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Does Climate Aid Affect Emissions? Evidence from a Global Dataset

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Abstract: We perform an empirical audit of the effectiveness of climate aid in tackling CO_2 and SO_2 emissions. Using a global panel dataset covering up to 131 countries over the period 1961 to 2011 and estimating a parsimonious model using the Anderson and Hsiao estimator we do not find any evidence of a systematic effect of energy related aid on emissions. We also find that the non-effect is not conditional on institutional quality or level of income. Countries located in Europe and Central Asia does better than others in utilising climate aid to reduce CO_2 emissions. Our results are robust after controlling for the Environmental Kuznets Curve, country fixed effects, country specific trends, and time varying common shocks.

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1 Introduction

Modern industrial society runs on fossil fuel. Burning fossil fuel releases thermal energy which is then transformed into electricity. Electricity is a key input in the production of goods and services destined for mass consumption. Consumers derive satisfaction from the consumption of these mass produced goods. In modern society, sustained improvement in the average level of consumption is a key indicator of material wellbeing and improved living standards. The use of fossil fuel not only generates thermal energy but it also releases greenhouse gases (carbon dioxide, sulphur dioxide, methane and others) into the atmosphere causing global warming and climate change. Until recently the environmental consequences of industrialisation were largely ignored. The global threat of a catastrophic climate change has helped raise awareness and brought countries together in favour of a coordinated policy response.

In a globalised world of free trade and migration (to a lesser extent), global governance of climate change mitigation is challenging. It is relatively inexpensive for industrial production to cross borders and move to cheaper locations. Indeed, starting from the 1980s the world has noticed a significant dislocation of industries from the industrialised nations to the emerging markets significantly increasing the latter's share of greenhouse gas emissions. Coupled with the global challenge of reducing greenhouse gas emissions the abovementioned migration of polluting industries brings in a key question of distributive justice in a Rawlsian sense[3]. To what extent the emerging market economies should be allowed to emit so that the twin objectives of sustainable development and reducing global greenhouse gas emissions could be achieved? Indeed these twin objectives are enshrined in many of the official documents on climate change commissioned and authored by multilateral

[3] Note that Rawls (1971) explicitly refrained from applying his principles of justice beyond the confines of a territorial state. Relevance of Rawlsian principles to global governance were discussed in later interpretations elsewhere (see Pogge, 1989).

institutions. For example, the Clean Development Mechanism (CDM)[4] defined in the Kyoto Protocol also emphasises the importance of these twin objectives (IPCC, 2007). In particular, the CDM aims to: (1) assist developing countries in achieving sustainable development while preventing catastrophic climate change, and (2) help industrialised countries reach their greenhouse gas emissions target.

At the operational level, states around the world have aimed to address these challenges by making use of both bilateral and multilateral institutional mechanisms. In particular, countries have used the mechanism of international transfers especially in the field of energy to achieve the twin objectives of emissions reduction and sustainable development. Policymakers have been using these policy tools for at least three decades now yet the effects are not very well known. To the best of our knowledge, there is hardly any systematic quantitative research on the effect of environmental aid on emissions in the aid recipient countries. In this paper, we seek to explore this very question: Do we notice a perceptible difference in the level of emissions in the aid recipient countries as a result of energy related aid going back to the 1960s?

A cursory look at the global aggregates reveals that both foreign aid commitment and disbursement for the energy sector (especially electricity generation) have exploded over the last decade. For example, per capita aid disbursement for power generation over the 2000s have grown by 4 percent on average every year whereas the annualised growth rate of aid commitment in power generation for the same period is approximately 5 percent. Carbon dioxide (CO_2) emissions however have increased at an annualised rate of 2.5 percent over the same period. Emissions of sulphur dioxide (SO_2) have declined since the mid-1990s largely due to the introduction and subsequent adoption of unleaded fuels for transport. Figures 1 – 4 presents this data.

[4] The CDM is a mechanism intended to produce emission reduction units through certified projects which then could be traded in emissions trading schemes (ETS).

Even though there has been some degree of co-movement between emissions and environmental aid it is problematic to interpret this association as causal. What we plot are global trends which ignore variations within and across countries. A third latent factor could also be responsible for the co-movement which hardly makes this perceived association causal. Furthermore, there is no obvious theoretical prior when it comes to the effect of environmental aid on emissions. On the one hand policymakers in donor countries would expect results in terms of reduced emissions through better targeting of the energy infrastructure in the recipient countries. On the other hand environmental aid could very well be off target and is spent on projects that have little discernible impact on emissions. Therefore, the lack of a strong prior either way makes this policy design a prime candidate for empirical audit. A more detailed and systematic modelling is necessary to understand the co-movement in the raw time series data.

In this paper we aim to systematically explore the effect of energy related aid on CO_2 and SO_2 emissions. In particular, we analyse the effect of an energy related aid shock on emissions using a panel data model. We exploit a global panel dataset covering up to 131 countries over the period 1961 to 2011. Note that our aid data is sourced from AidData.org. This dataset is an improvement over the Creditor Reporting System (CRS) maintained by the OECD's Development Assistance Committee (DAC) and offers far wider country coverage. Furthermore, our dataset also allows us to distinguish between renewable and non-renewable sources of power generation, and energy supply infrastructure. We estimate a parsimonious model using fixed effects, Arellano and Bond, and Anderson and Hsiao estimators and do not find any evidence of a systematic effect of energy related aid on emissions. Some would argue that the effect of aid is perhaps conditional on country specific fundamentals such as nature of policy or quality of institutions. We are unable to distinguish the average effect from zero even after interacting the aid variable with the rule of law index, corruption, degree of democracy, private property rights, government effectiveness, and openness to trade.

The zero effect could be driven by potential heterogeneity across very low income and relatively advanced economies. It is entirely plausible that relatively advanced economies are far more efficient in adopting greener technologies for power generation whereas the very low income economies are rather slack. If this is indeed the case then one would expect to see opposing effects across the two samples. To our surprise we observe no such evidence of non-linearity in the relationship and the average effect stays zero.

We also test any potential heterogeneity across continents by dividing the sample into Asia, Europe and Central Asia (ECA), Latin America and the Caribbean (LAC), and Middle East and North Africa (MENA). With the exception of ECA the average effect remains zero across all other continents. We notice some evidence of emission reduction as a result of environmental aid in ECA. Our results are robust to the inclusion of country fixed effects, country specific trends, time varying common shocks, GDP per capita, and GDP per capita squared as controls. The exclusion of outliers and the inclusion of additional covariates such as trade openness, urbanisation, human capital, investments, population density, and per capita energy use do not alter our fundamental result of zero average effect.

Empirically identifying the causal effect of environmental aid on emissions is challenging because potential biases from simultaneous and reverse causation. This challenge is not specific to the macro environmental economics literature but in fact part of a broader challenge associated with the aid and development literature. We follow the empirical methodology of Clemens et al. (2012) to tackle identification challenges. Clemens et al. (2012) argue that it may take time for most aid disbursement to have an impact on other macroeconomic variables as they are generally lumpy and work through multiple channels. Therefore, they show that transparent methods of lagging and differencing the data are superior to using poor quality instrumental variables which tends to magnify the problem of reverse causation. Following Clemens et al. (2012) we use five year averages as observations and use lags in the model. The model is estimated using the Anderson and Hsiao method along with fixed effects and Arellano and Bond dynamic panel data estimation methods. Clemens et al. (2012) present Anderson and Hsiao estimates as their preferred results.

The paper makes the following contributions. First, it performs a much needed econometric audit of the policy of environmental aid. Climate change is a major challenge of our generation and it is extremely important that some of the existing macro policies are thoroughly scrutinised using scientific means. To our surprise, we did not find any other study asking the obvious question: what impact energy related aid has on emissions? Second, by bringing this scientific result to the academy and the policymakers our paper opens the way for much needed future scientific scrutiny of policies in this arena.

Our paper is related to a large literature on the determinants of emissions. This literature could be divided into two strands: (1) a literature based on the Stochastic Impacts by Regressions on Population, Affluence and Technology (SIRPAT) methodology and (2) a literature based on the Environmental Kuznets Curve (EKC). Examples of the former are Narayan and Narayan (2010), Menz and Kühling (2011), and Menz and Welsch (2012). Narayan and Narayan (2010) focus on the effect of affluence by using economic growth as the key explanatory variable whereas Cole and Nemayer (2004), Menz and Kühling (2011) and Menz and Welsch (2012) focus on population size and population aging. Numerous other studies seek to verify the EKC. The EKC model predicts an inverted U shaped relationship between income and emissions. In other words, environmental pollution is increasing in income up to a certain threshold beyond which environmental pollution is in fact declining in the level of income. Torras and Boyce (1998), Auci and Becchetti (2006), and York et al. (2003) are good examples of empirical studies of EKC. Dinda (2004) presents a review of the EKC literature.

In addition to the SIRPAT and EKC based studies, a large literature examines additional determinants of pollution. This literature finds that trade openness (Grossman and Krueger, 1993), quality of political institutions (Scruggs, 1998; Farzin and Bond, 2006; and Bernauer and Koubi, 2009), and urbanisation (Zhu et al., 2012; and Sadorsky, 2014) affects air quality.

Finally, our paper is also related to a voluminous empirical literature on aid and development. Griffin and Enos (1970) launch this literature with bivariate regressions on aid and growth followed by Weisskopf (1972) and Papanek (1972). More recently some of the notable studies are Boone (1996), Burnside and Dollar (2000), Collier and Dollar (2002), Easterly (2003), Rajan and Subramanian (2008), and Clemens et al. (2012). In spite of the volume of time and energy that economists have dedicated to debate the empirical relationship between aid and growth, the issue still remains inconclusive.

The remainder of the paper is structured as follows: Section 2 discusses the empirical strategy and data. Section 3 presents evidence on the effects of environmental aid on emissions. It also distinctly examines the effects of aid in renewables, non-renewables, and energy supply infrastructure on emissions. Furthermore, this section thoroughly examines any potential good policy, governance or income based heterogeneity in the data. Section 4 reports on a battery of robustness tests and section 5 concludes.

2 Empirical Strategy

We use a panel dataset covering up to 131 countries observed over the period 1961 to 2011.[5] To estimate the direct effects of environmental aid on emissions, we use the following dynamic model:

$$E_{it} = \alpha E_{it-1} + \beta Aid_{it-j} + \mathbf{X}_{it}\Gamma + \delta_t + \lambda_i t + \psi_i + u_{it} \qquad (1)$$

[5] Due to data limitations, not all specifications cover 131 countries. In most specifications, the panel is unbalanced. The sample size is somewhat truncated for SO_2 emissions and covers the time period 1961-2005. Missing data is the only reason behind excluding a country-year from the sample. Appendix A1 presents a list of countries included in the sample.

where E_{it} represents emissions of CO_2 and SO_2 in country i at year t, ψ_i is the country fixed effects, δ_t is a year dummy variable controlling for time varying common shocks, $\lambda_i t$ are country specific time trends. Country specific trend captures potential country specific time varying factors that might affect emissions. The variable Aid_{it-j} is an indicator of energy related aid received by country i in the year $t-j$. We also control for additional covariates including GDP per capita and GDP per capita squared. This is represented by the vector $\mathbf{X}_{it}$. We estimate this model for contemporaneous effects and lags j thus $j \in \{0,1\}$. All variables in equation 1 are defined as per capita and expressed in natural logarithms with the exception of the aid variable. The aid variable Aid_{it-j} is defined using the generic transformation $\ln[1+x]$ to account for zero observations. This transformation eliminates excessive skewness and kurtosis in the data. Furthermore, all observations used to estimate equation 1 are five year averages. Thus, each country in the panel dataset includes a maximum of 11 vertical (time series) data points with the 2010 data point being the average of the years 2010 and 2011.

Our main focus of enquiry is the effect of energy related aid Aid_{it-j} on emissions E_{it}. Therefore, our coefficient of interest is β which represents the average marginal effect (or elasticity) of environmental aid on emissions. A negative and statistically significant coefficient would imply that environmental aid is effective in lowering the levels of CO_2 and SO_2 emissions. Alternatively, a positive and statistically significant coefficient would imply that a higher level of environmental aid is associated with adverse emissions outcome. Finally, another potential possibility is that the average marginal effect cannot be distinguished from zero which would imply that environmental transfers have very little discernible effect on emissions in the aid recipient countries.

We include GDP per capita and GDP per capita squared to account for a potential inverted U shaped relationship between the level of income and emissions commonly known as Environmental Kuznets Curve (EKC). Shafik and Bandyopadhyay (1992), Panayotou, (1993) and Grossman and Krueger (1993) were the first to detect such empirical relationship. They provide evidence that while economic growth is detrimental to the environment at early stages of development the relationship between environmental quality and economic growth reverses beyond a threshold level of development.

Our key dependent variables (E_{it}) are CO_2 and SO_2 emissions. The CO_2 emissions data is sourced from the World Development Indicators (WDI) database of the World Bank and is measured in metric tons. This data is collected by the Carbon Dioxide Information Analysis Centre of the Environmental Sciences Division, Oak Ridge National Laboratory of the United States located in Tennessee. Atmospheric CO_2 is a key contributor to climate change and global temperature rise. Combustion of fossil fuels is the predominant source of CO_2 emissions.

The SO_2 emissions data is sourced from Smith *et al*. (2010) who provide estimates of global and country-level emissions over the period 1850 to 2005. The dataset has been developed by using calibrated country-level inventories information compiled from a number of sources. Note that Smith *et al*. (2010) reports SO_2 emissions in gigagrams rather than kilotons. To facilitate uniformity of measurement across the two emissions variables we multiply SO_2 emissions by 1000 to convert it into metric tons.

Unlike CO_2, SO_2 is a local pollutant. SO_2 emissions mainly come from the combustion of coal and petroleum. Emission levels of SO_2 peaked in 1991 and since then it experienced a steady decline. The decline in coal fired power stations in Europe and the adoption of unleaded fuels for car may have contributed to this decline.

Environment quality is a multidimensional concept. Therefore there is some merit in using a composite measure of environmental quality as opposed to emissions of individual pollutants. One such measure is the Environmental Performance Index developed by Emerson *et al*. (2010). This index is based on a large number of variables ranging from the percentage of population with access to drinking water to CO_2 emissions by the industrial sector. However, poor data coverage is a major limitation of this dataset. Similarly, one could also consider indices of other forms of environmental degradation. For example, one could consider the measures of water quality, land degradation and deforestation. Again these variables are restricted to a limited number of countries and time periods. In contrast, the CO_2 and SO_2 emissions data are available for a large number of countries and time periods. They are also very widely used. It is worthwhile noting that we focus on emissions instead of concentration of CO_2 and SO_2 because the former closely track economic activity rather than the latter.

Rates of emission vary considerably across countries. For example, CO_2 emission ranges from 13.9 tons per capita in Chad over the period 1991 – 1995 to approximately 60 gigatons per capita in Qatar over the period 1996 – 2000. In contrast, SO_2 emission ranges from 0.2 tons per capita in Botswana over the period 1976 – 1980 to 403 tons per capita in Zambia over the period 1961 – 1965.

Our key independent variable is energy related aid. This data is sourced from the AidData.org, research release 2.1. This dataset is compiled by Tierney *et al*. (2011). The Tierney *et al*. (2011) database distinguishes between development finance as loans from governments or agencies from transfers. The AidData.org project is run by the Bingham Young University, the College of William and Mary, and the Development Gateway. It emerged out of two earlier projects on the Accessible Information on Development Activities and Project-Level Aid. Both projects compiled project level aid data.

The bulk of the data in AidData.org comes from the Creditor Reporting System (CRS), which collects annual data from 22 member countries dating back to 1973. In addition to CRS, AidData.org also includes data from other official sources. For instance, it records bilateral donations from non-OECD donors to non-DAC recipients as well as donations from multilateral organisations. In line with CRS, AidData.org adopts a five digit classification system of projects. The classification system identifies the sector, the activity code, and the purpose of each project. A major advantage of the dataset is that it distinguishes between aid commitment and aid disbursement. The 2.1 research release that we use covers a large number of countries over the period 1947 to 2011.[6]

AidData.org records aid commitment and disbursement for a large variety of projects. We limit our attention to aid for environmental projects. In particular, we focus on: (i) power generation projects from renewable sources, (ii) power generation projects from non-renewable sources and (iii) energy generation and supply projects. The energy generation and supply projects include power generation from renewables and non-renewables, energy policy and administrative management, energy transmission, energy education, and energy research.[7]

A zero value for the aid variable would imply that the donors did not commit or disburse any money. A quick scrutiny of the raw data reveals that Palau received the highest amount of energy related international financial assistance over the period 1996 – 2000 (USD 554 in 2009 constant prices) closely followed by Iceland 1966-1970 (USD 502 in 2009 constant prices) and Bahrain 1976-1980 (USD 432 in 2009 constant prices).

Other variables used in the study are: GDP per capita, law and order index, corruption, democracy scores, trade openness index, trade share, private property rights,

[6] We only use data from 1960 because the CO_2 emissions data starts at 1960.

[7] Note that power generation from renewables and non-renewables correspond to the purpose codes 23020 and 23030. The energy generation and supply corresponds to the following purpose codes: 23000, 23005, 23010, 23020, 23030, 23040, 23050, 23061, 23062, 23063, 23064, 23065, 23066, 23067, 23067, 23068, 23069, 23070, 23081 and 23082.

government effectiveness. Tables 1 reports summary statistics on key variables and Appendix A2 presents detailed definition of variables.

There are econometric challenges associated with estimating equation 1. These challenges are unobserved heterogeneity, non-stationarity of the variables, reverse causation, simultaneity bias, and bias due to the dynamic nature of the model. We closely follow Clemens *et al*. (2010) to tackle these challenges. We address the unobserved heterogeneity challenge by demeaning the data and estimating the model using fixed effects. However, the fixed effect estimator is unable to tackle the challenge of non-stationarity. In a time series dataset variables could have similar trends yielding statistically significant correlation. However, this correlation could simply be reflective of their co-movement and not a causal relationship. Therefore, estimating econometric models with variables that have a significant time dimension and are not stationary would lead to spurious inference of causality when there is none. To address this challenge we check stationarity of the variables by using the Fisher type Adjusted Dickey Fuller (ADF), Levin–Lin–Chu, and Harris–Tzavalis varieties of unit root tests. The Levin–Lin–Chu and the Harris–Tzavalis tests account for bias emanating from cross-sectional association. We find that the key variables are I(1) or difference stationary and therefore we use first difference of variables in the regressions. These tests are reported in table 2. Note that Clemens et al. (2012) also reports similar results in the context of aid and growth.

The level of emissions might dictate environmental aid flows rather than causality running in the opposite direction. We address reverse causation and simultaneity challenges by using five year averages and lags. An alternative approach is to use the instrumental variable (IV) method. However, Clemens et al. (2012) demonstrates that using lags is a much cleaner and transparent way of dealing with reverse causation as opposed to searching for an appropriate instrument. Furthermore, they also show that the paucity of strong and valid instruments permeates the aid and growth literature.

Finally, using a lagged dependent variable as an independent variable in the model invites additional challenges. In particular, the differenced lagged dependent variable ΔE_{it-1} could be correlated with the differenced error term Δu_{it} contaminating inference. However, for serially uncorrelated errors Δu_{it} would not be correlated with ΔE_{it-2} opening the possibility of using ΔE_{it-2} as an instrument for ΔE_{it-1}. This is precisely what the Anderson and Hsiao (1981) estimator does which we adopt here.

3 Evidence

3.1 Climate Aid and Emissions: Baseline Results

Table 3 conducts an empirical audit of the effects of climate aid on emissions. The key independent variable here is the aid for power generation using both renewable and non-renewable resources. We first concentrate on the effect of aid disbursement in panel A. In column 1 we estimate equation 1 using the fixed effect estimator. We find that 1 percentage point increase in aid for power generation using either renewable or non-renewable resources reduce per capita CO_2 emissions by 0.03 percent. To put this into perspective, a 0.03 percent decline in per capita CO_2 emission is equivalent to Qatar's emission over the period 1996 – 2000 declining from 60 gigatons per person to 59.8 gigatons per person. Even though the coefficient on aid is significant, we cannot be confident that it is precisely estimated. The estimate could very well be driven by omitted factors or reverse causation. In column 2, we replace the contemporaneous aid variable by lagged aid. The average effect of lagged aid on per capita CO_2 emission becomes indistinguishable from zero. In column 3 we estimate the model using the Anderson and Hsiao instrumental variable method and the null effect result remains. Note that this is also the preferred method of Clemens et al. (2012).

Since we are estimating a dynamic model with a lagged dependent variable, therefore there is merit in pursuing the Arellano and Bond estimation method. We do exactly that in column 4 without much difference in outcome. The average effect of lagged aid on per capita CO_2 emission cannot be distinguished from zero.

In columns 5 – 8 we repeat these estimates to explain variation in another important pollutant SO_2. Irrespective of the estimator used, we are unable to distinguish the average effect of aid disbursement for power generation using renewables and non-renewables from zero. In panel B we verify whether the effect is any different with aid commitment as the key independent variable as opposed to actual aid disbursement. It is plausible even though unlikely that aid commitments might affect expectations and preferences of policymakers in aid recipient countries incentivising them to implement emission reduction plans. We find that aid commitments have very little discernible impact on per capita emissions.

It is possible that by aggregating aid for power generation in renewable and non-renewable sources we are weakening statistical power. Perhaps there is heterogeneity in the data. At least in theory, increasing the share of power generation using renewable resources could rapidly reduce emissions. In contrast upgrading existing non-renewable resource based power plants or building new power plants may not have the desired emissions reducing effect. Therefore we divide the aid data for power generation into renewables and non-renewables in table 4 columns 1, 2, 4, and 5. The effect stays insignificantly different from zero.

In columns 3 and 6 we explore any potential impact of aid in energy generation and supply. Energy generation and supply is a broad measure of climate aid which includes power generation, energy policy and administration, energy transmission infrastructure, energy awareness education, and energy research. To our surprise we do not find any effect of such aid on per capita emissions after controlling for country specific and global factors.

3.2 Climate Aid and Emissions: The Role of Institutions and Policy

The effectiveness of aid could be conditional on the country specific initial conditions. Countries that have good policy and good institutions could be in a far better position to respond to aid than others. Emissions respond better to aid in these locations because efficient policy and institutions channel the funds effectively to the appropriate projects reducing waste and administrative obstacles. If this is indeed the case then we would expect to see non-linear effects of institutional quality on emissions.

We test the role of policy and institutions by introducing interaction terms in table 5. In particular, we interact the aid for power generation variable with the rule of law index, corruption, democracy scores, private property rights, government effectiveness, and Sachs and Warner trade openness index. We do not find any evidence of non-linearity in the data. The average effect of climate aid on CO_2 and SO_2 emissions is zero regardless of the quality of institutions.

3.3 Climate Aid and Emissions: Is there a Rich and Poor Divide?

Upgrading to a new energy infrastructure or building a new power plant is not costless. On the contrary these ventures are often expensive and require additional resources on top of the aid money. Richer nations could afford these ventures and therefore they are far more effective in upgrading their energy infrastructure or building new power plants. They could also tap into a relatively skilled labour force to work on energy related projects. All this taken together could contribute positively towards reducing per capita emissions.

If the hypothesis outlined above is indeed true then we would expect to see heterogeneity in the data along income lines. However, in table 6 we do not find any evidence that the level of income influences the effectiveness of climate aid.

3.3 Climate Aid and Emissions: The Role of Geography

Certain geographic locations could possess an advantage over others when it comes to implementing emission reduction policies. Cleaning up the energy sector, upgrading to a new energy infrastructure, and building new power plants require significant investments. It also requires importation of capital goods and skills. Therefore, proximity to these inputs matter. If a country is located in the same neighbourhood where green technology is advancing then it is likely to be part of the same network. The countries are more likely to utilise their climate aid money effectively.

We test this hypothesis in table 7 by estimating our canonical model separately for Asia, Europe and Central Asia (ECA), Latin America and the Caribbean (LAC), and Middle East and North Africa (MENA). We find that ECA countries are far more effective in reducing their CO_2 emissions using aid. Numerically, we find that 1 percentage point increase in aid for power generation would reduce CO_2 emissions by 0.31 percent. This amounts to approximately 0.3 ton reduction in per capita emission in an average ECA country.

4 Robustness

The non-relationship between climate aid and emissions could be driven by outliers or omitted variables. We check the robustness of our main result by controlling for outliers and omitted covariates. In table 8 we estimate the model by eliminating potential outliers from the sample. We do this systematically by identifying outliers using the formulas of DFITS, Cooks Distance, and Welsch Distance. Dropping outliers from the sample do not alter our main result.

In table 9 we introduce additional control variables. The environmental studies literature have identified trade openness, urbanisation, school enrolment, investments, energy use, and the fraction of population aged between 15 to 64 as important determinants of CO_2 and SO_2 emissions. We control for these variables and observe that the ineffectiveness of climate aid on emissions remains.

5 Conclusions

Climate change and global temperature rise are significant challenges of our generation. The recent climate change conference COP21 held in Paris in December 2015 calls for greenhouse gas emissions to a level consistent with an average global temperature rise of 2 degrees (possibly 1.5 degrees) above pre-industrial average temperature. A significant reduction in greenhouse gas emissions would be required in order to achieve this target. Nations and multilateral organisations have used a plethora of policy tools to achieve emissions reduction. One such policy is energy related international transfers. The idea is to assist aid recipient countries to clean up existing energy infrastructure, build new greener power plants, and switch from fossil fuel based energy mix to a renewables based energy mix. Undoubtedly this is a worthy cause and donor countries have devoted significant amount of resources to support this venture. Yet we know very little about the potential outcome of this policy.

In this paper we perform an empirical audit of this policy by systematically exploring the effect of energy related aid on CO_2 and SO_2 emissions. Using a global panel dataset covering up to 131 countries over the period 1961 to 2011 and estimating a parsimonious model using fixed effects, Arellano and Bond, and Anderson and Hsiao estimators we do not find any evidence of a systematic effect of energy related aid on emissions. To our surprise, we also find that the non-effect is not conditional on institutional quality or level of income. Countries located in ECA do better than others in utilising climate aid to reduce CO_2 emissions. Our results are robust to the inclusion of country fixed effects, country specific trends, time varying common shocks, GDP per capita, and GDP per capita squared as controls. The exclusion of outliers and the inclusion of additional covariates such as trade openness, urbanisation, human capital, investments, population density, per capita energy use, and the share of adult population do not alter our fundamental result of zero average effect.

This result calls into question the merit of climate aid as a policy tool to achieve the emission reduction objectives outlined in the Kyoto Protocol and beyond. It exposes that aid of this nature has been fairly ineffective in the past. Therefore, policymakers would need to be more circumspect while applying aid as a policy tool to address climate change. At the very least our result calls for more scientific scrutiny of energy related aid.

Appendices

A1. List of Countries in the Sample:

Afghanistan	Czech Republic	Liberia	Sao Tome & Principe
Albania	Djibouti	Libya	Senegal
Algeria	Dominica	Lithuania	Serbia
Antigua & Barb.	Dominican Rep.	Macedonia	Seychelles
Argentina	Ecuador	Madagascar	Sierra Leone
Armenia	Egypt	Malawi	Singapore
Azerbaijan	El Salvador	Malaysia	Slovak Republic
Bahamas	Equatorial Guinea	Maldives	Solomon Islands
Bahrain	Eritrea	Mali	South Africa
Bangladesh	Estonia	Malta	Sri Lanka
Barbados	Ethiopia	Marshall Islands	St. Kitts and Nevis
Belarus	Fiji	Mauritania	St. Lucia
Belize	Gabon	Mauritius	St. Vincent & Grenad.
Benin	Gambia	Mexico	Sudan
Bhutan	Georgia	Micronesia	Suriname
Bolivia	Ghana	Moldova	Swaziland
Bosnia & Herzeg.	Guatemala	Mongolia	Syrian Arab Republic
Botswana	Guinea	Morocco	Tajikistan
Brazil	Guinea-Bissau	Mozambique	Tanzania
Brunei Darussalam	Guyana	Namibia	Thailand
Bulgaria	Haiti	Nepal	Togo
Burkina Faso	Honduras	Nicaragua	Tonga
Burundi	Hungary	Niger	Trinidad and Tobago
Cabo Verde	Iceland	Nigeria	Tunisia
Cambodia	India	Oman	Turkey
Cameroon	Indonesia	Pakistan	Turkmenistan
Cent. African Rep.	Iran	Palau	Uganda
Chad	Iraq	Panama	Ukraine
Chile	Ireland	Papua N.Guinea	Uruguay
China	Jamaica	Paraguay	Uzbekistan
Colombia	Jordan	Peru	Vanuatu
Comoros	Kazakhstan	Philippines	Venezuela
Congo, Dem. Rep.	Kenya	Poland	Vietnam

Congo, Rep.	Kiribati	Portugal	Yemen
Costa Rica	Korea, Rep.	Qatar	Zambia
Cote d'Ivoire	Kyrgyz Republic	Romania	Zimbabwe
Croatia	Lao PDR	Russian Fed.	
Cuba	Latvia	Rwanda	
Cyprus	Lebanon	Samoa	
Czech Republic	Libya	Serbia	

A2. Data Appendix:

Variable	Description	Source
CO_2	Carbon Dioxide emissions (metric tons per capita)	World Development Indicator (World Bank)
GDP	GDP per capita (constant 2005 US$)	
Trade	Sum of exports and imports (% of GDP)	
Urban	Urban population	
School	Secondary school enrolment (% gross)	
Ki	Gross capital formation (% of GDP)	
Energy	Energy Use (kg of oil equivalent per capita)	
P15-64	Population, ages 15-64 (% of total)	
SO_2	Sulphur Dioxide emissions (gigagram)	Smith *et al.* (2010)
Aid (ren)	Aid disbursed (committed) for renewable power generation ($ 2009 USD)	Aid Data 2.1.
Aid(nonren)	Aid disbursed (committed) for non-renewable power generation ($ 2009 USD)	
Aid(energy)	Aid disbursed (committed) for general energy generation and supply ($ 2009 USD)	
Law and Order	Law and Order (0 to 6). Higher values indicate higher quality of government	ICRG
Corruption Index	Corruption (0 to 6). Higher values indicate lower levels of corruption	
Democracy Score	Democracy Index (-10 to 10). Higher values indicates higher degree of democracy	Marshall *et al.* (2013)
Openness Index	Dummy variable coded 1 for countries classified as open 0 otherwise	Sachs and Warner (1995)

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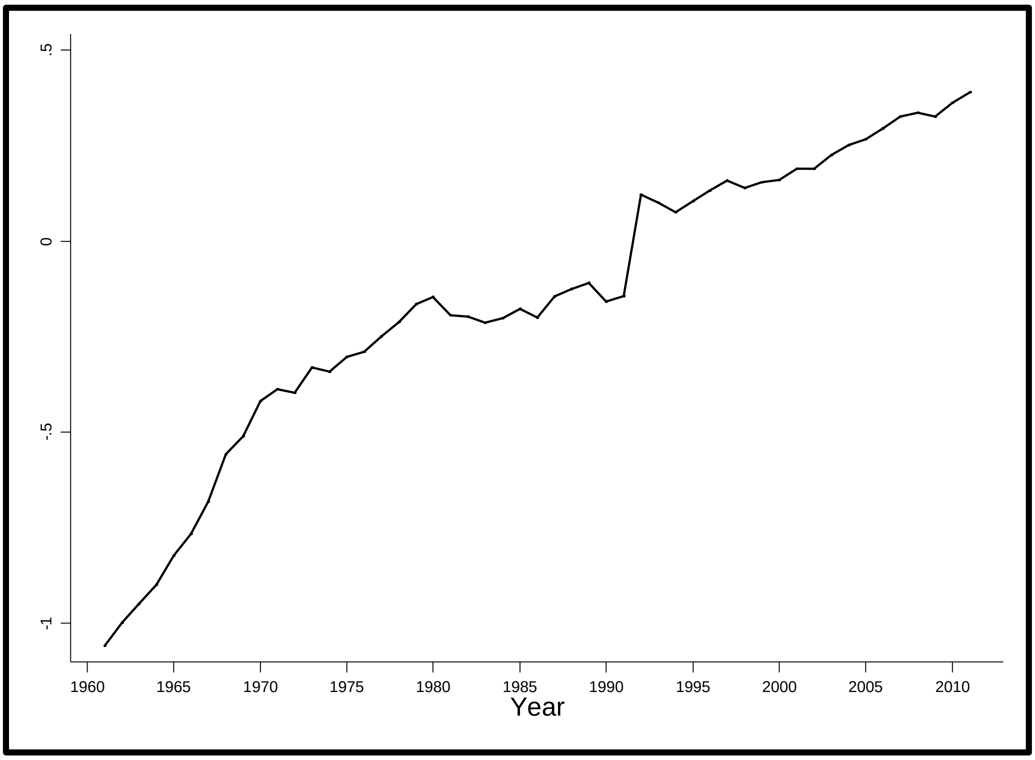
Figure 1: Global CO_2 Emission per capita since 1961

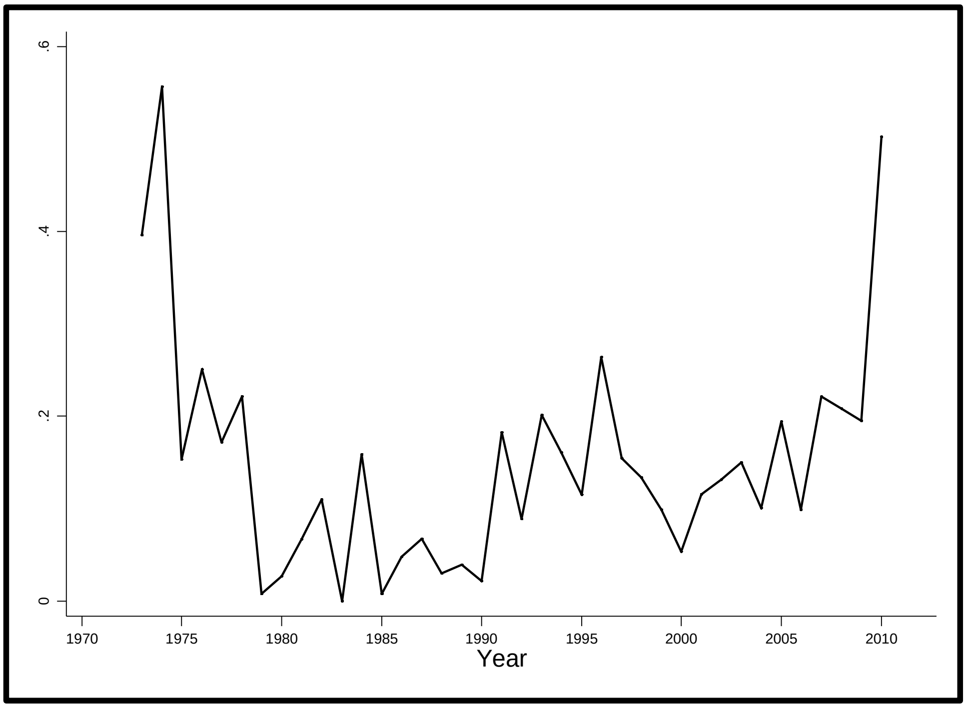


Notes: Natural log of global CO_2 emission per person covering the period 1961-2011. CO_2 emission measured in metric ton.

Figure 2: Global SO_2 Emissions per capita since 1961

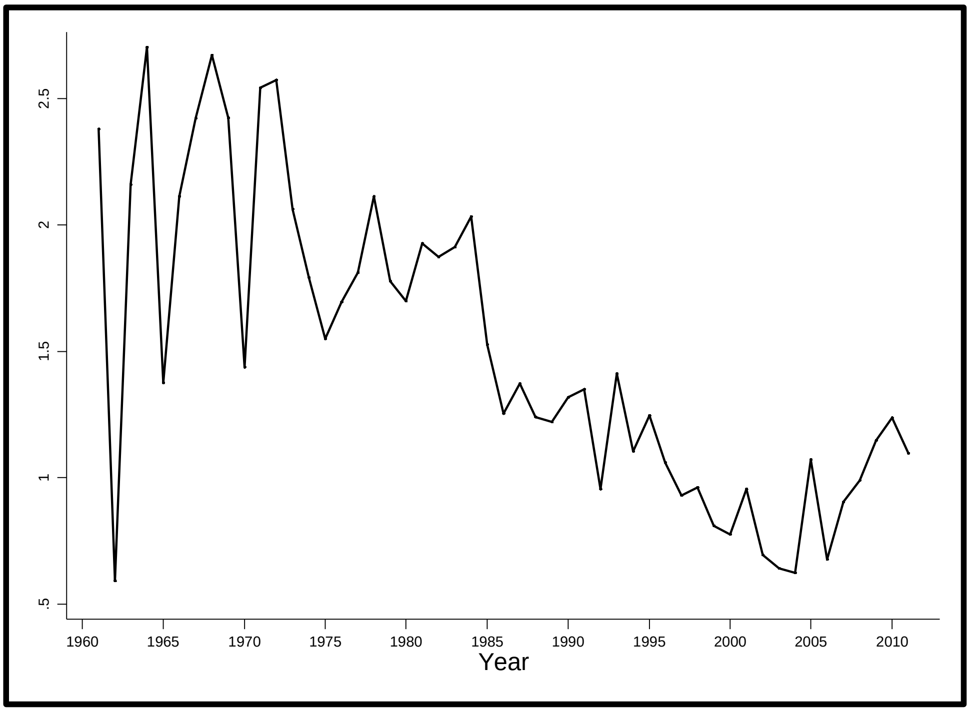
Notes: Natural log of global SO_2 emission per person covering the period 1961-2005. SO_2 emission measured in gigagram.

Figure 3: Foreign Aid Disbursement for Power Generation per capita from Renewable and Non-Renewable Sources since 1973



Notes: Aid disbursement per person is defined as $\ln(1+Aid/Population)$ covering the period 1973-2010. Aid disbursement measured in 2009 constant US dollars.

Figure 4: Foreign Aid Commitment for Power Generation per capita from Renewable and Non-Renewable Sources since 1961



Notes: Aid commitment per person is defined as $\ln(1+Aid/Population)$ covering the period 1961-2011. Aid commitment measured in 2009 constant US dollars.

Table 1: Summary Statistics

Variables	Mean	Std. Dev.	Min	Max
CO_2	-0.132	1.505	-4.273	4.103
SO_2	-4.825	1.452	-8.538	-0.913
Aid(ren+nonren) disb.	0.177	0.545	0.000	6.315
Aid(ren) disb.	0.075	0.263	0.000	2.549
Aid(nonren) disb.	0.200	0.642	0.000	6.315
Aid(energy) disb.	0.231	0.577	0.000	6.315
Aid(ren+nonren) comm.	1.353	1.234	0.000	6.590
Aid(ren) comm.	1.063	1.159	0.000	5.719
Aid(nonren) comm.	1.106	1.172	0.000	6.590
Aid(energy) comm.	1.761	1.161	0.001	7.007
GDP	7.278	1.169	4.816	10.879

Notes:. CO_2 and SO_2 emission are the key dependent variables. Aid(ren+nonren) is aid for power generation from both renewable and non-renewable sources. Aid (ren) is aid for power generation from renewable sources only. Aid(noren) is aid for power generation from non-renewable Sources only. Aid(energy) is aid for energy generation and supply. Disb. and comm. indicate disbursement and commitment, respectively. All variables are measured as logs of per capita terms. The aid variables are measured as $\ln(1+x)$. The analysis on CO_2 (SO_2) emission covers the years between 1961 and 2011 (1961 and 2005).

Table 2: Unit Root Test

	CO_2	SO_2	Aid Disb	Aid Comm
Panel A: Levels				
Inverse chi-squared	0.000	0.951	0.921	0.005
Inverse normal	0.218	0.996	0.844	0.102
Inverse logit t	0.038	0.998	0.264	0.000
Modified inv. chi-squared	0.000	0.945	0.915	0.002
Panel B: First Difference				
Inverse chi-squared	0.000	0.000	0.000	0.000
Inverse normal	0.000	0.000	0.000	0.000
Inverse logit t	0.000	0.000	0.000	0.000
Modified inv. chi-squared	0.000	0.000	0.000	0.000

Notes: The table illustrates the p-values from Fisher-type ADF unit root tests. All variables are measured as log of per capita terms. The aid variables are measured as $\ln(1+x)$. The Aid variables used in this table are the *'Aid for Power Generation using Renewable and Non-renewable Resources'* Commitment and Disbursement. Each line refers to a specific transformation used to combine the p-values form unit-root tests computed for each panel individually. We also conduct Levin-Lin-Chu and Harris-Tzavalis varieties of unit root tests. These tests account for bias emanating frm cross-sectional association. The results are qualitatively similar

Table 3: Climate Aid and Emissions

	CO_2 Emissions 1971-2011				SO_2 Emissions 1971-2005			
Panel A: Disbursement								
	(1) OLS	**(2) OLS**	**(3) A-H**	**(4) A-B**	**(5) OLS**	**(6) OLS**	**(7) A-H**	**(8) A-B**
y_{t-1}	0.157***	0.135*	0.421*	0.388***	0.157	0.166**	0.372**	0.319
	(0.050)	(0.075)	(0.237)	(0.085)	(0.136)	(0.072)	(0.175)	(0.347)
Aid_t	-0.032*				0.020			
	(0.018)				(0.065)			
Aid_{t-1}		-0.009	0.002	0.004		0.008	0.012	-0.021
		(0.029)	(0.026)	(0.024)		(0.049)	(0.051)	(0.076)
GDP_t	0.812	1.876***	1.793***	2.083***	2.448*	2.332	2.417**	3.245**
	(0.906)	(0.480)	(0.666)	(0.662)	(1.467)	(1.413)	(1.201)	(1.286)
GDP^2_t	0.003	-0.088***	-0.091**	-0.108**	-0.133	-0.163	-0.171**	-
	(0.071)	(0.033)	(0.045)	(0.046)	(0.103)	(0.101)	(0.086)	(0.092)
Observations	509	420	420	420	293	217	217	217
Countries	135	128	128	128	87	78	78	78
R^2	0.301	0.221			0.079	0.058		
Weak test			5.922				6.725	
AR(2)				0.428				0.309
Hansen test				0.034				0.042
	1961-2011				**1961-2005**			
Panel B: Commitment								
	(1) OLS	**(2) OLS**	**(3) A-H**	**(4) A-B**	**(5) OLS**	**(6) OLS**	**(7) A-H**	**(8) A-B**
y_{t-1}	0.164***	0.146**	0.611**	0.446***	0.173	0.179**	0.580***	0.229
	(0.049)	(0.072)	(0.276)	(0.150)	(0.134)	(0.080)	(0.221)	(0.230)
Aid_t	-0.000				0.077*			
	(0.010)				(0.046)			
Aid_{t-1}		-0.007	-0.013	-0.014		0.008	-0.037	0.003
		(0.008)	(0.009)	(0.009)		(0.026)	(0.031)	(0.029)
GDP_t	0.772	1.710***	1.701**	2.211***	1.786	1.159	1.569	1.872
	(0.852)	(0.536)	(0.755)	(0.632)	(1.495)	(1.539)	(1.127)	(1.548)
GDP^2_t	0.008	-0.068*	-0.081	-0.114***	-0.08	-0.057	-0.092	-0.099
	(0.067)	(0.038)	(0.051)	(0.044)	(0.105)	(0.111)	(0.081)	(0.116)
Observations	534	455	455	455	313	245	245	245
Countries	137	131	131	131	88	80	80	80
R^2	0.312	0.261			0.125	0.072		
Weak test			6.829				10.229	
AR(2)				0.374				0.164
Hansen test				0.039				0.045

Notes: The table reports Ordinary Least Squares (OLS), Anderson–Hsiao (A-H) and Arellano and Bond (A-B) estimates. All variables are expressed as first difference as they are I(1). They are also measured in logs of per capita. y_{t-1} denotes the lagged dependent variable. The aid variables here are expressed as $\ln(1+x)$. The Aid variable used in this table is the *'Aid for Power Generation using Renewable and Non-renewable Resources'*. The figures in the parentheses are clustered standard errors with clustering at the country level. The last two lines of the table reports the p-values of the Arellano and Bond test (AR2) and Hansen test. Weak test is the Stock-Yogo F-test for weak instruments. F-statistic greater than 10 implies strong instrument. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All specifications include country and year dummies, and country specific trend.

Table 4: Aid for Power Generation and Emissions

	CO_2 Emissions			SO_2 Emissions		
	Panel A: Disbursement					
	Renewables	**Non-renewables**	**Energy Generation & Supply**	**Renewables**	**Non-renewables**	**Energy Generation & Supply**
	(1) 1976-2011	**(2) 1971-2011**	**(3) 1961-2011**	**(4) 1976-2005**	**(5) 1971-2005**	**(6) 1961-2005**
Aid_{t-1}	-0.018	0.015	0.008	0.155	-0.037	0.022
	(0.038)	(0.033)	(0.018)	(0.206)	(0.026)	(0.031)
Controls	Country dummies, Year dummies, Country specific trend, y_{t-1}, GDP_t, GDP^2_t					
Observations	315	242	645	156	152	356
Countries	108	90	150	57	63	97
Weak test	4.383	1.937	13.699	14.466	4.863	12.799
	Panel B: Commitment					
	Renewables	**Non-renewables**	**Energy Generation & Supply**	**Renewables**	**Non-renewables**	**Energy Generation & Supply**
	(1) 1961-2011	**(2) 1961-2011**	**(3) 1961-2011**	**(4) 1961-2005**	**(2) 1961-2005**	**(3) 1961-2005**
Aid_{t-1}	-0.013	-0.029	-0.009	0.005	-0.068**	0.025
	(0.011)	(0.018)	(0.008)	(0.033)	(0.029)	(0.040)
Controls	Country dummies, Year dummies, Country specific trend, y_{t-1}, GDP_t, GDP^2_t					
Observations	351	247	653	188	157	364
Countries	109	92	150	58	65	97
Weak test	4.032	3.104	13.138	12.759	7.155	13.973

Notes: The table reports Anderson–Hsiao (A-H) estimates. All variables are expressed as first difference as they are I(1). They are also measured in logs of per capita. y_{t-1} denotes the lagged dependent variable. The aid variables here are expressed as $\ln(1+x)$. The Aid variable used in columns 1 and 4 is the *'Aid for Power Generation using Renewable Resources'*. The Aid variable used in columns 2 and 5 is the *'Aid for Power Generation using Non-Renewable Resources'*. The Aid variable used in columns 3 and 6 is the *'Aid for Energy Generation and Supply'*. The figures in the parentheses are clustered standard errors with clustering at the country level. Weak test is the Stock-Yogo F-test for weak instruments. F-statistic greater than 10 implies strong instrument. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All specifications include a constant.

Table 5: Climate Aid and Emissions: The Role of Institutions and Policy

	CO_2 emissions				SO_2 emissions			
	Panel A: Disbursement							
	(1) 1976-2011	**(2)** 1976-2011	**(3)** 1971-2011	**(4)** 1971-1995	**(5)** 1976-2005	**(6)** 1976-2005	**(7)** 1971-2005	**(8)** 1971-1995
Aid_{t-1}	0.012	0.013	-0.055	-0.114	-0.023	0.047	0.019	-0.094
	(0.028)	(0.028)	(0.037)	(0.080)	(0.058)	(0.063)	(0.091)	(0.080)
INS_t	0.033	0.011	0.003	0.138	0.079***	-0.015	0.004	0.156
	(0.023)	(0.018)	(0.003)	(0.112)	(0.027)	(0.030)	(0.006)	(0.110)
$INS_t \times Aid_{t-1}$	-0.014	-0.000	0.010	-0.145	0.131	0.070	-0.008	-0.061
	(0.075)	(0.049)	(0.008)	(0.145)	(0.089)	(0.084)	(0.061)	(0.155)
INS	Law and Order	Corruption Index	Democracy Score	Openness Index	Law and Order	Corruption Index	Democracy Score	Openness Index
Controls	Country dummies, Year dummies, Country specific trend, y_{t-1}, GDP_t, GDP^2_t							
Observations	304	304	391	129	187	187	215	98
Countries	88	88	112	65	70	70	78	48
	Panel B: Commitment							
	(1) 1976-2011	**(2)** 1976-2011	**(3)** 1961-2011	**(4)** 1961-1995	**(5)** 1976-2005	**(6)** 1976-2005	**(7)** 1961-2005	**(8)** 1961-1995
Aid_{t-1}	0.002	0.002	-0.018	-0.034	-0.015	-0.039	-0.036	-0.133
	(0.014)	(0.013)	(0.012)	(0.024)	(0.032)	(0.033)	(0.033)	(0.085)
INS_t	0.035	0.011	0.003	0.206	0.073***	-0.038	0.004	0.181
	(0.022)	(0.020)	(0.003)	(0.146)	(0.027)	(0.034)	(0.006)	(0.109)
$INS_t \times Aid_{t-1}$	0.002	-0.000	0.000	0.035	0	-0.088**	-0.001	0.073
	(0.023)	(0.015)	(0.003)	(0.083)	(0.027)	(0.042)	(0.005)	(0.131)
INS	Law and Order	Corruption Index	Democracy Score	Openness Index	Law and Order	Corruption Index	Democracy Score	Openness Index
Controls	Country dummies, Year dummies, Country specific trend, y_{t-1}, GDP_t, GDP^2_t							
Observations	294	294	513	161	246	246	307	126
Countries	88	88	115	69	70	70	80	52

Notes: The table reports Anderson–Hsiao (A-H) estimates. All variables are expressed as first difference as they are I(1). They are also measured in logs of per capita. y_{t-1} denotes the lagged dependent variable. The aid variables here are expressed as $\ln(1+x)$. The Aid variable used in this table is the *'Aid for Power Generation using Renewable and Non-renewable Resources'*. Law and Order, Corruption Index, Democracy Score, and Sachs and Warner Openness Index are used as proxy measures of institutions and policy. The figures in the parentheses are clustered standard errors with clustering at the country level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All specifications include a constant.

Table 6: Climate Aid and Emissions: The Effect of Income

	CO_2 emissions		SO_2 emissions	
	1961-2011		1961-2005	
	(1) Disbursement	(2) Commitment	(3) Disbursement	(4) Commitment
Aid_{t-1}	0.010	-0.007	-0.003	0.025
	(0.018)	(0.008)	(0.028)	(0.042)
Low	0.012	0.010	0.009	-0.018
	(0.023)	(0.024)	(0.040)	(0.051)
$Low*Aid_{t-1}$	-0.054	-0.017	0.488***	-0.005
	(0.087)	(0.039)	(0.182)	(0.098)
Controls	Country dummies, Year dummies, Country specific trend, y_{t-1}, GDP_t, GDP^2_t			
Observations	645	653	356	364
Countries	150	150	97	97

Notes: The table reports Anderson–Hsiao (A-H) estimates. All variables are expressed as first difference as they are I(1). They are also measured in logs of per capita. y_{t-1} denotes the lagged dependent variable. The aid variable here is expressed as $\ln(1+x)$. The Aid variable used in this table is the *'Aid for Power Generation using Renewable and Non-renewable Resources'*. Low is a dummy variable for low-income countries as classified by the OECD DAC. The figures in the parentheses are clustered standard errors with clustering at the country level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All specifications include a constant.

Table 7: Climate Aid and Emissions: Examining Heterogeneity Across Continents

	CO2 emissions				SO2 emissions			
	Panel A: Disbursement							
	1971-2011				1971-2005			
	(1) ASIA	(2) ECA	(3) LAC	(4) MENA	(5) ASIA	(6) ECA	(7) LAC	(8) MENA
Aid_{t-1}	0.051	-0.31***	0.063	-0.025	0.238	10.08	0.064	-0.001
	(0.035)	(0.10)	(0.117)	(0.045)	(0.288)	(170.01)	(0.165)	(0.051)
Controls	Country dummies, Year dummies, Country specific trend, y_{t-1}, GDP_t, GDP^2_t							
Observations	98	41	86	195	53	20	58	86
Countries	28	22	26	52	14	16	20	28
	Panel B: Commitment							
	1961-2011				1961-2005			
	(1) ASIA	(2) ECA	(3) LAC	(4) MENA	(5) ASIA	(6) ECA	(7) LAC	(8) MENA
Aid_{t-1}	-0.050	0.007	-0.020	-0.009	-0.122	0.15	-0.083	-0.053
	(0.041)	(0.028)	(0.018)	(0.015)	(0.105)	(0.08)	(0.078)	(0.040)
Controls	Country dummies, Year dummies, Country specific trend, y_{t-1}, GDP_t, GDP^2_t							
Observations	108	44	97	206	61	23	69	92
Countries	29	23	26	53	15	17	20	28

Notes: The table reports Anderson–Hsiao (A-H) estimates. All variables are expressed as first difference as they are I(1). They are also measured in logs of per capita. y_{t-1} denotes the lagged dependent variable. The aid variable here is expressed as $\ln(1+x)$. The Aid variable used in this table is the *'Aid for Power Generation using Renewable and Non-renewable Resources'*. ASIA, ECA, LAC and MENA indicate Asian (East and South Asia and Pacific), European and Central Asian, Latin American and Caribbean and Middle East and African region, respectively. The figures in the parentheses are clustered standard errors with clustering at the country level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All specifications include a constant.

Table 8: Climate Aid and Emissions: Outlier Sensitivity Tests

	CO2 emissions			SO2 emissions		
	Panel A: Disbursement					
	1971-2011			**1971-2005**		
	(1) DFITS	**(2) COOK**	**(3) WELSCH**	**(4) DFITS**	**(5) COOK**	**(6) WELSCH**
Aid_{t-1}	0.031	0.031	0.026	-0.004	-0.004	-0.019
	(0.020)	(0.020)	(0.018)	(0.060)	(0.060)	(0.051)
Controls	Country dummies, Year dummies, Country specific trend, y_{t-1}, GDP_t, GDP^2_t					
Observations	394	394	407	199	199	205
Countries	124	124	127	71	71	75
	Panel B: Commitment					
	1961-2011			**1961-2005**		
	(1) DFITS	**(2) COOK**	**(3) WELSCH**	**(4) DFITS**	**(5) COOK**	**(6) WELSCH**
Aid_{t-1}	-0.013	-0.013	-0.007	-0.035	-0.035	-0.032
	(0.010)	(0.010)	(0.010)	(0.026)	(0.026)	(0.026)
Controls	Country dummies, Year dummies, Country specific trend, y_{t-1}, GDP_t, GDP^2_t					
Observations	424	424	441	229	229	233
Countries	125	125	130	73	73	76

Notes: The table reports Anderson–Hsiao (A-H) estimates. All variables are expressed as first difference as they are I(1). They are also measured in logs of per capita. y_{t-1} denotes the lagged dependent variable. The aid variable here is expressed as $\ln(1+x)$. The Aid variable used in this table is the *'Aid for Power Generation using Renewable and Non-renewable Resources'*. In columns 1&4 observations are omitted if $|Cooksd_i|>4/n$; in columns 2&5 observations are omitted if $|DFITS_i|>2(k/n)^{1/2}$; and in columns 3&6 observations are omitted if $|Welschd_i|>3k^{1/2}$. Here n is the number of observation and k is the number of independent variables in the regression model including the intercept. The figures in the parentheses are clustered standard errors with clustering at the country level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All specifications include a constant.

Table 9: Climate Aid and Emissions: Additional Covariate Tests

	CO2 emissions						SO2 emissions					
	Panel A: Disbursement											
	1971-2011						1971-2005					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Aid_{t-1}	0.001	0.001	0.012	-0.007	0.02	-0.003	0.01	0.01	-0.04	0.02	0.05	0.01
	(0.024)	(0.026)	(0.024)	(0.038)	(0.02)	(0.035)	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)	(0.05)
Controls	Country dummies, Year dummies, Country specific trend, y_{t-1}, GDP_t, GDP^2_t											
Additional Covariates	Trade Share	Urban	Schooling	Cap Form	Energy Use	Pop 15-64	Trade Share	Urban	Schooling	Cap Form	Energy Use	Pop 15-64
Obs	409	420	350	396	314	416	213	217	184	215	217	217
Countries	124	128	112	120	101	125	77	78	70	78	78	78
	Panel B: Commitment											
	1961-2011						1961-2005					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Aid_{t-1}	-0.015	-0.013	-0.022	-0.005	-0.01	-0.01	-0.04	-0.04	-0.04	-0.02	-0.02	-0.04
	(0.010)	(0.009)	(0.014)	(0.009)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Controls	Country dummies, Year dummies, Country specific trend, y_{t-1}, GDP_t, GDP^2_t											
Additional Covariates	Trade Share	Urban	Schooling	Cap Form	Energy Use	Pop 15-64	Trade Share	Urban	Schooling	Cap Form	Energy Use	Pop 15-64
Obs	444	455	375	426	337	451	241	245	203	240	239	245
Countries	127	131	113	122	103	128	79	80	70	80	80	80

Notes: The table reports Anderson–Hsiao (A-H) estimates. All variables are expressed as first difference as they are I(1). They are also measured in logs of per capita. y_{t-1} denotes the lagged dependent variable. The aid variable here is expressed as $\ln(1+x)$. The Aid variable used in this table is the *'Aid for Power Generation using Renewable and Non-renewable Resources'*. Trade Share, Urban and Schooling indicate the sum of exports and imports as a percentage of GDP, size of urban population and secondary school enrolment respectively. Cap Form, Energy Use and Pop 15-64 indicate gross capital formation as a percentage of GDP, energy use (kg of oil equivalent per capita) and population aged 15-64, respectively. The figures in the parentheses are clustered standard errors with clustering at the country level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively. All specifications include a constant.