domestic investment, population growth and democratic institutions. α_i and τ_t are the country and time fixed effects. The time coverage extends from 1980 to 2013 and we compile the data in five-years averages to hinder short-term fluctuations so that we obtain 7 periods. Our sample includes 112 countries that ever received ODA, based on data from the AidData web portal. Because of the lagged dependent variable included in our regressors, estimating this equation by a fixed effects model would lead our results to suffer from Nickell bias (Nickell, 1981) which may be severe given the short time-dimension of our data[4]. We use a GMM-type estimator because it is asymptotically efficient compared to OLS (Arellano and Bond, 1991; Arellano and Bover, 1995). Specifically, we rely on the GMM-system estimator of Blundell and Bond (1998) which is deemed to be more consistent than its predecessors. It estimates a system of two equations: one equation in level and the other in first difference[5]. It uses lagged variables in level as instruments for the equation in first difference and inversely, it uses lagged first difference variables as instruments for the equation in level. We also add another external instrument in addition to lags: CO_2 emissions of donor countries. To do so, we matched the CO_2 emissions data to bilateral aid data, using donor countries as key. We were then able to compute, for each recipient country and each period, the mean of its donors' emissions. Donor emissions reflect the environmental preferences of donors, and thus may affect their level of environmental aid provided. On the other hand, they cannot directly affect emissions from recipient countries.

In comparison to its predecessors which become less robust when ϕ_1 tends to 1, the GMM-system estimator adds an average stationarity condition on the dependent variable which makes it more robust. It is also appropriated for "small T, large N" panel datasets as ours (Roodman, 2009a). Given our relatively small number of periods, we confidently expect not to be confronted with the problem of instruments proliferation (Roodman, 2009b).

In order to test the validity of our results, we use Hansen's overidentification test, which null hypothesis states that the instrumental variables are not correlated to the

[4] Nickell (1981) shows that this bias if of order 1/T, where T represents the number of periods. Since we have 7 periods available, this bias would account for about 14%

[5] This approach allows to expunge the country fixed effects

error term and also the second order serial correlation test AR(2) which null hypothesis states that the errors do not present a second order serial correlation. We use the two-step version, which is more efficient, even if its standards errors can be biased[6] on small sample. However, we present the one-step version in robustness checks.

3.2 Data sources and description of variables

3.2.1 CO_2 emissions

Carbone dioxyde emissions is a widely employed pollution measure in the literature (Arvin and Lew, 2009; Brock and Taylor, 2010) and is at the center of all the debates relative to climate change. Moreover, beyond its global issue, data on CO_2 emissions are available for many countries and over relatively long periods in comparison to other pollution measures. We measure this variable, in terms of logged grams per capita. Consistent with the literature, we take the natural logarithm that exhibits close to a gaussian distribution. The data are from the World Bank Development Indicators (WBDI). In Figure 1, we use these data to compare CO_2 emissions from high income countries and low and middle income countries.

We observe that pollution remains very small in developing countries, compared to developed countries' emissions. Even though their emissions have been quiet stable during a long period, we can however observe a small upward trend starting from the 2000s that could be explained by an acceleration of industrialisation and growth in emerging economies. It is therefore clear that these countries are not primarily responsible for climate change, given their relatively small emissions, and may not find an incentive to participate in climate change mitigation. Thinking this way would be wrong because they are still the most vulnerable to climate change (Adger et al., 2003; Mirza, 2003). Then, in order to significantly and globally reduce emissions, it is necessary to break this upward trend in developing countries while simultaneously

[6]The Windmeijer correction (Windmeijer, 2005) is used to correct them

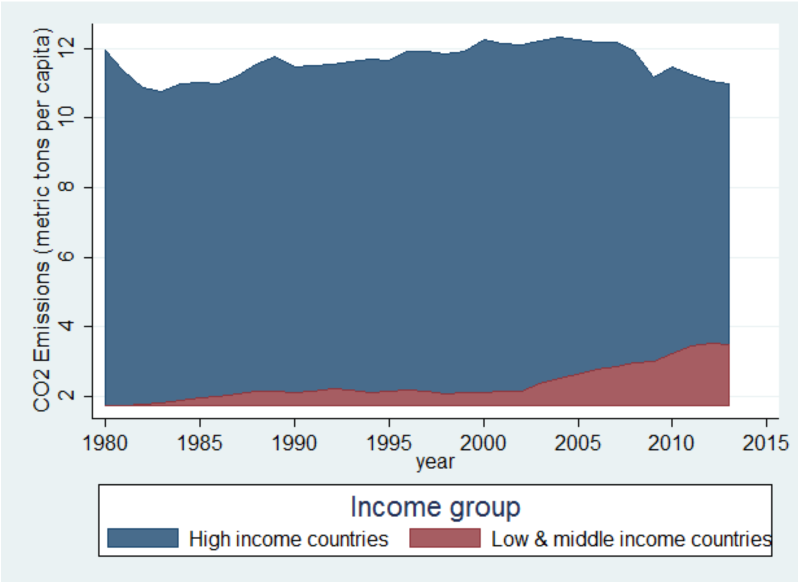

Figure 1: CO_2 Emissions per income group

reducing those in high-income countries, rather than just focusing on the latter. It is in this context that aid could be used as an instrument for mitigation.

3.2.2 Aid data

We rely on "project" level aid data[7] to more precisely assess the environmental impact of aid. This new dataset is available on the AidData web portal and includes more donors and more types of aid than existing datasets. Each aid flow is assigned a unique purpose code refering to a particular sector (health, education, etc.), using the OECD's Credidor Reporting System (CRS). Hicks et al. (2008), basing on these codes, used the 1.9 version of this data and assigned an environmental impact code (neutral, dirty, etc.) to each aid flow in the database, for the purpose of their study. Unfortunately, these environmental impact codes are not available on recent versions of the dataset: they

[7]As mentionned by Michaelowa and Michaelowa (2011), the aid activities that are listed in this database also include non-project aid, but since the vast majority of these activities are traditional aid projects, and since these distinctions do not really matter in our context, we can use the term "projects" when referring to these flows

are just available for the 1.9 version which stops in 2008. Since we are using the 3.0 version of the data that is more complete and filled in until 2013, we had to apply their coding scheme[8] to this version of the data, so that we obtain environmental impact codes for our data.

We applied the same methodology as Hicks et al. (2008) to provide these environmental impact codes (neutral, dirty, friendly) to each aid flow in our dataset, relying on its purpose. The repartition of ODA over our period of study and following its expected environmental impact is represented in Figure 2.

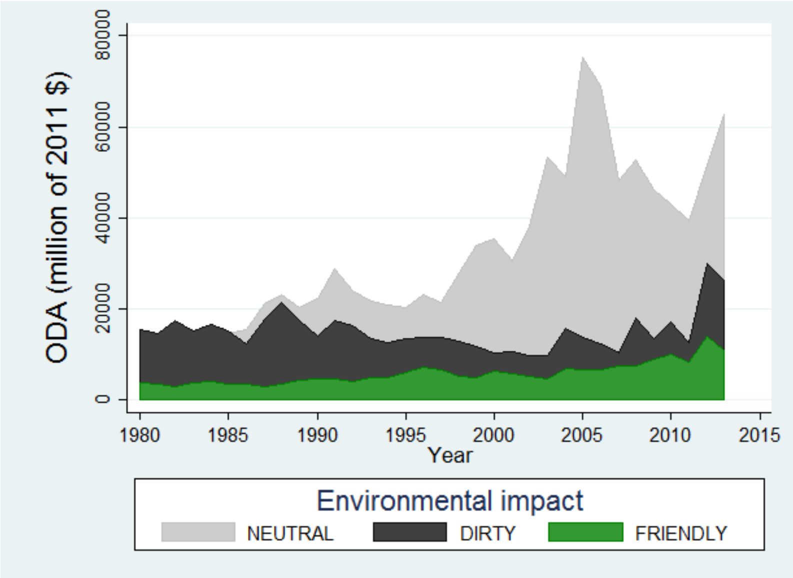

Figure 2: Repartition of ODA by environmental impact

As we see, environmental aid, still represents a very small share of total aid, compared to dirty or neutral aid flows. This provides a first answer to why several studies have failed to find evidence of environmental benefits of ODA, since its environmental friendly component represents a very small share, compared to dirty or neutral aid: the less is the share of environmentally friendly aid, the less likely for its effect to

[8]We are particularly indebted to the AidData research team who provided us the codebook which was used for coding the 1.9 version of the data. It was very useful for us to expand these codes on the 3.0 version

be detected. However, we observe that it is slightly increasing perhaps because of an awakening of consciousness on the part of certain donors. Relying on the foreign aid literature (Alesina and Dollar, 2000), we use ODA per capita (in constant 2011 dollars) in natural logarithm.

3.2.3 Control variables

We measure domestic investment as the ratio of gross capital formation to GDP. According to Brock and Taylor (2010) high investment rates increase carbon dioxide emissions per capita during transitional dynamics, since investments are the engine of economic growth. The data are from the WBDI.

We also control for population growth; for a given country i at period t, it is measured as the growth rate, in percent, of population over period t. There are studies which have analysed the impact population growth could have on environment (Birdsall and Sinding, 2001; Cropper and Griffiths, 1994). A larger population could lead to an increased demand for fuel, food, energy, industry and transportation. A fast population growth could also lead to increased deforestation, changes in land use and combustion of fossil fuels.

We use the *Polity 2 Score*, which is a measure for democratic institutions in a country, to capture the effect of regime type on environmental degradation. Indeed, there are studies that have focused on the impact democratic institutions could have on environment. While most recent studies find opposite direct and indirect effects (Kinda et al., 2011), previous researches find evidence of pollution reducing effects for democratic institutions (Bernauer and Koubi, 2009; Li and Reuveny, 2006). Moreover, democratic institutions influence the amount of foreign aid a country receives[9]. The data for this indicator are from Polity IV (2015) and its values lie between -10 (autocraty) and +10 (democraty).

[9] For instance, institutions are included in the Country Performance Rating of the Performance Based Allocation formula used by the World Bank International Development Association (IDA)

We also control for additional variables that could possibly confound the effect of aid on CO_2 emissions. These include trade openness and urbanisation rate. We measure trade openness as the share of trade flows in GDP, and urbanisation rate is measured as the share of urban population in total population.

There are two competing arguments on how the former could affect pollution in exporting countries: the "pollution haven" hypothesis (Eskeland and Harrison, 2003) which suggests that trade openness leads to an increase of pollution in developing countries through a relocation of dirty industries from the developed countries; and the "california effect" hypothesis (Prakash and Potoski, 2006) which suggests the opposite effect (Frankel and Rose, 2005). Exporting toward markets with stringent environmental standards could lead developing countries to adopt these standards at home, for instance (Perkins and Neumayer, 2012). Thus, the adoption of these stringent standards will result in lower emissions and then lead to an improvement of their own environmental quality. Trade openness can also affect the amount of received aid, since less opened countries can receive more aid as an incentive to liberalize their economies (Wagner, 2003).

Urbanisation is considered as a consequence of development (Moomaw and Shatter, 1996) and may then influence the amount of received aid since the latter is a function of the recipient's level of development[10]. ODA can also play a role in a country's urbanisation process, since it is supposed to promote development. Lastly, urbanisation can affect the level of pollution, according to some studies which argue that countries with higher urbanisation rates experience more environmental degradation (Shahbaz et al., 2014; Dewan et al., 2012).

Data on both, urbanisation rate and trade openness, are obtained from the WBDI database. The descriptive statistics of our main variables are provided in Table 1.

[10]The Performance Based Allocation formula which is used by the main Multilateral Development Banks includes the GNI

Table 1: Summary statistics of used variables

Variable	Obs	Mean	S.D	C.V	Min	Max
CO_2 per capita (metric tons)	865	1.82	2.36	1.30	0.002	16.41
ODA per capita ($ 2011)	882	84.91	218.76	2.58	0	4508.55
Bilateral ODA per capita ($ 2011)	882	69.57	204.29	2.94	0	4508.55
Multilateral ODA per capita ($ 2011)	882	14.04	40.44	2.88	0	834.72
Dirty Bilateral ODA per capita ($ 2011)	882	17.62	48.52	2.75	0	775.39
Environmental Bilateral ODA per capita ($ 2011)	882	5.12	11.65	2.28	0	161.42
Investment (% GDP)	755	22.70	8.61	0.38	0	60.78
Population growth (%)	881	7.56	5.36	0.71	-17.41	31.96
Polity 2 Score	752	0.61	6.36	10.50	-10	10
Urban population (% of total)	882	43.36	21.03	0.49	4.68	100
Trade (%GDP)	798	76.45	38.13	0.50	0.22	310.58

Notes Descriptive statistics are based on the whole sample

As we can see, our sample is characterized by a very high degree of heterogeneity, both for CO_2 emissions and other variables. This heterogeneity is more important for the aid variables compared to other variables, exception made for the *Policy 2 Score*.

On the other hand, we remark that the bilateral channel is still very privileged by the donors, since bilateral ODA is on average 5 times higher than multilateral ODA. We also observe that the environmentally friendly component of bilateral ODA remains very small compared to its dirty component, since it is on average 3 times smaller than the latter. Both are also characterized by an important heterogeneity as total bilateral aid.

4 Results

4.1 Baseline results

Our results from the two-step system GMM estimation are shown in Table 2. In column 1 and 2, we estimate the effect of ODA on CO_2 emissions and we find no statistically significant effect. This result is not very surprising since we are measuring the average overall effect of aid as previous studies (Lim et al., 2015) suggest. In fact, ODA taken as an aggregated flow may contain components that could have opposite environmental impacts. For instance, aid may have different impacts on environment depending of the type of donor. Some authors (Wagner, 2003; Faye and Niehaus, 2012) think that bilateral ODA is more likely to be driven by common interests like political survival of the recipient's governement or the exploitation of the recipient's market by the donor. Then, this could lead the recipient government to pursue economic growth, completely ignoring environmental issues.

On the other hand, multilateral ODA seems to have good reputation in terms of environmental protection among scholars (Buys et al., 2004; Lebovic and Voeten, 2009). For instance, Lebovic and Voeten (2009) argue that it is more sensitive to the long-run sustainability of the recipient's development strategy and then, might encourage recipient governments to commit in environmental protection as a condition for future aid. If so, by disaggregating ODA into bilateral and multilateral, we should find a strong pollution-reducing effect for multilateral ODA that should be weaker, null, or even of opposite sign for bilateral ODA.

To adress this issue, we proceed to a first level of disaggregation: we split ODA into bilateral and multilateral and we estimate their effects from column 3 to column 6. Our results are in line with the previous intuitions, since we find a negative and significant effect of multilateral ODA on CO_2 emissions in columns 5 and 6, a 1% increase in multilateral ODA per capita leading to a 0.3% decrease in per capita CO_2 emissions.

Table 2: Environmental effects of Aid

Dependent Variable	Log of CO2 (per capita)					
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged D.V	0.609**	0.813***	0.627**	0.840***	0.716***	0.777*
	(0.263)	(0.183)	(0.294)	(0.251)	(0.243)	(0.430)
ODA per capita (Log)	-0.005	0.049				
	(0.066)	(0.102)				
Bilateral ODA per capita (Log)			-0.021	0.065		
			(0.072)	(0.111)		
Multilateral ODA per capita (Log)					-0.302***	-0.324*
					(0.111)	(0.195)
Investment (% GDP)	0.021***	0.018***	0.021***	0.017***	0.017**	0.013**
	(0.007)	(0.003)	(0.007)	(0.004)	(0.007)	(0.006)
Population growth (%)	-0.026	-0.008	-0.024	-0.007	-0.013	-0.003
	(0.028)	(0.017)	(0.030)	(0.021)	(0.020)	(0.034)
Democratic Institutions (Polity 2 Score)	0.012**	0.009	0.012**	0.008	0.012**	0.009
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.008)
Constant	5.078	2.117	4.875	1.802	3.850	3.198
	(3.662)	(2.594)	(4.110)	(3.435)	(3.308)	(5.808)
Urban Population (% of total)		-0.002		-0.002		0.002
		(0.004)		(0.004)		(0.007)
Trade (% GDP)		0.001		0.000		0.003
		(0.002)		(0.002)		(0.004)
Time dummies included	Yes	Yes	Yes	Yes	Yes	Yes
Observations	585	580	585	580	585	580
Countries	112	112	112	112	112	112
Instruments	19	29	19	21	14	17
AR1	0.000	0.005	0.001	0.022	0.001	0.001
AR2	0.397	0.190	0.320	0.422	0.604	0.781
Hansen test	0.224	0.123	0.152	0.167	0.420	0.930

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Bilateral ODA, on the other hand, seems to have no effect, as total aid; its results are presented in columns 3 and 4. Does this mean it has absolutely no effect on pollution? Probably no: we suspect this result to be driven by composition effects in its environmental impact. In fact, beyond the type of donor, the purpose for which this aid is provided to the recipient country should be taken into account. Following Hicks et al. (2008), we provided an environmental label to each aid flow in our database according to its purpose[11] and then, we proceeded to a second level of disaggregation: we splitted bilateral ODA into an environmental friendy component (hereafter "Environmental Aid") and an environmental harmful component (hereafter "Dirty Aid")[12]. The estimation results are reported in Table 3. In column 1 we have the baseline specification with the total bilateral aid. In columns 2 and 3 we estimate the effect of bilateral "Dirty Aid" and not surprisingly we find it has a positive and significant effect on per capita CO_2 emissions, a 1% incease in bilateral dirty aid leading to a 0.14% increase in emissions.

However, surprisingly, we also find an unexpected positive effect for "Environmental Aid" on CO_2 emissions in columns 4 and 5. This counter intuitive result might be driven by the presence of a possible non-linear relationship between environmental aid and pollution (Kennedy, 2005). In fact, it is possible that the pollution-reducing effect arises beyond a certain treshold value of environmental ODA. We could imagine for instance that for small amounts, donors' pressure is just as low, and thus the effect of environmental aid less present. But for large amounts, donors are more involved and this results in a more pronounced pollution-reducing effect of environmental aid. And since the latter is still not very important for many countries in our sample, one could find a positive relation between it and CO_2 emissions when assuming a linear function in the Data Generating Process.

We adress this issue by adding a quadratic term of environmental aid in the Data Generating Process. If our previous intuition is right, then we should obtain a negative coefficient associated to this square-term while the term in level should have a positive coefficient. We estimate this relation in columns 6 and 7 and we obtain a negative coefficient associated to our square-term, confirming the presence of an inverted-U relationship between environmental bilateral ODA and pollution: environmental bilateral aid is associated with low pollution only beyond a certain treshold.

[11] For instance, if the flow purpose is "Coal-fired power plant", the "Dirty" label is provided while the "Environmental" label is provided for flows like "Solar power plant".

[12] We do not use the neutral component which is by definition environmentally neutral

Table 3: Compositions Effects of Bilateral ODA

Dependent Variable	Log of CO_2 (per capita)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged D.V	0.840***	0.766***	0.794***	0.890***	0.929***	0.896***	0.871***
	(0.251)	(0.121)	(0.010)	(0.149)	(0.193)	(0.138)	(0.134)
Bilateral ODA per capita (Log)	0.065						
	(0.111)						
Dirty Bilateral Aid (Log)		0.131*	0.144**				
		(0.067)	(0.063)				
Environmental Bilateral Aid (Log)				0.212***	0.201***	0.344***	0.359***
				(0.067)	(0.062)	(0.116)	(0.115)
Environmental Bilateral Aid^2						-0.048**	-0.053*
						(0.023)	(0.029)
Investment (% GDP)	0.017***	0.014***	0.015***	0.010***	0.012***	0.012***	0.011***
	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Population growth (%)	-0.007	-0.010	-0.008	-0.003	-0.000	-0.003	-0.010
	(0.021)	(0.012)	(0.011)	(0.014)	(0.020)	(0.014)	(0.012)
Democratic Institutions (Polity 2 Score)	0.008	0.008*	0.008	0.003	0.005	0.003	0.006
	(0.006)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)
Constant	1.802	2.652	2.375*	1.057	0.728	0.884	1.479
	(3.435)	(1.725)	(1.342)	(2.112)	(2.595)	(1.979)	(1.803)
Urban Population (% of total)	-0.002		-0.001		-0.003		-0.004
	(0.004)		(0.005)		(0.004)		(0.004)
Trade (% GDP)	0.000		0.000		-0.000		0.000
	(0.002)		(0.001)		(0.001)		(0.001)
Time dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	580	585	580	585	580	585	580
Countries	112	112	112	112	112	112	112
Instruments	21	18	22	18	25	24	28
AR1	0.022	0.001	0.000	0.001	0.001	0.001	0.000
AR2	0.422	0.410	0.479	0.370	0.340	0.517	0.676
Hansen test	0.167	0.569	0.162	0.461	0.364	0.585	0.332

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Non-renewable energy as potential transmission channel

Non- renewable energy is known as a major driver of a country GHG emissions, principally CO_2 emissions (Shafiei and Salim, 2014). Non-renewables' consumption could therefore be a potential mediator for the effect of both dirty and environmental aid on pollution. Dirty aid projects could increase CO_2 emissions by increasing non-renewables consumption, while environmental aid would rather decrease CO_2 by increasing renewables (and thus, reducing the share of non-renewable energy).A traditional way of testing this channel would be to add it as an additional regressor in our model,

$$Y_{it} = \phi_1 Y_{i,t-1} + \beta_1 ODA_{it} + \beta_2 NR_{it} + X_{it}\beta_3 + \alpha_i + \tau_t + \epsilon_{it} \tag{2}$$

where NR represents the share of non renewables in total energy consumption, and to interpret β_1 as a direct effect. But this interpretation is only true if and only if we make the assumption of no intermediate confounders, which is an unrealistic assumption according to Imai et al. (2010). These intermediate confounders are represented by Z in Figure 3, while pretreatment confounders are represented by P, both set of covariates included in vector X above.

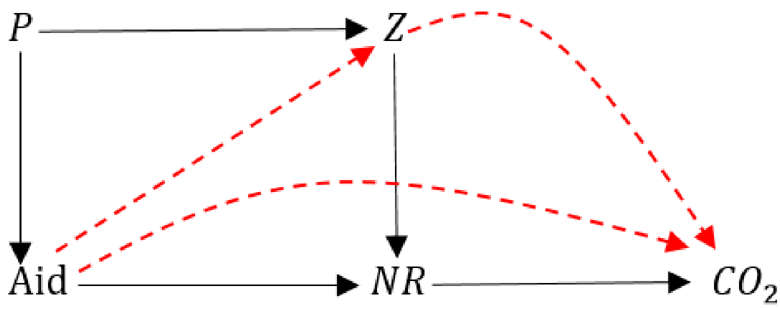

Figure 3: Directed acyclic graph of the causal relationships

Including them in the equation would lead β_1 not to be equal to the direct effect of aid, since conditioning on a posttreatment variable can induce spurious relationships between the treatment and the outcome (Rosenbaum, 1984). However, assuming that there are no intermediate confounders and including our mediator NR without adding them results in selection bias unless we include all of them as well[13] (Acharya et al., 2016).

To deal with this dilemma, we rely on sequential g-estimation[14] (Vansteelandt, 2009; Joffe and Greene, 2009) which is appropriated to estimate direct effects in the case of

[13]This bias is often called M bias

[14]also called reverse sequential twostage (RS2S)

parametric models with continuous treatment and continuous mediator such ours. We proceed in two steps:

First stage: estimation of a demediation function

We start estimating Equation 2 (with vector X including P and Z) from which we calculate the sample version of the demediation function:

$$\widehat{\gamma}(NR_{it}) = \widehat{\beta_2} NR_{it} \tag{3}$$

Second stage: demediating output and estimating direct effect

With this estimate of the demediation function, we demediate our outcome:

$$\widetilde{Y}_{it} = Y_{it} - \widehat{\gamma}(NR_{it}) \tag{4}$$

which is equivalent to

$$\widetilde{Y}_{it} = Y_{it} - \widehat{\beta_2} NR_{it} \tag{5}$$

We then obtain the direct effect of aid by estimating the following equation:

$$\widetilde{Y}_{it} = \phi_1 \widetilde{Y}_{i,t-1} + \beta_1 ODA_{it} + X_{it}\beta_2 + \alpha_i + \tau_t + \epsilon_{it} \tag{6}$$

Where β_1 is the direct effect of ODA. Obtaining $\beta_1 = 0$ would imply that the effect of ODA is completely mediated by NR. We applied this methodology for dirty aid and environmental aid; the results are presented in Table 4. In column 1 we run a specification with dirty bilateral ODA and NR, while in column 2 we have environmental bilateral ODA and NR. From these estimates we computed two demediation functions $\widehat{\gamma}_{dirty}(NR_{it})$ and $\widehat{\gamma}_{env}(NR_{it})$ that we use to determine the demediated outcomes $\widetilde{Y}_{dirty}$ and $\widetilde{Y}_{env}$ which are explained in column 3 and 4 respectively. Our results suggest that the effect of dirty bilateral ODA is completely mediated by non-renewable energy; in other words, dirty aid increase CO_2 emissions by increasing the share of non-renewable energy in total energy consumption.

Table 4: Non-renewables as potential transmission channel

Dependent Variable	Log of CO2 (per capita) (1)	(2)	$\widetilde{Y}_{dirty}$ (3)	$\widetilde{Y}_{env}$ (4)
Lagged D.V	0.601***	0.650***	0.978***	0.968***
	(0.166)	(0.152)	(0.088)	(0.077)
Non renewables (% of total energy consumption)	0.018***	0.018***		
	(0.006)	(0.006)		
Dirty Bilateral Aid (Log)	0.040		0.083	
	(0.058)		(0.055)	
Environmental Bilateral Aid (Log)		0.259***		0.342***
		(0.097)		(0.108)
Environmental Bilateral Aid^2		-0.048***		-0.073***
		(0.019)		(0.027)
Investment (% GDP)	0.014**	0.012**	0.011*	0.010**
	(0.006)	(0.005)	(0.006)	(0.005)
Democratic Institutions (Polity 2 Score)	0.006	0.006	-0.017*	-0.025***
	(0.010)	(0.009)	(0.009)	(0.009)
Population growth (%)	0.025	0.021**	0.010	0.017*
	(0.017)	(0.009)	(0.015)	(0.010)
Urban Population (% of total)	0.007	0.004	-0.003	-0.001
	(0.007)	(0.005)	(0.004)	(0.004)
Trade (% GDP)	0.000	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	3.660**	3.096**	0.149	0.080
	(1.600)	(1.579)	(1.056)	(0.879)
Time dummies included	Yes	Yes	Yes	Yes
Observations	497	497	409	409
Countries	112	112	110	110
Instruments	44	49	24	44
AR1	0.008	0.007	0.002	0.000
AR2	0.186	0.426	0.176	0.197
Hansen test	0.131	0.315	0.560	0.544

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For environmental aid, its effect still remains even after ruling out the non-renewables mechanism; this suggests that its effect is only partially mediated by non-renewable energy. Its remaining nonzero effect can be interpreted either as direct effect or as a remaining effect which is mediated by other alternative mechanisms. For instance, an other transmission channel could be new pollution-abatement technologies' transfer through Clean Developement Mechanism projects. Unfortunately, the latter started to be implemented in the post Kyoto-protocol period; testing it in this configuration would not be possible due to small number of observations.

To confirm the presence of an inverted U-shape relationship between environmental aid and CO_2 emissions, we perfomed a U-test (Lind and Mehlum, 2010) using the regression in column 4 of Table 4 and the results are presented in Appendix. These results help to understand why we find an average positive effect of environmental bilateral ODA when assuming a linear function in the Data Generating Process: in fact, 86.73% of our observations are below the treshold value of \$10.57 per capita that the U-test indicates. This result has important policy implications since it means that environmental bilateral aid remains very insufficient and should be increased, if one expects it to produce environmental benefits.

4.3 Robustness Checks

In Table 2 and Table 3, we estimated our equations with the two-step GMM-system estimator which is more efficient than the one-step GMM-system estimator. However, its standard errors can be severely downward biased in a small sample. This bias can be solved using the Windmeijer correction (Windmeijer, 2005). To make sure our results are not sensitive to the estimation technic, we re-estimate our equations using the one-step GMM-system estimator. The results we obtain are similar to those with the two-step GMM-system estimator and are reported in Table 5 and Table 6 in Appendices.

We also change the measure of aid; in Table 7, for total ODA, we take its natural logarithm without taking it per capita. We also take bilateral ODA and multilateral ODA as a share of total aid, instead of measuring them per capita as in previous tables. In Table 8, bilateral aid is still measured in % of total aid while bilateral dirty and bilateral environmental aid are measured in % of total bilateral aid. Our results remain the same.

5 Conclusion

Even if aid could be used as a tool for shaping environmental-friendly policies in developing countries, small number of empirical studies have focused on the environmental impact on foreign aid, finding inconclusive results (Arvin and Lew, 2009) or conditional effects of ODA which rely on assumptions that are not unanimous (Lim et al., 2015). These results may also be driven by incomplete or wrong informations on different aid flows (Tierney et al., 2011).

In this paper we use a more complete and new source of aid data to re-explore the link between ODA and CO_2 emissions in 112 aid recipient countries over the period 1980- 2013, using GMM-system estimator. While we find aggregated ODA has no effect on pollution as previous studies (Lim et al., 2015), our results show evidence of a pollution reducing effect for multilateral ODA and no effect for bilateral ODA. This could explain the choice by the Cancun conference stakeholders to delegate the management of pledged funds to a multilateral agency (the Green Climate Fund).

However, our results do not suggest that bilateral aid has no role to play in the fight against climate change. Following the methodology of Hicks et al. (2008), we provided an environmental impact code to each bilateral flow in our data set, and we disaggregated bilateral ODA according to this scheme. We find evidence of a pollution-increasing effect for the dirty component of bilateral aid, working pricipally through the increase of non-renewable energy.

Our findings suggest that the composition of bilateral aid should change if one expects it to provide environmental benefits: bilateral donors should finance less polluting activities and reallocate their funding to more environmentally friendly activities. This will help increasing environmental bilateral aid, which we found more performant for important amounts only, and which remains insufficient for a large majority of countries in our sample. These results are robust to other estimation technic and alternative measures of aid flows.

We remain aware that beyond the donor characteristics and the flows' purpose, recipient countries' incentives to engage in climate change mitigation also matter. These incentives can vary because of many factors, leading environmental aid, even when increased, to be more fungible and then less effective. Further empirical research should explore the link from this view, taking these recipient countries' political and social characteristics into account, in order to improve environmental aid effectiveness.

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6 Appendices

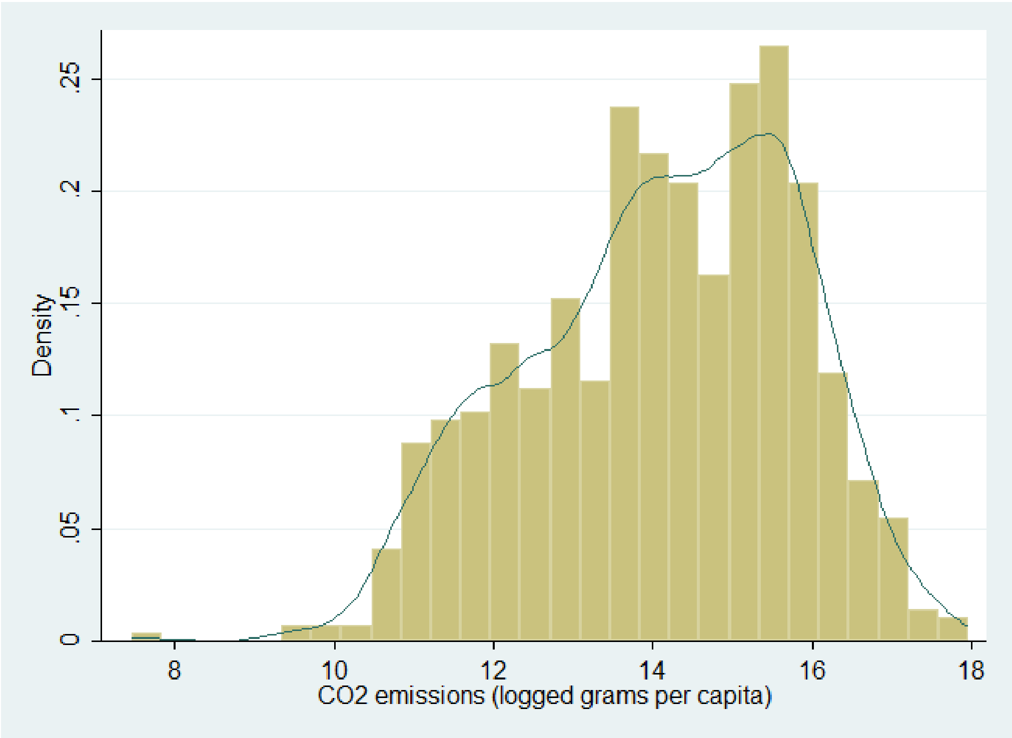

Figure 4: Distribution of CO_2 Emissions

```
Specification: f(x)=x^2
Extreme point:  2.357978

Test:
     H1: Inverse U shape
 vs. H0: Monotone or U shape
```

	Lower bound	Upper bound
Interval	0	5.090206
Slope	.3424568	-.3968104
t-value	3.180717	-2.219822
P>|t|	.0007905	.0134893

```
Overall test of presence of a Inverse U shape:
     t-value =      2.22
     P>|t|   =     .0135

95% Fieller interval for extreme point: [1.7345906; 4.0973387]
```

Figure 5: Test of presence of an inverted U-shape

Table 5: Environmental effects of Aid (One Step GMM)

Dependent Variable	Log of CO2 (per capita)					
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged D.V	0.768***	0.813***	0.810***	0.840***	0.898***	0.777*
	(0.222)	(0.183)	(0.256)	(0.251)	(0.315)	(0.430)
ODA per capita (Log)	0.046	0.049				
	(0.097)	(0.102)				
Bilateral ODA per capita (Log)			0.027	0.065		
			(0.081)	(0.111)		
Multilateral ODA per capita (Log)					-0.243**	-0.324*
					(0.115)	(0.195)
Investment (% GDP)	0.019***	0.018***	0.018***	0.017***	0.014*	0.013**
	(0.006)	(0.003)	(0.007)	(0.004)	(0.008)	(0.006)
Population growth (%)	-0.011	-0.008	-0.007	-0.007	0.004	-0.003
	(0.021)	(0.017)	(0.024)	(0.021)	(0.029)	(0.034)
Democratic Institutions (Polity 2 Score)	0.009	0.009	0.008	0.008	0.008	0.009
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
Urban Population(% of total)		-0.002		-0.002		0.002
		(0.004)		(0.004)		(0.007)
Trade (% GDP)		0.001		0.000		0.003
		(0.002)		(0.002)		(0.004)
Constant	2.661	2.117	2.162	1.802	1.287	3.198
	(3.217)	(2.594)	(3.631)	(3.435)	(4.369)	(5.808)
Time dummies included	Yes	Yes	Yes	Yes	Yes	Yes
Observations	585	580	585	580	585	580
Countries	112	112	112	112	112	112
Instruments	19	29	19	21	14	17
AR1	0.004	0.005	0.013	0.022	0.001	0.001
AR2	0.199	0.190	0.191	0.422	0.859	0.781
Hansen test	0.224	0.123	0.152	0.167	0.420	0.930

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Compositions Effects of Bilateral ODA (One Step GMM)

Dependent Variable	Log of CO2 (per capita)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged D.V	0.840***	0.819***	0.794***	0.923***	0.929***	0.956***	0.871***
	(0.251)	(0.159)	(0.100)	(0.218)	(0.193)	(0.122)	(0.134)
Bilateral ODA per capita (Log)	0.065						
	(0.111)						
Dirty Bilateral Aid (Log)		0.155**	0.144**				
		(0.074)	(0.063)				
Environmental Bilateral Aid (Log)				0.200***	0.201***	0.408***	0.359***
				(0.059)	(0.062)	(0.130)	(0.115)
Environmental Bilateral Aid^2						-0.061*	-0.053*
						(0.034)	(0.029)
Investment (% GDP)	0.017***	0.014***	0.015***	0.011**	0.012***	0.010***	0.011***
	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)	(0.003)
Population growth (%)	-0.007	-0.006	-0.008	0.002	-0.000	0.002	-0.010
	(0.021)	(0.017)	(0.011)	(0.021)	(0.020)	(0.011)	(0.012)
Democratic Institutions (Polity 2 Score)	0.008	0.007	0.008	0.003	0.005	-0.000	0.006
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)
Urban Population (% of total)	-0.002		-0.001		-0.003		-0.004
	(0.004)		(0.005)		(0.004)		(0.004)
Trade (% GDP)	0.000		0.000		-0.000		0.000
	(0.002)		(0.001)		(0.001)		(0.001)
Constant	1.802	1.823	2.375*	0.569	0.728	0.008	1.479
	(3.435)	(2.258)	(1.342)	(3.000)	(2.595)	(1.733)	(1.803)
Time dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	580	585	580	585	580	585	580
Countries	112	112	112	112	112	112	112
Instruments	21	18	22	18	25	22	28
AR1	0.022	0.002	0.000	0.004	0.001	0.001	0.000
AR2	0.422	0.424	0.479	0.307	0.340	0.548	0.676
Hansen test	0.167	0.569	0.162	0.461	0.364	0.808	0.332

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Environmental effects of Aid (changing measure of aid)

Dependent Variable	Log of CO2 (per capita)					
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged D.V	0.572**	0.658***	0.983***	0.984***	0.971***	0.972***
	(0.280)	(0.207)	(0.047)	(0.033)	(0.084)	(0.108)
Log of ODA	0.034	0.056				
	(0.092)	(0.096)				
Bilateral ODA (% of total)			0.003	0.002		
			(0.003)	(0.002)		
Multilateral ODA (% of total)					-0.010**	-0.008**
					(0.005)	(0.004)
Investment (% GDP)	0.022***	0.018***	0.011***	0.013***	0.008**	0.009***
	(0.007)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)
Population growth (%)	-0.031	-0.020	0.006	0.005	0.005	0.002
	(0.027)	(0.015)	(0.005)	(0.003)	(0.008)	(0.010)
Democratic Institutions (Polity 2 Score)	0.013***	0.011*	0.004	0.006***	0.004	0.007*
	(0.005)	(0.006)	(0.003)	(0.002)	(0.003)	(0.004)
Urban Population(% of total)		0.001		-0.003		-0.002
		(0.007)		(0.002)		(0.003)
Trade (% GDP)		0.003*		0.000		0.000
		(0.001)		(0.000)		(0.001)
Constant	4.913	3.037	-0.185	-0.045	0.270	0.643
	(5.350)	(3.979)	(0.732)	(0.406)	(1.165)	(1.413)
Times dummies included	Yes	Yes	Yes	Yes	Yes	Yes
Observations	585	580	584	579	584	579
Countries	112	112	112	112	112	112
Instruments	22	29	22	37	21	24
AR1	0.002	0.006	0.000	0.000	0.001	0.001
AR2	0.624	0.364	0.253	0.222	0.879	0.959
Hansen test	0.204	0.128	0.222	0.452	0.143	0.141

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Compositions Effects of Bilateral ODA (changing measure of aid)

Dependent Variable	Log of CO2 (per capita)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged D.V	0.984***	0.891***	0.886***	0.900***	0.954***	0.922***	0.930***
	(0.0329)	(0.0896)	(0.0732)	(0.0533)	(0.0687)	(0.0904)	(0.0854)
Bilateral ODA (% of total aid)	0.0022						
	(0.0022)						
Dirty Aid (% Bilateral aid)		0.0065**	0.0070**				
		(0.0033)	(0.0035)				
Environmental Aid (% Bilateral aid)				0.0176***	0.0151***	0.0379**	0.0268**
				(0.0053)	(0.0053)	(0.0148)	(0.0116)
Environmental Aid^2						-0.0005*	-0.0004*
						(0.0003)	(0.0002)
Investment (% GDP)	0.0130***	0.0108***	0.0096***	0.0107***	0.0098***	0.0116***	0.0097**
	(0.0024)	(0.0030)	(0.0025)	(0.0019)	(0.0020)	(0.0027)	(0.0041)
Democratic Institutions (Polity 2 Score)	0.0061***	0.0078	0.0076	0.0056**	0.0087***	0.0035	0.0094**
	(0.0020)	(0.0048)	(0.0065)	(0.0023)	(0.0032)	(0.0031)	(0.0044)
Population growth (%)	0.0049	0.0027	0.0005	0.0025	0.0014	0.0041	-0.0036
	(0.0034)	(0.0075)	(0.0047)	(0.0056)	(0.0059)	(0.0084)	(0.0084)
Urban Population(% of total)	-0.0027		-0.0002		-0.0055**		-0.0055
	(0.0020)		(0.0039)		(0.0024)		(0.0036)
Trade (% GDP)	0.0001		0.0009		0.0004		-0.0005
	(0.0003)		(0.0006)		(0.0006)		(0.0018)
Constant	-0.0447	1.187	1.222	0.964	0.495	0.528	0.857
	(0.406)	(1.181)	(0.848)	(0.722)	(0.904)	(1.223)	(1.266)
Time dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	579	584	579	584	579	584	579
Countries	112	112	112	112	112	112	112
Instruments	37	30	37	23	27	18	29
AR1	0.000	0.001	0.001	0.000	0.000	0.000	0.000
AR2	0.222	0.198	0.265	0.106	0.114	0.139	0.182
Hansen test	0.452	0.274	0.194	0.814	0.412	0.957	0.389

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: List of Countries

Afghanistan	Cote d'Ivoire	Kyrgyz Republic	Philippines
Albania	Cuba	Lao PDR	Rwanda
Algeria	Djibouti	Lebanon	Senegal
Angola	Dominican Republic	Liberia	Sierra Leone
Argentina	Ecuador	Libya	Solomon Islands
Armenia	Egypt, Arab Rep.	Lithuania	Somalia
Azerbaijan	El Salvador	Macedonia, FYR	South Africa
Bangladesh	Eritrea	Madagascar	Sri Lanka
Belarus	Ethiopia	Malawi	Sudan
Benin	Fiji	Malaysia	Suriname
Bhutan	Gabon	Mali	Swaziland
Bolivia	Gambia, The	Mauritania	Syrian Arab Republic
Botswana	Georgia	Mauritius	Tajikistan
Brazil	Ghana	Mexico	Tanzania
Bulgaria	Guatemala	Moldova	Thailand
Burkina Faso	Guinea	Mongolia	Togo
Burundi	Guinea-Bissau	Morocco	Tunisia
Cambodia	Guyana	Mozambique	Turkey
Cameroon	Haiti	Namibia	Turkmenistan
Cape Verde	Honduras	Nepal	Uganda
Central African Republic	India	Nicaragua	Ukraine
Chad	Indonesia	Niger	Uruguay
Chile	Iran, Islamic Rep.	Nigeria	Uzbekistan
China	Iraq	Pakistan	Venezuela, RB
Colombia	Jamaica	Panama	Vietnam
Comoros	Jordan	Papua New Guinea	Yemen, Rep.
Congo, Rep.	Kazakhstan	Paraguay	Zambia
Costa Rica	Kenya	Peru	Zimbabwe