Dynamic relationship between China's engineering projects overseas and the environmental quality of host countries

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Considering the looming concerns over the environmental consequences of China's global presence, this research paper attempts to empirically explore the dynamic bidirectional relationship between its engineering projects overseas and the environmental quality of host countries, as measured by their carbon dioxide (CO_2) emissions per capita. The overarching goal is to examine whether China backed global projects lead to an increase in emissions of the host countries and whether in turn the current-day environmental quality is a signal to Chinese contractors about the presence of policy laxity. The research question is answered using a panel-vector autoregression model, which is chosen for the purpose of overcoming endogeneity in the econometric approach. It is found that China's engineering projects in low-income countries tend to be pollution intensive.

Key words: Chinese economic cooperation, environment, low-income countries, panel-vector autoregression.

JEL Classification F23 . F64 . O13 . Q53 . Q56 .

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1. Introduction

Since establishing itself as an economic superpower in the early 21st century, China has sought to increase its global influence in recent years. A testament to this shift is China's multi-billion-dollar Belt and Road Initiative (BRI) which was initiated in 2013 with the aim of connecting over seventy countries in Asia and Europe through infrastructure development for the purpose of global trade. As a result of its emphasis on globalization, China is presently ranked third in the world in highest outward foreign direct investment (FDI) as reported by United Nations Conference on Trade and Development. A different aspect of China's global presence which receives far less attention in the literature is its economic cooperation projects, which mainly involve the Chinese government awarding contracts to Chinese contractors for conducting engineering activities overseas. In 2018, China's net overseas direct investments amounted to 143 billion U.S. dollars, and this was overshadowed by the turnover of economic cooperation contracts which valued to 169 billion U.S. dollars (National Bureau of Statistics of China). Mainly in developing countries, these projects serve to build physical infrastructure such as highways, roads, bridges, railways, dams and powerplants and are a route to subsequent rounds of foreign direct investments by China. In 2004, Chinese construction companies repaired Angola's broken railway lines and built transportation infrastructure and hydropower dams in Iran. Soon after the completion of the construction projects, Chinese oil mining companies received licenses to operate oil fields in those countries, which drove them to relocate parts of their businesses overseas (Bhaumik and Yap, 2010). By allowing poorer and cash-strapped countries to pay for infrastructural development through natural resources, Chinese economic cooperation projects accelerate their growth trajectory. Despite this beneficial aspect of China's overseas involvement, what is often of great concern to local communities and climate advocates is the environmental footprint left behind. As validated by Bhaumik and Yap (2010), the flow of Chinese economic cooperation projects increases sharply with a decline in development status of a country. Considering the pollution intensive nature of developmental activities in these countries and their environmental policy laxity, there is great deal of skepticism over the overarching environmental effect of China's involvement globally. Though other developed countries like the United States are active financiers of foreign aids and investments, none of their projects are comparable in magnitude and stature to that of China, especially in developing parts of the world. The United States has the Millennium Challenge Corporation, which is a bilateral foreign aid program, but it is not streamlined towards engineering activities and hence its major concerns are not environmental but rather political. The case for China is different in that it covers an extensive region of the world through government backed economic cooperation projects in construction and engineering activities and has massive ramifications on the local environment[1].

After the United States' temporary withdrawal from the Paris Agreement, China reiterated its intention to be the new global leader on the fight against climate change. On September 22, 2020 the president of China pledged to aim for carbon neutrality by 2060[2]. To a body of scholars this comes as no surprise since the Environmental Kuznets Curve theory predicts that countries will attain better environmental quality once they achieve higher income. However, whether the higher quality of environment will be achieved at the expense of having pollution intensive companies/industries conduct their operations overseas and degrade the local environmental quality remains a tricky question left to be answered. At the same time, it is equally important to consider what factors determine the destination of China's economic cooperation contracts. As is discussed in the literature review section, multiple studies have posited that the environmental quality of a country is a signal of its environmental regulation laxity, a potential determinant of foreign investments. This results in the possibility of a bi-directional relationship between the two variables: economic cooperation contracts and environmental quality. The purpose of this research paper is to make use of existing world data and statistical methods to examine this relationship.

Specifically, this study looks at engineering and construction related projects carried out by China globally. Engineering, procurement, and construction (EPC) has been one of the dominant forms of Chinese investments abroad whereby upon having a bid accepted by the Chinese government, a Chinese construction company designs a project, procures the necessary material and equipment, and engages in the construction of an infrastructure as specified in the contract. Even in the first half of 2020 when the COVID-19 pandemic halted a lot of international investment activities, China's Ministry of Commerce reported that there was a 5% growth in newly signed outbound EPC contracts. Chinese conglomerates such as the China Civil Engineering Construction Corporation, China Railway International Co. Ltd., and Sinohydro

[1]Carr, E. (2020). The US versus Chinese Investment in Africa. *Forbes.com* https://www.forbes.com/sites/earlcarr/2020/09/04/the-us-versus-chinese-investment-in-africa/?sh=2cfd591465d4

[2] Farand, C., & Darby, M. (2020). Xi Jinping: China will aim for carbon neutrality by 2060. Climate Home News. https://www.climatechangenews.com/2020/09/22/xi-jinping-china-will-achieve-carbon-neutrality-2060/ .

Corporation Ltd., are at the forefront of most of the foreign EPC projects. They are engaged mainly in the construction of factories, roads, railway-lines, buildings, powerplants, tunnels, and other forms of physical infrastructure in the host countries. Because a lot of these activities are detrimental to the environment, it is worth considering the broader effect of the construction related investments made by China.

The research question I address is: How do China's government backed construction and engineering projects abroad and the local environmental quality of the host countries influence each other over time? I address this question using a panel-vector autoregression (panel-VAR) model which is designed to account for the dynamic interactions between the variables of interest and overcome the problem of endogeneity. The model is constructed by including GDP per capita and the cumulative FDI from all other sources as the two other endogenous variables, because of their close association with engineering contracts and the environmental quality. Controlling for FDI also helps discern whether environmental concerns pertaining to foreign investments is an issue specific to China and its engineering activities, or if it applies to foreign investments from other countries too. I also consider the heterogenous effects across different categories of recipient countries based on their income levels. I find that Chinese economic cooperation projects in low-income countries are pollution intensive and their detrimental effect persists two to three years after the initial contracting. The rest of the paper proceeds as follows. Section 2 surveys the existing literature and theories pertaining to this topic. Section 3 explains the empirical approach by focusing on the data and the econometric model. Section 4 presents the findings of the research and finally section 5 links the findings to answering the research question and concludes.

2. **<u>Literature Review & Theory</u>**

Before diving deep into evaluating the prevailing literature surrounding the research question, it is important to distinguish China's economic cooperation projects from its outward FDI. According to the Organization for Economic Cooperation and Development's (OECD) globally accepted definition, "FDI has the goal of establishing a lasting interest by a resident enterprise in one economy (direct investor), in an enterprise that is resident in an economy other than that of the direct investor (direct investment). Direct or indirect ownership of ten percent or more of the voting power of an enterprise resident in one economy by an investor resident in another economy constitutes such a relationship". In the case of China's FDI overseas, most of these investments function under the framework of “Build, own, operate and transfer” (BOOT) models (Shinn, 2016). In these forms of investments, a Chinese company is involved top to bottom in the operations of an investment venture: it constructs a facility, operates it to earn revenues and ultimately transfers control back to the domestic government or a local enterprise once returns to investments are secured. Based on this structure, a Chinese company takes on the risk of the investment failing but can access local natural resources better. At this point, I note again that FDI and BOOT models are not the focus of this research.

What this research focuses on is economic cooperation projects that function based on Engineering, Procurement, and Construction (EPC) models, in which the Chinese government contracts a Chinese company to construct a physical infrastructure for the host country through a bidding process. The contracting company’s role is limited to carrying out the construction activity by managing labor and capital, hence it does not have any forms of equity holdings overseas in the activity that it is engaged in at any point (Sanfilippo, 2010). Foster et. al (2009) imply that it is the Chinese government who pays for these projects because of its strategy to “give infrastructure and take natural resources”. According to Chueng et. al (2014), these projects also play a pivotal role in facilitating future rounds of FDI by Chinese companies. Hence, even though engineering activities associated with economic cooperation projects are not FDIs per se, they are still an investment made by the Chinese government to acquire returns in the future through accession to natural resources and creation of a path for its local companies to capitalize on international markets. It should be noted that in some instances, the Chinese government funds these projects temporarily with the expectation that the host country pays back at some point in the future. Hence depending on the situation, the funding of these projects can take the form of a loan as well.

In the current literature, China’s economic cooperation projects receive far less emphasis than its foreign direct investments. Current studies are oriented on analyzing the determinants of the destination countries of these projects. Bhaumik and Yap (2011) conclude that the factors which determine FDI such as natural resource endowment and economic fundamentals in the host country are important in explaining economic cooperation too. Sun et. al (2020) further reinforce the claim that these projects are drawn towards countries that have an abundance of natural resources and provide a lower cost in its extraction. There are no studies that focus on the environmental fallouts of economic cooperation projects, not just from China’s perspective but from that of other countries too. Ametepey and Ansah (2015) highlight the extent to which engineering and construction activities, as a whole, lead to accumulation of pollutants in the environment. Likewise, Levin (1997) makes the case that the construction sector is responsible for approximately 40 percent of atmospheric emissions globally. Given the scale at which China is involved in these activities overseas, these findings denote the importance of exploring their interactions with the local environmental quality. Furthermore, Chinese contractors and investors have built a notorious reputation for maintaining practices that promote their gains at the expense of underming the regulations and the broader democracy of host countries on economic as well as environmental matters[3]. The environmental interactions of Chinese foreign economic cooperation contracts can be theorized based on their individual links:

Economic cooperation contracts to environmental quality

The two conflicting theories that explore the effect of economic cooperation on environmental quality are the pollution haven hypothesis and the halo hypothesis. Though these theories are originally intended to explain the effect of foreign direct investments on the environmental quality, they can be extrapolated for economic cooperation contracts because it involves the Chinese government "investing" overseas through its contracting companies. According to the pollution haven hypothesis, developed countries are attracted to invest in their developing counterparts as a result of the latter's weak environmental regulations. Protective measure in the environmentally conscious developed countries increases the costs for contracting companies to engage in domestic operations. When they move their line of operation abroad, they exploit the weaker regulations through haphazard practices, thereby degrading the local environmental quality. The adoption of Kyoto Protocol in 1997 is attributed as having sown the seeds of the pollution haven ideology. Though this treaty mandated developed countries to strive towards carbon neutrality, some of them were able to avoid this obligation by offshoring their pollution intensive activities. Hence, the net effect on global emissions was nil and instead the brunt pertaining to environmental degradation was borne by the developing countries (MacDermott, 2009). The studies that have analyzed the pollution theory from China's perspective mainly deal with outward foreign direct investments. Nevertheless, since economic cooperation projects are expected to seal future rounds of foreign direct investments, making the

[3] Shullman, D. (2019). Protect the Party: China's growing influence in the developing world. *The Brookings Institution.* https://www.brookings.edu/articles/protect-the-party-chinas-growing-influence-in-the-developing-world/

two forms of global involvement highly correlated (Cheung et. al 2014), I consider these studies too. Because both variables denote the presence maintained by China globally in specific activities, theories and literature that link FDI to environmental quality should have significant bearings on economic cooperation as well.

Employing a Copeland Taylor model, Yubo & Wu (2017) show that a one percentage point increase in China's outward foreign direct investments (OFDI) is associated with a 0.02 percentage point increase in the aggregate CO_2 emissions and a 0.06 percentage point reduction in per capita emissions of host countries. They find a similar relationship for other greenhouse gases such as methane, nitrates and sulfides as well as heterogeneity across different income levels of countries. The rise in overall emissions resulting from Chinese investments is expected to be greater for lower-income host countries and less for high income countries. Several studies employ the Granger causality test to scrutinize the investment to pollution (unidirectional) link, where the major emphasis is given to developing and middle-income nations. Blanco & Ruiz (2012) explore the environmental impact of the FDI for Latin American countries. Using a multivariate vector autoregression (VAR), the researchers find that a 1 standard deviation increase in FDI in the 'dirty' sector causes CO_2 emissions per capita to rise by 0.96 percent in the next two periods after the initial rise in FDI. However, this association is not found to be significant for other sectors, and a link from emissions to FDI is also not validated. Bakirtas & Cetin (2017) construct a panel-VAR similar to that in this paper and observe a positive response of CO_2 emissions to a shock in FDI received for Mexico, Indonesia, South Korea, Turkey and Australia. More specifically, they determine that CO_2 emissions rises by 0.4 percent following a positive shock to FDI. A similar modeling technique is deployed by Zhu & Ye (2018) whose research is based on China as an FDI receiving country. Their panel-VAR includes six endogenous variables: FDI, total factor productivity, environmental pollution, GDP, income disparity and inclusive green total factor productivity. In the short run, they find FDI explains over 5.2 percent variation in pollution. However, in the long run, they find that FDI contributes to inclusive green development.

Apart from these empirical studies, qualitative research has also examined the effects of China's foreign investments. Shinn (2016) emphasizes on how Chinese firms have capitalized on African countries' weaker regulatory capacity and higher degree of corruption to maximize their returns to investment. Through construction works in Sudan supervised by the Chinese National Petroleum Corporation (CNPC), oil extraction processes have led to excessive seismic surveying which has resulted in destruction of farmland and deforestation. Likewise, the haphazard discharge of contaminated water from oil reservoirs have killed livestock and caused illnesses. CNPC backed projects in Chad have had similar results, and this led the Chad government to suspend all CNPC operations in the country. On the brighter side, this paper highlights recent emphasis by the Chinese government to mandate its companies to be cognizant of the local environment while investing. Agreements like the Forum on China-Africa Cooperation, and membership to the United Nations Global Compact are institutional changes that are being brought about to address this. However, the major concern now is that these policy changes work on volunteering basis and have no significant means of holding the violators accountable. These case-studies are indications of the in-ground embodiment of the theories I am exploring.

The halo hypothesis in contrast, is more optimistic in that it forecasts foreign investments to lead to positive and cleaner technological spillover effects which eventually translate into an enhancement in the environmental quality. Yubo & Wu (2017) argue that since majority of China's outward foreign investments go towards the service-driven tertiary sector which is less emission-intensive, China's FDI is not found to be very detrimental on per capita terms. The researchers further establish that to a certain degree, the primary and secondary industry also benefit from technological spillover effect whereby they contribute to lesser pollution. This is corroborated by Lee's (2013) findings. Lee's research rejects the hypothesis that FDI flows translate directly into environmental degradation for all countries and concludes that FDI has no effect on the CO_2 emissions of G20 nations, a group comprising of twenty countries that make up approximately 85 percent of global GDP. Similarly, Dardati & Mereyem's (2011) analysis of Chile, a country that exports substantial minerals to China, establishes that by consuming less fuel per unit of output, foreign firms employ cleaner technology than domestic ones. They conclude that foreign firms are more likely to meet environmental regulations imposed by the government than domestic firms which may not have the financial means of doing so. Examining Middle Eastern and North African (MENA) countries using a fixed effects estimator and controlling for economic growth, trade openness, population, and stringency of environmental regulations, Ashghari (2013) concludes that foreign direct investments trigger a decline in CO_2 emissions. They attribute their finding to innovations in techniques of production and managerial skills introduced by foreign investments which further pass down to domestic firms through different channels.

Environmental quality to Economic Cooperation Contracts

My consideration of the pollution haven hypothesis thus far has evaluated the possible impact of higher foreign investments on the environment of the (less developed) recipient countries. We also need to account for the factors that drive higher investments to these countries in the first place: their weaker environmental regulations. However, many studies have underscored the difficulty of observing a standard measure of environmental regulation stringency across a panel of global countries. Xing & Kolstad (2001) were successful in getting around this issue by quantifying sulfur dioxide emissions as a proxy of environmental regulation laxity; this enabled them to set up an instrumental variable-based estimator to get to the finding that when laxity rises by 1 percent, host countries will draw an additional 0.27 million dollars in American FDI. Such an approach of using environmental quality as a measure of stringency is intuitively sensible. For instance, if at time t, a country X engages in environmentally destructive behavior which results in high emissions, in some subsequent time periods (t,t+1,t+2,….), foreign countries will receive the signal of potential cost minimizing opportunity of moving their operations to country X. Of course, there will probably be a lag until the signaling translates into a business decision, but this is something that will happen down the line. Therefore, considering the effect of the environmental quality variable on foreign investments is equally important.

Building on Xing & Kolstad's (2001) approach, MacDermott (2009) explains that using alternatives like the signing of multilateral environmental agreements as measures of laxity can be problematic, because countries do not necessarily enforce these. Using per GDP sulfur oxides, nitrogen oxides, and carbon dioxide emissions as the proxies, MacDermott (2009) concludes that OECD nations do tend to be attracted towards countries with weaker environmental regulations. Likewise, Hoffman et, al. (2005) find evidence that the causality runs from environmental quality to the FDI. Granger causality tests show that for low-income countries, higher carbon emissions result in significantly greater FDI received. Terzi & Pata (2019) employ variance decomposition and impulse response functions based on a panel-VAR model to study the hypothesized relationship for Turkey; they find that CO_2 accounts for 29 percent variation in the forecast error of FDI, which supports their identification of a causality running from CO_2 emissions to FDI. Liu & Kim (2018) get to a similar finding for China, but they acknowledge that their model is not robust since they fail to consider country specific heterogeneities.

<u>Dynamic link between economic cooperation contracts and environmental quality (with the inclusion of economic growth)</u>

There are some studies that explore the simultaneous and dynamic bidirectional-link between the two major variables of interest, where connection is established primarily through their relationship with the economic growth variable. Abdouli & Hammami (2018) employ a VAR framework to a selection of MENA countries. They develop their model by transforming an augmented Cobb-Douglas function including FDI and emissions, into a growth format. They find that CO_2 emissions from period t-1 lead to a higher FDI in period t. This shines light on the pollution haven theory whereby higher emissions through laxity in a country, signals foreign investors to channelize their money here. The increased volume of foreign investments triggers a higher growth in the recipient country in period t. This is because FDI is used to finance development projects that create higher employment and yield greater output. However, it is found that through a direct mechanism, CO_2 emissions in periods t-1 deter GDP in period t. This may be attributed to the negative impacts of pollution on the health and safety of the workforce which diminishes their productivity over the long run. Further, though it is found that higher emissions incentivize foreign investments, eventually these investments lead to lower emissions, suggesting that foreign investors bring about technological spillover effect whereby their plants are cleaner and are less harmful to the environment. The paper is also able to find that GDP growth leads to higher emissions. This is because the capital that is key in the production process is pollution intensive. Thus, growth comes at the expense of higher degree of pollution. Omri et, al. (2014) use a GMM estimation approach on dynamic simultaneous equations to quantify the effect within the nexus for a global panel. Similar to Abdouli & Hammami (2018), they uncover the existence of a bidirectional relationship between GDP and CO_2 emissions whereby GDP growth leads to higher pollution, which counteractively takes a toll on factors causing growth and thus reduces income. A feedback link is also found between income and foreign direct investments. The increased GDP resulting from FDI, ensures the facilitation of infrastructure and resources which yield more certain and higher return to investments. Though the researchers obtain a bidirectional relationship between FDI and CO_2, in contrast to Abdouli & Hammami, the sign of the causality is just the opposite. Both for the global panel, as well as for the Asian and African panel, Omri et, al. (2014) find that FDI leads to higher pollution, which in turn deters future foreign investment.

To summarize, most of the existing literature evaluates the FDI-environment nexus for countries based on their receipt of FDI and none of them specifically deal with construction and engineering related investments through economic cooperation projects. There are very few papers that focus specifically on China as a global investor and those that do, fail to consider the bi-directional link. Finally, prior literature demonstrates importance in observing the heterogeneities across countries of different income levels. My research overcomes these limitations and strives to provide a clear picture of the dynamic interactions between Chinese engineering contracts through economic cooperation projects and the environmental quality of host countries.

3. Empirical Approach

Data

The panel-vector autoregression approach in this study makes use of four endogenous variables: value of Chinese engineering contracts overseas, the environmental quality of host countries, GDP per capita of the host countries, and FDI received from all sources by the host countries. Each of the variables are measured per country per year. The timeframe under consideration is 2004-2017. Statistics on China Statistical Yearbook show that economic cooperation contracts signed by China took off in in the early 2000s, and 2017 is the last year until which data is available. There are a total of 142 recipient countries in this study, and these are countries that China has invested into in at least one year during the timespan under consideration. It should be noted that countries: Eritrea and Sudan are removed from the sample because consistent data on other variables that this study uses is not available for them.

I decide to narrow my focus specifically on "engineering" projects of China's economic cooperation projects since construction and engineering activities are directly linked to environmental degradation, particularly air pollution. Data on *Chinese engineering contracts overseas* are derived from China Statistical Yearbook, a governmental data source through a Chinese database, cnki.net. This variable is measured in 10,000 United States dollars. As reiterated in the literature review, this variable should not be confused for FDI, nor is it representative of aid, grants, and loans. It is simply the value of cumulative Chinese construction/engineering contracts signed per country per year. These contracts include (but are not limited to) the building of infrastructure such as highways, roads, bridges, schools, shopping centers, water conservancy, dams, and power plants. Hence, though this variable does not capture “FDIs” per se, since it is being funded by the Chinese government, it is their investments overseas through Chinese contracting companies and the purpose of this research is to observe its interactions with the local environmental quality.

Environmental quality is primarily proxied by carbon dioxide (*CO_2*) *emissions per capita*, which is extracted from Our World in Data (OWID), published by University of Oxford. The use of CO_2 emissions as a prime measure of environmental effect of foreign investments is common across a wide range of studies (Yubo et. al 2015, Lee 2013, Blanco & Ruiz 2012, Abdouli & Hammami 2018). Since my research focuses specifically on the construction and engineering sector, this variable seems appropriate. On average, 23 % of air pollution is attributed to the construction sector globally, where carbon dioxide gases are the major emissions. Though CO_2 is not necessarily the most toxic of the pollutants (despite being the main greenhouse gas), it is a byproduct of the combustion activities that are very prominent in the construction sector. Since other toxic air pollutants such as sulfurous oxides, carbon monoxides and PM2.5s are not measured as extensively, CO_2 captures overall air quality degradation effectively. This reasoning is justified by Lazovic and Zivkovic (2014) whose research finds a strong correlation between CO_2 emissions and PM2.5s, notoriously known for causing smog worldwide.

GDP per capita is extracted from World Bank’s online database and is measured in current US dollars. Though a country’s economic condition does not relate directly to my research question on the relationship between (Chinese) contracting investments and the environment, prior studies have included GDP per capita as a covariate because of the simultaneous causality it has with the other two variables. The environmental Kuznets curve theory which posits an inverted U-relationship between the two variables has also been validated by numerous studies. For example, in their research on the pollution haven hypothesis in the Gulf region, Al-mulali & Tang (2013) conclude that a country’s GDP growth is a major determinant of carbon emissions. Likewise, Saboori & Sulaiman (2003) study this link for a selection of ASEAN countries where China has invested significantly. They determine that a nonlinear inverted-U-shaped curve exists only for more developed economies like Singapore and Thailand, whereas countries like Philippines and Indonesia are still stationed in the rising part of the curve. Despite the conflict in the direction of the relationship, it is clear that a country’s national income strongly affects CO_2 emissions, and I account for this through GDP per capita.

A secondary endogenous covariate (control) that this study employs in order to ascertain that environmental effects associated with Chinese engineering projects are solely associated with the lax practices maintained by Chinese contractors and not the fact that a country is being sought after by all forms of global investors (which could be the root cause of their environmental degradation), is the cumulative foreign direct investment (FDI) received by all the countries in the sample. My literature review cites several studies that have validated the existence of this link. Holding this variable constant identifies that if there is an effect of Chinese engineering contracts on the environment of recipient countries, this is solely attributable to the presence and practices maintained by Chinese contractors and hence overcomes omitted variable bias to a certain degree. This variable is extracted from the World Bank database and is measured in US dollars.

Additionally, my study imposes control on the governance quality of each of the recipient countries. Doing so allows my study to determine whether Chinese contractors are able to engage in environmentally degrading practices solely because of the weak governance and policy regulation in the recipient countries or whether they are intrinsically likely to capitalize on any opportunity available regardless of the quality of governance. Quality of governance is proxied by the World Bank's World Governance Indicators (WGI) score for each of the countries, which is the percentile rank ranging from 0(low quality of governance) to 100 (high quality of governance). Quality of governance is used as an exogenous variable in the panel-VAR model.

The variable that this study uses to explore the relationship in question for different categories of countries is their development status, which is captured by the dummy variable *high income*. I make the categorization based on World Bank's 2019 classification: low income (GNI per capita below $1026), lower middle income (between $1026 to $3995), higher middle income (between $3996 to $12,375) and high income (above $12,375). My *high income* indicator takes on a value 1 if the World Bank classified the country as high income or higher middle income and 0 otherwise. Because there will not be a great deal of traversal of countries across different bands over time, basing the classification solely on 2019 values should be reasonable.

The final variable is the population of each of the recipient countries in the time frame under consideration. This data is used to convert the FDI and Chinese engineering project value variables into a per capita form to isolate the impact of a country's size in the relationship being studied. Data on this variable is acquired from the world bank database as well.

The descriptive statistics of these variables are presented in Table 1. Though all the variables are presented in the original form they are extracted in, all the variables that are treated as endogenous in the panel-VAR model are converted to a per capita form.

Table 1

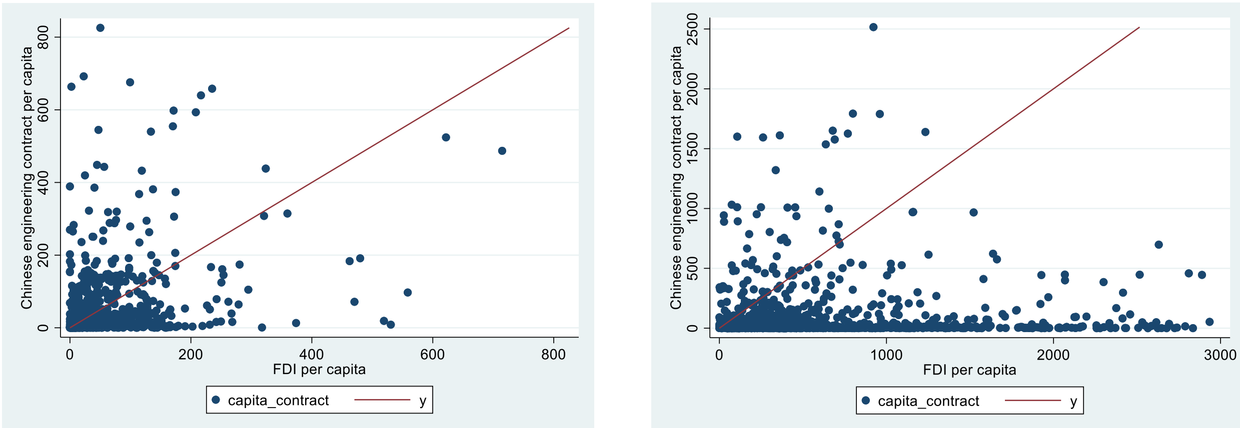
Variable	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Annual Chinese engineering contracts in 10,000 US dollars	77,255.9	174,955	0.0	2,500,000
Carbon dioxide emissions per capita in metric tones	4.78	6.58	0.0	62.5
GDP per capita in US dollars	13,537.0	18,734.4	128.3	107,361
Foreign direct investments in 10, 000US dollars	1,177,458	4,209,294	0.0	73,400,000
Quality of governance	48.13	27.99	0.0	100.0
Population	34,200,000	112,000,000	9869	1,340,000,000
High income	0.592	0.492	0	1

Based on CO_2 emissions. Time period observed: 2004-2017. Number of countries: 142. Total number of observations (N): 1,988.

Though the mean foreign direct investments of the sample countries in the study appears to be significantly greater than the mean Chinese engineering contracts, this should not be interpreted as indicating that Chinese contracts are not comparable to FDI in terms of their magnitude and the effect they are going to have on emissions. It is important to note that this differential is likely to be a result of skewness caused by very high FDI received by a few high-income countries. In fact, Chinese engineering contracts have a substantial impact in context of the infrastructural development, particularly in low-income countries. This is perfectly represented by Figure-1, where the dollar value of Chinese engineering contracts per capita is plotted against the dollar value of FDI per capita (with the removal of some outliers). By including a y=x line, we see that FDI per capita and Chinese engineering contracts per capita are comparable in their magnitudes particularly in low-income countries and there seems to be a proportional spilt between cases where one is greater than the other. This is true to a certain degree even for high income countries but for most data observations, FDI per capita seems larger. The observation that FDI and Chinese engineering contracts are comparable becomes essential later on while we make comparisons across their effects on the environmental variables.

Figure-1

Low-income　　　　High-income

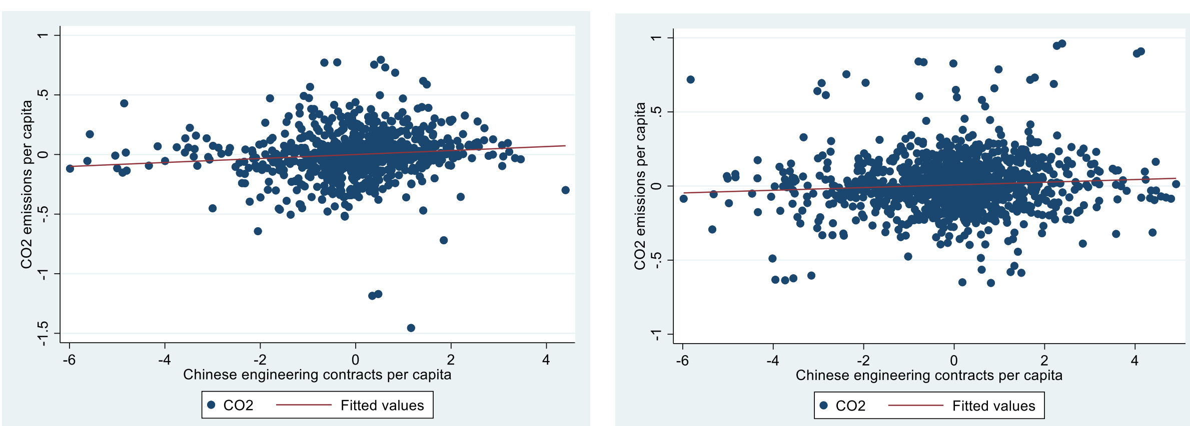


Scatter plot showing Chinese contract per capita vs FDI per capita (both in US dollars). Categorization made according to income level.

Figure-2 depicts the relationship between emissions and engineering contracts that this study is attempting to model. A pooled scatter diagram with a line of best fit is plotted after the variables are logged and detrended (discussed in detail in the econometric segment). Nothing reasonable can be inferred about the relationship between emissions and Chinese engineering contracts across the two categories from the figures. The purpose of this research is to verify the causality in this relationship and observe its dynamics.

Figure-2

Low-income　　　　High-income



Scatter plot showing detrended logs of CO_2 emissions per capita vs detrended logs of Chinese engineering contracts per capita. Categorization made according to income level.

Econometric Model

A panel-vector autoregression (VAR) is a dynamic model where the variables of interest are treated as endogenous and are accounted for by their own lagged values and the lagged values of other variables in the system and include fixed effects outcomes. It augments a standard VAR by including a cross country dimension. Most panel-VAR models are used as an alternative to a dynamic stochastic general equilibrium model (DSGE) while studying economic issues in interdependent economies in cases where it is reasoned that the extent of theoretical restrictions imposed by a DSGE are not in line with statistical data (Canova and Ciccarelli 2013). First introduced by Holtz-Eakin et. al (1988), this model is widely used in analyzing the spillover effects of macroeconomic and financial shocks.

My research employs a panel-VAR model with the primary objective of overcoming the endogeneity, which is created by the bidirectional causality between environmental quality and Chinese economic cooperation contracts, as described in the literature review section. I attempted to overcome endogeneity in my previous research on the same topic, in which contract values were instrumented for by the number of contracts signed with each country. However, because the goal was also to solve for measurement errors in the investment variable, and there were no additional instrumental variables to conduct an overidentification test, the exogeneity criteria could not be validated. Considering the difficulty in finding a relevant instrument, I decide to adopt panel-VAR in addressing my research question.

Here is a multi-variate panel-VAR of order 1 with country fixed effects that I use in my research:

$$\mathbf{Z_{it} = \beta_0 + \beta_1 Z_{it-1} + \beta_2 X_{it} + u_{it} + e_{it}}$$

where Z_{it} is a two-variable vector (CEC, CO2) in model-1 and a four-variable vector (CEC, FDI, CO2, GDPC) in model-2. CEC: value of Chinese engineering contracts per capita, FDI: foreign direct investment inflows per capita and CO2: carbon dioxide emissions per capita and GDPC: GDP per capita. X_{it} is a single variable vector of the exogenous variables which in this case is GOV (quality of governance). u_{it} and e_{it} are dependent variable specific fixed effects and idiosyncratic errors respectively. Depending on the number of variables in the model (k), β_0 and β_1 are (1xk) and (kxk) vector of parameters to be estimated respectively.

Since my research question pertains specifically to Chinese engineering contracts through economic cooperation projects and their environmental repercussions, I first attempt to structure my panel-VAR as a bivariate model. The choice of doing so is supported by the system GMM estimation that is used, which uses lagged values as instruments to address endogeneity and provide unbiased estimates. Having fewer explanatory variables saves degrees of freedom but because most past research papers on this topic include economic growth or GDP per capita as one of the endogenous variables since it captures other unobserved factors that affect both investments and emissions, I choose to include it in my second model. Likewise, the second model also includes FDI received by the countries in order to identify CEC's unique impact on CO2, which is isolated from other factors that might be interrelated. Hence the second model comprises of the following endogenous variables: *Chinese engineering contracts per capita, FDI inflows per capita, CO_2 emissions per capita,* and *GDP per capita.* My findings from the second model allow me to see if endogeneity is overcome in the first one.

The decision to choose a lag order of 1 is taken on the basis of model selection criteria laid out by Abrigo and Love (2015). They derive their criteria based on Andrews and Lu's (2000) model selection guidelines for GMM estimation, which compares the J statistic testing overidentifying restrictions with the number of parameters employed. In case of my research, I follow Abrigo and Love (2015) in using the Bayesian Information Criteria (BIC), Hann-Quinn Information Criteria (QIC) and Akaike Information Criteria (AIC). These metrics likewise capture the trade-off between overspecification and precision. The goal is to choose the lag order that minimize these metrics, and with my model, I get a period 1 order.

Like with any other dynamic model, ensuring stationarity in the data is essential to make inferences from the sample that are generalizable to other members of the population. A common approach to achieve stationarity is taking the log of the variables and detrending them. This is done for all four endogenous variables in the system: *Chinese engineering contracts, FDI inflows per capita ,CO_2 emissions per capita,* and *GDP per capita*. It is important to note here that there are some observations in the dataset with zero values for certain variables. Upon log transformation, the *panel-VAR* package in Stata, which is used for implementing the model, by default removes these observations and gives rise to unbalanced panels. Chueng et. al (2014) gets around this issue by converting the 0 value x to x+1, before logging it. I use the same approach in my study. This ensures that all the observations are used in estimating the panel-VAR model. It is only 50 out of a total of 2030 observations that undergo this procedure, hence there should not be a great deal of scepticism about the efficacy of it and the impact it will have on my overall results. Following the transformation, I implement a Harris-Tzavalis unit root test[4], and the presence of stationarity is validated for all four variables. This particular test is appropriate because it is suited for cases where number of individuals is significantly greater than the number of time periods. The results of the unit root test are presented in Table-2 and they show

[4] Reference Stata guide: https://www.stata.com/features/overview/panel-data-unit-root-tests/

that all the variables used in the panel-VAR are stationary since the null hypothesis of the presence of a unit root is rejected.

Table 2

Variable	Statistic	Z-value	P-value
Detrended log of Chinese contracts per capita	0.333	-27.5	0.001
Detrended log of FDI per capita	0.603	-11.43	0.001
Detrended log of CO_2 emissions per capita	0.694	-6.23	0.001
Detrended log of GDP per capita	0.698	-5.97	0.001

The unit root tests show that all variables are stationary at the 1% level after they have been log transformed and detrended.

The next big step in the empirical analysis of my research is obtaining estimates for the parameters in the panel-VAR model. In any dynamic model with a lagged dependent variable present as an explanatory variable, ordinary least square (OLS) estimates tend to be biased even in instances with large N (Abrigo and Love, 2015), due to the correlation between unobserved fixed effects and the lagged dependent variable. One possible way of getting around this issue is using GMM estimation, which is ideal for datasets similar to mine where number of panels(N) is significantly larger than the number of time periods (T). My model uses a system GMM estimation, where fixed effects are removed through forward orthogonal transformation. The benefit of this approach over a first differenced GMM is that data loss is minimized through subtraction of average of all future observations such that instances without lagged values are still accounted for. Since past observations do not get utilized in the transformation, they are used by the estimation approach as instruments. Specifically, the model uses the first four lags of the endogenous variables as instruments. Such an approach is proposed by Arellano and Bond (1991), who argue that the autoregressive path created by the presence of lagged dependent variable in the equation satisfies the relevance condition and the exogeneity condition is maintained by the exclusion assumption in the build-up of the model whereby past values are not correlated with future error terms. This instrumenting approach is another aspect of my research that plays a part in addressing endogeneity concerns, and hence having a small number of variables in the model should not be a big issue in obtaining consistent and unbiased estimates.

4. Results

The system GMM estimates of my bi-variate and quad-variate models are presented in Table-3 and Table-4 respectively. Within each of the models, I attempt to make distinctions between countries based on their income levels, and hence run separate sub-models for low-income countries (column 2) and high-income countries (column 3). Column-1 presents the model estimates for all countries, without making income level distinctions. Upon running the GMM estimation, the standard analytical process for a panel-VAR model is followed whereby Granger causality is first tested, stability of the model is ensured, and impulse response functions and variance decomposition measures are derived and interpreted. The significance level of the GMM estimation is the basis for conducting Granger causality tests and hence, causality inferences can be made from Table-3 & 4 directly. Nonetheless, for reference, Granger causality output is attached to the technical appendix section.

Table-3

	(1)	(2)	(3)
	CEC_t	**CEC_t**	**CEC_t**
CEC_{t-1}	.358***	.326***	.209
	(.051)	(.076)	(.218)
$CO2_{t-1}$	.25	.980*	-.326
	(.162)	(.55)	(.305)
GOV_t	3.67	1.72	13.06
	(1.79)	(1.75)	(8.57)
	(1)	(2)	(3)
	$CO2_t$	**$CO2_t$**	**$CO2_t$**
CEC_{t-1}	.003	.014**	.001
	(.003)	(.005)	(.009)
$CO2_{t-1}$	.768***	.831***	.934***
	(.070)	(.040)	(.048)
GOV_t	.069	-.335***	.055
	(.177)	(.120)	(.509)
Observations	1704	696	1008

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

(1): all countries, (2): low-income countries, (3): high-income countries. Upper tier of the table presents estimates for investments, middle tier presents that for co2emissions, and lower tier presents for GDP per capita. Each variable is accounted for by both the period 1 lagged values of itself and the other two variables in the system. For each variable, the coefficient estimates, and standard error (in parentheses) is presented. The panel-VAR package on Stata makes use of only 12 observations per country even though there is data over 14 years. This is consistent with other studies that use the package too. Some coefficients in (1) not being bounded between (2) and (3) is a result of the dynamic nature of the model and not an econometric error.

My bi-variate estimates in Table-3 for all countries (column 1) show the inexistence of causalities between emissions and Chinese engineering contracts. However, looking specifically at low-income countries (column 2), the existence of a positive bidirectional relationship is validated, i.e., there is a cyclical reinforcing effect whereby a higher emission in period t-1(low environmental standard) attracts a higher volume of engineering contracts in period t, and in period t+1 this goes on to increase emissions (brings greater environmental harm). It is also found that the coefficients are much larger in magnitude compared to both columns 1 and 3, indicating that the extent of the impact is much larger for low-income countries. Looking at column 3 for high income countries, neither channels of the causality is validated.

Comparing the bi-variate model's estimates (Table-3) to the quad-variate case (Table-4), most estimates and their significance levels change considerably, which is an indication of endogeneity being present in the bi-variate model. Hence, with some skepticism over it, I choose to make dynamic inferences only from the quad-variate (Table-4) model. It should be noted that moving forward, all analytical inferences are made from the quad-variate case unless stated otherwise.

Estimates from Table-4 reveal the positive effect that both Chinese engineering contracts and foreign direct investments from all other sources have on the subsequent carbon dioxide emissions of low-income host countries. Based on the coefficient magnitudes, we can infer that the emissions caused by Chinese engineering contracts are larger than FDI. The quality of governance variable also takes on a coefficient that is statistically significant and negative, which is reasonable since it means that low-income countries with higher quality of governance have lower carbon dioxide emissions per capita. However, in the broader context of the research, the fact that CEC has a significant impact on CO2 even after controlling for quality of governance, is an indication that Chinese contractors do not only capitalize on low-income countries with lax environmental measures, but rather their practices are intrinsically pollution intensive regardless of the policy stringency of the low-income country they are in.

Table-4

	(1)	(2)	(3)
	FDI_t	**FDI_t**	**FDI_t**
FDI_{t-1}	.693***	.534***	.757***
	(.089)	(.149)	(.076)
CEC_{t-1}	-.007	-.008	-.008
	(.024)	(.096)	(.028)
$CO2_{t-1}$	-.082	-.826	.571***
	(.133)	(.835)	(.157)
$GDPC_{t-1}$	-.072	.517	-.361***
	(.078)	(.456)	(.091)
GOV_t	1.837*	-1.58	1.911

	(1.039)	(2.336)	(1.304)
	CEC_t	**CEC_t**	**CEC_t**
FDI_{t-1}	.019	-.004	.051
	(.021)	(.021)	(.067)
CEC_{t-1}	.345***	.219***	.276***
	(.046)	(.06)	(.095)
$CO2_{t-1}$	-.121	.286	.449
	(.228)	(.256)	(.344)
$GDPC_{t-1}$	.352**	1.37***	-.706***
	(.145)	(.235)	(.274)
GOV_t	3.387**	-.831	7.577**
	(1.576)	(.888)	(3.811)
	$CO2_t$	**$CO2_t$**	**$CO2_t$**
FDI_{t-1}	.003	.008***	.003
	(.002)	(.002)	(.006)
CEC_{t-1}	.002	.009**	-.009
	(.003)	(.004)	(.006)
$CO2_{t-1}$	.706***	.845***	.997***
	(.061)	(.033)	(.056)
$GDPC_{t-1}$	-.046	.021	-.155***
	(.03)	(.013)	(.047)
GOV_t	.292*	-.249***	.367
	(.154)	(.079)	(.262)
	$GDPC_t$	**$GDPC_t$**	**$GDPC_t$**
FDI_{t-1}	-.002	-.016***	.01
	(.012)	(.004)	(.008)
CEC_{t-1}	-.012	-.005	-.011
	(.013)	(.006)	(.01)
$CO2_{t-1}$	-.107	-.157***	.459***
	(.097)	(.041)	(.094)
$GDPC_{t-1}$	.666***	.986***	.492***
	(.091)	(.063)	(.101)
GOV_t	1.376**	.405***	.427
	(.55)	(.103)	(.441)
Observations	1704	696	1008

(1): all countries, (2): low-income countries, (3): high-income countries. Topmost tier of the table presents estimates for FDI, upper-middle presents that for CEC, lower-middle tier presents that for co2emissions, and finally lowest tier presents for GDP per capita. Each variable is accounted for by both the period 1 lagged values of itself and the other two variables in the system. For each variable, the coefficient estimates, and standard error (in parentheses) is presented. The panel-VAR package on Stata makes use of only 12 observations per country even though there is data over 14 years. This is consistent with other studies that use the package too. Some coefficients in (1) not being bounded between (2) and (3) is a result of the dynamic nature of the model and not an econometric error.

Prior to moving on to the dynamic aspects of the research, namely impulse response functions and variance decomposition measures, it is important to check for the stability condition, which is an indication of the fact that the panel-VAR is invertible and has an infinite-order vector moving average representation (Abrgio and Love, 2015). These criteria guarantee that any dynamic inferences made are valid. The confirmation of the stability criteria is presented for each of the three models in Figure 3. Figure 4 in the technical appendix provides a visual representation of the fulfillment of this condition.

Figure-3

Overall (column1)

Eigenvalue stability condition

Eigenvalue Real	Eigenvalue Imaginary	Modulus
.7532352	0	.7532352
.6918076	0	.6918076
.6061699	0	.6061699
.3598368	0	.3598368

Low income (column 2)

Eigenvalue stability condition

Eigenvalue Real	Eigenvalue Imaginary	Modulus
.8945288	-.0504712	.8959515
.8945288	.0504712	.8959515
.5755173	0	.5755173
.2189298	0	.2189298

High income (column 3)

Eigenvalue stability condition

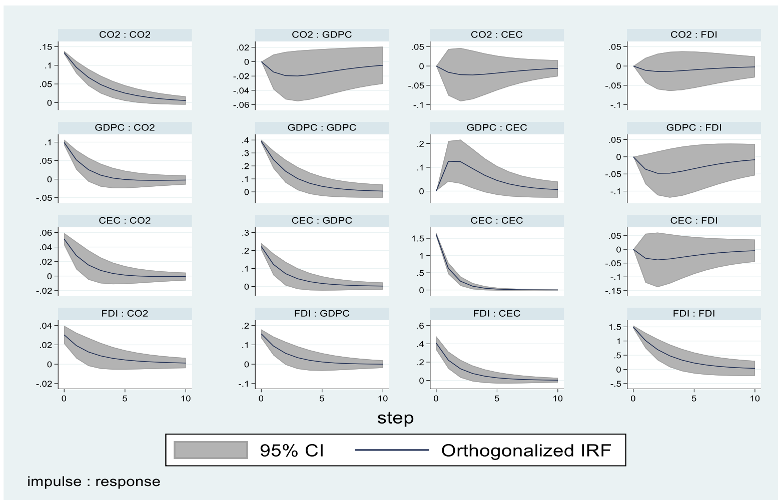
Eigenvalue Real	Eigenvalue Imaginary	Modulus
.7485334	-.0910791	.7540541
.7485334	.0910791	.7540541
.7533065	0	.7533065
.2718886	0	.2718886

This figure confirms the existence of stability of the panel VAE across the three models. A panel-VAR is stable if all the moduli of the companion matrix are less than 1 (Abrigo and Love, 2015).

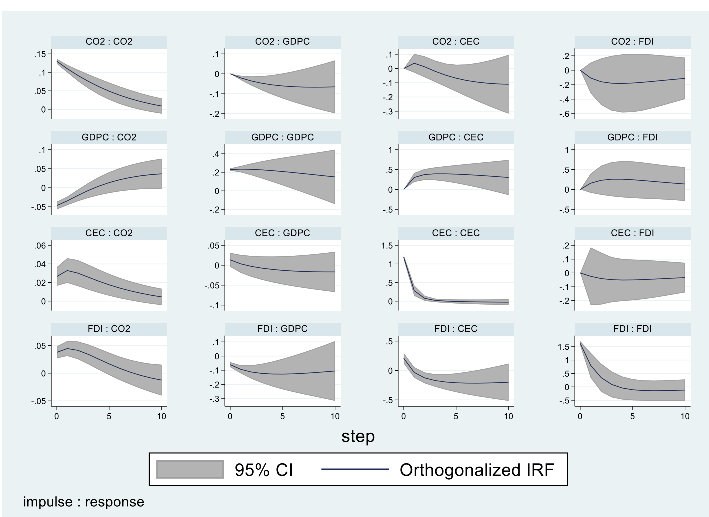
Impulse response functions (IRFs) show how each of the endogenous variables respond to a shock to another variable in the system, holding shocks to all other variables at zero. IRFs can be derived post estimating the panel-VAR model through system GMM. The derivation is facilitated by Cholesky decomposition which takes into account the order of the variables listed in the panel-VAR model. Variables listed later are considered more endogenous than the ones that are placed earlier (Abrgio and Love, 2015). The ordering ensures that shocks to a single variable are isolated by decomposing the residuals in such a way that become orthogonal (Love and Zicchino, 2006). In my model, I choose to assign emissions as the variable that is most endogenous, i.e., it is affected by engineering contracts, FDI and GDP per capita both contemporaneously as well as with a lag. This assumption is plausible because once engineering projects and FDI begin materializing, construction activities start very soon, and this causes greater emissions within the same period. The same logic holds for how GDP per capita affects emissions too: once an economy starts expanding its productive capacity to grow economically, emissions follow suit very soon (Environmental Kuznets Curve hypothesis). However, emissions and GDP per capita affect engineering investments and FDI only with a lag because it takes time for companies to make a business decision by observing the environmental quality and economic status. The effect of emissions on GDP per capita is also a long run phenomenon, as it mainly involves the effect on the availability of natural resources and the productive capacity of the workforce. The impulse response functions for each of the three sub-models for the quad-variate case are presented below in Figure 5.

Figure-5

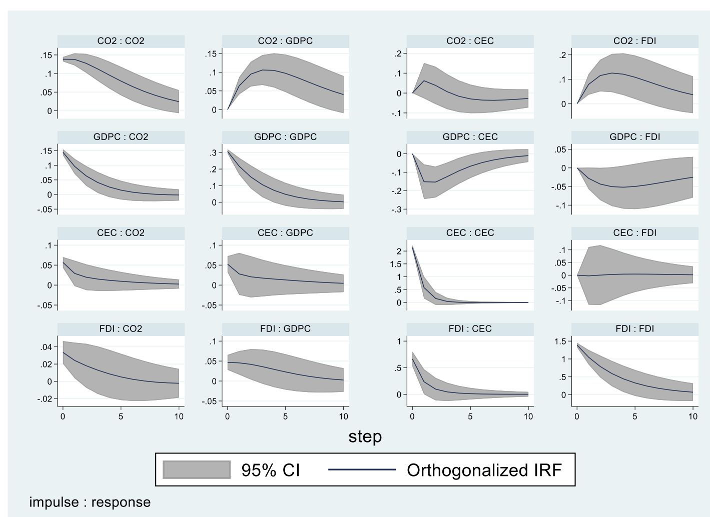
IRFs for all income-levels of countries (Panel-1)



IRFs for low-income countries (Panel-2)



IRFs for high-income countries (Panel-3)



Separate panels show separate categories of countries, as classified by their income level. On each graph the variable preceding the ":" sign is the impulse variable and that following it is the response variable. Significance level as depicted in the estimates' tables should be referred while analyzing these graphs.

The figures reinforce the estimation findings. In the overall case (Panel-1, Figure-5), the impact of Chinese engineering contracts on carbon emissions is positive and significant over the short run. The peak is acheieved instantaneously upon the start of the shock, after which the response decays and slowly become insignificant after the second year. Carbon emissions' response to FDI is also very similar, but the magnitude of the positive effect is smaller. Low income countries (Panel-2, Figure-5) exhibit a similar trend for the relationship, with the difference being that the magnitude of the positive response of emissions to both FDI and CEC takes time to build and is more persistent i.e. it remains significant even in the long run. High income countries (Panel-3, Figure-5) do not exhibit a significant response of emissions to CEC and FDI neither in the short run nor the long run, but it does seem to be the case that their response is immediate and short lived relative to low income countries. Analyzing the other side of the relationship, it is found that the effect of emissions on engineering contracts is insignificant for the overall, low-income and high income models. The coefficient magnitude of the response function stays at the 0 level for the most part, and occasionally fluctuates between negative and positive values. Conclusive inferences can not be drawn for this aspect of the hypothesis. Though the interactions of GDP per capita with emissions and Chinese engineering contracts are not associated directly with answering the research question of this paper, it can still be seen that higher GDP per capita plays a significant role in brining in more Chinese engineering contracts in the subsequent periods to low income countries. This eventually goes on to increase emissions in the future. Hence though GDP per capita has an insignificant effect on emissions directly, it facilitates Chinese engineering projects which are emission intensive in the future.

Another dynamic element of a panel-VAR is forecast error variance decomposition (FEVD) measures. These are measurement values of the contributions of each source of shock to the variance of the endogenous variable over a ten year period. Tables-6,7 and 8 in the technical appendix present these values for the overall, low-income and high-income models respectively. The findings suggest that FDI and GDP per capita are more significant than carbon emissions in explaining the variance of Chinese engineering contracts for all three models (overall, low income, and high income). For low income countries, as much as 30 % variance in engineering contracts is explained by GDP per capita whereas carbon emissions only explains 9.3% of it. Likewise, engineering contracts and FDI seem to hold varying degree of explanantion power in the variation of carbon emissions. In the low-income case, FDI explains 10.3% variation in emissions, whereas CEC explains only 6.4% of it. In case of high income countries, these values are 1.7% and 3.7% for FDI and CEC respectively. These values are considerably less because for high income countries GDP per capita plays a key role in determining carbon emissions.

The findings from all three aspects of my panel-VAR model: system GMM estimation, impulse response functions and variance decomposition measures suggest that there is a positive unidirectional causality running from Chinese engineering contracts to carbon emissions for low income countries, which implies that they exhibit the pollution haven hypothesis. Interestingly, there is also strong evidence for the positive effect of foreign direct investments on carbon emissions, though the effect appears to be relatively small and short lived in comparison to Chinese engineering contracts. What can be deduced from these findings is that both FDI and CEC are pollution intensive for less developed countries (the per capita values of FDI and CEC are comparable as the descriptive statistics showed) . In the context of my research question, what I can reasonably conclude is that after disentangling the nested relationship between FDI and CEC (controling for FDI), there is enough statistical proof for the environmental harm that CEC brings about in low income countries. Intrinsically, these countries have lax environmental regulations and it seems like China's engineering companies have capitalized on it by adopting a pollution intensive strategy, which comes at the benefit of a minimized cost structure. On the other hand, in the case of high income countries, is it likely that Chinese companies are constrained by tighter environmental regulations and hence even though they are engaged in construction and engineering actvities, they are bound to use cleaner sources of energy to fuel their plants and equipments, which is why they do not trigger environmental damage. This finding aligns with the Lee's (2013) conclusion that richer countries do not incur enivronmental consequences resulting from foreign investments. Though it is ambiguous whether high income countries exhibit the pollution haven hypothesis, it is unlikely that they manifest the halo theory because the insignificant estimates are not negative. Hence Chinese construction companies do not foster a conducive environment to improve the environmental quality. Observing the dynamics carefully, it can be seen that the effect of engineering contracts on emissions persists for two to three years for low income countries, however, it is instantanous and short lived for high income countries. This is concrete support for Bhaumik and Yap's (2010) finding that Chinese engineering contracts through economic cooperation projects in less developed countries are means of establishing relationship with a host country to extract natural resources and conduct subsequent rounds of FDI. The overall environmental harm that these contracts bring are not limited to the emissions resulting from the construction of infrastructure that they fund, but also have a bearing on the ensuing risk factors that they facilitate. Lastly, this study does not find evidence for the signalling mechanism whereby higher emissions today attract Chinese engineering companies in the subsequent periods. Since it is found GDP per capita is in fact a key variable in attracting these companies, the findings imply that Chinese engineering companies are more concerned about capitalizing on developing markets and earning high returns than about their environmental regulations.

5. Conclusion

This research evaluates the dynamic bidirectional relationship between China's engineering contracts through its economic cooperation projects overseas and the environmental quality of the host countries. China has manifested itself as one of the leading facilitators of global infrastructural development programs. Primarily through engineering projects undertaken as a part of the Belt and Road Initiative (BRI), it has made significant contributions in the construction of infrastructure like roads, ports, railway lines and other forms of physical infrastructure world-wide. However, there has been significant criticisms of the environmental fallouts of these activities and how they tend to exploit the laxity in the policy measures especially in less developed countries of the world. Through this research I attempt to evaluate whether Chinese engineering contracts lead to greater environmental damage, in the form of higher carbon dioxide emissions in the recipient countries, and whether the existence of higher pollution is a signal to Chinese companies of the policy laxity, which in turn incentivizes them to take up more contracts. I conduct a quantitative study of this relationship through the means of a panel-vector autoregression model, with the central goal of overcoming endogeneity. I include FDI as an additional endogenous variable in the panel-VAR system in order to isolate its close ties with Chinese engineering contracts and discern the unbiased relationship between Chinese engineering contracts and environmental quality. I further explore heterogeneities across countries based on their income levels.

The major finding of this research is that Chinese engineering contracts lead to higher carbon dioxide emissions in low-income countries. There is not enough statistical evidence to validate this for high-income countries. Though FDI from other countries are found to be pollution intensive in low-income countries too, the dynamics of their effect is weaker and less persistent. This finding aligns well with my initial hypothesis. Majority of China's engineering investments made to low-income countries go directly to construction of physical infrastructure, which is carried out through means of machinery that are pollution intensive and are not constrained by the need to comply with environmental regulations. Even though the governments of these countries are inclined to protect their environment, they are hesitant to enact measures because doing so will potentially deter future projects and investments from China, which is key for their growth. Therefore, it is imperative for the Chinese government and international organizations such as United Nations Environment Program (UNEP) to step in and minimize the environmental footprint being left by Chinese contractors overseas. Though in 2013, the Chinese government issued the Guidelines for Environmental Protection in Foreign Investment and Cooperation to its companies operating overseas, it is believed that this regulation works on volunteering basis only and does not hold the violators accountable. I also find evidence that it is the positive economic growth trajectory exhibited by low-income countries that makes them sought after by Chinese investors. Hence it is important for these countries to be wary of the risk factors associated with the foreign contracts they receive as they develop. Furthermore, I find that Chinese engineering contracts cause pollution even after holding the quality of governance in the host countries constant, which highlights the idea that Chinese contractors maintain lax practices regardless of the stringency of the host countries' rules and regulations. Meanwhile, in the case of high-income countries, China still engages in engineering activities, but their activities undergo strict environmental policy measures and are devoted towards projects that make use of cleaner sources of energy and hence are not associated with higher carbon emissions. The dynamics of the impulse response functions seem to suggest that the environmental harm associated with Chinese economic cooperation projects are stronger in magnitude and more persistent for low-income countries relative to high income ones.

There is not enough support to validate the signaling mechanism that I hypothesized in my research through which having a sub-par environmental quality (higher emissions today) attracts more Chinese engineering contracts in the future. Though this causality is supported by the bivariate model, once GDP per capita is added to the system, the significance of the causality diminishes and instead the coefficient on GDP becomes significant implying that emissions were accounting for the fact that it is higher economic growth that brings in more emissions, since the two are correlated.

Though I answer my research question with relatively strong evidence, this is not to say that it comes without limitations. There is no guarantee that the system GMM estimation overcomes endogeneity completely since it is possible for the lagged instruments to not be exogenous. My findings can be supported through robustness checks that employ alternative means of estimations and make use of other forms of environmental damage. Heterogeneities across other categories of countries can also be explored by including dummy variables as exogenous variables in the system. These are areas that future research on this topic can focus on.

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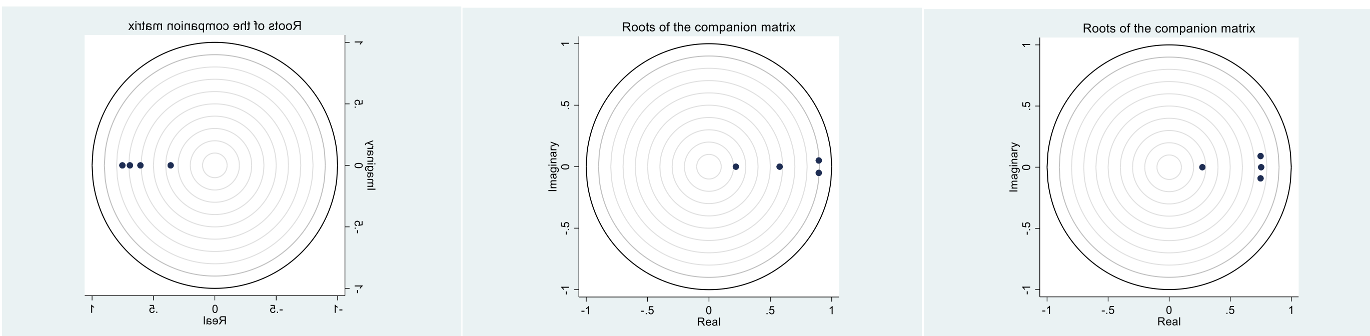
<u>Technical Appendix</u>

Figure-4

Overall (column1) **Low income (column 2)** **High income (column 3)**



Stability condition fulfilled through unit root tests.

Granger Causality Test Results

Overall (column 1):

```
panel VAR-Granger causality Wald test
  Ho: Excluded variable does not Granger-cause Equation variable
  Ha: Excluded variable Granger-causes Equation variable
```

Equation \ Excluded	chi2	df	Prob > chi2
FDI			
CEC	0.095	1	0.758
CO2	0.382	1	0.536
GDPC	0.843	1	0.359
ALL	5.530	3	0.137
CEC			
FDI	0.859	1	0.354
CO2	0.284	1	0.594
GDPC	5.906	1	0.015
ALL	9.948	3	0.019
CO2			
FDI	1.628	1	0.202
CEC	0.202	1	0.653
GDPC	2.312	1	0.128
ALL	3.706	3	0.295
GDPC			
FDI	0.017	1	0.896
CEC	0.907	1	0.341
CO2	1.214	1	0.271
ALL	2.222	3	0.528

Low income (column 2):

```
panel VAR-Granger causality Wald test
  Ho: Excluded variable does not Granger-cause Equation variable
  Ha: Excluded variable Granger-causes Equation variable
```

Equation \ Excluded		chi2	df	Prob > chi2
FDI				
	CEC	0.007	1	0.934
	CO2	0.979	1	0.323
	GDPC	1.283	1	0.257
	ALL	1.893	3	0.595
CEC				
	FDI	0.034	1	0.854
	CO2	1.243	1	0.265
	GDPC	33.828	1	0.000
	ALL	39.337	3	0.000
CO2				
	FDI	9.150	1	0.002
	CEC	4.379	1	0.036
	GDPC	2.566	1	0.109
	ALL	17.466	3	0.001
GDPC				
	FDI	15.252	1	0.000
	CEC	0.727	1	0.394
	CO2	14.585	1	0.000
	ALL	26.189	3	0.000

High income (column 3):

```
panel VAR-Granger causality Wald test
  Ho: Excluded variable does not Granger-cause Equation variable
  Ha: Excluded variable Granger-causes Equation variable
```

Equation \ Excluded		chi2	df	Prob > chi2
FDI				
	CEC	0.070	1	0.791
	CO2	13.220	1	0.000
	GDPC	15.793	1	0.000
	ALL	17.137	3	0.001
CEC				
	FDI	0.573	1	0.449
	CO2	1.698	1	0.193
	GDPC	6.637	1	0.010
	ALL	9.791	3	0.020
CO2				
	FDI	0.260	1	0.610
	CEC	2.008	1	0.156
	GDPC	10.958	1	0.001
	ALL	11.117	3	0.011
GDPC				
	FDI	1.526	1	0.217
	CEC	1.268	1	0.260
	CO2	23.704	1	0.000
	ALL	25.865	3	0.000

Table-6

Forecast	Impulse		variable	
horizon	FDI	CEC	CO2	GDPC
FDI				
0	0	0	0	0
1	1	0	0	0
2	0.999	0.000	0.000	0.000
3	0.998	0.001	0.001	0.000
4	0.997	0.001	0.001	0.001
5	0.997	0.001	0.001	0.001
6	0.996	0.001	0.001	0.001
7	0.996	0.001	0.002	0.001
8	0.996	0.001	0.002	0.001
9	0.996	0.001	0.002	0.001
10	0.996	0.001	0.002	0.001
CEC				
0	0	0	0	0
1	0.060	0.940	0	0
2	0.067	0.928	0.001	0.004
3	0.070	0.921	0.002	0.008
4	0.071	0.917	0.002	0.010
5	0.071	0.915	0.003	0.011
6	0.071	0.914	0.003	0.012
7	0.072	0.914	0.003	0.012
8	0.072	0.914	0.003	0.012
9	0.072	0.913	0.003	0.012
10	0.072	0.913	0.003	0.012
CO2				
0	0	0	0	0
1	0.029	0.083	0.888	0
2	0.029	0.077	0.889	0.005
3	0.029	0.073	0.886	0.012
4	0.029	0.071	0.881	0.019
5	0.029	0.069	0.877	0.025
6	0.029	0.068	0.873	0.029
7	0.029	0.068	0.871	0.032
8	0.029	0.068	0.869	0.034
9	0.029	0.067	0.868	0.036
10	0.029	0.067	0.867	0.036
GDPC				
0	0	0	0	0
1	0.109	0.219	0.238	0.435
2	0.107	0.207	0.232	0.454
3	0.106	0.201	0.227	0.466
4	0.105	0.198	0.224	0.473
5	0.105	0.197	0.222	0.476
6	0.104	0.197	0.221	0.478
7	0.104	0.196	0.220	0.479
8	0.104	0.196	0.220	0.480
9	0.104	0.196	0.220	0.480
10	0.104	0.196	0.220	0.480

Variance decomposition measures for the overall model. Columns represent impulse variables and rows represent response variables. Response is analyzed over a ten-year horizon since the initial shock.

Table-7

Forecast horizon	Impulse FDI	CEC	variable CO2	GDPC
FDI				
0	0	0	0	0
1	1	0	0	0
2	0.989	0.000	0.007	0.004
3	0.967	0.001	0.022	0.011
4	0.940	0.001	0.039	0.020
5	0.914	0.002	0.056	0.028
6	0.892	0.003	0.071	0.035
7	0.874	0.003	0.083	0.040
8	0.860	0.003	0.092	0.044
9	0.850	0.004	0.099	0.047
10	0.842	0.004	0.105	0.049
CEC				
0	0	0	0	0
1	0.030	0.970	0	0
2	0.028	0.915	0.003	0.054
3	0.034	0.835	0.010	0.121
4	0.046	0.756	0.021	0.177
5	0.059	0.688	0.034	0.219
6	0.073	0.631	0.047	0.250
7	0.085	0.583	0.060	0.272
8	0.096	0.544	0.072	0.287
9	0.106	0.512	0.083	0.298
10	0.115	0.486	0.093	0.306
CO2				
0	0	0	0	0
1	0.067	0.033	0.900	0
2	0.091	0.047	0.861	0.001
3	0.105	0.055	0.837	0.003
4	0.111	0.059	0.820	0.009
5	0.113	0.062	0.807	0.018
6	0.112	0.064	0.794	0.030
7	0.109	0.065	0.781	0.045
8	0.107	0.065	0.766	0.062
9	0.105	0.065	0.751	0.080
10	0.103	0.064	0.735	0.097
GDPC				
0	0	0	0	0
1	0.065	0.003	0.107	0.825
2	0.103	0.002	0.131	0.765
3	0.132	0.001	0.151	0.716
4	0.155	0.001	0.168	0.676
5	0.173	0.001	0.182	0.644
6	0.186	0.001	0.195	0.618
7	0.196	0.002	0.205	0.596
8	0.205	0.002	0.215	0.578
9	0.211	0.002	0.223	0.563
10	0.217	0.003	0.230	0.551

Variance decomposition measures for the low-income model. Columns represent impulse variables and rows represent response variables. Response is analyzed over a ten-year horizon since the initial shock.

Table-8

Forecast horizon	Impulse FDI	variable CEC	CO2	GDPC
FDI				
0	0	0	0	0
1	1	0	0	0
2	0.998	0.000	0.000	0.002
3	0.994	0.000	0.001	0.005
4	0.990	0.000	0.002	0.009
5	0.986	0.000	0.002	0.012
6	0.984	0.000	0.002	0.014
7	0.981	0.000	0.002	0.016
8	0.980	0.000	0.003	0.018
9	0.979	0.000	0.003	0.019
10	0.978	0.000	0.003	0.019
CEC				
0	0	0	0	0
1	0.088	0.912	0	0
2	0.092	0.903	0.001	0.004
3	0.092	0.898	0.002	0.007
4	0.092	0.895	0.003	0.009
5	0.092	0.894	0.004	0.009
6	0.092	0.893	0.005	0.009
7	0.092	0.892	0.006	0.009
8	0.092	0.892	0.006	0.009
9	0.092	0.892	0.007	0.009
10	0.092	0.891	0.007	0.009
CO2				
0	0	0	0	0
1	0.025	0.073	0.902	0
2	0.023	0.055	0.907	0.015
3	0.021	0.047	0.896	0.035
4	0.020	0.043	0.881	0.056
5	0.019	0.040	0.867	0.073
6	0.018	0.039	0.856	0.087
7	0.018	0.038	0.847	0.097
8	0.017	0.038	0.841	0.104
9	0.017	0.037	0.836	0.109
10	0.017	0.037	0.833	0.113
GDPC				
0	0	0	0	0
1	0.022	0.028	0.495	0.455
2	0.028	0.023	0.584	0.365
3	0.032	0.021	0.641	0.305
4	0.035	0.020	0.674	0.271
5	0.036	0.020	0.691	0.253
6	0.036	0.019	0.698	0.246
7	0.036	0.019	0.701	0.244
8	0.036	0.019	0.700	0.245
9	0.035	0.019	0.699	0.246
10	0.035	0.019	0.698	0.248

Variance decomposition measures for the high-income model. Columns represent impulse variables and rows represent response variables. Response is analyzed over a ten-year horizon since the initial shock.