BOSTON UNIVERSITY Global Development Policy Center

GCI WORKING PAPER 007 • 4/2019

The Environmental Impact of China-financed Coal-fired Power Plants in South East Asia

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ABSTRACT

While Multilateral Development Banks have been gradually phasing out their finance support for coal-fired power plants, China recently became a major player. This paper examines the impact of Chinese financed coal plants on sulfur dioxide (SO2) emissions in four countries: India, Indonesia, Vietnam and Philippines. Using satellite measures, we first show that the SO2 increased substantially after the operation of Chinese financed power plants. We further compared the performance of coal plants financed by China with the rest of coal plants in the region. Due to small number of Chinese-financed plants that started operating during the period of 2006-2016, we have only limited results from our comparison of Chinese and non-Chinese financed plants. We find no significant difference in SO2 impact in general, but observe higher SO2 increase after operation for the ones financed by China among the plants using subcritical technologies and lower for those using supercritical technologies, though not significantly different from the rest. Among plants larger than 500 MW, the percentage of supercritical power plants among Chinese financed coal plants is higher than the rest.

Key Words: environmental impact, development finance, coal-fired power plants, satellite data

JEL Classification Numbers: F3, Q4, Q5

Introduction

About 1 billion people – roughly three times the population of the United States – still lack access to electricity (World Bank, 2017). International Energy Agency (2017) estimated that power plants alone would require $2.7 trillion investment from 2017 to 2025. In poor countries where more sustainable electricity supply has the potential to foster higher economic growth, fossil fuel based power generation remains an attractive option under many circumstances (Morris and Pizer, 2013). Meanwhile, multilateral development banks (MDBs) have 'greened' power-generation portfolios in the past decade, phasing out lending for coal-fired power plants after more than five decades (Steffen and Schmidt, 2018). The World Bank, among most other MDBs, decided to provide financial support for coal-power generation projects only in rare cases such as when countries have no feasible alternatives to meet basic energy needs (World Bank, 2013). In 2015, the Arrangement on Export Credits – a "Gentlemen's Agreement" among participants from most OECD members – restricted the official export credits[1] for the least efficient coal-fired power plants, encouraging both exporters and buyers to transit from low-efficiency to high-efficiency technologies. In contrast, public funding agencies and commercial banks in Asian countries, especially Japan, Korea and China, are becoming the lead arrangers of project finance in coal power plants overseas (Baruya, 2017).

In recent years, China has become a major funder of energy-related infrastructure in developing countries (Dollar, 2018; Gallagher et al, 2018). Between 2000 and 2014, almost 40% of the total overseas financing from China has gone into the power sector – the highest among all sectors (Dreher et al., 2017). According to the China Global Energy Finance database, the China Development Bank (CDB) and China Export-Import Bank (CHEXIM) provided $225.75 billion in energy finance overseas between 2000 and 2017. These loans are highly concentrated in fossil-fuel based energy generation, especially coal-fired power plants. More specifically, from 2005 to 2017, more than 40% of the power generation projects financed by the CDB and the CHEXIM were coal-fired power plants (Gallagher et al., 2018).

Is there an environmental cost to China stepping into this role of financing coal-fired power plants? This paper examines one aspect of this question: is China financing coal-fired power plants that have observably higher pollution than power plants financed without China's support? If those plants are more polluting, it suggests a downside to the choice by the MDBs and some western governments to step away from financing such plants. While the goal may have been to reduce environmental impacts by stepping away, they may have inadvertently worsened pollution by encouraging China to step in. On the other hand, if they are not more polluting, it suggests that the presumed reduction in total global financing for coal-fired power plants is a net positive for the environment.

Our concern about environmental impacts follows from the significant environmental footprint for coal-fired generation. While having the potential to alleviate energy poverty and fuel economic growth, coal-fired power plants can lead to serious environmental issues and potential health problems (see Section 2.3). However, very few studies have examined the environmental impact of the coal-fired power plants financed by China overseas, partially due to lack of data. On the finance side, there is no official data from Chinese government on its overseas finance at the project level. On the outcome measures, unlike the US where the Environmental Protection Agency (EPA) collects detailed emission data from coal-fired power plants, the on-ground emission data in the developing countries are often missing or not comparable.

This paper fills the gap by combining the CoalSwarm Global Coal Plant Tracker and China's Global Energy

1 Offical export credits are provided by governments to support national exporters competing for overseas sales.

Finance (CGEF) datasets along with satellite data from NASA. That is, we look at direct measures of pollution levels rather than bottom-up emission calculations. Compared to such approaches, which may or may not be consistent with observed outcomes directly related to health outcomes, our work offers important and complementary insights. Our outcome measure, the Ozone Monitoring Instrument (OMI) retrieved atmospheric SO2 column amounts, has already been used to study large point emission sources (e.g. Karplus et al., 2018; Li et al., 2010). It also offers a relatively objective view, as on-ground emission data may be susceptible to manipulation (Ghanem and Zhang, 2014). However, those existing studies mainly focus on power plants inside of China rather than those overseas, and are not trying to compare Chinese and non-Chinese financed plants.

We examine a total number of 638 power plant units built between 2006 and 2016 in four countries in the Southeast Asia: India, Indonesia, Vietnam and Philippines, as the majority of operating coal-fired power plants financed by China are in these countries. Using a simple difference method based on the start year of power plants, we show that the operation of coal-fired power plants leads to observable increases in the SO2 column amounts. The impact of the power plants has the largest magnitude when we draw a circle of 20 km around the power plant and use 95% quantile to calculate the SO2 level: the SO2 increases almost 10% after the start-up of coal-fired power plants larger than 500 MW. The magnitude of impact decreases with the radius of buffer we use to extract the SO2 levels around the power plants, and increases when we look at a higher percentile of the SO2 over the year.

At this point, we have only limited results from our comparison of Chinese and non-Chinese financed plants. The general comparison of the plants financed by China with the rest shows no significant differences, using a difference-in-difference approach. However, when we limit the sample to plants using sub-critical technology, we observe that the coal-fired power plants financed by China leads to higher SO2 increase than the other plants (for plants larger than 300 MW), though not statistically significant. This may reflect looser SO2 controls, but we could not prove this due to lack of information. On the other hand, we observe that the coal-fired power plants using supercritical technology2 leads to lower SO2 increase, though also not statistically significant. For power plants larger than 500 MW, a larger proportion of the plants financed by China use supercritical technology. Ideally, we would want to assign randomly a project to be financed by China versus by others. In reality, the financing decision is complicated and often involve multiple stakeholders. Hence, the diff-in-diff result should be interpreted as preliminary evidence on characterizing the Chinese-financed power plants, not necessarily the casual impact of finance from China.

The rest of the paper proceeds as follows. Section 2 provides the background on energy finance, infrastructure gap and environmental impact. Section 3 describes the data, followed by Section 4 and 5 explaining the empirical strategies and findings in two steps—initially identifying the pollution from power plant start-up, generally, and then identifying the difference between Chinese and non-Chinese plants. Section 6 concludes.

2 Supercritical power plants have much higher heat efficiencies (46%) while subcritical power plants have efficiency of within 40%. The temperature and pressure in supercritical power plants are much higher, keeping the water as a supercritical fluid – neither a liquid nor a gas.

Energy Finance, Infrastructure Gap and Environmental Impact

This section establishes the background on China's energy finance overseas, infrastructure gap and energy poverty, and environmental and health impacts of coal-fired power plants. Section 2.1 describes the larger trend of Chinese overseas investment, among which energy sector is an important component. Section 2.2 highlights the global infrastructure gap and the need for more investment. Although this paper focuses only on the environmental impact, we have to acknowledge the development needs in the developing countries and least developed countries, which requires increasing investment to pursue economic growth. Section 2.3 summarizes the previous studies on the impact of coal-fired power plants.

China's Overseas Energy Finance

The surge of Chinese overseas investment started in early 2000s as the result of China's "going out" policy (Kong and Gallagher, 2017). Since 2013, China more formally 'branded' the overseas investment under the Belt and Road Initiative (BRI) – a multi-trillion dollar initiative. The initiative covers more than 70 countries that account for over 60% of global GDP and 70% of world population (Chen and Lin, 2018), aiming at strengthening infrastructure, trade, and investment links. The immense scale of the initiative has drawn huge public attention but the exact scope and characteristics of projects remain vague.

Though renewable choices are widely available, China continued to finance coal projects overseas. Among the pull factors, the recipient countries may prefer coal plants due to lower construction costs or ignorance of better choices. On the push-factor side, China has excessive coal capacity (Lin et al., 2016) due to historical issues along with stringent domestic policies to reduce emissions and to prioritize renewable energy (Li et al., 2019). Based on the China Global Energy Finance database, during the period of 2001-2017, among the $225.75 billion energy finance from the CDB and CHEXIM, nearly $50 billion (20%) was spent on coal projects. In terms of regional distribution of coal finance, Southeast Asia and South Asia received 70% of the total finance amount, compared to 30% for the rest of world (22% in Europe/Central Asia, 7% in Africa and 1% in LAC).

Among the power generation projects, more than 43% of the total number of projects use coal, followed by hydropower (40%). While China have funded hydropower projects across continents and especially in Africa and LAC, its current coal portfolio is much more concentrated in Southeast Asia, South Asia and Central Asia. China's leading role in coal power plants is also reflected in the trade flows. In recent years, China has become the largest exporter of equipment for coal power generation, such as boilers and steam turbines (Ueno et al., 2014).

Infrastructure gap

It is widely accepted that infrastructure investments are fundamental to many countries' pursuit of economic development (World Bank 2012). Under the framework of United Nations Sustainable Development Goals, infrastructure affects people's wellbeing and economic productivity through multiple channels, including "building resilient infrastructure" in Goal #9, "water" in Goal #6, and "energy" in Goal #7.

The infrastructure investment need around the world remains huge. Based on the Global Infrastructure Outlook[3], infrastructure investment will need to reach $94 trillion by 2040 to keep pace with the 25% increase in population, rural to urban migration, and economic development, globally. To achieve universal provision of clean water, sanitation and electricity under UN Sustainable Development Goals (SDGs), the total infrastructure cost adds up to $97 trillion, among which almost 20% would not be fulfilled by forecasted investments based on current trends. Mckinsey Global Institute estimated that the current trajectory of investment would lead to a shortfall of roughly $350 billion annually in infrastructure including transportation, power water and telecom systems (Woetzel et al., 2016).

3 https://outlook.gihub.org/

Among countries, over half of global infrastructure investment needs are in Asia, requiring more than $1.5 trillion per year through 2030 ($0.4 trillion for South Asia and $0.2 trillion for Southeast Asia). The infrastructure investment gap is estimated to equal 5% of projected GDP from 2016 to 2020 factoring climate mitigation and adaptation costs for Asian countries without China[4] (ADB, 2017). Among sectors, power sector counts for half of the investment needs, followed by transportation (35%), telecommunications (10%) and water and sanitation (4%). As ensuring access to affordable, reliable, sustainable and modern energy for all is listed as the Goal 7 in the Sustainable Development Goals committed by more than 190 world leaders in 2015, designing efficient and effective electrification programs is crucial to achieve universal energy access, especially in developing countries. The huge infrastructure gaps call for more investments from all parties, including Multilateral Development Banks, policy banks and private actors.

From this perspective, the substantial amount of investment from China, especially under the BRI, could be potentially beneficial to fill in the global infrastructure gap and to improve economic productivity. Utilizing an original dataset of geo-located Chinese Government-financed projects during 2000-2014, Bluhm et al. (2018) finds that Chinese development projects have led to reduction in economic inequality, especially for the transportation projects connecting and facilitating economic activities. Electrification could potentially have ripple effects on the economic development, but the existing evidence is mixed. Studies have found positive impact of electrification on income, household consumption and other dimensions of human wellbeing (e.g. Van de Walle et al., 2017, Dinkelman, 2011; Chakravorty et al., 2016), while other studies do not find significant positive impacts (e.g. Burlig and Preonas, 2016).

Environmental and health impacts of coal-fired power plants

Along the production of power, coal-fired power plants generate numerous local externalities, including pollutants such as sulfur dioxide (SO2), nitrogen oxides, low levels of radioactive elements, ash, and other residues. In the neighborhood of power plants, households may also suffer from other local externalities, including visual dis-amenities of tall stacks and noise. SO2 emissions in less developed regions are of particular concern, as the regulatory environment to install scrubbers in those countries are generally weaker.

The potential adverse health effects from high-level SO2 exposures and acid rain are well recognized. The U.S. EPA conducted extensive evaluation of previous epidemiologic and laboratory studies and concluded that short-term exposure to SO2 would cause respiratory health effects, as summarized in the Integrated Science Assessment for Oxides of Sulfur – Health Criteria (U.S. EPA, 2008). In the Regulatory Impact Analysis of Sulfur Dioxide (SO2) Primary Standards (U.S. EPA, 2010), the monetized health effects of SO2 include respiratory hospital admissions, asthma emergency department visits, asthma exacerbation, and acute respiratory symptoms. Other effects such as premature mortality, other respiratory emergency department visits, visibility and recreation in terrestrial and aquatic ecosystems from acid rain are much harder to estimate. A recent paper estimated that the likelihoods of having a low birth weight baby and having a preterm birth increases in areas downwind of power plants (Yang and Chou, 2018). Koplitz et al. (2017) estimated roughly 20,000 excess deaths per year due to Southeast Asian coal emissions at present, which will further increase to near 70,000 by 2030.

The impact of coal plants on the neighborhood is complicated by migration patterns and sorting. Kahn (2009) shows that the population growth within 2.5 miles of the one hundred dirtiest power plants in the United States have experienced slower population growth, suggesting a migration pattern towards cleaner areas. This re-confirms that the negative impact of welfare for households closer to power plants due to environmental and health concerns. The migration dynamics could also help alleviate the negative impacts. Davis (2011) shows that the property value decreases in area near power plants. The paper also sheds light on taste-based sorting, where households with lower income, educational attainment and ownership live closer to the plants. Hence, the local impact near the power plants could disproportionately affect those with limited ability and resources to migrate. It is worth noting that both papers are conducted in the US,

4 With China, the gap is 2.4% of GDP.

where the property right, ability to sell and move, awareness of environmental issues, priority of goals, among others, may differ from the situation in less developed countries.

Data and descriptive statistics

To understand the impact of overseas coal-fired power plants financed by China, we use the Global Coal Plant Tracker to provide information on existing coal plants, and the China's Global Energy Finance dataset to identify the ones financed by China. As power plants spread across countries, we use the sulfur dioxide measured by satellites as the environmental outcome to ensure comparability. Other control variables (mainly temperature and precipitation) are also from globally gridded data sets.

For the purpose of this study, we focus on four countries in the Southeast Asia: India, Indonesia, Philippines, and Vietnam. Global Coal Plant Tracker and the China's Global Energy Finance data sets are merged manually because the power plant names have small variations. The SO2 data and other gridded data are then merged to the coal plants' data by location in R. The previous atmospheric studies and environmental studies on the emissions from power plants do not offer clear guidance on the radius of buffer to be used to extract SO2 data. Therefore, we experiment with different buffer sizes in the analysis (more details are provided in Section 4).

Coal power plants: CoalSwarm Global Coal Plant Tracker (Tracker)

CoalSwarm – the global reference on coal – maintains the Global Coal Plant Tracker (referred to as the Tracker hereafter), providing information on about 12,500 existing and proposed coal-fired power plant units with a capacity of 30 MW and above across the world (CoalSwarm, 2018). Among the 12,500 units, half are operating[5]. For each power plant, the database records its capacity, start year, technology, and location, and provides estimates on the annual carbon dioxide emissions. The Tracker gathers data from public and private sources including Global Energy Observatory, national reports, Platts UDI World Energy Power Plant database, among others[6]. This is the most comprehensive power plants data across global that are publicly available, and hence is the one we use in this study.

Another comparable source, the S&P Global Platts World Electric Power Plants (WEPP) Database[7], provides data on coal-fired power plants at a cost. The Platts database is widely used in energy industry. It provides information on emission controls, in addition to name, capacity, and technology type. The major shortcoming is that it does not provide latitude and longitude of the plants' location[8], making it hard to be merged with other datasets based on location.

For the 1,103 coal plant units in the four countries across all the available years and operating, we only keep the plants that are operating and started operation between 2006 and 2016 (638 units). This period experiences rapid increase in coal power plant constructions in the four countries, captures the majority of Chinese coal finance, and allows enough satellite observation on SO2 before and after. Before 2006, there were only two recorded finance flows into coal power plants in Vietnam from CHEXIM. From 2006 to 2016, new plants added roughly 180 GW capacity, with the majority built after 2010 (Figure 1). We do not include power plants built in 2017 because we need a full year observation after the operation start year. India leads the new operation of coal power plants in the region, while Vietnam and Indonesia experienced significant

5 Among the 14,000 units, 54% are operating. Retired, cancelled and shelved plants account for 14%, 14% and 8% respectively. 4% are under construction while the rest are pre-operation (announced, pre-permit or permmitted).

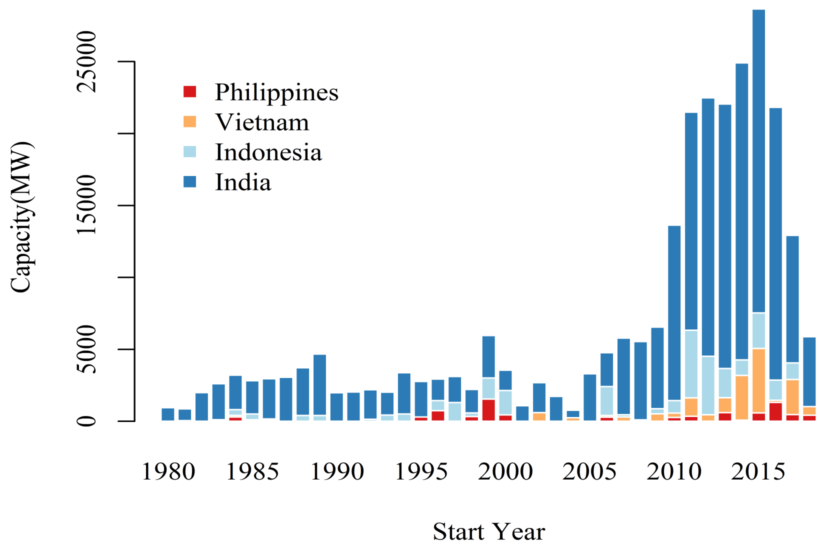
6 For methodology, see https://endcoal.org/global-coal-plant-tracker/methodology/.

7 See https://www.spglobal.com/platts/en/products-services/electric-power/world-electric-power-plants-database

8 See more details on the geodata in WEPP on page 21 of the database documentation. Available at: https://www.platts.com/IM.Platts.Content/downloads/udi/wepp/descmeth.pdf

expansion from 2011 to 2016. The coal plant capacity in Philippines is limited. We do not include Pakistan in our analysis as only one power plant started operating during our study period, though it attracts lots of Chinese investment through the China-Pakistan Economic Corridor – the signature connection in the Belt and Road Initiative.

FIGURE 1. THE TOTAL CAPACITY OF COAL-FIRED POWER PLANTS BY YEAR



Chinese investment: China's Global Energy Finance (CGEF)

The Tracker does not contain information on funding sources. In order to separate the coal-fired power plants financed by China with the rest, we utilize the China's Global Energy Finance database, collected by researchers at Boston University's Global Development Policy Center (Gallagher, 2017). The CGEF covers the annual flow of development finance into energy sector, including coal power plants, from the China Development Bank (CDB) and China Export-Import Bank (CHEXIM) since 2000. CDB and CHEXIM are China's two policy banks, holding more assets than the total global assets from the Western-backed multilateral development banks, including the World Bank (Gallagher et al., 2018). Given that no official data are published by Chinese agencies, the CGEF is built upon information from a wide range of sources, including official websites at the banks or host country ministries, news reports and other documents on the relevant deals[9]. Whenever possible, the records are verified by multiple sources and through interviews with Chinese stakeholders in the collection process, resulting in a relatively conservative number of coal finance flows.

We complement the CGEF with the information from AidDATA's Global Chinese Official Finance (GCOF) Dataset 2000-2014. AidDATA captures funding from Chinese government at all levels with development, commercial or representational intent (Dreher et al., 2017). The data are collected using the Tracking Underreported Financial Flows (TUFF) method, which involves extensive internet searching algorithms in initial data collection and several quality control steps to verify and refine the data[10]. The GCOF covers all sectors including Energy Generation and Supply, Transport and Storage, Industry, Mining, Construction, etc. and different stages from pledge to completion. The data do not provide sub-categories under Energy Generation and Supply, but we could identify the coal-fired power plants from the finance flow description.

9 For methodology description, see China's Global Development Finance: A Guidance Note for Global Development Policy Center Databases, available at: https://www.bu.edu/gdp/files/2018/08/Coding-Manual-.pdf

10 For more detials, see AidDATA Methodology: Tracking Underreported Financial Flows (TUFF), available at: http://docs.aiddata.org/ad4/pdfs/AidDataTUFF_Methodology_1.3.pdf

Of the 638 power plant units in the four countries between 2006 and 2016, we identify 70 units that are financed by China (2 in Philippines, 18 in Vietnam, 35 in Indonesia and 15 in India). Some power plants have multiple units. If we count plants, not the units, our sample has 308 power plants in total, including 33 financed by China (1 in Philippines, 10 in Vietnam, 18 in Indonesia and 4 in India). It is clear that the power plants China financed mainly concentrate in Vietnam and Indonesia, with only a few in India and Philippines. For Philippines, this is consistent with the general small number of power plants in the country, while for India, this may reflect geo-political factors that disfavor Chinese finance in India's power sectors. It is worth mentioning that Indonesia, Vietnam and Philippines are all covered by the Belt and Road Initiative (BRI), while India is not part of BRI.

The capacity financed by China over year fluctuates with that of the rest, and the majority of the power plants started operating from 2011 to 2015 (Figure 2). Of the 180 GW newly added capacity, 27 GW (roughly 15%) are financed by China. The ones financed by China are relatively larger in capacity, as smaller ones have a higher chance of receiving enough funding locally. The mean and median of Chinese-financed units are 390 MW and 330 MW, higher than 260 MW and 150 MW for the rest. In terms of technology, as shown in Figure 3, supercritical technology was only used for power plants larger than 500 MW, while the majority of smaller plants use subcritical technology. Among plants >500 MW, 65% of the plants financed by China use supercritical technology, higher than the 54% for the rest of plants in the region.

FIGURE 2. THE COAL CAPACITY FINANCED BY CHINA AND THE REST

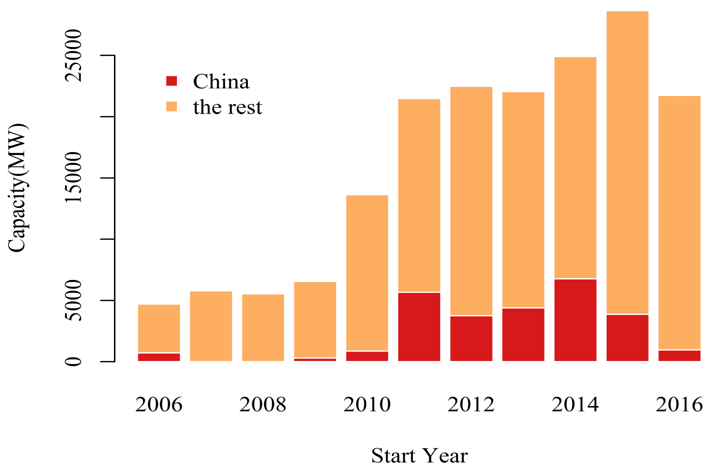
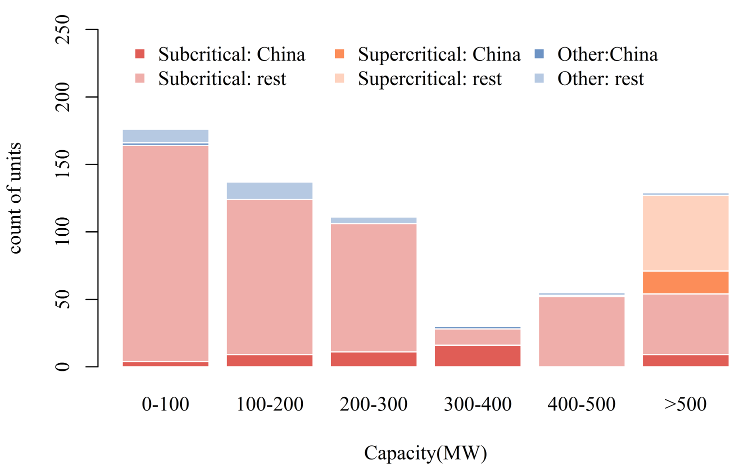


FIGURE 3. TECHNOLOGY MIX OF POWER PLANTS BY CAPACITY (FINANCED BY CHINA VS. THE REST)



Our task is to estimate the levels of SO2 emissions from Chinese coal plants, relative to the rest of power plants in the region. For environmental outcomes, to ensure comparability, we use SO2 measures with broad spatial coverage based on satellite observations from OMSO2e: Ozone Monitoring Instrument (OMI)/Aura Sulfur Dioxide (SO2) Total Column L3 1d Best Pixel in 0.25°×0.25°[11] V3 (NASA, 2017). The Aura satellite was launched on 15 July 2004, and measures sunlight backscattered from the Earth over a wide range of ultraviolet and visible wavelengths. The L3 data are provided by NASA using retrieval algorithms and principal component analysis. The OMSO2e data stores the "best pixel" of original pixels collected by OMI in each grid cell. The unit of measurement is molecule per square centimeter. The OMI derived data have also been used to capture the spatial and temporal variations in SO2 (e.g. Li et al., 2010, Zhang et al., 2018), to quantify coal power plant responses to emission-control policies (e.g. Karplus et al., 2018) and to compare SO2 emissions across countries (e.g. Li et al., 2017).

Because there are no consensus on the optimal size of the circle to be used to extract SO2 around power plants, we experiment with different radiuses for a given power plant location. The size of the buffer has to be large enough to capture the SO2 traveling with wind, and has to be small enough to avoid introducing too much background noise as SO2 from the stacks gets diluted and mixed with SO2 emissions from other sources. Instead of making an arbitrary decision, we run a regression model to find the radius that gives us the strongest signal. We use SO2 data from 2005 to 2017, ensuring at least one year before and after for every plant in our sample.

Empirical analysis I: signal of power plants in satellite data

The first step in our analysis is to prove empirically that the satellite data are able to capture the effect of a new power plant. More specifically, we need to show that controlling for other variables and time trends, the SO2 measure increased significantly after the start year of a power plant. A clear signal in SO2 in this first step is fundamental to comparing the power plants financed by China with the rest.

To get the SO2 measure used as the outcome, we encounter two decisions to make. First, we need to decide the radius of the buffer we use to draw the circle around each power plant to extract the SO2 measures from the 0.25°×0.25° grids. Second, we need to decide the percentile we use to summarize the daily SO2 to an annual measure. The daily SO2 have to be aggregated to annual level, because we do not know the exact date or month of the plant operation. Due to this limitation, we are only able to compare the annual SO2 level before and after the year during with a power plant started operating. As studies examining the environmental impact of power plants using satellite data are limited, we need to determine the best radius and the best percentile by running the regression with all the combination of reasonable radiuses and percentiles.

For buffer size, Karplus et al. (2018) uses 35 km circle in their analyses, covering between 4 and 8 grids, without offering detailed justification to support this choice. Atmospheric studies studying the speed of oxidization of SO2 usually reports results for distances between 0 and 100 km (e.g. Forrest & Newman, 1977; Brock et al., 2002). Hence, we experiment with 26 different radiuses (denoted by r) in this range[12] and 21 different percentiles (denoted by p) with increments of 5% (e.g. 0, 5%, 10%).

11 0.25°×0.25° corresponds to different sizes in km×km as the earth is an oblate spheroid. Roughly, 0.25 degree corresponds to 20-30 km in the four countries we study.

12 The 26 different radiuses (in km) we use are [0.1, 1, 2, 4, 5, 6, 8, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100].

Model

We estimate the impact of new power plants using a simple difference model. For each combination of radiuses and percentiles () in generating the SO2 measures, we run the following econometric model for six different capacity ranges (larger than 0, 100MW, 200MW, 300MW, 400MW, and 500MW respectively). We show results by different capacity, as we hypothesize that the signal of the power plants may only be visible in the satellite data when the capacity is larger than a certain threshold. The total number of regressions we run is 3276 (26 x 21 x 6).

$$SO2_{i,t} = \beta_0 + \beta_1 I(gap_{i,t} > 0) + \beta_2 NAcount_{i,t} + \beta_3 maxtemp_{i,t} + \beta_4 precip_{i.t} + \beta_5 trend_t + \beta_6 trend_t^2 + \delta_i + \epsilon_{i,t} \tag{1}$$

Where i denotes the area around a combined observation (i.e. units at the same location and with the same start year), and t denotes the year. Since not all units of the power plants started operating in the same year, we combine the units at the same location and starting in the same year to one observation in the analysis as they experience the same change in SO2 level around them. Each combined observation has a unique combination of location and start year. In other words, if two units of the same power plant (same location) were built in two different years, they would be two separate observations. Our final sample consists of 474 observations, roughly 10% of them financed by China.   represents the indicator for treatment of 'new power plants operating', which equals 1 for each observation after the start year. As the power plant actually starts operating within the start year, this definition of the treatment corresponds to the lower bound of the impact of the power plant.

All of the control variables are extracted from gridded data covering the globe. We follow Karplus (2018) in adding climate controls, including average daily max temperature () and average precipitation, and a control for the number of missing values. The temperature and precipitation data, calculated from daily data from NASA, have lower resolution than the SO2 data at 0.5°×0.5° (around 50×50 km). We extract temperature and precipitation in a circle of 50 km, as it is the smallest circle that we have no missing value for any of the observation. captures the total number of missing values of daily SO2 for observation i in year t, to control for the noises introduced by the way satellite operates. We also tried filling in the missing value by linear extrapolation, and the result is not very different. As using a certain method to impute the missing values could be arbitrary and the missing value pattern would be consistent for each power plant as we control for fixed effects, we do not fill in missing values in the main results we show below.

To isolate the impact of power plants from general increase in SO2, we model the time trend in quadratic form. This captures the general growth trend in SO2 without taking up too many degrees of freedom. Finally, we control fixed effects at the plant level, so essentially captures the increase in SO2 after a power plant operates. The standard errors are clustered at the plant level, using the "arellano" method (Arellano, 1978), allowing a fully general structure regarding heteroscedasticity and serial correlation. The errors are much smaller when clustered by year or without clustering.

Results

We run the same regression (1) for all combinations of radiuses, percentiles and capacity cutoffs (). We first show the results using buffer of 20 km and 0.95 percentile for power plants larger than 300 MW in Table 1. All the model specifications control individual fixed effects at the plant level. Model 1 only controls the indicator for power plant operation and time trend. Model 2 adds the temperature, precipitation and count of missing values. Model 3 controls year fixed effects instead of time trend. One identification concern is that the increase in pollution level we observe in   may capture general industrialization and economic development in the area that are not from power plant emissions. We therefore control the background SO2 level of a much larger buffer (100 km) in Model 4, and only use the difference between the SO2 in the 20 km circle and the SO2 average in the surrounding area (between 20km circle and 100 km circle) as the outcome variable (denoted 'SO2 diff') in Model 5.

In general, for plants larger than 300 MW, we observe a significant increase of around 0.03 in the column SO2, roughly 5% of the pre-operation SO2 average. For plants larger than 500 MW, the increase is around 10%. This estimate is relatively stable across specifications. When the background SO2 is controlled (as in model 4) or the difference SO2 is used on the left-hand side (as in model 5), the estimated is slightly smaller. This reflects that there is some degree of general development around the power plant, but the SO2 increase we observe in 20 km buffer is mainly from the power plant. The effect of the number of missing value is relatively limited and become insignificant in model 4 and 5. Higher temperature would lead to higher SO2 level as cooling demand increases with the temperature, while precipitation would absorb SO2.

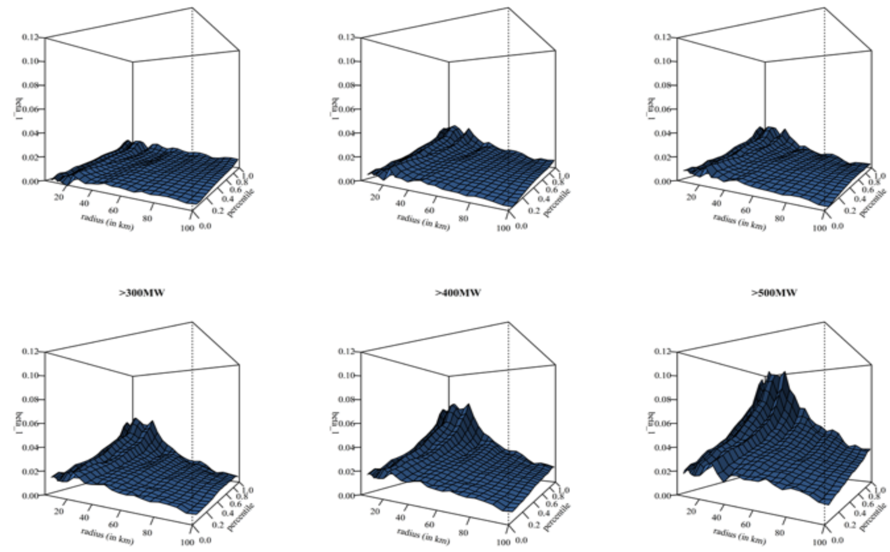
TABLE 1. REGRESSION RESULTS FOR FIRST STAGE

:	*Dependent variable (20km, 0.95, >300MW)*				
	(1) SO2	(2) SO2	(3) SO2	(4) SO2	(5) SO2 diff
I(gap > 0)	0.026*** (0.010)	0.030*** (0.009)	0.030*** (0.009)	0.027*** (0.007)	0.028*** (0.007)
NAcount		0.001*** (0.0001)	0.002*** (0.0002)	-0.00005 (0.0001)	0.00004 (0.0001)
SO2_100km				1.120*** (0.041)	
maxtemp		0.013*** (0.003)	0.015*** (0.004)	0.012*** (0.003)	0.013*** (0.003)
precipitation		-0.004* (0.003)	-0.006** (0.003)	0.001 (0.002)	0.001 (0.002)
trend	0.016*** (0.002)	0.001 (0.003)		0.005*** (0.002)	0.005** (0.002)
trend2	-0.00004 (0.0002)	0.001*** (0.0002)		-0.0003** (0.0001)	-0.0002* (0.0001)
Year Indicators	NO	NO	YES	NO	NO
Plant fixed effects	YES	YES	YES	YES	YES
Observations	2,587	2,587	2,587	2,587	2,587
R2	0.307	0.331	0.356	0.574	0.067
F Statistic	351.529***	196.491***	82.081***	457.766***	28.563***

Note: *p<0.05 **p<0.01 ***p<0.001

Coefficient captures the signal of power plant in the satellite data so we plot the 3276 on the vertical axis (z-axis) in Figure 4. X-axis shows the 26 different buffers and the y-axis shows the 21 different quantiles. Each of the six panels shows the results for a different capacity cutoff. As we expected, the signal of power plants' emissions enhances as we focus on power plants with higher capacity.

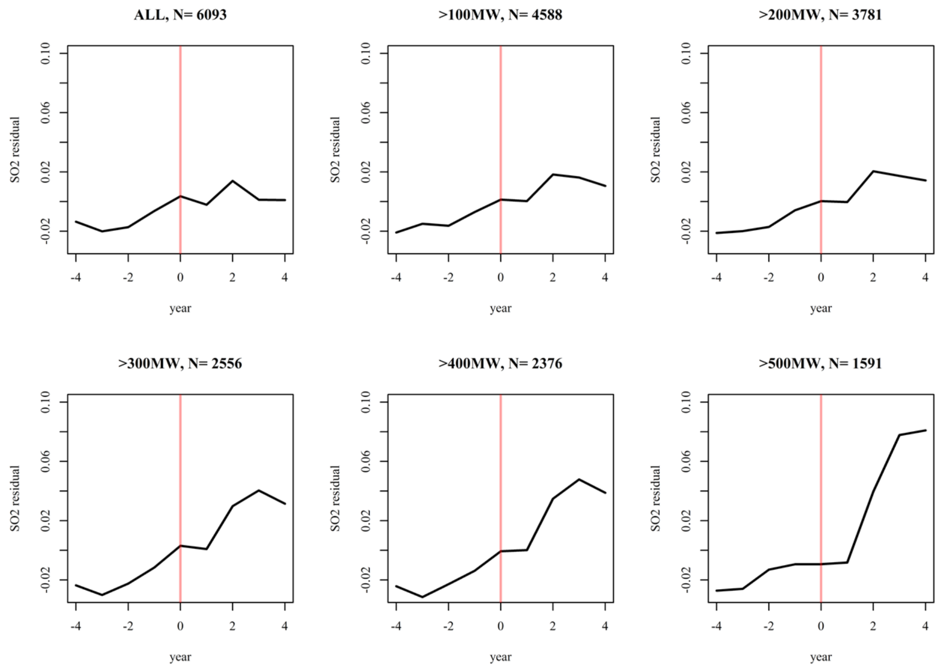
FIGURE 4. IMPACT OF POWER PLANTS ON SO2 BY BUFFER, QUANTILE AND CAPACITY CUTOFFS



Within each panel of Figure 4, the increases smoothly with the percentile. Given our linear function form, this means that after a power plant starts operating, the larger daily SO2 percentile over the year will increase in larger magnitude. To avoid extremes, we use 95 percentile in the next step. This corresponds to the 15^{th} worst day out of 365 days in a year (hereafter referred to as 'SO2 level' directly). The results with a lower percentile (e.g. median) are still significant, but with smaller magnitudes. These magnitudes are smaller than the 18% reduction of SO2 satellite measure under new emissions standards in China in Karplus et al. (2018), because the power plants covered in Karplus et al. (2018) have capacity larger than 1,000 MW. Nonetheless, they represent a substantial increase in SO2 levels.

For radius, we observe the maximum signal at around 20 km radius. The fluctuates when radius is below 20 km and steadily decreases with radius larger than 20 km. As the SO2 emission spreads with the wind, it makes sense that the highest signal appears at a certain distance rather than at the center (radius = 0). When the buffer falls smaller than the grid and the grid has missing values due to cloud coverage, the extraction method will generate missing values at the daily level. This would lead to lower annual measure at 95 percentile. Balancing the signal strength and missing values, we choose a radius of 20 km (covering 1-4 grid cells) where the signal is strongest.

FIGURE 5. DEMEANED SO2 COLUMN MEASURES BY CAPACITY CUTOFFS (N: THE NUMBER OF PLANT-YEAR OBSERVATIONS, YEAR 0 REFERS TO THE START YEAR OF A POWER PLANT)



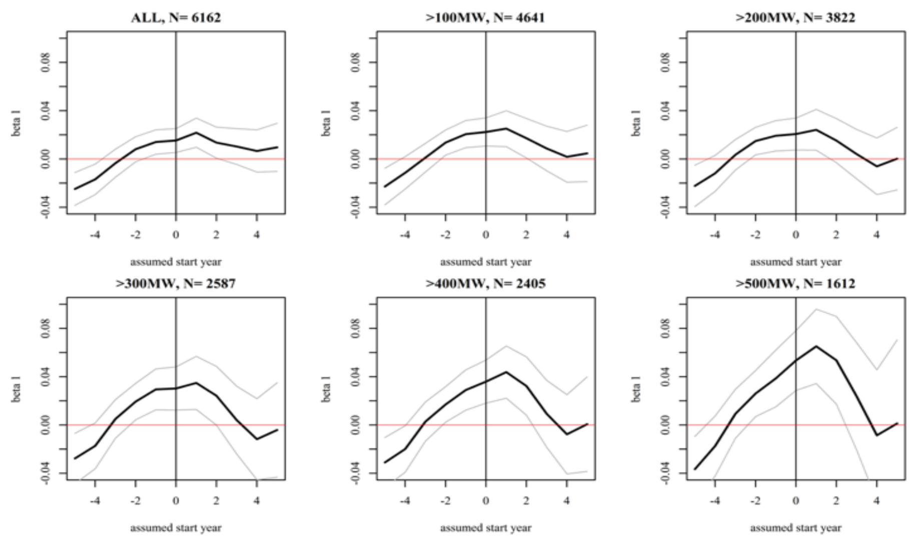
A more straightforward way of showing the impact of power plants is to plot the SO2 along different years and see if we could observe the increase in SO2 at the start year (denoted year 0). This is difficult as the SO2 in the region increased in general over the period we study and the background noises prevent us from seeing a clear signal. Hence, we obtained the residuals of SO2 from a regression similar to regression (1) without the indicator for treatment (with the radius of 20 km and 95 percentile). The demeaned SO2 measures are shown in Figure 5. Year 0 represents the start year of a power plant. As expected, we observe much higher average SO2 after the start year of each power plant. Similar to Figure 4, the signal is much stronger for larger power plants, especially above 500 MW.

Falsification tests

One major concern of the identification above is that the represents the increase in general SO2 trend in the region, and has nothing to do with the operation of power plants. If this were true, then we would expect to see similar results regardless of the start year we use. To test this hypothesis, we assume a range of different start years (e.g. systematically move the start year 1 year backward or forward), and rerun the above regressions (using 20 km radius and 95 percentile).

Figure 6 shows the results of the falsification tests. are plotted with 95% confidence interval. Only the result at year 0 is the true result with the actual start year in the data. The estimate at assumed start year 1 means assuming the plants started operating one year after the actual start year. As expected, the estimates peak around year zero. For the few years before and after, the estimates are significantly larger than zero because the compare all the years after the start year to all the years before. For example, at the fake start year -2, the years after the fake start year capture all the real operating years and include two non-operating years, while the years before the fake start year miss two non-operating years. Hence the estimates are lower as the treatment effect is diluted, but still above zero. To conclude, the falsification results align with the timing of power plants' operation, proving that the estimate is not due to a general increase in SO2 level.

FIGURE 6. FALSIFICATION TESTS OF EMPIRICAL ANALYSIS I



To sum up, we have shown in section 4 that SO2 measures increase significantly after the start year of power plants. The signal is strongest at the radius of 20 km and with 95 percentile. Using these two parameters, the following section explores the comparison of the power plants financed by China with the rest. Ideally, we would use power plants above 500MW in the next step, as the signal is strongest. However, the total number of power plants in the four countries we focus is limited, so we provide results for >300MW, which is a compromise between having more observations and having strong SO2 signal in the satellite data. As we increase the capacity cutoff, we are more certain that the estimate before captures the effect of power plants, while at the same time we lose observations substantially such that we lose statistical power in comparing the Chinese-financed power plants with the rest.

Empirical analysis II: China vs. the rest

Built upon the previous section, we move on to examine whether the coal-fired power plants financed by China experience higher SO2 increases after operation.

Model

The model we use in this section builds upon the first difference shown in regression (1). Adding the comparison between the China and non-China financed plants adds another difference. Hence, we use the following diff-in-diff regression, interacting the indicator of plants financed by China () with the treatment. As the plants financed by China may have different location features, we also model two different time trends. The key parameter of interest is , which shows China-financed plants are emitting more SO2 if is significantly larger than zero. As the power plants financed by China differ in capacity with the rest, we also control the capacity of observation (could be more than one unit in the same location, denoted *totalcap*) interacted with the indicator for operation.

$$SO2_{i,t} = \theta_0 + \theta_1 I(gap_{i,t} > 0) * FinanceChina_i + \theta_2 totalcap_i * I(gap_{i,t} > 0) + \theta_3 NAcount_{i,t} + \theta_4 maxtemp_{i,t} + \theta_5 precip_{i.t} + \theta_6 trend_t * FinanceChina_i + \theta_7 trend_t^2 * FinanceChina_i + \theta_8 FinanceChina_{i,t} + \theta_9 I(gap_{i,t} > 0) + \theta_{10} trend_i + \theta_{11} trend_i^2 + \delta_i + \epsilon_{i,t} \quad (2)$$

Results

Figure 7 summarizes the result. The five models follow similar specifications in Table 1, all controlling the interaction between indicator for operation (and the finance by China indicator (. In addition to the interaction, Model 1 only controls the time trend while Model 2 adds the other controls. Model 3 uses year fixed effects instead of quadratic trend. Model 4 controls the general SO2 in the 100 km buffer and Model 5 uses the SO2diff on the left-hand side as defined in Table 1. Overall, as shown in panel (a) for all plants above 300 MW, we do not find China-financed plants to perform differently than their counterparts. Given the number of China-financed plants are relatively small (31 plants >300 MW), the confidence interval is large, making most estimates of not significantly from zero. In other words, our statistical analysis do not support China-financed plants to be dirtier or cleaner in general. If we did not model a separate time trend for China, most of the estimates under model 1-3 for all plants and subcritical plants would be significantly negative. This difference in results reflects that the places where China financed power plants experienced a slower increase in SO2 absent power plants operation.

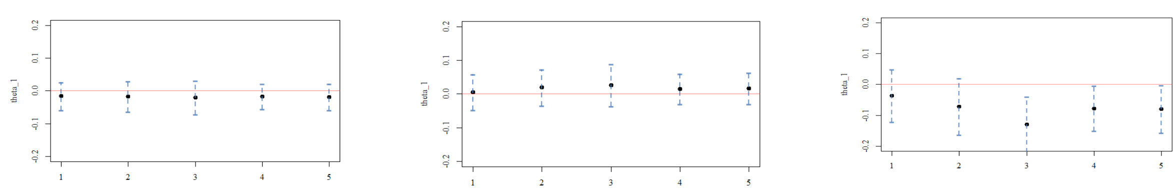
The impact of coal-fired power plants could differ by technology. We now narrow our sample to only subcritical or supercritical plants and rerun regression (2). The results are shown in panel (b) and panel (c) in Figure 6. Compared to the rest of power plants in the region, the subcritical power plants financed by China have higher SO2 emissions while the supercritical power plants financed by China have lower SO2 emissions, though most of the estimates are not significant. One potential explanation is that the domestic advance of more efficient technology under stricter environmental regulations in China could have spillover effect on power plants' construction overseas. A previous study comparing the coal plants in China and the ones in the US showed that China's new coal-fired power plants are cleaner than anything operating in the United States does, as a much higher percent of Chinese coal plants uses supercritical technology[13].

FIGURE 7. THE COMPARISON OF CHINA-FINANCED PLANTS WITH THE REST. THE FIVE ESTIMATES FOR EACH PANEL CORRESPOND TO THE FIVE DIFFERENT MODEL SPECIFICATIONS FOLLOWING TABLE 1.

(a) All plants
N.China = 31, N.rest = 168

(b) Subcritical plants
N.China = 20, N.rest = 118

(c) Supercritical plants
N.China = 10, N.rest = 55



13 See Melanie Hart, Luke Bassett, Blaine Johnson, Everything you think you know about coal in China is wrong. Available at: https://www.americanprogress.org/issues/green/reports/2017/05/15/432141/everything-think-know-coal-china-wrong/

Discussion and Conclusion

As China becomes a leading player in global energy finance, it is critical to understand the environmental implication of its investment. In this paper, we examine a total number of 638 coal-fired power plant units, among which 70 units were financed by China, in Southeast Asia: India, Indonesia, Vietnam and Philippines. Our study is the first to estimate empirically the environmental impact of these coal-fired power plants using satellite data, and to compare the performance of power plants financed by China with the rest. As the power plant data and information on finance flows are not official data, our sample represents the best available sources but is not guaranteed to be 100 percent accurate and comprehensive. Better data transparency on these coal finance deals would help us gain more insights that could guide policy making to make the energy investment more sustainable and clean in the future.

Using simple difference based on the start year of power plants, we find that the operation of coal-fired power plants leads to significant increase in SO2 column amounts. The magnitude of impact decreases with the radius of buffer we use to extract the SO2 levels around the power plant, and increases with the quantile we use to summarize the daily SO2 measures to the annual observation. The signal of power plant impacts in the satellite data increases in magnitude with capacity. It is hard to observe the impact for plants under 300 MW. The impact of the power plants has the largest magnitude when we draw a circle of 20 km around the power plant and use 95% quantile. The SO2 increases almost 10% after the operation of coal-fired power plants larger than 500 MW.

While the signal of power plants in satellite-based SO2 column data is clear and survives falsification tests, it is much harder to compare the performance of plants financed by China with the rest due to relatively small sample size. When we examine all the power plants together, we find no significant differences for power plants financed by China. However, for plants larger than 300 MW, we observe that the coal-fired power plants financed by China leads to higher SO2 increase than the other plants using sub-critical technology, though not statistically significant. On the other hand, plants using supercritical technology financed by China have been shown to be cleaner, but again not statistically different from the rest.

The heterogeneous impact of Chinese-financed power plants could be conceptualized using the framework proposed by Grossman and Krueger (1993) on mechanisms through which trade and investment liberalization impact environmental outcomes. On the one hand, energy finance from China leads to an expansion of the polluting point sources, and economic activity in the region, thus increasing the local pollution ("scale effects"). As the environmental stringency in the recipient countries is generally looser than in China, the construction of subcritical power plants reflects a trend of 'race-to-the-bottom'. On the other hand, energy finance from China could be beneficial in bringing cleaner technologies to the developing countries, hinted by both the higher percentage of supercritical plants financed by China for >500 MW capacity and the cleaner outcome from supercritical power plants.

This paper focuses on the local environmental impact. It is worth noting that Chinese overseas investments in coal-fired power plants have also led to concerns on carbon emissions. The carbon consequence of the overseas fleet of power plants is significant. More than fifty coal-fired power plants has been supported by Chinese financial institutions between 2001 and 2016, which are estimated to release near 600 million metric tons of carbon dioxide annually – more than 10% of total US emissions in 2015 (Gallagher, 2016). In the long-term, if power generation, together with improvements in roads and railways, successfully spurs local businesses and economic growth, we would expect even more emission due to development investments (Zhang et al., 2017). This continuation of coal plants construction could make it very difficult or even impossible to achieve the goal of limiting temperature change to below 2° Celsius, set in Paris Agreement on Climate Change (Shearer et al., 2018).

While this study has shed light on the environmental impact of coal-fired power plants by China, in comparison with the rest, it has a few limitations. First, satellite data provides a comparable measure across different countries on environmental outcomes, but the measurements are less accurate than those captured by on-ground monitors are. Previous studies (e.g. Karplus et al., 2018) showed consistent results using the same satellite data and using the on-ground monitors in China. Nonetheless, the relationship between satellite data and on-ground measures may be complicated and different in South Asia and Southeast Asia. Second, our analysis may be subject to selection bias, as the siting decisions of power plants financed by China may be different from the rest. We modeled different time trends for the Chinese financed plants to address this potential difference partially. A more rigorous way would be to model the siting decision directly, which would require more geo-located data on socio-economic and geo-political variables. Third, the environmental impact of small power plants (<300 MW), though not clearly captured by satellite data, could have substantial influence on the health and wellbeing of residents nearby. Fourth, many power plants are co-financed by multiple institutions. This paper focuses on the power plants that received finance from Chinese policy banks, but the performances could differ when co-financing partners are different.

Finally, our study points to a number of questions for future analysis, many of which require mixed methods, better plant-level data and deeper on-ground case studies. First, what factors could have led to the observed slightly worse environmental performance of subcritical power plants financed by China? Is it mainly because of whether the plants have installed SO_2 scrubbers, the quality of coal used or the daily operational practice of the power plants (e.g. schedules)? Second, what is the underlying decision process of financing a coal power plant by the Chinese policy banks? Which player in the process decides the capacity, technology and operation details? Third, to what extent does China or the recipient country monitor the environmental performance of these power plants? Understanding these underlying mechanisms would be helpful to design policies to 'green' Chinese energy finance.

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