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Analysis of the impact of ODA and FDI on the carbon footprint of developing countries.

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Advanced Econometrics: Panel Data
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May 2024

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Introduction

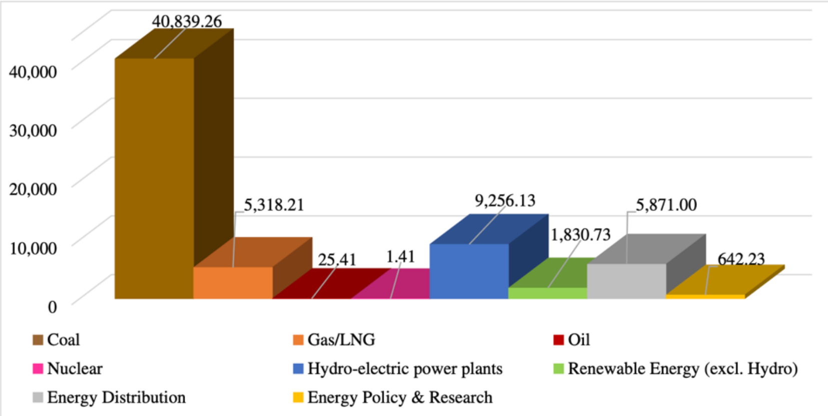
In the global fight to mitigate climate change, both development finance and private finance have been identified as crucial sources to set the world on the right path to meet international climate pledges, first after the signing of the Kyoto protocol in 1997 and particularly after the ratification of the Paris Agreement in 2014, which set a global target of mitigating climate change to well below 2 degrees above pre-industrial levels.

ODA

Official Development Assistance (ODA) has generally been perceived to be an effective mean of achieving international development objectives, and has been empirically assessed to be positively associated with metrics such as access to healthcare (Herzer, 2019), economic growth (Boateng et al., 2021; Park and Jung, 2020; Martinez-Zarzoso et al., 2017), income inequality (Herzer and Nunnenkamp, 2012) or trade openness (Gnangon, 2019) and increasingly the transition towards renewable energy (Wang and Dong, 2021).

The international development agenda is currently largely dictated by the 2030 Development Agenda, which set 17 sustainable development goals such as reduction in poverty (SDG 1), global hunger (SDG 2), gender equality (SDG 5) or the development of strong and sustainable industry and infrastructure (SDG 9). However, with the ratification of the objectives of the Paris Agreement there has been an increased focus on the question of facilitating the energy transition in order to mitigate global greenhouse gas emissions. However, many have raised doubts as to the extent to which mitigating climate change and reaching development objectives can be simultaneously reached (Iacobuţă et al., 2021). This is the inherent intuition behind the energy trilemma, which states that energy systems can be assessed on three key metrics: sustainability (how polluting is it), affordability (to what extent is the system affordable) and security (to what extent does the system ensure a stable and resilient source of energy), and progress on all three of these metrics is hardly ever achievable simultaneously. This triple dimension is present in the Development Assistance Committee's (DAC) plan to Sub-Saharan Africa (SSA) which includes three priorities: "The first is to slow down the requirements of climate change, and the second is to meet the energy supply of enterprises established by donor countries in the local area, and the third is to meet the energy consumption needs of SSA people." (Wang and Dong, 2021). For example, many international development actors financed important coal projects until as recently as 2021 (BBC, 2021), arguing that this was the most efficient way of using development capital to reach development coal such as access to affordable and reliable power, despite the fact that they contributing to emitting greenhouse gases (see figure 1).

Figure 1. Total amount of ODA disbursement per technology type for the period 2003-2018 in Southeast Asia (Bertheau and Linder, 2021)



This raises question as the extent to which ODA can meaningfully contribute to the energy transition without compromising too much on other key dimensions such as supply reliability and affordability of the system. Furthermore, ODA has been argued to be a fungible flow, which gets included in the budget of the recipient country and may thus not be spend according to the donor's original intention (Gyamfi, 2016; Briggs, 2018), thus reducing its efficiency.

There has therefore been a lot of debate on whether ODA should contribute to the energy transition (Ialnazov and Keeley, 2020), if it can even have a positive impact (Juselius et al., 2014), whether private capital is more efficient (Farooq, 2022) and if ODA may not simply be "just a new bottle of old wine, and its essence is no different from the foreign direct investment" albeit a less successful one (Wang and Dong, 2021). Furthermore, most agree that coordinated action through FDI and ODA has been key in making progress on the Millennium Development Goals, the predecessors of the SDGs (Asongu and Nwachulkwu, 2018).

FDI

Since the late 90s, Foreign Direct Investment (FDI) has been seen as an important source of potential investment that could be used to advance international development goals. The wave of liberalisation of developing economies' market, strongly encouraged by development actors such as the World Bank or the IMF aimed at increasing the amount of FDI invested in developing economies, by creating the necessary conditions for private investors to invest

(Kobrin, 2005). FDI is seen as a crucial source for financing in developing countries, particularly in the energy transition, as the green technologies necessary for the energy transition are owned by the private sector and their deployment tends to be particularly capital intensive compared to traditional fossil fuel assets (Kim, 2019). Therefore, some view ODA and aid programmes as necessary to create the appropriate conditions to create private investment in green technologies in developing countries, to allow FDI to contribute to the leapfrogging of the developing countries' energy system, meaning that they avoid going through a phase of carbon-intensive system and develop directly using clean energy sources. By this logic, ODA would not directly contribute to decreasing the carbon intensity of a country, but would rather focus on the factors that facilitate investment in clean energies such as through capacity building, finance guarantees or directly by influencing the recipient countries' policies. In fact, the literature has identified international donors as the major influence over developing countries' energy policies (Newell and Phillips, 2016). For example, large power projects such as large natural gas or coal power plans carry important financial and political risk which FDI has traditionally shied away from making these traditionally carbon-intensive projects a focus of ODA finance (see figure 1). This creates an opportunity for FDI to instead invest in smaller RE projects for which it is easier to adapt the project to the investor's risk appetite through an appropriate sizing of the project as renewable energy projects (particularly solar) are easier to scale up or down. The literature that studied the impact of FDI on the energy transition of developing countries found FDI to be associated with a reduction in the carbon footprint of SSA countries (Acheampong, et al., 2019), that globalisation such as increase in FDI have led to an increase in adoption of renewable energy (Li et al., 2022), although other studies have found that the competition to attract FDI can lead to a worsening of environment regulations and thus a deterioration of the carbon footprint (Stavropoulos et al., 2018; Sapkota and Bastola, 2017).

There has thus been for many attempts at linking ODA and FDI flows, where the former was used to steer the latter to contribute to international development objectives. The literature has identified multiple ways in which linkages between ODA and FDI can happen: through a 'vanguard effect' whereby ODA flows from a donor also lead to FDI from that same country, by a development of infrastructure and institutions through aid which creates conditions that facilitate increase in FDI, but also through a 'Dutch disease' effect, whereby ODA increase the supply of tradable goods and depreciates the value of non-tradable goods, which reduces FDI flows to the country, and through a 'positive financing effect' whereby the recipient country of

ODA improve its ability to finance outflows of profit repatriation from FDI (Amusa et al., 2016).

In recent years, there has also been important policy decisions made by international donors that may have an important consequence on the relationship between ODA and the carbon footprint of recipient countries. All international donor countries have pledged to stop funding coal in ODA while some have gone further such as the European Investment Bank or the French Development Agency announcing they would stop funding any fossil fuel project (Financial Times, 2022), prompting angry reactions from many developing countries which argue that this goes against the need to meet the basic needs of their population (African Business, 2024), which echoes back the challenges of the trilemma introduced above. This increase in focus on climate policies may lead to more ODA being spent on climate projects such as renewable energy. For example, the crowding out effect of ODA described by Fahinde et al., 2015 on domestic investments, could also affect FDI's impact on a country's energy transition as projects that would have been financed by private finance may instead be directly invested in by development actors, leaving FDI to focus on less climate-friendly projects. In addition to the linkages between ODA and FDI there is thus also the question of whether FDI and ODA could compete in financing projects that mitigate climate change.

Understanding the relationship between ODA and FDI is therefore particularly relevant in the context of the energy transition as considering the competing needs that arise in international development, and particularly in energy policies, can contribute to understanding whether ODA and FDI are flows that solve different problems, or are similar in which case ODA through government investment may crowd-out FDI or may instead reinforce each other's objectives. There does not seem to have been empirical analyses testing this relationship yet in the literature.

There are thus three theories that will be investigated in this paper:

1. ODA and FDI both contribute to the decarbonization of the economies. They are, in this regard, similar investments.
2. ODA does not contribute to decarbonization directly, either because its fungibility means it is redirected to other spendings, or because its main impact is on facilitating FDI inflows, while FDI does contribute to reducing the carbon footprint of the recipient country.

3. A final observation aims to account for the recent policy developments in the past decade in order to accelerate global efforts towards climate change mitigation:
   3.1. ODA did not contribute to the decarbonization of the economy because it has historically financed other sustainable development objectives and large projects with important economic and financial risk such as coal plants, while FDI was invested on smaller scale projects such as renewable energy.
   3.2. Policy changes in donor organisations has led to a change in the relationship between ODA and decarbonization as climate change becomes more of a priority for donor organisations and as they stop funding fossil fuel projects.

In order to test the first statement, we will test the following hypothesis:

H1: Both FDI and ODA are negatively associated with the carbon footprint of the recipient country.

The second statement will be tested with the following hypothesis:

H2: ODA is not significantly associated with changes in carbon footprint of an economy while FDI is negatively associated with the carbon footprint of the recipient country.

The final statement will be tested with the following hypothesis:

H3a: ODA in the late 90s was not associated with the carbon footprint of the recipient country;

H3b: ODA after 2015 is negatively associated with the carbon footprint of the recipient country.

Dataset

In order to test our hypotheses, we will investigate the relationship of ODA and FDI flows with the carbon footprint of the recipient countries. The sample of countries was restricted to African countries that benefited from ODA between the period 1990 – 2020. In total, our sample covers 26 countries over 31 years.

In order to investigate our hypotheses, the following variables will be used:

$$(1)\ \mathrm{CARB}_{it} = f(\mathrm{ODA}_{it}, \mathrm{FDI}_{it}, \mathrm{DENS}_{it}, \mathrm{ELEC}_{it}, \mathrm{GDP}_{it})$$

Where *i* is the country and *t* is the year. The Carbon footprint variable (CARB) is the CO_2 emissions per capita of a country, modelled as a function of total flows of Official Development Assistance (ODA), net flows of Foreign Direct Investment (FDI), Population Density (DENS), the Electrification Rate (ELEC) and the gross domestic product per capita (GDP). A description of each variable and its source can be found in table 1 and summary statistics of each variable can be found in table 2. Table shows us that we have important enough standard deviations to perform relevant panel data analysis.

Control variables

While the relevance of assessing carbon footprint in relation to ODA and FDI has been discussed in the previous sections, a lack of control variables would fail to properly isolate the effects of our explanatory variables on the dependent variable. The literature generally includes the following variables when engaging in models of carbon footprints:

<u>Electrification rate</u>

The electrification of a country has an important impact on the population's energy consumption, which naturally impacts the county's carbon footprint. While electrification in the context of the energy transition in developed countries is associated with a reduction in carbon intensity, in the context of developing countries, particularly in the period analysed, electrification efforts are largely dominated by either an expansion of the national grid, which is largely dominated by coal and natural gas in Africa, or by diesel generators. While recent policy shifts, particularly by development actors, changed electrification policies giving more importance to increasing the share of renewables in electrification efforts, over the period analysed, it is expected that an increase in electrification will be associated with an increase in the carbon footprint of the economy (Qin et al., 2024).

<u>GDP per capita</u>

Controlling for economic growth is crucial as energy consumption is strongly dependent on economic activity, both because an increase in industrial activity mechanically leads to an increase in energy demand and because an increase in disposable income for the population generally leads to an increase in consumption and thus in energy demand as well (Rahman et al., 2018). In developed countries, there has been a successful decoupling of economic growth and carbon emissions, however, this is not yet the case in the countries analysed (IEA, 2024). The relationship between economic growth and carbon footprint is thus expected to be positive.

Population density

Population density is also commonly used in the literature as a control variable. It may seem counter intuitive to include density in a model measuring the relationship between external investment flows and carbon emissions, but Wang, Quo and Dong (2021) found that social structures, measured through a certain threshold of population density does impact the relationship between ODA and the deployment of RE. These results were confirmed by Du and Xia (2018), who also find a constantly positive relationship between urbanisation rates and carbon footprint.

Table 1. Variables used

Variable	Acronym	Description	Unit	Source
Carbon footprint	CARB	CO2 per capita	Metric tonne per capita	World Bank, 2024
Official Development Assistance	ODA	Total flow of ODA per year	Current USD, millions	OECD, 2024
Foreign Direct Investment	FDI	Net flow of FDI per year, the sum of equity capital, reinvestment of earnings, and other capital	Current USD, millions	World Bank, 2024
Gross Domestic Product	GDP	Gross Domestic Product per capita	Current USD	World Bank, 2024
Electrification	ELEC	Electrification rate	%	World Bank, 2024
Density	DENS	Population density	People per square kilometre (ppl/km^2)	World Bank, 2024

Table 2. Descriptive statistics of the model variables

	CARB	DENS	ELEC	FDI	ODA	GDP
Obs	805	803	689	793	795	795
Mean	1.10	79.57	38.25	527.99	646.42	1715.02
Std. Dev.	2.07	128.87	27.59	1081.40	1236.53	2371.55
Min.	0	1.66	0.53	-286.95	-2182.37	110.46
Max.	0.98	633.96	100	9885.01	14413.60	15765.42
Between var.	2.08	129.27	8.86	666.39	811.81	128.89
Within var.	0.33	21.71	8.16	858.40	966.59	21.71

Initial graphical analyses highlighted nonlinear distributions for ODA, CARB, GDP, DENS and FDI, which will impact the reliability of our OLS regression (Shafique et al., 2021). We have thus applied a logarithmic transformation on these variables, giving the following equation:

$$(2)\ ln\text{CARB}_{it} = f(\text{ODA}_{it}, ln\text{FDI}_{it}, ln\text{DENS}_{it}, \text{ELEC}_{it}, ln\text{GDP}_{it})$$

Figure 2. Histograms of the non-linear variables before their log transformation

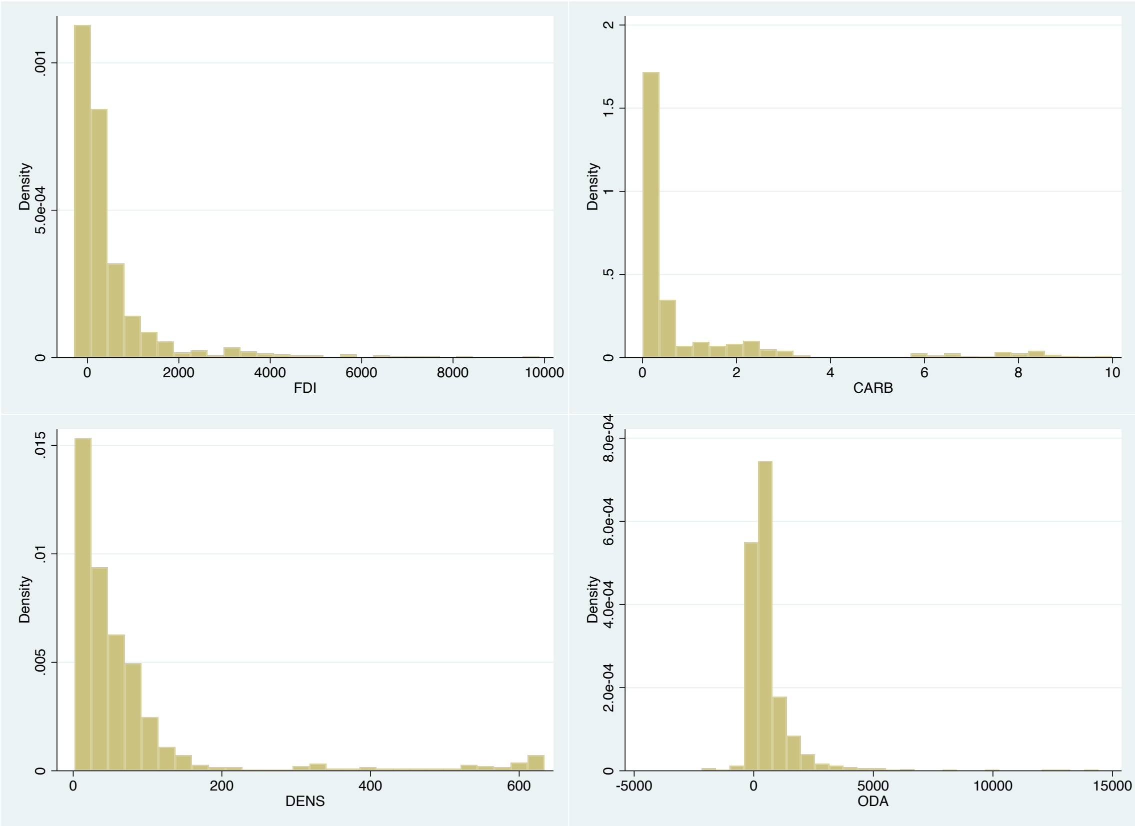
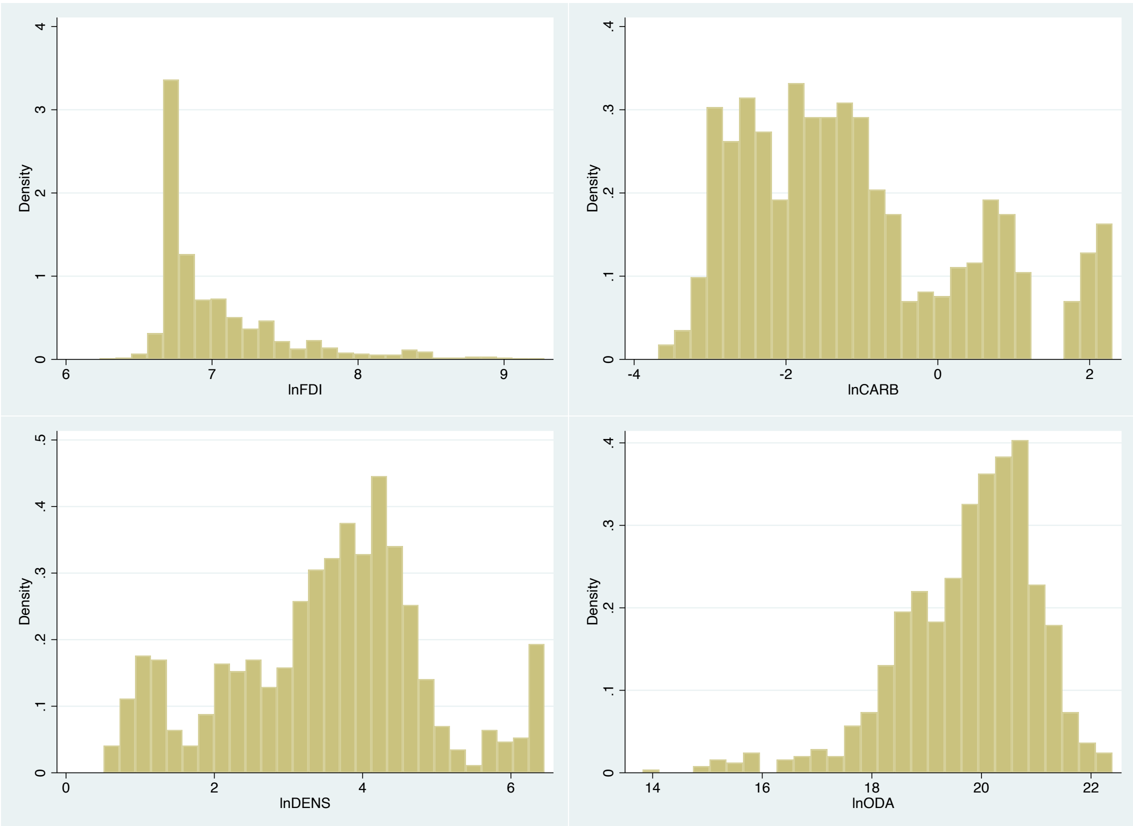


Figure 3. Histograms of the non-linear variables after their log transformation



Econometric model

This paper uses a panel data as this provides significant benefits over alternatives. By combining observations from different countries and over multiple periods of time, it increases the number of observations which increases the degrees of freedom and allows to reduce the issue of collinearity among the independent variables. Panel data allows us also to control more easily for questions of individual heterogeneity and thus capture more complex relationships compared to pure cross-sectional or time series models (Munir and Ameer, 2016). Furthermore, table 2 shows us that we have enough variation within the time and case dimension of each variable to have a meaningful panel data analysis.

Modelling the relationship

Overall, we are expecting to use a fixed effect model, as using random effects would assume that individual characteristics of countries play no role in the carbon footprint of the country. Indeed, considering the wide range of countries in our dataset, which consists in different political regimes, different economies, cultures, geography and religion, to name a few factors of difference, it seems implausible to expect our observations not to contain individual characteristics relevant for our model. A Hausman test in the following section will be used to confirm how the slopes and coefficients should be modelled.

$$(3)\ y_{\mathrm{it}} = \alpha_{\mathrm{i}} + \beta \mathrm{X}_{it} + \ \varepsilon_{it}$$

Where y_{it} is the dependent variable, α_{i} is the individual effect, X_{it} is a vector of explanatory varibales, β is a k-dimensional vector of unknown parameters, and ε_{it} is the idiosyncratic error term.

The relationship between FDI, ODA and the carbon footprint of an economy is expected to be dynamic as the impact of investment flows on the carbon footprint of the economy is expected to be diffuse over time. This means that static models using a simple lag of the variables will not be enough to account for the relationship between the explanatory variables and the dependent variable. Importantly, we do not expect a feedback loop between the carbon footprint of an economy and the investment flows. Additionally, we expect an omitted variable bias as additional factors not accounted for in this model are likely to impact CARB. Changes to the structure of an economy will impact the carbon intensity of an economy through processes of industrialisation or de-industrialisation, which may not simply be captured by GDP growth as an economic growth fuelled by industrialisation from energy-intensive industries will result in a higher increase in CARB compared to an economic growth fuelled by the service sector for example. Additionally, the model does not account for government policies such as fossil fuel subsidies which will also impact the stickiness of fossil fuels in an economy and thus CARB. Finally, the presence of fossil resources in the economy such as coal mines or oil and gas fields will also impact the carbon footprint of a country. If we fail to account for the fact that we expect to have an omitted variable problem, the individual effect and the lag of the dependent variables and the explanatory variables will be correlated, leading to biases in the coefficients due to endogeneity (Arellano and Bover 1995).

GMM model

Our model will need to capture the impact of investment flows on the carbon footprint of economies. However, this is expected to be a dynamic relationship as the impact of ODA and FDI is likely to be diffuse over time. Additionally, we also expect our sample of countries to be influenced by individual characteristics of countries that are not captures by our model.

The generalized method of moments (GMM) model is thus a relevant model to consider as it combines a pooling of individual groups, creating homogenous slopes, while the intercepts differ across cases. This allows us to account for two key features, the individual characteristics of the sampled economies and the dynamic relationship between investment flows and carbon footprint. Furthermore, the GMM model is suited to account for the endogeneity that arises from omitted variable bias, likely to be present in our model. To deal with this issue, a first differencing approach can allow us to remove the time invariant individual effect by doing a first difference of our model (Arellano and Bond, 1991):

$$(4) y_{\mathrm{it}} - y_{it-1} = \alpha(y_{it-1} - y_{it-2}) + (\mathrm{X}_{it} - \mathrm{X}_{it-1})'\beta + (\varepsilon_{it} - \varepsilon_{it-1})$$

Because of omitted variable bias $y_{\mathrm{it}} - y_{it-1}$ in (4) is expected to be endogenous. Following Arellano and Bond (1991), we will use a lag of the dependent variable: y_{it-2}. Applied to our variables in (2), we use the following GMM model:

$$\begin{aligned}(5)\ \Delta lnCARB_{it} &= \alpha\Delta ln\mathrm{CARB}_{it-1} + \beta_1\Delta ln\mathrm{ODA}_{it} + \beta_2\Delta ln\mathrm{FDI}_{it} + \beta_3\Delta ln\mathrm{ELEC}_{it} \\ &\quad + \beta_4\Delta ln\mathrm{GDP}_{it} + \beta_5\Delta ln\mathrm{DENS}_{it} + \Delta\varepsilon_{it}\end{aligned}$$

Where Δ denotes the first difference.

However, GMM models are vulnerable to issues of cross-sectional dependence, which will lead to autocorrelation in the error term which biases the estimates of the model (Ditzen, 2018). In case of homogenous cross-sectional dependence, period-fixed effects by creating time-dummies or demeaning the data, can resolve the issue, however, this does not work in case of heterogeneous cross-sectional dependence (Ullah et al., 2018). The literature on the energy, economy and finance nexus points out that cross-sectional dependence is a concern (De Hoyos and Sarafidis, 2006) and the large T dimension of our sample increases the risk that the model will suffer from heterogenous cross-sectional dependence making time-dummies and data demeaning inefficient. Furthermore, issues of non-stationarity can become a concern once the sample size is sufficiently large (Ibid.). Nonetheless, a GMM approach is appropriate for the smaller T-dimension necessary to answer H_3, for which two periods of 10 years are compared. Three GMM models will therefore be analysed: one that encompasses the entire period, and which will be compared to the ARDL model explained below, and two models covering 10 years each, a first one covering 1990-1999 and a second one covering 2011-2020 (the earlier and latest 10-years periods in the dataset).

ARDL model

Our data is also particularly suited for an AutoRegressive Distributed Lag (ARDL) approach. Kripfganz and Schneider (2023) argue that ARDL techniques provide efficient inference when there are no reasons to be concerned with contemporaneous effects creating endogeneity issues. As we do not expect investment flows to respond to changes in the level of carbon footprint of an economy, the ARDL is thus a good model for our research. The literature on the investment, energy and carbon nexus thus commonly uses panel single-equation autoregressive distributed lag models (ARDL) (Qin et al., 2024). The ARDL method can also deal with stationarity issues. Among the different techniques proposed, the literature finds that Pesaran, Shin, and Smith's (1999) pooled mean group approach which allows the intercept, short-run coefficients, and error variances to differ across the groups but constrains the long-run coefficients to be equal across groups, provides a model that has enough flexibility in cases when the data poses heterogenous slopes, which a traditional fixed effect would fail to capture (Ditzen, 2018). This approach thus has the benefit of providing short term and long-term estimates of the relationship, which is particularly relevant in the case of our research.

However, ARDL models are vulnerable to endogeneity issues arising from omitted variable bias, which will result biased coefficients. As we have good reasons to believe that our model will suffer from an omitted variable, this is a major cause of concern. The GMM and ARDL models thus are complementary, and both will be used in order to strengthen the reliability of our findings. An ARDL model allows to distinguish between short and long-term dynamics by calculating the error correction term (ECT) and the error correction speed parameter to model the adjustment process towards long-term equilibrium. While the ECT calculates the long-term relationship between the variables, the error correcting speed parameters estimates the speed at which the variables restore the long-term relationship after short-term shocks (Ditzen, 2018).

$$(5)\Delta y_{it} = \rho_i(y_{it-1} - \beta_i \mathrm{X}_{it-1}) + \sum_{i}^{p} \vartheta_i \Delta y_{it-1} + \sum_{i}^{q} \vartheta_i \Delta(\mathrm{X}_i)_{t-j} + \alpha_i + \varepsilon_{it}$$

Where ρ_i is the error correcting speed of the adjustment parameter and is expected to be negative if there is to be a long-term relationship, ϑ_i represents the short-term coefficients, β_i are the long-run coefficients. p and q are the number of lags in the dependent and dependent variables respectively. $(y_{it-1} - \beta_i \mathrm{X}_{it-1})$ is the ECT.

Fitting our variables in (2), we get the following model:

$$\begin{aligned}(6)\Delta lnCARB_{\mathrm{it}} = {} & \rho ECT_{t-1} + \vartheta_i \\ & + \sum_{i=1}^{t} \vartheta_1 \Delta lnCARB_{it-1} \\ & + \sum_{i=1}^{t} \vartheta_2 \Delta ODA_{it-1} + \sum_{i=1}^{t} \vartheta_3 \Delta lnFDI_{it-1} + \sum_{i=1}^{t} \vartheta_4 \Delta ELEC_{it-1} \\ & + \sum_{i=1}^{t} \vartheta_5 \Delta lnDENS_{it-1} + \sum_{i=1}^{t} \vartheta_6 \Delta lnGDP_{it-1} + \varepsilon_{it}\end{aligned}$$

The necessary tests, such as cross dependence, cointegration and unit root tests are discussed below.

Our paper will therefore use two types models: the ARDL which will allow us to measure the long-term impact of investment flows, but considering that it is likely to suffer from an omitted variable bias, and three GMM models that can control for this bias, but will not provide us with the same flexibility regarding long-term relationships.

Specification tests

The Hausman test was used to compare a simple fixed and random model in order to verify the hypothesis that a fixed effect model is more suited, with the test's H_0 being that a random effect model is a more efficient model. We strong reject H_0, with $p<0.001$ and thus confirm that a fixed effect model is more suited. Serial correlation was also found by conducting a Wooldridge test for autocorrelation, which also rejected the H_0 of no serial correlation ($p<0.001$). Standards errors will thus be clustered per country. Finally, a modified Wald test for groupwise heteroskedasticity was applied on a basic fixed effect model with clusters per country, rejecting H_0: $\sigma_i^2 = \sigma_i^2$ for all i. ($p<0.001$), thus finding heteroskedasticity within the panel, meaning that robust standard errors will be required.

A cross sectional dependence test was conducted using Pesaran (2004) test for cross sectional dependence. For a model with fixed effect but no time dummies (see table 4), the test strongly rejected the H_0 of no cross-sectional dependence ($p<0.001$). For a model with fixed effect and time dummies, the Pesaran test still found cross-sectional dependence, albeit with lower confidence ($p<0.05$). This suggest that the cross-sectional dependence is heterogeneous and thus only partly mitigated by the inclusion of period-fixed effects. This is particularly important for the GMM model and can lead to incorrect statistical inference (Ditzen, 2018). Similar results were found for the GMM 1990-1999 and GMM 2012-2024 models. Finally, the ARR test for the GMM model was also conducted and showed that the first difference is statistically significant ($p<0.001$). Likewise, for the GMM1990-1999 and GMM 2012-2024 models, albeit both had a relatively smaller statistical significance for AR1 ($p=0.001$).

For the ARDL a correlation analysis was conducted to ensure that the explanatory variables do not suffer from multicollinearity issues. Which identified a strong correlation between *ln*GDP and ELEC. ELEC was thus dropped as it is the variable for which the relationship to *ln*CARB is also the least clear theoretically[1]. The rest of the variables do not show important correlation between them. A model Pesaran's CADF test, a second-generation panel unit root test, was conducted to account for cross-sectional correlation in the data. The result shows us that all our variables are stationary at the level and thus don't need first difference (see table 4). Using the

[1] As explained in the introduction, there are reasons to believe electrification could impact *ln*CARB in either direction.

ardl command (Tchetchik, 2014), the optimal lag was identified, which is reported for each variable in table 5.

Considering that we have heterogeneous panel data, and need to take into account panel-specific time trend, a Pedroni test is concluded to investigate the presence of long-term relationship, which is found in most tests (see table 6). Alternatively, the long-term relationship of our variables will be tested by looking at the significance of the error correction term and of the long-term coefficients, thanks to the hypothesis of long-run homogeneity of our data (Qin et al., 2024). The ARDL model is conducted using a dynamic fixed effect (DFE), which, similarly to a fixed effect in GMM, all parameters, except intercepts, are constrained to be equal across panels.

Table 3. Correlation matrix

	ODA	*ln*FDI	*ln*GDP	*ln*DENS	ELEC
*ln*ODA	1				
*ln*FDI	0.52	1			
*ln*GDP	0.26	0.41	1		
*ln*DENS	0.16	0.05	-0.06	1	
ELEC	0.28	0.41	**0.81**	0.27	1

Table 4. Pesaran's test of cross-sectional independence

Fixed effect	5.61***
Fixed effect and time dummies	-2.824**

, ** and * represent the 10%, 5% and 1% significance levels, respectively*

Table 4. CADF test (constant)

Variables	Constant (lag0)
lnCARB	-2.708***
lnODA	-2.760***
lnFDI	-2.555**
ELEC	-4.914***
lnGDP	-6.023***
lnDENS	-6.591***

, ** and * represent the 10%, 5% and 1% significance levels, respectively*

Table 5. Optimal lag length per variable

Variables	Lag length
*ln*CARB	1
*ln*ODA	1
*ln*FDI	1
*ln*GDP	0
*ln*DENS	0

Table 6. Pedroni cointegration test

Statistic	Constant
Modified Phillips–Perron t	1.1924
Phillips–Perron t	-4.7082***
Augmented Dickey–Fuller t	-3.5922***

, ** and * represent the 10%, 5% and 1% significance levels, respectively*

Results

Table 7. Models results

Dependent variable	ARDL	GMM	GMM (1990-1999)	GMM (2011-2020)
lag*ln*Carb (instr.)		0.76*** (0.04)	0.49** (0.14)	0.69*** (0.04)
*ln*ODA	-0.06 (0.05)	0.04 (0.01)	0.08** (0.05)	-0.02 (0.02)
*ln*FDI	0.21** (0.06)	0.03** (0.02)	-0.02 (0.03)	0.02** (0.12)
*ln*GDP	0.23** (0.09)	0.04** (0.02)	0.07* (0.05)	0.06* (0.03)
*ln*DENS	0.29 (0.26)	-0.06 (0.07)	-0.30 (0.5)	0.12 (0.13)
ELEC		-0.0008 (0.001)	-0.004 (0.006)	0.0002 (0.001)
Short-run coefficients				
ECT	-0.17*** (0.02)			
Δ *ln*ODA	0.01 (0.01)			
Δ *ln*FDI	0.03** (0.01)			
Δ *ln*GDP	0.08** (0.03)			
Δ *ln*DENS	-0.24 (0.30)			
Constant	-0.62** (0.18)			
AR1		-3.50***	-1.10**	-3.14**
AR2		-1.04	-0.02	-0.73

*Note: *, ** and *** represent the 10%, 5% and 1% significance levels, respectively. Robust standard errors are presented in parentheses. Δ denotes the first difference operator.*

Results reporting

For the ARDL model, the estimated ECR for the model is negative and statistically significant. Which indicates the rate at which *ln*CARB adapts to changes in the model before converging to its equilibrium. This thus indicates a long-term relationship. With an ECT of -0.17, this indicates that *ln*CARB adapts at a rate of 17% per year towards long-run equilibrium of the model.

Both control variables are associated with an increase in carbon footprint. *ln*GDP is statistically significant in both the short and long-run while *ln*DENS only has a statistically significant impact on the long-run ($p<0.05$). The direction of the relationship is as expected.

Regarding our variables of interest, ODA has a negative relationship with *ln*CARB in the long-run of 0.06% and a positive relationship of 0.001% in the short run, however neither are statistically significant. *ln*FDI does instead have a statistically significant impact on *ln*CARB, particularly on the long-run ($p<0.001$). The short-term impact of a 1% increase in *ln*FDI is a 0.03% increase in carbon footprint, while its long-term impact is a 0.21% increase in carbon footprint.

Regarding the GMM models, it is interesting to note that the general model finds a positive relationship between FDI and carbon footprint, also at the 5% level, while, unlike the ARDL model, it finds a positive relationship between *ln*ODA and carbon footprint but also a non-statistically significant one. This difference between the direction of the coefficient of *ln*ODA could be due to a shifting relationship between *ln*ODA and carbon footprint during the period analysed, which the ARDL's long-term equilibrium captures while the GMM does not. This could explain the fact that the 1990-1999 model has a statistically significant relationship between *ln*ODA and carbon footprint while the 2011-2020 model finds a negative relationship, although not statistically significant. While the two smaller GMM models capture a shift in the relationship between *ln*ODA and carbon footprint, going from positive to negative, they capture the opposite for *ln*FDI, with a negative relationship between *ln*FDI and carbon footprint, statistically insignificant for the period 1990-1999 and a positive relationship, significant at the 5% level, between the two variables.

Results analysis and discussion

H1 posited that *ln*FDI and *ln*ODA had a similar impact on the carbon footprint of the recipient country, suggesting that they are either mutually reinforcing flows or potentially competing flows:

> H1: Both FDI and ODA are negatively associated with the carbon footprint of the recipient country.

While our models capture different and changing coefficients for *ln*ODA and *ln*FDI, none captures both variables having a negative impact on *ln*CARB simultaneously, in fact there is a simultaneous shift in the direction of the coefficient between the 1990-1999 and the 2011-2020 models. As will be discussed below, this simultaneous shift could suggest that *ln*ODA and *ln*FDI are competing flows.

H2 posited that ODA may not directly decrease carbon footprint of recipient countries but may favour FDI flows that are associated with a reduction in carbon footprint:

> H2: ODA is not significantly associated with changes in carbon footprint of an economy while FDI is negatively associated with the carbon footprint of the recipient country.

Except for the 1990-1999 model, *ln*ODA does not have a statistically significant impact on *ln*CARB, however *lnFDI* is only found to have a negative impact on the carbon footprint of an economy in the 1990-1999 model. Our model therefore does not provide support for this theory, although the methodology of this paper only provides a partial examination of this theory and therefore more empirical research on this point is needed.

H3 posited that the increasing focus of international development actors on climate policies has a significant impact on the relationship between ODA and the carbon footprint of the recipient country.

> H3a: ODA in the late 90s was not associated with the carbon footprint of the recipient country;
>
> H3b: ODA after the 2010s is negatively associated with the carbon footprint of the recipient country.

The 1990-1999 and 2011-2020 models do show the expected switch in the coefficient of *ln*ODA, suggesting that the impact of *ln*ODA on the carbon footprint follows what H3 expects. However, while the impact of *ln*ODA on *ln*CARB is significant at the 5% level in the 1990-1999 model, the negative relationship between the two variables in the later model is not ($p= 0.453$), limiting the extent to which conclusions can be made regarding this switch.

Overall, our model shows that external investment flows seem to have a statistically significant impact on the reduction of the carbon footprint of recipient countries. The ARDL model captures a long-term effect of *ln*ODA on the reduction of carbon footprint, which the general GMM model does not. This difference could be due to the ARDL model giving more weight to the long-term impact of variables and isolating the long-term effect which the GMM model does not. It is interesting to note the simultaneous switch in the direction of the relationship of *ln*ODA and *ln*FDI with *ln*CARB, this could suggest two things:

1. International policy decisions may indeed have a strong impact in steering the direction of ODA flows to prioritise policies reducing greenhouse gases compared to policies advancing other objectives of the SDG. In this regard, it would be interesting to investigate whether this shift in the impact of ODA on the carbon footprint of recipient countries comes at the expense of other dimensions of the SDGs (in the case where this increase in focus has led to a redirection of aid flows) or whether the increase in focus on climate policies has instead led to an increase in total aid flows, thereby limiting the trade-off between the energy transition and other SDGs.
2. Secondly, the fact that the relationship between ODA and CARB seems to mirror the relationship between FDI and CARB between 1990-1999 and 2011-2020 could suggest that there is an effect of crowding out FDI from low-carbon projects, and that in this regard, both flows play a similar role regarding the energy transition. It could also suggest that prior to the policy shift from international donors, it is possible that FDI still played a role in facilitating FDI's investment in clean technologies, albeit less directly, for example through institutional capacity building. These are only hypotheses that require further research and more granular models that account for the many shortcomings of this model.

Overall, this paper provides insights into the dynamics between FDI, ODA and carbon footprint and finds evidence for a shift in the impact of ODA on the carbon footprint of recipient countries, which seems to lead to a change in the type of FDI investments. However, these findings need to be conditioned on multiple weaknesses. Firstly, an important omitted variable bias is present, which risks impacting the results of our ARDL model. In this regard, additional research that takes into account factors such as the levels of fossil fuel subsidies, the presence of natural resources such as coal, oil or natural gas, and the structure of the economy, would be welcome additions. Secondly, the 1990-1999 and 2011-2020 models suggest a shift in the relationship between ODA/FDI and CARB. A time series analysis of this relationship over the period of this study would be interesting to add clarity and to confirm or infirm this dynamic and potentially identify certain explanatory factors other than those proposed in this paper.

Conclusion and policy recommendations

Overall, this paper analysed the relationship between external investment flows, ODA and FDI, on the carbon footprint of recipient countries. It did so through 3 general hypotheses: 1) that

FDI and ODA had a similar impact on the carbon footprint of the recipient country, suggesting that they are either mutually reinforcing flows or potentially competing flows , 2) that ODA may not directly decrease carbon footprint of recipient countries but may favour FDI flows that are associated with a reduction in carbon footprint and 3) that the increasing focus of international development actors on climate policies has a significant impact on the relationship between ODA and the carbon footprint of the recipient country. To investigate these questions, this paper built an ARDL and a GMM model while two additional GMM models were used to look at the first and final 10 years of the sample. The use of ARDL and GMM techniques was justified by the fact that each model had different shortcomings.

Overall, this paper finds no support for the first hypothesis, some support for the second and more for the third one. This provides evidence that ODA is an important tool for decision makers to contribute to international climate policies, however they should be mindful of the impact that ODA may have on FDI and should thus investigate where ODA investments are most needed to maximise the impact of climate policies. Indirect ODA investment that focusses on creating the necessary conditions for FDI flows in the appropriate sectors, may also have a positive impact towards achieving climate policies.

Declaration

As per Sciences Po's guidelines regarding the usage of generative ai, the usage of ChatGPT is declared for the generation of Stata code and to verify equations 5 and 6.

Bibliography

Acheampong, A. O., Adams, S., & Boateng, E. (2019). Do globalization and renewable energy contribute to carbon emissions mitigation in Sub-Saharan Africa?. *Science of the Total Environment*, *677*, 436-446.

African Business, (2024). *Keep it in the ground? Africa's race to develop its oil and gas resources*. Accessed via: https://african.business/2024/04/resources/keep-it-in-the-ground-africas-race-to-develop-its-oil-and-gas-resources

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, *58*(2), 277-297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, *68*(1), 29-51.

Asongu, S. A., & Nwachukwu, J. C. (2018). Increasing foreign aid for inclusive human development in Africa. *Social Indicators Research*, *138*(2), 443-466.

Amusa, K., Monkam, N., & Viegi, N. (2016). Foreign aid and Foreign direct investment in Sub-Saharan Africa: A panel data analysis. *Economic Research Southern Africa (ERSA)*, *612*, 1-23.

BBC, (2021). China pledges to stop building new coal energy plants abroad. Accessed via: https://www.bbc.com/news/world-asia-china-58647481

Bertheau, P., & Lindner, R. (2022). Financing sustainable development? The role of foreign aid in Southeast Asia's energy transition. *Sustainable Development*, *30*(1), 96-109.

Blackburne III, E. F., & Frank, M. W. (2007). Estimation of nonstationary heterogeneous panels. *The Stata Journal*, *7*(2), 197-208.

Boateng, E., Agbola, F. W., & Mahmood, A. (2021). Foreign aid volatility and economic growth in Sub-Saharan Africa: Does institutional quality matter?. *Economic modelling*, *96*, 111-127.

Briggs, R. C. (2018). Poor targeting: A gridded spatial analysis of the degree to which aid reaches the poor in Africa. *World Development*, *103*, 133-148.

De Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. *The stata journal*, *6*(4), 482-496.

Ditzen, J. (2018). Estimating dynamic common-correlated effects in Stata. *The Stata Journal*, *18*(3), 585-617.

Du, W. C., & Xia, X. H. (2018). How does urbanization affect GHG emissions? A cross-country panel threshold data analysis. *Applied energy*, *229*, 872-883.

Fahinde, C., Abodohoui, A., Mohiuddin, M., & Su, Z. (2015). External financial inflows and domestic investment in the economies of WAEMU: Crowding-out versus crowding-in effects. *The Journal of Developing Areas*, 229-248.

Farooq, U. (2022). Foreign direct investment, foreign aid, and CO 2 emissions in Asian economies: does governance matter?. *Environmental Science and Pollution Research*, 1-16.

Financial Timesn (2021). *European Investment Bank resists pressure to fund gas projects*. Accesed via: https://www.ft.com/content/b00ea2e5-78a0-46c5-b2b0-33e6a40b96af

Gnangnon, S. K. (2019). Financial openness and aid for trade in developing countries. *South African Journal of Economics*, *87*(1), 46-64.

Gui-Diby, S. L., & Renard, M. F. (2015). Foreign direct investment inflows and the industrialization of African countries. *World Development*, *74*, 43-57.

Gyamfi, B. O. (2016). *The effect of official development assistance and foreign direct investment on economic growth in Ghana (1975-2014)* (Doctoral dissertation).

Herzer, D., & Nunnenkamp, P. (2012). The effect of foreign aid on income inequality: Evidence from panel cointegration. *Structural Change and Economic Dynamics*, *23*(3), 245-255.

Iacobuţă, G. I., Höhne, N., van Soest, H. L., & Leemans, R. (2021). Transitioning to low-carbon economies under the 2030 agenda: Minimizing trade-offs and enhancing co-benefits of climate-change action for the sdgs. *Sustainability*, *13*(19), 10774.

Ialnazov, D., & Keeley, A. (2020, July). Motivations, enabling factors and barriers to the energy transition in Indonesia and Vietnam. In *IOP Conference Series: Earth and Environmental Science* (Vol. 505, No. 1, p. 012044). IOP Publishing.

Unceta, K., Gutierrez, J., & Amiano, I. (2010). Financing development: ODA versus FDI and Remittances in the most vulnerable Countries. *Current Research*, *9*, 165-186.

Juselius, K., Møller, N. F., & Tarp, F. (2014). The long-run impact of foreign aid in 36 African countries: Insights from multivariate time series analysis. *Oxford Bulletin of Economics and Statistics*, *76*(2), 153-184.

Kim, J. E. (2019). Sustainable energy transition in developing countries: the role of energy aid donors. *Climate Policy*, *19*(1), 1-16.

Kobrin, S. J. (2005). The determinants of liberalization of FDI policy in developing countries: a cross-sectional analysis, 1992-2001. *Transnational Corporations*, *14*(1), 67-104.

Kripfganz, S., & Schneider, D. C. (2023). ardl: Estimating autoregressive distributed lag and equilibrium correction models. *The Stata Journal*, *23*(4), 983-1019.

Li, F., Zhang, J., & Li, X. (2022). Research on supporting developing countries to achieve green development transition: Based on the perspective of renewable energy and foreign direct investment. *Journal of Cleaner Production*, *372*, 133726.

Martínez-Zarzoso, I., & Nowak-Lehman, D. F. and Reewald, K.(2017). Is Aid for Trade Effective? A Panel-Quantile Regression Approach. *Review of Development Economics*.

Munir, K., & Ameer, A. (2018). Effect of economic growth, trade openness, urbanization, and technology on environment of Asian emerging economies. *Management of Environmental Quality: An International Journal*, *29*(6), 1123-1134.

Newell, P., & Phillips, J. (2016). Neoliberal energy transitions in the South: Kenyan experiences. *Geoforum*, *74*, 39-48.

Park, G., & Jung, H. J. (2020). South Korea's outward direct investment and its dyadic determinants: Foreign aid, bilateral treaty and economic diplomacy. *The World Economy*, *43*(12), 3296-3313.

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American statistical Association*, *94*(446), 621-634.

Qin, Y., Xu, Z., Luo, C., & Skare, M. (2024). Investigating the nexus among resource curse, energy transition and sustainable development: Evidence from a global panel data. *Resources Policy*, *88*, 104445.

Rahman, M. M., Bindu, K. J., & Islam, M. K. (2018). Linking per capita GDP to energy consumption, ecological footprint, and carbon dioxide emission in a developing economy in the world: The case of Bangladesh. *Journal of Banking and Financial Dynamics*, *2*, 9-15.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *The stata journal*, *9*(1), 86-136.

Sapkota, P., & Bastola, U. (2017). Foreign direct investment, income, and environmental pollution in developing countries: Panel data analysis of Latin America. *Energy Economics*, *64*, 206-212.

Shafique, M., Azam, A., Rafiq, M., & Luo, X. (2021). Investigating the nexus among transport, economic growth and environmental degradation: Evidence from panel ARDL approach. *Transport Policy*, *109*, 61-71.

Stavropoulos, S., Wall, R., & Xu, Y. (2018). Environmental regulations and industrial competitiveness: evidence from China. *Applied Economics*, *50*(12), 1378-1394.

Tchetchik, A. (2014). Optimal lag length for ARDL in panel. *Statalist forum*. Accessed via: https://www.statalist.org/forums/forum/general-stata-discussion/general/1333077-optimal-lag-length-for-ardl-in-panel

Ullah, S., Akhtar, P., & Zaefarian, G. (2018). Dealing with endogeneity bias: The generalized method of moments (GMM) for panel data. *Industrial Marketing Management*, *71*, 69-78.

Wang, Q., Guo, J., & Dong, Z. (2021). The positive impact of official development assistance (ODA) on renewable energy development: evidence from 34 Sub-Saharan Africa Countries. *Sustainable Production and Consumption*, *28*, 532-542.

Appendix

Stata syntax for the models

Heteroskedasticity

ssc install xttest3
xtreg lnCARB ODA lnFDI lnDENS ELEC LGDP, fe robust
xttest3

Hausman test

xtreg lnCARB lnODA lnFDI LGDP ELEC lnDENS, fe
estimates store fixed
xtreg lnCARB lnODA lnFDI LGDP ELEC lnDENS, re
estimates store random
hausman fixed random, sigmamore

Pesaran test

tsset pays year
xtreg lnCARB lnODA lnFDI LGDP ELEC lnDENS, fe
xtreg lnCARB lnODA lnFDI LGDP ELEC lnDENS i.year, fe

xtreg lnCARB lnODA lnFDI LGDP ELEC lnDENS i.year if P1 == 1, fe
xtreg lnCARB lnODA lnFDI LGDP ELEC lnDENS i.year if P22 == 22, fe
xtcsd, pesaran abs

CADF tests

* pescadf lnFDI, lags(0) p = 0.000
* pescadf lnODA, lags(0) p = 0.000
* pescadf lnCARB, lags(0) p = 0.003
* pescadf LGDP, lags(0) p=0.000
* pescadf lnDENS, lags(0) p=0.017

Optimal lags

```
forval i = 1/26 {
        ardl lnCARB lnODA, lnFDI, if (pays==`i'), maxlag(3 3 3 3 3)
        matrix list e(lags)
        di
    }
```

Correlation analysis

corr lnODA lnFDI LGDP lnDENS ELEC
corr lnODA lnFDI LGDP lnDENS

Hausman tests to identify appropriate model ardl:

xtpmg d.(lnCARB ODA lnFDI LGDP lnDENS ELEC), lr(L.lnCARB L.ODA L.lnFDI LGDP lnDENS ELEC) mg
xtpmg d.(lnCARB ODA lnFDI LGDP lnDENS ELEC), lr(L.lnCARB L.ODA L.lnFDI LGDP lnDENS ELEC) pmg
xtpmg d.(lnCARB ODA lnFDI LGDP lnDENS ELEC), lr(L.lnCARB L.ODA L.lnFDI LGDP lnDENS) dfe
hausman mg pmg, sigmamore
hausman dfe pmg, sigmamore
hausman dfe mg, sigmamore

GMM 2011-2020

- xtabond2 lnCARB l.lnCARB lnODA lnFDI LGDP ELEC lnDENS if P22 == 1, gmmstyle(L.lnCARB) ivstyle(lnODA lnFDI LGDP ELEC lnDENS) robust small noleveleq

GMM 1990-1999

- xtabond2 lnCARB l.lnCARB lnODA lnFDI LGDP ELEC lnDENS if P1 == 1, gmmstyle(L.lnCARB) ivstyle(lnODA lnFDI LGDP ELEC lnDENS) robust small noleveleq

GMM general

- xtabond2 lnCARB l.lnCARB lnODA lnFDI LGDP ELEC lnDENS, gmmstyle(L.lnCARB) ivstyle(lnODA lnFDI LGDP ELEC lnDENS) robust small noleveleq

ARDL

- xtpmg d.(lnCARB lnODA lnFDI LGDP lnDENS ELEC), lr(L.lnCARB L.lnODA L.lnFDI L3.LGDP L.lnDENS ELEC) dfe