The World Bank and China: Comparing the Impacts of Their Development Projects in Africa*

Qingyuan Chai
Boston University

Zhongyi Tang
Boston University

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Abstract

While a growing body of literature has documented the distinct characteristics of aid projects from China and traditional donors, a significant knowledge gap exists concerning their differences in project impacts. This paper compares the impacts of Chinese and World Bank development projects on African local economies. We leverage detailed, geocoded project data and employ a stacked difference-in-differences identification strategy. Our findings demonstrate that Chinese infrastructure projects significantly increase nighttime light in the recipient regions, and the effects persist over time. World Bank projects, however, do not exhibit significant impacts on nighttime light. Common factors often highlighted in the aid effectiveness literature, such as project location and specific characteristics, could not fully explain the differences in project impacts. Furthermore, we rule out the complementarity effects from follow-up projects, political favoritism, and implementation by Chinese companies as potential mechanisms for those differences. Finally, by utilizing Demographic and Health Surveys (DHS), we establish that both World Bank and Chinese infrastructure projects positively influence women's education attainment and health outcomes.

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1 Introduction

China's growing involvement in financing development projects has provoked heated debates over its intentions and influence, with many expressing concerns that China's economic and political interests may harm the recipients. News articles and research have extensively discussed how this emerging donor differs from the practices of traditional donors, particularly in terms of lacking aid conditionality[1] and transparency, and these deviations could lead to negative consequences. In contrast, the World Bank is renowned for its commitment to poverty alleviation and the promotion of sustainable economic growth in recipient countries. Although criticisms exist regarding the differing characteristics of aid between emerging and traditional donors potentially leading to unintended consequences, empirical evidence supporting these claims remains scarce. This paper aims to bridge this gap by comparing the economic impacts of World Bank and Chinese development finance projects in Africa. Given that the literature has not reached a consensus on why some development projects are more successful than others, contrasting two distinct donor types can offer valuable insights into the critical factors that contribute to the enhancement of local economic growth through aid projects.

This paper finds that Chinese infrastructure projects significantly increase nighttime light more than World Bank projects, even when accounting for various factors that previous literature has identified as influential in aid effectiveness. Previous literature has documented that China and the World Bank allocate projects differently (Brazys et al., 2017; Tseng and Krog, 2017; Humphrey and Michaelowa, 2019). Chinese projects tend to be located in countries with weaker institutional qualities and focus more on large-scale infrastructure projects, whereas the World Bank predominantly engages in smaller-scale, non-infrastructure projects. Using detailed, geocoded project data, our research contributes by offering descriptive evidence of differing location selection, project types, and project implementation approaches employed by the two donors. Remarkably, even after controlling for these

[1] The term "aid conditionality" here refers exclusively to "non-financial" conditions. For instance, the World Bank might institute prerequisites such as anti-corruption measures or gender equality initiatives as conditions for loan approval. On the other hand, Chinese aid projects typically do not require such conditions but instead, impose "financial" requirements like collateral for loans or asset seizure in the event of default. Some recent news reports highlight the negative consequences when China has seized assets or land when beneficiaries cannot repay loans.

discrepancies, Chinese infrastructure projects continue to exhibit a more substantial impact on nighttime illumination compared to their World Bank counterparts. To the best of our knowledge, our paper stands as the first comprehensive comparative analysis of the effectiveness of Chinese and World Bank projects in Africa.

Furthermore, we investigate three potential mechanisms that could explain the differences in project impacts: the number of follow-up projects, the influence of political favoritism, and the role of implementation by Chinese companies. However, none of these factors can account for the more pronounced impacts observed in Chinese infrastructure projects on nighttime light. Importantly, we have also discovered that both Chinese and World Bank infrastructure projects lead to significant improvements in other development outcomes, including women's education attainment. Taken together, these findings suggest that World Bank projects may affect local development through channels nighttime light.

In terms of our methodology, we employ a stacked difference-in-differences (DiD) strategy to identify the causal impacts of development projects. The key assumption underlying this approach is that locations receiving development projects earlier and those receiving projects later would have experienced parallel changes over time if the treatment had not been implemented. The event study plots we present show parallel pre-trends, offering support for this assumption. Our approach contributes to the existing literature in several crucial ways. First, we investigate the long-term impacts of these projects, extending beyond the short-term focus of previous research that has primarily documented the immediate benefits of Chinese development finance projects in the local economy (Guo and Jiang, 2020; Dreher et al., 2021; Mueller, 2023). Second, we address econometric challenges arising from time-varying treatment effects, a consideration often overlooked in prior studies that predominantly employ the traditional two-way fixed effects (TWFE) approach (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2020). As we identify that the impacts of aid projects are time-variant, the stacked DiD method proves to be better suited to mitigate this econometric concern. Lastly, our comparative analysis extends beyond previous work, which often relies on specific instruments tailored to the context of Chinese projects and, therefore, does not apply to World Bank projects.[2] Our approach is applicable to both Chinese and World Bank projects,

[2]One exception is Gehring et al. (2022), where the authors use shift-share IVs for both Chinese and World

enabling a direct comparison of their effectiveness.

Examining the impact of Chinese and World Bank projects on local economies while controlling for potential confounding factors poses a challenge due to the scarcity of granular data in Africa. Previous literature often had to confine its analysis to country-level outcomes, aggregating projects solely by their numbers or total funding amounts. This approach lacked the utilization of more detailed project-level characteristics, such as local economic conditions and project scales. To overcome this data challenge, we harnessed frequent and fine-grained nighttime light data, in combination with a comprehensive list of variables from various sources. Our methodology involved merging detailed, geocoded project data from AidData with nighttime light data and DHS survey data, facilitating within-county analyses of both economic (nighttime light) and social (health and education) outcomes. We also incorporated a diverse set of control variables aimed at controlling for the factors contributing to the differences in impacts between Chinese and World Bank projects. Our dataset encompasses a wide range of geographic features, economic circumstances, institutional attributes, and regime changes across the African continent, allowing us to account for location-specific characteristics. Additionally, we integrated project-specific attributes, including scale and sectors, into our analysis. To provide a more nuanced understanding, we employed state-of-the-art Natural Language Processing algorithms to categorize projects in a highly detailed manner based on project descriptions. This enabled us to examine how the impacts of Chinese and World Bank projects differ, even after controlling for the content and nature of each project.

Our empirical analyses consist of three main parts: contrasting the differences in project impacts between the two donors, exploring potential underlying mechanisms, and examining alternative outcomes. We primarily focus on nighttime light as our key outcome variable.

To ensure a proper comparison of the project impacts of the two donors, we pool Chinese and World Bank projects in the same regression and control for various characteristics. Even after accounting for location factors, Chinese infrastructure projects continue to yield a greater increase in nighttime light compared to World Bank projects. Conversely, Chinese non-infrastructure projects initially result in a slightly larger increase in nighttime light

Bank projects. Their focus is the impact of aid projects on local political stability.

compared to World Bank projects. However, this difference dissipates once we consider location factors, implying that location characteristics explain the disparities in the effects of non-infrastructure projects but not those of infrastructure projects. We then investigate if project features could explain the differences in project impacts between the two donors. Although the scale of Chinese projects significantly differs from that of traditional donors and could potentially lead to substantial increases in nighttime light, controlling for the expenditure per project site does not alter this difference. Additionally, even within the same sectors, Chinese projects exhibit a significant and larger impact on nighttime light compared to World Bank projects. To further differentiate projects within the same sector but with varying content,[3] we employ state-of-the-art Natural Language Processing algorithms to categorize projects based on their descriptions. These results are consistent with our previous findings, indicating that disparities in project impacts could not be attributed to the scope of projects.

Subsequently, we explore three potential mechanisms proposed by existing literature or anecdotal evidence: follow-up projects, political favoritism, and implementation by Chinese companies. Specifically, the differences in effects might arise because Chinese projects have a higher occurrence of subsequent complementary projects following the initial one, are often situated in areas favored by political leaders (Burgess et al., 2015), or are implemented by Chinese contractors with greater construction expertise. To test these hypotheses, we calculate the number of follow-up infrastructure and non-infrastructure projects, identify projects located near political leaders' birthplaces or ethnic homelands, and analyze World Bank projects' procurement data to determine if they were predominantly contracted out to Chinese firms. However, even after accounting for these three factors, the differences in project impacts between the two donors remain unexplained..

Finally, we extend our outcome measures beyond nightlight and examine social outcomes from the DHS data. Applying the same stacked difference-in-differences design, we introduce never-treated DHS clusters selected using propensity score matching to the control group.[4] Specifically, clusters that have never been treated are matched to treated ones based on

[3] For example, projects under the Transport and Storage sector could be building a road, highway, or railway.
[4] A cluster is a group of about 25-30 households in an Enumeration Area (EA).

baseline nightlights, land suitability, distance to the capital city, coast to coal mines, and petroleum mines. We find that Chinese and World Bank infrastructure projects exhibit similar positive impacts on women's education attainment and health. The differences in these outcomes between Chinese and World Bank projects are mostly not statistically different.

This paper is related to the literature in three strands. First, it contributes to research examining the impacts of Chinese aid on recipient countries. Prior studies have indicated that Chinese aid projects have a positive effect on the economic development of recipient countries, particularly in the short term. For instance, Dreher et al. (2021) finds that Chinese aid boosts short-term economic growth in the recipient countries. Mueller (2023) also shows that Chinese aid positively affects country-level outcomes, including GDP, trade, consumption, and employment, by using local labor unrest in China as an instrument. Additionally, Guo and Jiang (2020) discovers that local employment increases in the first two years but decreases after the third year of launching a Chinese project. Finally, Bluhm et al. (2018) documents that Chinese transportation projects have positive economic spillovers that reduce the inequality of the distribution of economic activity. Our paper complements the literature by examining within-country variations and investigating the persistence of the impacts of Chinese development projects on the economy.

Second, this paper extends the literature that compares development finance projects from the World Bank and China. Prior research has predominantly focused on disparities in project allocation and attributes, with limited exploration of differences in their impacts on economic development. Brazys et al. (2017) find that World Bank projects tend to be located at places with a lower level of corruption, but the pattern disappears when co-locating with Chinese projects. Dreher et al. (2019) provide evidence that political leaders' birth regions receive more Chinese projects, while no such bias exists for World Bank projects. As for the comparison of project impacts, Gehring et al. (2022) find no evidence that either World Bank or Chinese aid increases conflict in Africa. Our paper contributes by examining the differences in their effects on local economic development and evaluating how variations in project distribution and characteristics account for impact disparities in economic development.

Finally, this paper complements the literature on identifying factors that affect aid effectiveness. Previous research suggests that bureaucrat performance (Limodio, 2021), project preparation (Kilby, 2015), local public finance situation (Presbitero, 2016), and institutional quality (e.g. Svensson, 1999; Burnside and Dollar, 2000) significantly affect aid impacts. China as an emerging donor remains unexplored in this literature. Our paper deepens the understanding of what matters for a project to be effective by comparing projects from China and a traditional donor.

The remainder of the paper proceeds as follows. Section 2 introduces the data used for analysis and provides descriptive statistics. Section 3 describes the identification strategy. Section 4 presents the main empirical results. Section 5 discusses potential mechanisms. Section 6 shows complementary results using DHS data. Section 7 concludes.

2 Data

In this paper, we construct a dataset that includes comprehensive information on project and location characteristics. Detailed and geocoded project-level data on both donors, China and the World Bank, is from AidData. Specifically, we use AidData's Geocoded Global Chinese Official Finance Dataset (Version 1.1.1) (Dreher et al., 2022; Bluhm et al., 2018) and World Bank Geocoded Research Release (Version 1.4.2) (AidData, 2017).[5] For each project, we collect information on location longitude and latitude, project start/commitment year, and other project and location characteristics.

To measure local economic development, we draw on two sources of data: nighttime light and the Demographic and Health Survey (DHS). We take nighttime light from 2000 to 2014 from the harmonized nighttime light data constructed by Li et al. (2020). We choose to use the harmonized version rather than the radiance values directly from either DMSP or VIIRS satellite because DMSP and VIIRS cover non-overlapped periods and are not comparable in terms of resolution and scale of radiance values. Li et al. (2020) calibrates the nightlight to suit the data for temporal comparison. DHS provides information on education attainment and health outcomes. Each household is associated with a cluster that has latitude and longitude,

[5]For World Bank, we only use projects from the International Bank for Reconstruction and Development (IBRD) and International Development Association (IDA) lending lines. This dataset has been utilized widely in previous research, such as Gehring et al. (2022).

and therefore, they could be matched with nearby Chinese or World Bank projects. In this paper, we use three different outcomes from DHS data from 2000 to 2014: child mortality rate, women's years of schooling, and women's BMI.[6]

Control variables are constructed to account for the variations among locations across the African continent. Specifically, we calculate distances to the national capital city, coast, coal mines, and petroleum mines for every project location. Land suitability is also constructed to capture access to natural resources. The average nightlight from 2000 to 2002 is used as the baseline nightlight. Measures of country-level institutional quality come from the World Governance Indicators (WGI). Specifically, WGI contains six dimensions of governance quality.[7] We take an average of 2004 to 2014 for all the six dimensions because national institutions remain almost the same over the years in the data. Then, we apply Principal Component Analysis (PCA) and take the first component as the institutional quality index. Additionally, as regime changes in countries could influence development, we take time-variant variables from the Database of Political Institutions (DPI), including the indicator for changes of the chief executive, the indicator for chief executive close to the end of the current term, the indicator for change of the leading party, the indicator for being autocratic, and changes of veto players in the central government. The DPI also provides data on the number of conflicts.

To investigate the potential mechanisms, we collect additional data on African leaders' birth regions and ethnicity, as well as procurement details of World Bank projects. African leaders' birth regions and ethnicity data are from Dreher et al. (2019), which allows us to identify whether projects are located in regions with political ties to the leaders. The implementation details of Chinese projects are already included in the project data, and most Chinese projects involve at least one Chinese firm. In contrast, World Bank projects typically go through a procurement process, and we use World Bank API to obtain contract amounts and contractors' countries for each project. From this data, we constructed measures of the share of a project contracted to Chinese firms.

We took several steps to prepare the data. For locations that received multiple aid projects or

[6] The DHS outcome measures are constructed by Yeh et al. (2021)

[7] The six dimensions are Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption

those with other projects within a 5km distance, we keep only the earliest project to mitigate potential spillover effects.[8] We then calculate the mean nightlight illumination in the area within 25km of the project location based on latitude/longitude for the nightlight intensity analyses.[9] Most cities/villages in Africa have radii smaller than 25km, making 25km a reasonable scope for analysis. Additionally, we divide the projects into two categories: infrastructure and non-infrastructure projects, as they may have different impacts. Based on the sector classification in AidData, we categorized projects as follows: 1) water supply and sanitation, 2) transport and storage, 3) energy generation and supply, 4) industry, mining, construction, and 5) communications are classified as infrastructure, while the remaining sectors were classified as non-infrastructure.

Despite sector information being available in AidData, projects classified under the same sector could be wildly different. Take the health sector as an example. Chinese health projects focus on sending medical teams, donating medicine and equipment, building anti-malaria centers, and constructing hospitals. World Bank projects, on the other hand, center around family planning, maternal, neonatal, and children's health care services. Due to the imprecise labeling of the project content, we use machine learning tools to re-label projects and then control for the labels in regressions. Specifically, we apply topic-modeling algorithms to project descriptions. Sentences in project descriptions are converted to vector representations via SentenceTransformer, a state-of-the-art Python framework for computing sentence, text, and image embeddings (Reimers and Gurevych, 2019). As World Bank and Chinese project descriptions are written in different styles, we first extracted keywords from the vector representations and then clustered them using a pre-trained model, BERTopic.[10] This procedure generates 40 topics, and we group them into 18 based on the topic similarity from the model. Among the 18 topics, some have World Bank projects only, such as "health_maternal_child_sector" or "urban_access_basic_improve"; some topics have Chinese projects only, including "building_stadium_hospital_construction" and "radio_television _broadcasting_confucius". There are seven topics that have both World Bank and Chinese projects: "education_ schools", "humantarian_aids", "improve_road", "power_electricity",

[8]We also tried dropping all the multi-treated locations and found quantitatively similar results

[9]We performed analysis on various radii, and the results are qualitatively similar.

[10]See https://github.com/MaartenGr/BERTopic for details

“productivity_agricultural_ irrigation”, “railway”, and “water_supply_sanitation_urban”.

2.1 Descriptive Statistics

Figure 1 maps all the Chinese and World Bank project locations. There is a substantial overlap in the project locations between the two donors, indicating that China and the World Bank have launched projects in close regions. A few countries, for example, Sudan, Namibia, and Botswana, have Chinese projects only. This is consistent with the fact that China holds a non-interference policy, while loans from the World Bank come with conditions that some countries fail to meet.

Table 1 provides more detailed summary statistics on Chinese and World Bank project locations. For infrastructure, Chinese projects are much larger in scale than World Bank projects. They also tend to be located in places with lower degrees of democracy and larger distances from the coast. Chinese non-infrastructure projects show a slightly different pattern from their infrastructure counterparts. Compared to World Bank non-infrastructure projects, Chinese projects are closer to the capital city and coast and have a higher level of baseline nightlight. On the other hand, they are located in places with worse land suitability and more conflicts. Overall, there are differences between Chinese and World Bank development projects in site selection and project characteristics. Chinese projects concentrate on the infrastructure sector, while World Bank projects are more evenly distributed across sectors.

3 Empirical Strategy

3.1 Stacked Difference-in-Differences

This paper uses stacked difference-in-differences as the identification strategy. The key assumption is that these receiving-project-early locations have parallel trends as the receiving-project-later locations if the treatment had not been implemented. Specifically, our sample is constructed in the following way. In the dataset, projects’ start years range from 2003 to 2014. A separate data set, which we refer to as a cohort, is created for each start year. For each cohort, locations that received a project started in the cohort year are labeled as treated locations, while locations that received a project later are considered control locations. Only the observations before its own project began are included for the control locations. For example, for cohort 2006, a location with a project that began in 2006 would be labeled as treated and have its observations included for all the calendar years. A location with a project that started in 2009 would be labeled as control and only have its observations before 2009 included. All the cohort data sets are then appended to one dataset. For each location, only information on its first project is used, meaning that the estimations only capture the impacts of the first project that treated the location.

For projects from each donor, the equation below is estimated:

$$Y_{ltg} = \beta_1(Treated_{lg} \times Post_{tg}) + \theta_{lg} + \gamma_{tg} + \eta_{ct} + \varepsilon_{ltg} \tag{1}$$

where Y_{ltg} is the outcome for location l in year t in cohort g. This paper considers two types of outcomes: economic outcomes (nighttime light) and social outcomes (health and education). $Treated_{lg}$ is 1 when the project has start year g in location l and 0 otherwise; $Post_{tg}$ is equal to 1 for all periods ≥ 3 years after year g. Three years is used as the cutoff as it is the median project duration in the sample. $Post_{tg}$ is constructed in this way because the main focus is on the impact on local development after a project is completed.[11] θ_{lg}, γ_{tg}, and η_{ct} are the cohort-specific location fixed effects, the cohort-specific year fixed effects, and the country-year fixed effects, respectively. β_1 is the coefficient of interest and shows the treatment effect. The standard errors are clustered at the project level.

This stacked DID approach has been adopted in many published papers (Cengiz et al., 2019; Deshpande and Li, 2019). As pointed out in the literature (e.g. Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021), the traditional two-way fixed effects (TWFE) approach can be problematic with staggered treatment, especially if the treatment effect is time-variant, which is very likely the case in our setting. The TWFE approach can lead to biased estimations as it does "forbidden" comparisons that use "already-treated" observations as controls. Stacked DID resolves the issue by using only "not-yet-treated" observations as

[11] The results remain robust when $Post_{tg}$ is equal to 1 for all periods ≥ 0 years after year g and are presented in the appendix.

controls.

3.2 Pooled Specification

As shown in the descriptive statistics, the World Bank and China allocate projects in locations with different characteristics. Controlling for geographic characteristics (distance to the capital city, distance to the coast, land suitability, etc.) and project characteristics (e.g., the amount spent per project site) is thus necessary for understanding the differences in project impacts. Specifically, some locations could have conditions that magnify the impacts of infrastructure projects. If China has more projects in locations with such conditions, we would observe a larger impact of Chinese projects. To examine the impacts of location characteristics on project outcomes, we estimate the equation below. We also pool the projects from China and the World Bank to test whether the differences in the project impacts between the two donors are statistically different.

$$\begin{aligned} Y_{ltg} =& \beta_1(Treated_{lg} \times Post_{tg}) + \beta_2(Treated_{lg} \times Post_{tg} \times China_l) + \sum_k \tau_k(Treated_{lg} \times X_l^k) \\ &+ \sum_k \alpha_k(Post_{tg} \times X_l^k) + \sum_k \delta_k(Treated_{lg} \times Post_{tg} \times X_l^k) + Z_{lt} + \theta_{lg} \times China_l + \\ &\gamma_{tg} \times China_l + \tilde{\theta}_{lg} + \tilde{\gamma}_{tg} + \eta_{ct} + \varepsilon_{ltg} \end{aligned} \tag{2}$$

where time-invariant control variables X_l^k include the distances to the capital city, coast, coal mines, and petroleum mines, baseline nightlight, measures of institutional quality, and commitment amount per project site. Time-variant controls Z_{lt} are measures of changes in national political regimes.[12] β_1 shows the impacts of World Bank projects, and β_2 indicates whether Chinese projects have a significantly different impact compared to World Bank projects.

[12]The measures include the indicator for change of the chief executive, the indicator for chief executive close to the end of the current term, the indicator for change of the leading party, the indicator for being autocratic, and changes of veto players in the central government.

4 Results

4.1 Baseline Results

In this baseline specification, we first examine Chinese and World Bank projects separately and then pool the observations from both donors to examine impact differences. Table 2 demonstrates the results. Both Chinese infrastructure and non-infrastructure projects have statistically significant and positive effects on the nightlight, whereas World Bank projects do not. The Chinese infrastructure projects increase the nightlight radiance value by 13.1% of the mean nightlight, and non-infrastructure projects increase nightlight by 9.3% of the mean nightlight. On the contrary, World Bank projects show no significant impacts on nightlights.

The differences in project impacts between Chinese and World Bank projects are stark in the regressions. Columns (3) and (6) Table 2 indicate that Chinese projects increase nightlights 12.9% and 6.3% more than the World Bank projects, respectively, for infrastructure and non-infrastructure ones. One could argue that the differences might come from China and the World Bank investing in different locations and different types of projects, and therefore, their projects are not comparable. To address this concern, we compile a comprehensive list of variables for location and project characteristics. Previous research has highlighted these dimensions as key factors in explaining why certain development projects have greater impacts than others.

4.2 Control for site characteristics

Firstly, site selection may contribute to this impact gap we observe. Specifically, China could seek places with suitable conditions that magnify projects' impacts on nightlights, whereas the World Bank does not. Table 3 reports the results from the pooled regressions controlling for site characteristics. We observe that in columns (1) and (5), without adding any control, Chinese projects display larger treatment effects than World Bank projects. In columns, (2) and (6), including geographic controls does not eliminate the difference for infrastructure projects but the impact differences for non-infrastructure projects between the two donors disappear. These findings suggest that investing in different places accounts for the differences in the effects of non-infrastructure projects between the two donors but not infrastructure projects. We further add baseline economic conditions in columns (3) and (7), and the impact difference remains.

As we have only controlled for time-invariant characteristics, it remains possible that some time-variant variables confound our estimation of the treatment effects, such as local conflicts and political reforms. To address this concern, we control for a series of variables measuring national regime changes in columns (4) and (8).[13] The differences between Chinese and World Bank projects remain.

The last row of Table 3 presents the F-tests for whether treatment effects for Chinese projects are zero. All columns of the infrastructure sector show a p-value lower than 0.01, indicating that receiving Chinese infrastructure projects significantly increases the nightlights of the local areas. The impacts of Chinese non-infrastructure projects are of smaller magnitudes and are less significant.

Though having included a comprehensive list of control variables, we might still miss some important site characteristics. Therefore, Table 4 examines the treatment effects when Chinese and World Bank projects are located closely, namely within 50km away from each other. Within this range, most unobservables are similar, and the differences in project effectiveness captured should thus not be attributed to site selection. Columns (1) and (4) in Table 4 are copied from Columns (4) and (8) in Table 3. Columns (2) and (5) are projects that have the other donor's project within a 50km distance. Compared to the full sample, the magnitude of the key coefficient for infrastructure projects is slightly smaller but not statistically different from column (1). For non-infrastructure projects, the impacts of Chinese projects cannot be distinguished from the World Bank projects. Lastly, Columns (3) and (6) are the rest of the projects with no close neighbors from the other donor. They present similar results as the full sample. Taking all the columns in this table together, we observe that Chinese infrastructure projects lead to more positive impacts on nightlight than World Bank projects. The differences in impacts do not disappear even for nearby projects with similar site characteristics.

[13] These controls are the indicator for change of the chief executive, the indicator for chief executive close to the end of the current term, the indicator for change of the leading party, the indicator for being autocratic, and changes of veto players in the central government.

4.3 Control for project characteristics

The differences in effectiveness could be because the projects themselves are different. One advantage of our approach is that we have detailed information on each project, so we can explore project characteristics in the analysis. Specifically, existing literature and anecdotes have pointed out two main distinctions between Chinese and World Bank projects: scale and sectors. Chinese projects focus primarily on large-scale infrastructure projects, while World Bank projects are smaller and distributed more evenly between infrastructure and non-infrastructure sectors. In the following subsections, we examine whether these two project characteristics could explain why we observe differences in project effects.

4.3.1 Amount per site

To account for project scales, we first define the amount per site. For example, if a project sends medical teams to three locations, the amount per site is the total amount committed for this project divided by three. We then run the regressions controlling for the amount per site. Table 5 shows the estimation results accounting for project characteristics. Specifically, Columns (1) and (5) in Table 5 are the same as columns (4) and (8) in Table 3. Columns (2) and (5) in Table 5 control for the inverse hyperbolic sine of the amount per site. The coefficient for the Chinese infrastructure projects remains large.

Linear control can be insufficient if there is no overlap between the scales of Chinese and World Bank projects or if the relationship between nightlight and scale is nonlinear. To address these concerns, we plot the relationship between the nightlight change five years after the project started and the inverse hyperbolic sine of the amount per site for each location in Figure 2. We notice that while the mean scale differs much between Chinese and World Bank projects, there is a large overlap of scales both for infrastructure and non-infrastructure projects from the two donors. Also, there is no obvious relationship between nightlight increase and project scale.

Finally, we normalize nightlight by dollars spent. By re-scaling our main outcome variable, we now have a measure indicating how much impact a project has per log dollar . Figure A.1 suggests that Chinese infrastructure projects still display positive, significant impacts on nightlights, consistent with baseline results. However, the effects of Chinese non-infrastructure projects are positive but no longer significant. Event study plots for World Bank projects in Figure A.2 are very similar to the ones in the baseline results section with no significant impact. Taken together, results after the normalization are mostly consistent with our findings, demonstrating that the differences in project effectiveness cannot be explained by the fact that Chinese projects are of larger scales.

4.3.2 Sectors and topics

Another explanation for why Chinese infrastructure projects present a larger magnitude of impacts on nightlight than World Bank projects could be that the two donors focus on different sectors of projects. Chinese projects could invest heavily in nightlight-generating industries, like building fancy stadiums with lights on all the time, while World Bank projects could focus on the type of projects with less impact on the nightlight. Hence, we zoom in on the sector composition of projects from two donors. It turns out that both donors allocate substantial money across diverse sectors. While Chinese projects invest heavily in infrastructure, especially in the Energy Generation and Transport sectors, the World Bank allocates more funds than China to the Water Supply and Sanitation sectors. Both China and the World Bank give a similar amount of money to Health and Education. To take a closer look at project characteristics, we break down the baseline results by sector in Figure 3. The findings are consistent with the baseline results. Chinese projects show larger, more significant effects across most infrastructure sectors. For the World Bank, further analyses suggest that its water supply and transport projects demonstrate positive impacts, while other projects have close to zero effects.

The sector decomposition might still not be detailed enough to capture what the projects really do. To further ensure we are comparing similar Chinese and World Bank projects, we use machine learning algorithms to re-classify the projects. Specifically, we apply text analysis to the descriptions of projects and sort them into different topics. The topics, interacted with treated indicators, are then controlled for in the regressions. Table 5 column (3), (4), (7), and (8) presents the results controlling for sectors or topics. Columns (3) and (7) control for the sector fixed effects interacted with the post-treatment indicator. The differences between the Chinese and World Bank projects remain. This indicates that the disparities in impacts cannot be solely attributed to China and the World Bank's divergent sectoral focuses. We then address the imprecise labeling of sectors by regrouping the projects into more specific and detailed topics. Columns (4) and (8) control for the topics generated from the text analysis interacted with the post-treatment indicator. The difference becomes even more significant for infrastructure projects. Taking these results together, we conclude that project characteristics like sector or topic could not be the main driver of Chinese projects having larger impacts than World Bank projects.

4.4 Event-study Plot and Persistent Impacts

Previous literature has documented the impacts of Chinese projects in the short term. In this subsection, we investigate whether the impacts persist over time and compare the impacts to World Bank projects. Figures 4 and 5 show the event study plots controlling for the location and project characteristics, respectively, for Chinese and World Bank development projects.[14] All event study plots present no obvious pre-trend, suggesting no systematic difference between early-treated and later-treated locations. For Chinese infrastructure projects, from post-period two onward, the increase in nightlight is statistically significant and persists over time. This implies that locations that have received projects two years prior observed a more substantial rise in nightlight intensity compared to places that will receive projects but have not yet done so. For Chinese non-infrastructure projects, there is no detectable impact, and we do not observe statistically significant impacts on nightlight for either infrastructure or non-infrastructure World Bank projects.

4.5 Inverse Probability Weighting

An important concern about the current empirical strategy is that Chinese and World Bank projects are very different, and with non-negligible differences in covariates, estimations can be sensitive to model specification (Imbens and Rubin, 2015). To address this issue, we use inverse probability weighting (IPW) to generate a "pseudo-population" where the Chinese and World Bank projects have more balanced covariates.

[14] Sector or topic fixed effects are not included when generating these event study plots to enhance statistical power. As previously discussed, variations in sectors or topics cannot explain the divergences in impacts between the two donors. The plots that factor in sectors or topics produce qualitatively similar results.

Specifically, we take the following steps. First, we estimate the propensity score for a project to be from China against the World Bank. We adopt the stepwise procedure suggested in Imbens and Rubin (2015) to select the covariates and higher-order terms for inclusion in the propensity score estimation. Then we trim the sample using two trimming approaches suggested in Imbens and Rubin (2015) and Crump et al. (2009) respectively. Finally, we do Weighted Least Squares (WLS) estimations weighting Chinese projects by the inverse of the propensity to be Chinese and World Bank projects by the inverse of the propensity not to be Chinese.

Table 6 presents summary statistics for the projects adjusted using inverse probability weighting and trimmed based on Crump et al. (2009). Compared to the descriptive statistics shown in Table 1, the Chinese and World Bank projects after adjustment are more similar, and none of the differences in covariates are statistically significant. The last two variables, "Have a nearby project from the same donor" and "Temperature Suitability for Malaria," are not targeted in the propensity score estimation procedure. The fact that they are not statistically different between the projects from the two donors suggests that the balancing property holds for the adjusted sample.

Table 7 shows the IPW estimation results. The specification is the same as Table 5 Column (2). Columns (1) and (3) trim the sample based on Imbens and Rubin (2015), and Columns (2) and (4) trim the sample based on Crump et al. (2009). For infrastructure projects, the coefficients of $Treated \times Post \times China$ are positive and significant. The magnitudes of the coefficients are even larger than our results using the full sample. For non-infrastructure, the coefficients are insignificant, consistent with the previous results. For both trimming approaches, the estimations are very close. Therefore, we conclude that there is no evidence that the positive coefficients of $Treated \times Post \times China$ are sensitive to model specification due to the lack of balance.

5 Hypotheses of Mechanisms

5.1 Follow-up Projects

As our identification requires the parallel assumption to hold, we only use the information of the earliest project when a location has multiple projects. It means the estimated treatment effect captures both the direct impacts from the first project and the indirect impacts from the follow-up projects. If the Chinese projects have the same impacts on nightlight as World Bank projects but are more likely to have subsequent complementary projects, we will also observe larger estimated treatment effects of Chinese projects.

To address this issue, we first discuss descriptive statistics on follow-up projects and then run regressions taking follow-up projects into account. Descriptive evidence does not suggest that Chinese projects are more likely to have follow-ups. Only 12% of Chinese projects have follow-ups, while 36% of World Bank projects have follow-ups. Though conditional on having follow-up projects, Chinese projects have 2.1 follow-ups on average, while World Bank projects have 1.6 follow-ups.

We then run regressions taking follow-up projects into account. As the functional form of the impacts of follow-up projects on nightlight is unknown, we include follow-ups in several ways. For infrastructure projects, we interact $Treated \times Post$ with the indicator for having any infrastructure follow-up projects and the indicator for having any follow-up projects in the other division, namely non-infrastructure. We estimate the coefficients for non-infrastructure projects the other way around.

Columns (1), (2), (7), and (8) in Table 8 show the results. For infrastructure projects, the coefficients of $Treated \times Post \times China$ in all columns remain positive and significant, suggesting that follow-up projects do not explain the difference in impacts on nightlight between the two donors.[15] For non-infrastructure projects, the coefficients of $Treated \times Post \times China$ remain insignificant. In Column (8), the positive coefficients of follow-up projects from the other division imply that infrastructure projects are more relevant for nightlight increase than non-infrastructure projects.

[15] For robustness, instead of indicators, we use the number of follow-up projects from the same and the other division as the measure of follow-up projects and find similar results.

5.2 Political Favoritism

In the context of Africa, Burgess et al. (2015) has provided evidence that under a low degree of democracy, leaders favor their hometowns and regions where large populations of their ethnicity reside. As a result, they allocate more resources to build public infrastructure in those regions. Meanwhile, Dreher et al. (2019) has documented that more Chinese aid is allocated to the birth regions of political leaders, while no favoritism in spatial distribution is observed for World Bank development projects. Hence, there exists a possibility that the impacts of projects on nightlights are amplified by the favorable presence of better public infrastructure in the birth regions of political leaders, where Chinese projects are more likely to be located. This could explain the differences in project impacts between the two donors.

To examine this mechanism, we leverage African leaders' data collected by Dreher et al. (2019). Knowing leaders' birth regions and ethnicity allows us to construct two measures of political ties for each project location: the indicator for whether the project is located in places with the same tribe as the political leader and the indicator for whether the project is located in the leader's birth region. Both measures have been adopted in the previous literature.

We re-run the regression, including interactions of the favoritism measures and the treatment indicator. Columns (3), (4), (9), and (10) in Table 8 show the results. Infrastructure projects located in the same tribes as the political leader display larger project impacts. This is consistent with the hypothesis that regions with political ties may have better conditions that complement aid projects. However, the coefficients of $Treated \times Post \times China$, though slightly smaller, remain positive and significant, indicating that political favoritism cannot fully explain the differences in project impacts between China and the World Bank.

5.3 Implementation Agency

Anecdotal evidence suggests that Chinese and World Bank projects are implemented differently. Looking at the project data, we observe that Chinese construction firms mostly implemented Chinese infrastructure projects. On the other hand, the World Bank always lets the local governments procure contractors for project implementation, so they could be from any country. The fact that the implementation of Chinese projects does not rely much on the recipient government could be related to the project's effectiveness, especially when the recipient countries have low capacity and few resources.

We construct the measures of the fraction of Chinese companies in implementing agencies for each project. Specifically, we use two measures. $AnyChina$ is an indicator of any participation of Chinese companies in implementation. $China\_mhalf$ is an indicator denoting instances where the amount-weighted Chinese participation exceeds 50%.[16] We then run the regressions, including the interactions of the Chinese implementation measures and the treatment indicator.

Table 8 columns (5), (6), (11), (12) show the results. For infrastructure, projects that have Chinese companies participate in implementation do not seem to have larger impacts on nightlights. The coefficients of $Treated \times Post \times China$ remain positive although less significant when $China\_mhalf$ is controlled for. This loss of significance may be due to the fact that few World Bank projects have Chinese participation more than 50%, and the high correlation between $China$ and $China\_mhalf$ decreases the statistical power. The magnitudes of the coefficients barely change compared to previous estimations. We thus conclude that the implementation by Chinese companies cannot explain the differences in project impacts from the two donors.

6 DHS Results

Solely focusing on using nightlight to measure the effectiveness of development projects might not provide a comprehensive perspective. China and the World Bank are known to have different objectives as China focuses greatly on economic growth, and the World Bank, on the other hand, emphasizes letting the recipient countries learn, engaging with the local community, and pursuing democratic norms. It is possible that while nightlights do not exhibit a significant increase, World Bank projects have better performances in other outcomes such as female empowerment and women and children's health. This section shows results on the related

[16] For Chinese projects, both $AnyChina$ and $China\_mhalf$ are coded as 1 if there is a Chinese company among the implementing agencies and 0 otherwise. This is because we do not have data on the amount of each procurement contract for Chinese projects. Instead, we make the assumption that China holds a prominent role in implementation whenever a Chinese firm is among the implementing agencies.

outcome variables.

Using DHS data, we focus on three outcomes: child mortality rate, women's years of schooling, and women's BMI. Women's BMI is the reported BMI of all women aged 15-49 divided by 100. The child mortality rate is the number of deaths per 1,000 children aged 0-5. Women's educational attainment is the years of education before 18 among women between aged 15-49. All the measures are cluster-level averages. These outcomes describe alternative dimensions of development and provide suggestive evidence of how Chinese and World Bank projects affect health and education outcomes.

We construct the DHS sample as follows. Any DHS cluster that is within 25km away from a project is deemed as a treated cluster. From the never-treated clusters, we construct the control group using the propensity score matching approach. Baseline nightlights, land suitability, distance to the capital city, distance to the coast, distance to coal mines, and distance to petroleum mines are used in estimating the propensity scores. We further restrict the matched treated and control clusters to be within the same country and the same year. We implement one-to-one nearest neighbor matching with replacement based on the propensity score estimated using logistic regression of the treatment on the covariates.[17] In addition, as in the main analysis, we include in our control group the not-yet-treated clusters, namely the clusters within a 25km radius of a project that had not yet been launched at the time of the survey. We then apply the stacked difference-in-differences strategy to examine the impacts.

Table 9 summarizes our findings. Evidence suggests that Chinese infrastructure projects improve women's years of schooling and BMI, while Chinese non-infrastructure projects decrease the child mortality rate. World Bank infrastructure projects have significant and positive effects on women's education, but World Bank non-infrastructure projects have negative impacts on women's education. Overall, there is some evidence that World Bank projects significantly improve some of the outcomes. Unfortunately, the differences in these impacts between Chinese and World Bank projects are mostly not statistically different.

[17] We tried different restrictions for calipers, and the results are similar.

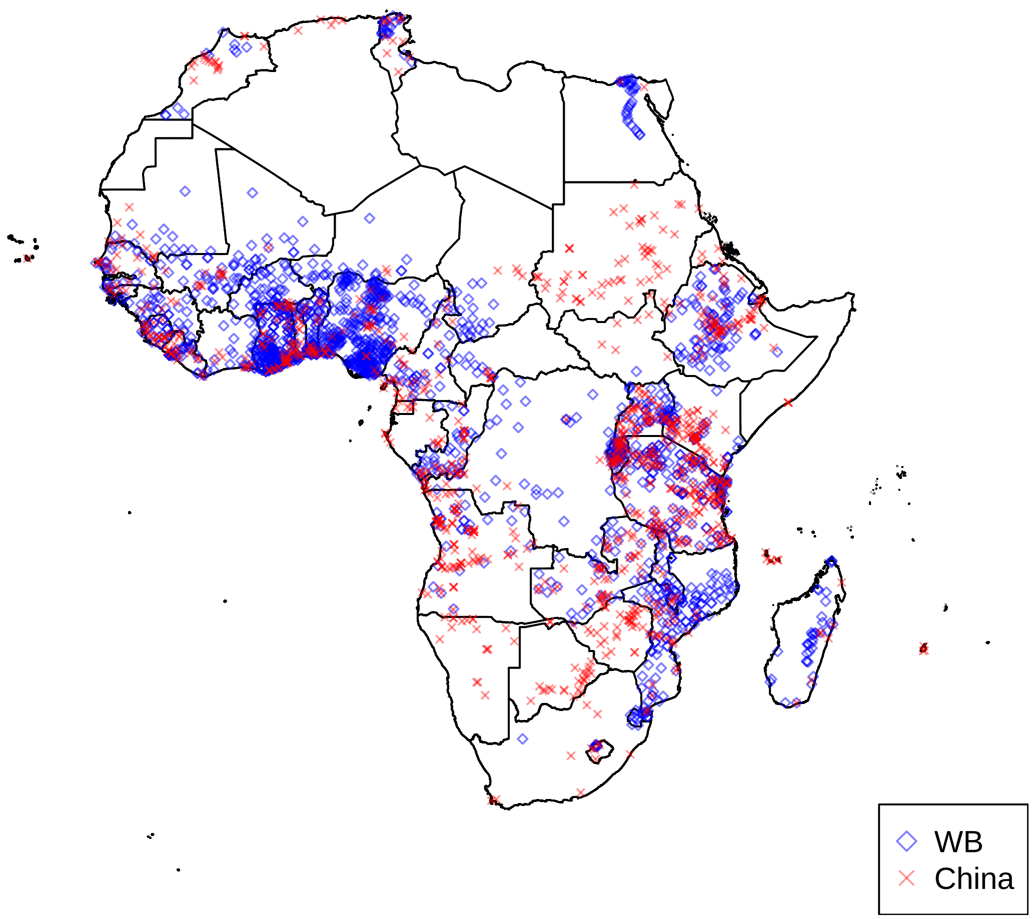
7 Conclusion

Our findings add to the existing knowledge of the differences between China and traditional donors and their impacts on African local economies. We find that Chinese infrastructure projects have a more significant impact on nighttime light in recipient regions than projects from the World Bank. Furthermore, the study highlights two important findings. Firstly, the differences in impacts between Chinese and World Bank projects cannot be explained by the factors that have been emphasized in the literature as influencing project effectiveness. Secondly, the study found that infrastructure projects from both donors have positive impacts on women's education attainment.

In terms of explanations for the differences in project impacts between the two donors, due to constraints in data availability, there are a number of hypotheses that cannot be empirically tested. Firstly, a significant portion of the World Bank projects might not primarily target the improvement of the nighttime light. For example, the World Bank could place greater emphasis on objectives such as alleviating local income inequality, curbing government corruption, or enhancing female empowerment. Secondly, World Bank projects might carry more stringent requirements compared to Chinese projects. For example, the World Bank could demand thorough assessments and interventions to address issues like environmental contamination, construction quality, and workers' human rights, etc. While these examinations offer advantages, they could increase project costs, impede construction progress, or limit the potential development benefits of projects. Finally, from a political-economic perspective, the Chinese government might possess more experience and strategies to navigate a heavily corrupt environment. While this expertise could exacerbate local corruption, it could also make it easier to implement development projects, thereby generating economic gains.

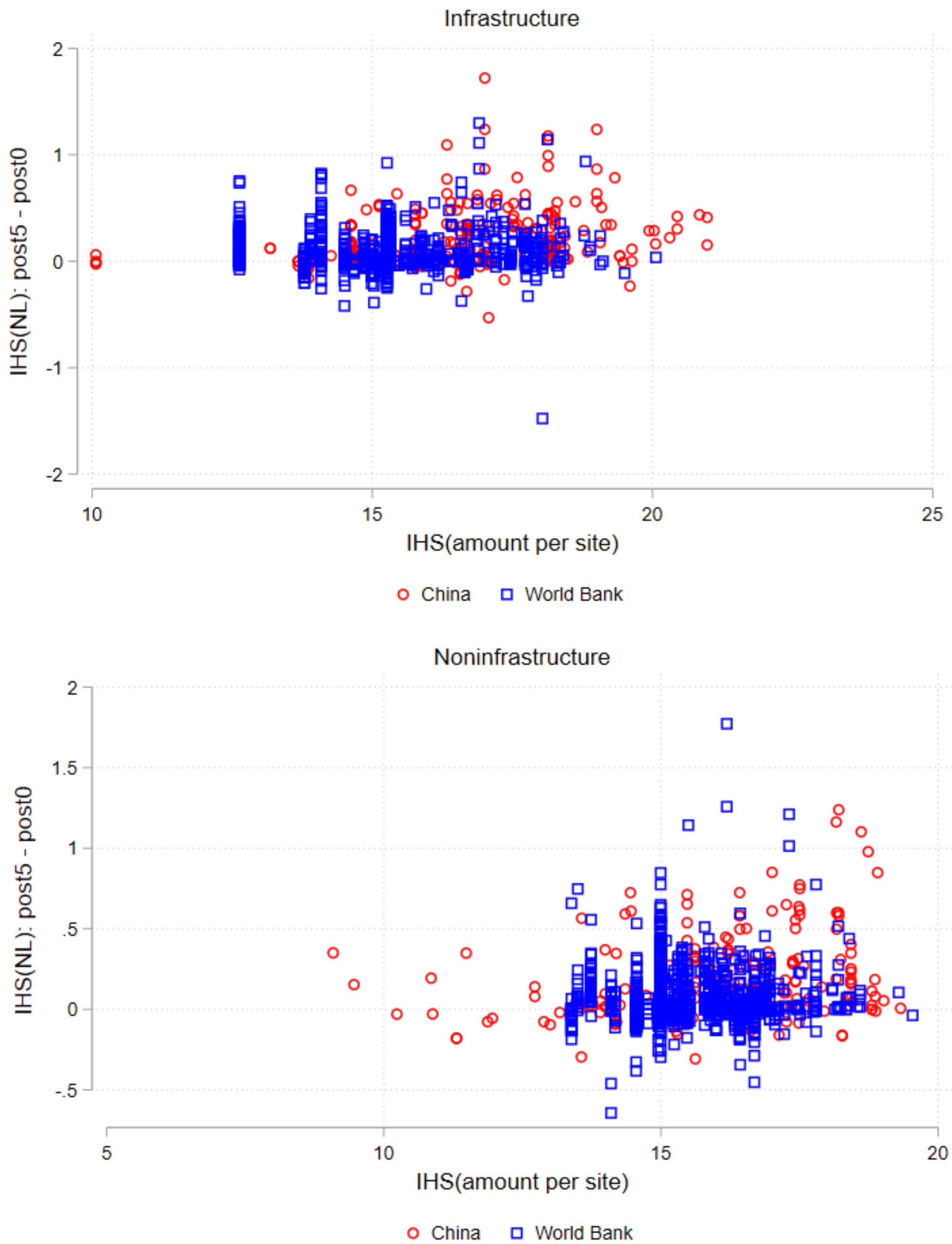
Figures

Figure 1: Map of Chinese and World Bank project site



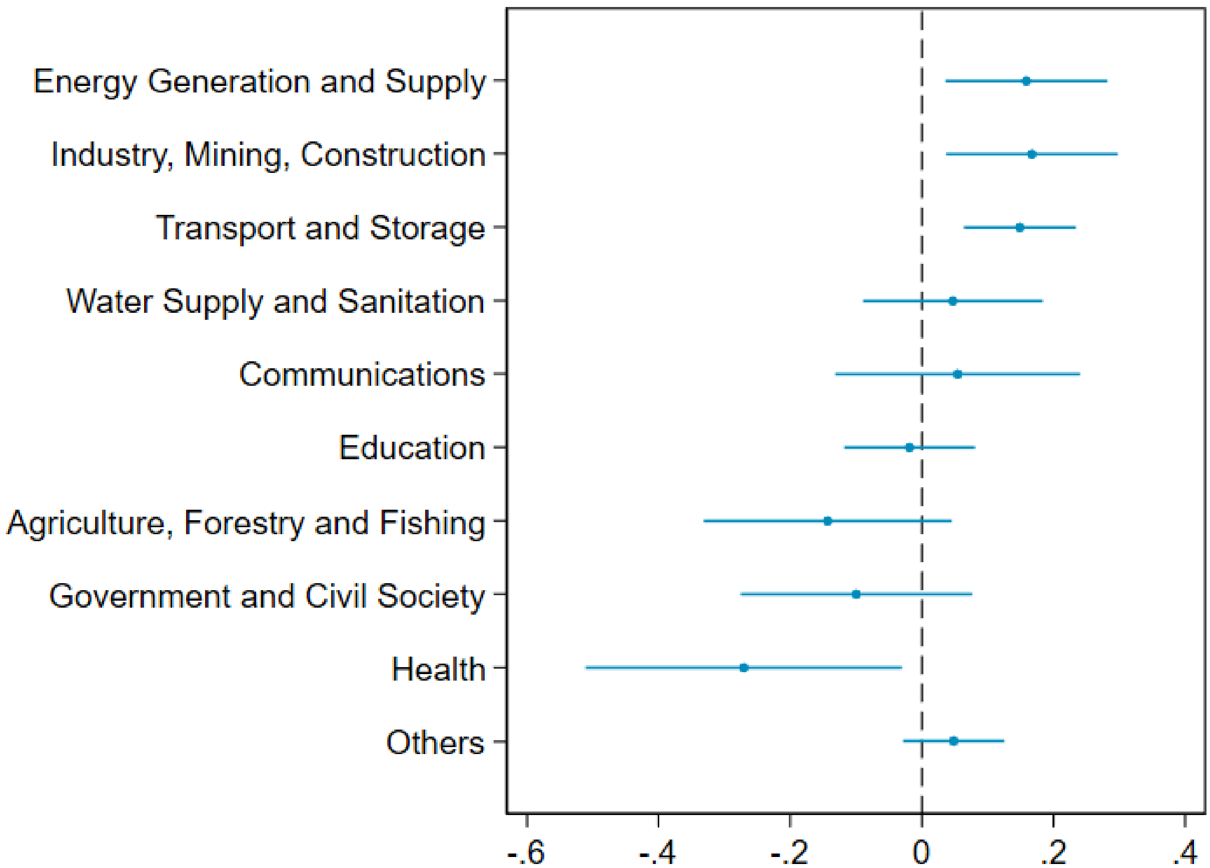
Notes: This figure illustrates the locations of both World Bank (WB) and Chinese projects. Borders refer to countries. For most countries, there are overlaps of projects from both WB and China. There are also some countries with only WB or Chinese projects, suggesting that WB and China have different preferences for site selection. Sources: AidData's Geocoded Global Chinese Official Finance Dataset (Version 1.1.1) (Dreher et al., 2022; Bluhm et al., 2018) and World Bank Geocoded Research Release(Version 1.4.2)(AidData, 2017)

Figure 2: Relationship between nightlight change and amount



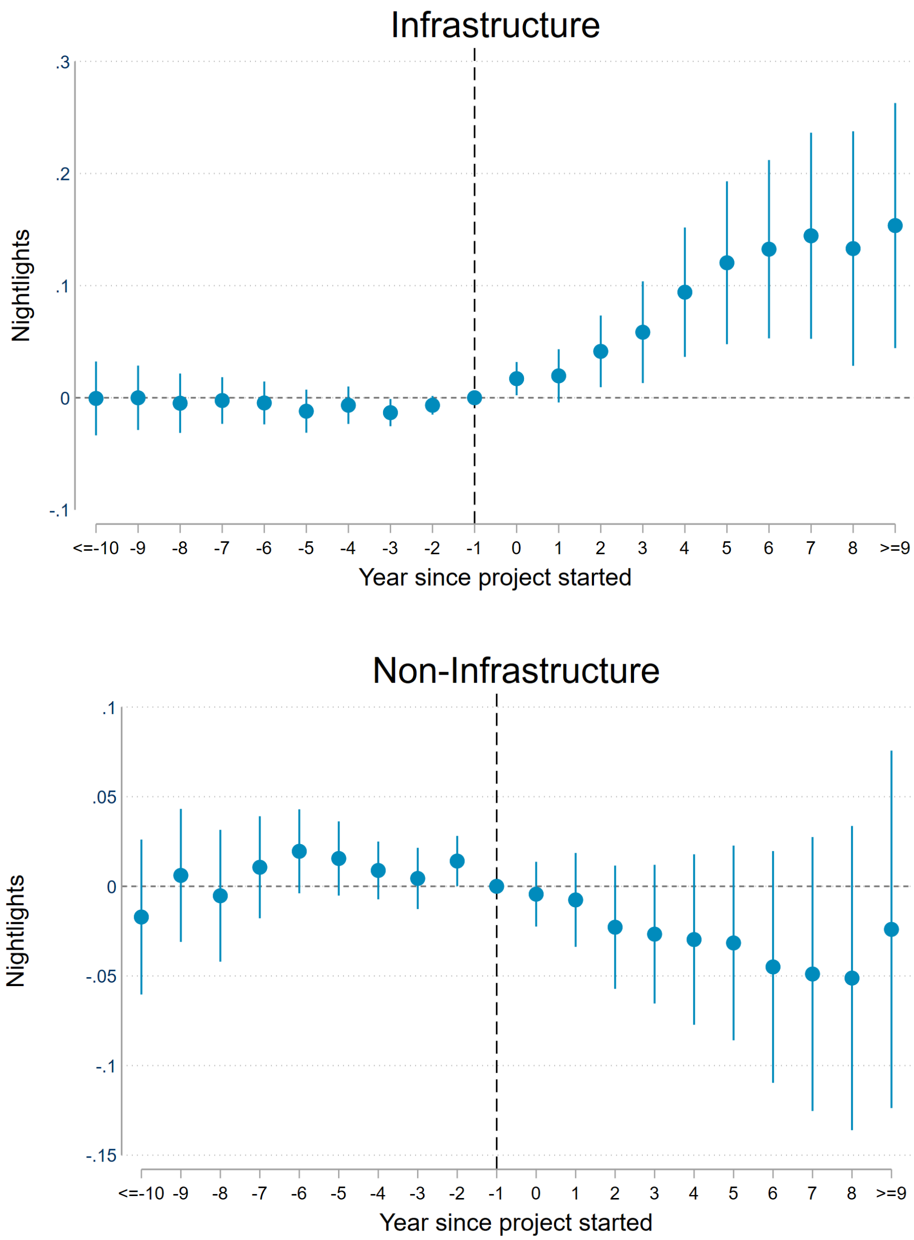
Notes: Figures show the relationship between post-project nightlight change and the log of the committed amount per project site. The post-project nightlight change is measured by the difference between the nightlight 5 years after the project started and the nightlight in the year when the project started. Other year gaps such as using 3 or 7 years give similar patterns. We emphasize 2 observations from the figures: first, World Bank and Chinese projects have much overlap in terms of the amount per site; second, there is no obvious relationship between the nightlight changes and amount per site.

Figure 3: Treatment Effects by Sector



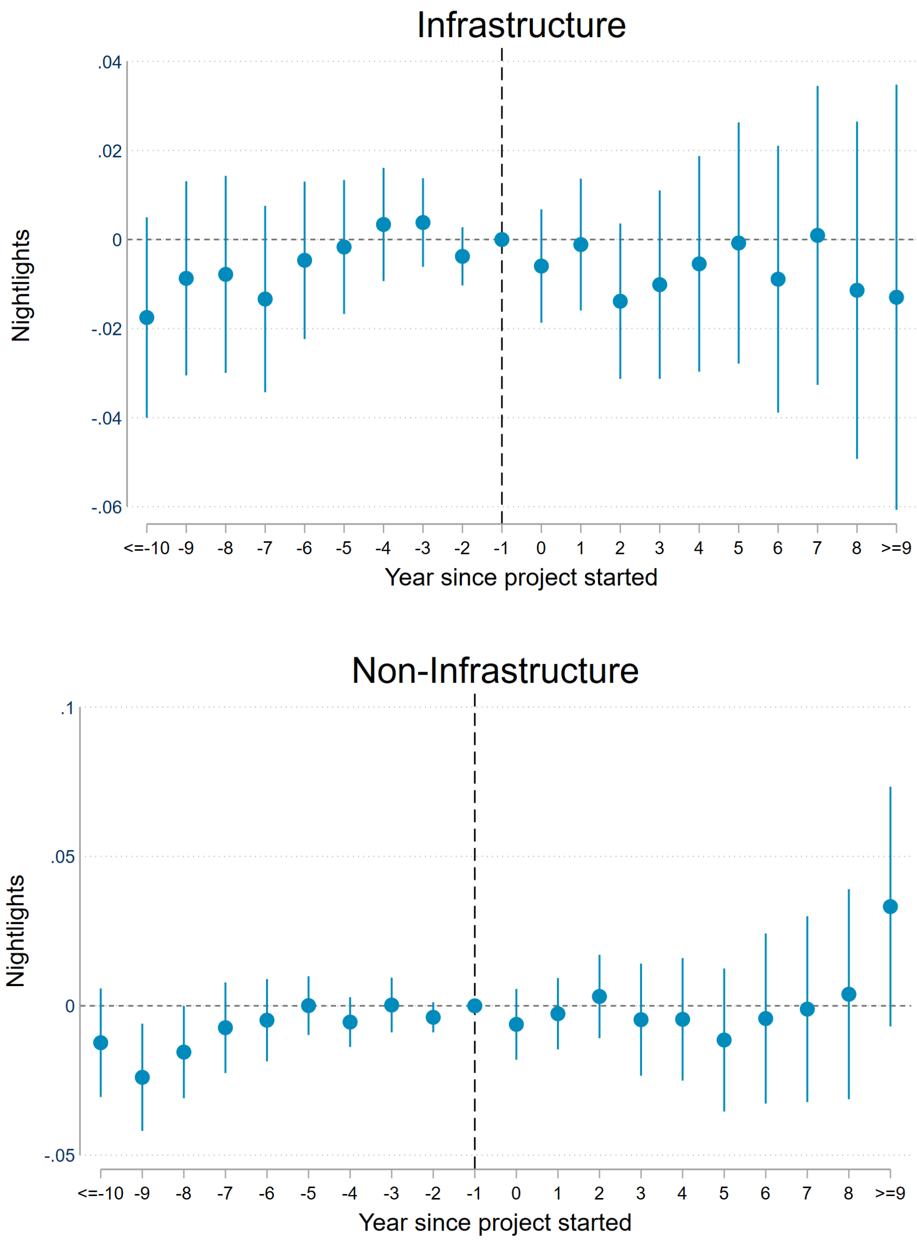
Notes: Figure shows the estimates of treatment effects by sectors using Equation (1). For most sectors, Chinese projects appear larger effects than World Bank projects, suggesting that the project effectiveness difference between the two donors cannot be explained by China having more projects in nightlight-boosting sectors. 95 percent confidence intervals clustered at the project level are displayed.

Figure 4: Chinese Development Project



Notes: Figures show the event study estimates for Chinese projects. It implies that there are no systematic differences between earlier-treated and later-treated locations before the projects were launched. Once the projects started, the nightlight of treated locations began to increase, and the effects persist even after 9 years, especially for infrastructure projects. 95 percent confidence intervals clustered at the project level are displayed.

Figure 5: World Bank Development Project



Notes: Figures show the event study estimates for World Bank projects. While the pretrends are noisier, there is no strong evidence for systematic differences between earlier-treated and later-treated locations before the projects were launched. Once the projects started, the nightlight of treated locations began to increase for infrastructure projects, but the increase is not jointly significant. No effect is detected for non-infrastructure proects. 95 percent confidence intervals clustered at the project level are displayed.

Tables

Table 1: Descriptive Statistics

	Infrastructure			Non-Infrastructure		
Variable	China	World Bank	Diff	China	World Bank	Diff
Dist. Capital (km)	291.787	318.575	-26.788	184.300	352.871	-168.572***
	(286.101)	(276.755)	(41.078)	(227.080)	(289.519)	(28.377)
Dist. Coast (km)	385.408	317.243	68.165*	241.209	364.997	-123.788***
	(329.013)	(298.748)	(35.748)	(284.344)	(301.421)	(32.479)
Dist. Coal (km)	297.250	277.486	19.764	274.385	286.106	-11.721
	(255.177)	(266.600)	(48.953)	(281.167)	(238.575)	(48.551)
Dist. Petro (km)	751.082	693.074	58.008	689.256	670.561	18.695
	(391.235)	(410.169)	(75.342)	(429.910)	(371.279)	(59.399)
Baseline Nightlight	2.247	1.657	0.590	3.384	1.583	1.801***
	(3.918)	(4.846)	(0.500)	(6.007)	(4.556)	(0.616)
Land Suitability	0.375	0.400	-0.026	0.338	0.409	-0.072**
	(0.252)	(0.228)	(0.031)	(0.229)	(0.253)	(0.030)
Institutional Quality	-0.130	0.276	-0.406	0.042	0.011	0.031
	(1.933)	(1.530)	(0.324)	(2.142)	(1.521)	(0.275)
Degree of Democracy	0.839	2.696	-1.857***	1.571	1.386	0.185
	(4.501)	(4.014)	(0.697)	(4.666)	(4.204)	(0.676)
Number of Conflicts	1.180	1.174	0.006	2.855	0.839	2.016***
	(3.283)	(3.567)	(0.353)	(10.510)	(2.299)	(0.540)
Amount (in M 2017 US$)	52.187	12.085	40.101***	13.545	5.304	8.241***
	(115.712)	(116.059)	(8.934)	(20.327)	(10.268)	(2.089)
Observations	613	1,340	1,953	425	1,582	2,007

Sources: project amount per site, locations' longitudes and latitudes are from AidData's Geocoded Global Chinese Official Finance Dataset (Version 1.1.1) (Dreher et al., 2022; Bluhm et al., 2018) and World Bank Geocoded Research Release (Version 1.4.2) (AidData, 2017). Distances to capital, coast, coal mines, and petroleum mines are calculated by authors using the location longitude and latitude. Land suitability are from Ramankutty et al. (2002). Baseline nightlights are calculated using the harmonized nightlight data from Li et al. (2020). Institutional quality is from the WGI dataset.

Table 2: Baseline Results

	Infrastructure			Non-Infrastructure		
	China	World Bank	Pooled	China	World Bank	Pooled
IHS(Nightlights)	(1)	(2)	(3)	(4)	(5)	(6)
$Treated \times Post$	0.086***	-0.012	0.001	0.030**	0.004	0.017*
	(0.024)	(0.014)	(0.013)	(0.013)	(0.010)	(0.010)
$Treated \times Post \times China$			0.084***			0.037*
			(0.025)			(0.019)
Observations	55,754	92,024	147,848	29,776	98,770	128,593
Adjusted R-squared	0.992	0.992	0.992	0.994	0.992	0.992
Mean of Dep. Var	0.976	0.706	0.809	1.074	0.561	0.680

Notes: This table shows estimations for Equation 1. Both Chinese infrastructure and non-infrastructure projects increase nightlights. World Bank infrastructure projects also show positive impacts but with smaller magnitudes and less significance. Standard errors presented in the paraphrases are clustered at the project level. ***: significant at 1%, **: significant at 5%, *: significant at 10%.

Table 3: Controlling for location characteristics

	Infrastructure				Non-Infrastructure			
IHS(Nightlights)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treated \times Post$	0.001	-0.000	0.004	0.006	0.017*	0.014*	0.013	0.015*
	(0.013)	(0.012)	(0.012)	(0.012)	(0.010)	(0.008)	(0.008)	(0.009)
$Treated \times Post \times China$	0.084***	0.081***	0.068***	0.061**	0.037*	0.010	0.009	0.007
	(0.025)	(0.026)	(0.026)	(0.025)	(0.019)	(0.022)	(0.023)	(0.023)
Dist to Resources	-	Y	Y	Y	-	Y	Y	Y
Baseline NL & Land Suitability	-	-	Y	Y	-	-	Y	Y
Inst Qual, Democracy & Conflicts	-	-	-	Y	-	-	-	Y
Observations	147,848	147,848	145,208	144,730	128,593	128,593	125,506	124,885
Adjusted R^2	0.992	0.992	0.992	0.992	0.992	0.992	0.992	0.992
Mean of Dep. Var.	0.809	0.809	0.788	0.789	0.680	0.680	0.677	0.680
Treatment effect of Chinese project = 0	0.000127	0.000577	0.00216	0.00315	0.00211	0.232	0.285	0.302

Notes: This paper shows estimations using Equation (2). Time-invariant controls include distances to the capital city, coast, and natural resources, baseline nightlight; Time variant controls are the indicator for change of the chief executive, the indicator for chief executive close to the end of the current term, the indicator for change of the leading party, the indicator for being autocratic, and changes of veto players in the central government. Standard errors presented in the paraphrases are clustered at the project level. The results suggest that Chinese projects perform still better after controlling for location characteristics and project amount per site. Standard errors presented in the paraphrases are clustered at the project level. ***: significant at 1%, **: significant at 5%, *: significant at 10%.

Table 4: Nearby Projects

	Infrastructure			Non-Infrastructure		
	Pooled	< 50 km	> 50 km	Pooled	< 50 km	> 50 km
IHS(Nightlights)	(1)	(2)	(3)	(4)	(5)	(6)
$Treated \times Post$	0.006	-0.013	-0.017	0.015*	0.017	-0.014
	(0.012)	(0.014)	(0.017)	(0.009)	(0.012)	(0.015)
$Treated \times Post \times China$	0.061**	0.044*	0.131***	0.007	-0.005	0.127***
	(0.025)	(0.025)	(0.032)	(0.023)	(0.026)	(0.037)
Observations	144,730	75,238	69,472	124,885	56,345	68,522
Adjusted R^2	0.992	0.994	0.992	0.992	0.992	0.992
Mean of Dep. Var.	0.789	0.964	0.599	0.680	0.894	0.504
Treatment effect of Chinese project = 0	0.00315	0.185	3.32e-05	0.302	0.626	5.55e-05

Notes: This table shows results comparing Chinese and World Bank projects located within 50km or beyond. Columns (1) and (4) copy Columns (4) and (8) in Table 3 except for controlling for the amount per site in addition. Columns (2) and (5) show results for projects that have a project from the other donor within 50km. Columns (3) and (6) show results for projects that have no project from the other donor within 50km. Results suggest that the differences in project impacts remain for Chinese projects that locate within 50km of a World Bank project. Standard errors presented in the paraphrases are clustered at the project level. Significant at 1%, **: significant at 5%, *: significant at 10%.

Table 5: Controlling for project characteristics

	Infrastructure				Non-Infrastructure			
IHS(Nightlights)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treated \times Post$	0.006	0.008	0.004	-0.014	0.015*	0.009	-0.011	0.005
	(0.012)	(0.012)	(0.030)	(0.028)	(0.009)	(0.009)	(0.012)	(0.012)
$Treated \times Post \times China$	0.061**	0.061**	0.063**	0.091***	0.007	0.003	-0.002	-0.016
	(0.025)	(0.028)	(0.031)	(0.033)	(0.023)	(0.029)	(0.030)	(0.046)
$Treated \times Post \times IHS(amt\ per\ site)$		0.012**	0.011*	0.033***		-0.000	-0.000	0.005
		(0.005)	(0.005)	(0.008)		(0.005)	(0.005)	(0.006)
Sector FE	-	-	Y	-	-	-	Y	-
Topic FE	-	-	-	Y	-	-	-	Y
Observations	144,730	140,501	140,501	100,999	124,885	112,759	112,759	90,057
Adjusted R^2	0.992	0.992	0.992	0.993	0.992	0.992	0.992	0.992
Mean of Dep. Var.	0.789	0.793	0.793	0.964	0.680	0.640	0.640	0.601
Treatment effect of Chinese project = 0	0.00315	0.00449	0.0266	0.00234	0.302	0.681	0.644	0.820

Notes: This table shows results comparing Chinese and World Bank projects controlling for project characteristics. Columns (3) and (7) control for the sector fixed effects interacted with post-treatment effects. Columns (4) and (8) control for the topic generated from text analysis interacted with treated indicators. Standard errors presented in the paraphrases are clustered at the project level. Significant at 1%, **: significant at 5%, *: significant at 10%.

Table 6: Inverse Probability Weighting: Summary Statistics

	Infrastructure				Non-Infrastructure			
Variable	China	World Bank	Diff	p-value	China	World Bank	Diff	p-value
Dist. Capital (km)	334.075	319.250	-35.904	0.547	197.496	249.559	-28.909	0.508
Dist. Coast (km)	373.129	353.315	-35.782	0.536	203.134	243.228	4.864	0.908
Dist. Mines (km)	273.563	251.769	12.540	0.747	250.651	205.817	28.455	0.388
Dist. Petro (km)	803.583	837.155	-8.690	0.913	622.978	732.334	0.069	0.999
Baseline Nightlight	1.276	1.127	-0.151	0.761	2.560	1.533	0.113	0.831
Land Suitability	0.379	0.411	-0.030	0.464	0.379	0.461	-0.011	0.760
Institutional Quality	-0.017	0.321	-0.018	0.964	0.108	0.340	-0.037	0.885
Degree of Democracy	1.180	1.392	-0.145	0.875	0.552	0.849	-0.460	0.584
Number of Conflicts	1.042	0.977	-0.050	0.889	1.845	1.074	0.059	0.860
Amount (in mils 2017USD)	25.529	14.750	4.383	0.462	16.624	5.353	8.706	0.010
Have a nearby project from same donor	0.285	0.459	-0.069	0.481	0.427	0.474	-0.106	0.216
Temperature Suitability for Malaria	0.423	0.418	0.011	0.784	0.392	0.414	-0.041	0.356
Observations	221	290	511		206	361	567	

Notes: This table presents summary statistics for the projects adjusted using inverse probability weighting and trimmed based on Crump et al. (2009). Compared to descriptive statistics shown in Table 1, the Chinese and World Bank projects after adjustment are more similar and none of the differences in covariates are statistically significant. The last two variables "Have a nearby project from same donor" and "Temperature Suitability for Malaria" are not targeted in the propensity score estimation procedure. The fact that they are not statistically different between the projects from the two donors suggests that the balancing property holds for the adjusted sample.

Table 7: Inverse Probability Weighting: Regression Results

	Infrastructure		Non-Infrastructure	
IHS(Nightlight)	(1)	(2)	(3)	(4)
$Treated \times Post$	-0.009	-0.005	0.025	0.023
	(0.024)	(0.028)	(0.018)	(0.017)
$Treated \times Post \times China$	0.131***	0.131***	-0.007	-0.010
	(0.041)	(0.042)	(0.029)	(0.026)
Trimming standard	Imbens	Crump	Imbens	Crump
Observations	48,385	38,403	46,384	29,143
Adjusted R^2	0.991	0.991	0.992	0.994
Mean of Dep. Var.	0.589	0.599	0.666	0.836
Treatment effect of Chinese project = 0	0.00765	0.00960	0.496	0.625

Notes: The table shows the Inverse Probability Weighting estimation results. The specification is the same as 5 Column (2) but use the IPW sample and weighted by the inverse probablity. Column (1) and (3) trim the sample based on Imbens and Rubin (2015) and Column (2) and (4) trim the sample based on Crump et al. (2009). Standard errors presented in the paraphrases are clustered at the project level. ***: significant at 1%, **: significant at 5%, *: significant at 10%.

Table 8: Hypotheses of Mechanisms

	Infrastructure						Non-Infrastructure					
IHS(Nightlights)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$Treated \times Post$	-0.008	-0.006	0.001	0.008	0.021	0.015	-0.009	-0.013	0.006	0.010	0.002	0.002
	(0.015)	(0.015)	(0.012)	(0.013)	(0.021)	(0.021)	(0.010)	(0.012)	(0.009)	(0.009)	(0.014)	(0.013)
$Treated \times Post \times China$	0.067**	0.069**	0.059**	0.059**	0.070**	0.060	0.005	0.013	0.001	0.001	0.040	0.031
	(0.029)	(0.030)	(0.028)	(0.028)	(0.033)	(0.038)	(0.030)	(0.030)	(0.030)	(0.029)	(0.050)	(0.064)
$Treated \times Post \times Follow-up$	0.024						0.024					
	(0.018)						(0.014)					
$Treated \times Post \times Follow-up(Otherdivision)$		0.019						0.038***				
		(0.016)						(0.014)				
$Treated \times Post \times PolTieTribe$			0.048**						0.019			
			(0.021)						(0.021)			
$Treated \times Post \times PolTieBpl$				-0.001						-0.004		
				(0.022)						(0.017)		
$Treated \times Post \times AnyChina$					-0.035						-0.013	
					(0.025)						(0.025)	
$Treated \times Post \times China\_mhalf$						-0.017						-0.004
						(0.035)						(0.051)
Observations	140,501	140,501	140,501	140,501	104,740	104,740	112,759	112,759	112,759	112,759	84,803	84,803
Adjusted R^2	0.992	0.992	0.992	0.992	0.992	0.992	0.992	0.992	0.992	0.992	0.992	0.992
Mean of Dep. Var.	0.793	0.793	0.793	0.793	2.566	2.566	0.640	0.640	0.640	0.640	1.869	1.869

Notes: The table shows the results examining 3 mechanisms. $follow-up$ is the indicator for having any follow-up projects in the same division. Other division means non-infrastructure follow-up projects for infrastructure projects and infrastructure follow-up projects for non-infrastructure projects. Standard errors presented in the paraphrases are clustered at the project level. ***: significant at 1%, **: significant at 5%, *: significant at 10%.

Table 9: DHS Results

	Child Mortality	Women Education	Women BMI
Chinese - Infrastructure			
Treated × *Post*	-2.1092	0.3435*	0.3202**
	(2.722)	(0.196)	(0.155)
Observations	21,338	23,321	19,060
World Bank - Infrastructure			
Treated × *Post*	1.8165	0.2946**	0.1347
	(2.800)	(0.136)	(0.128)
Observations	70,422	74,315	67,207
Chinese - NonInfrastructure			
Treated × *Post*	-6.9114**	0.0273	-0.0116
	(3.434)	(0.146)	(0.121)
Observations	17,364	18,232	15,849
World Bank - NonInfrastructure			
Treated × *Post*	6.1459	-0.2915*	-0.1985
	(3.847)	(0.173)	(0.129)
Observations	62,843	66,203	58,822

Notes: This table show results for outcomes other than nightlight using the DHS data. Women's BMI is the reported BMI of all women between the ages of 15 and 49 divided by 100. The child mortality rate is the number of deaths per 1,000 children age 5 or younger. Women's educational attainment is the education in single years before 18 among women between the ages of 15 and 49. All measures are cluster-level averages. Both World Bank and Chinese infrastructure projects perform well in some aspects. Data are from Yeh et al. (2021). Standard errors presented in the paraphrases are clustered at the project and cluster level. ***: significant at 1%, **: significant at 5%, *: significant at 10%.

A Appendix

Figure A.1: Chinese Development Project: Nighttime Light per log dollar

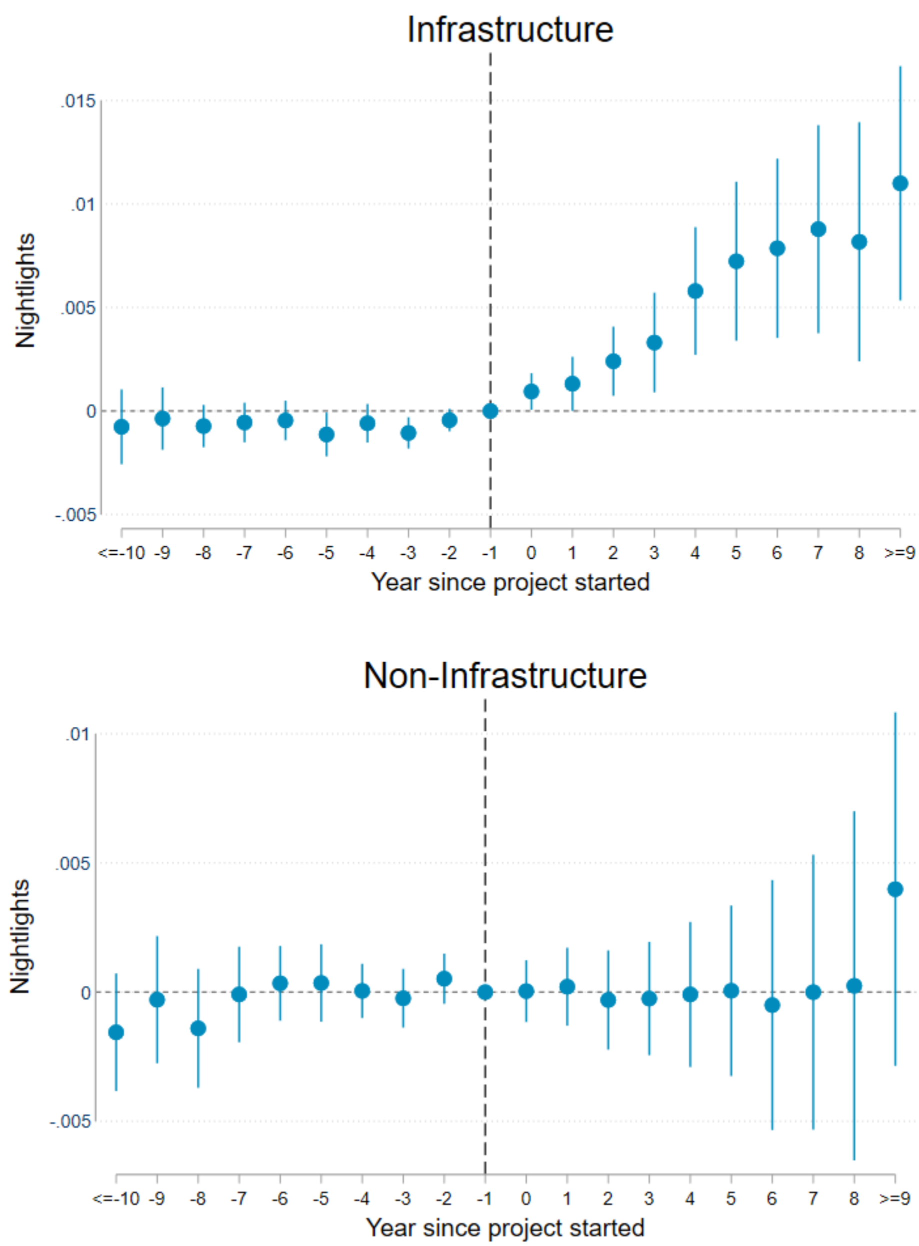


Figure A.2: World Bank Development Project: Nighttime Light per log dollar

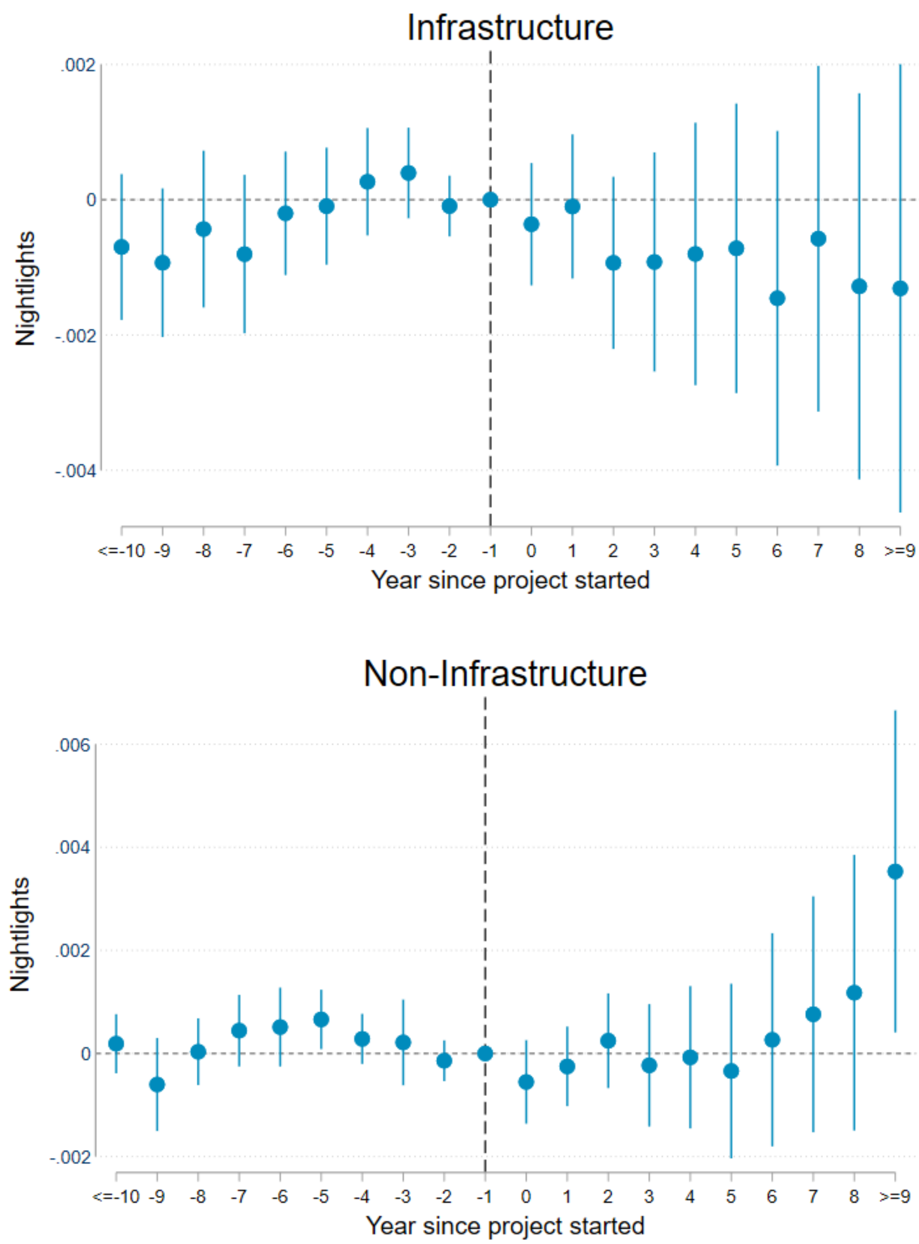


Table A.1: Baseline Results: Post0

	Infrastructure			Non-Infrastructure		
	China	World Bank	Pooled	China	World Bank	Pooled
IHS(Nightlights)	(1)	(2)	(3)	(4)	(5)	(6)
$Treated \times Post$	0.045***	-0.010	0.001	0.012	-0.009	0.017*
	(0.017)	(0.012)	(0.013)	(0.010)	(0.008)	(0.010)
$Treated \times Post \times China$			0.084***			0.037*
			(0.025)			(0.019)
Observations	55,754	92,024	147,848	29,776	98,770	128,593
Adjusted R-squared	0.992	0.992	0.992	0.994	0.992	0.992
Mean of Dep. Var	0.976	0.706	0.809	1.074	0.561	0.680

Notes: This table shows estimations for Equation (1), but here *Post* is an indicator for the project having started rather than having started for over 3 years as in the baseline. Standard errors presented in the paraphrases are clustered at the project level. ***: significant at 1%, **: significant at 5%, *: significant at 10%.

Figure A.3: Treatment Effects by Topic

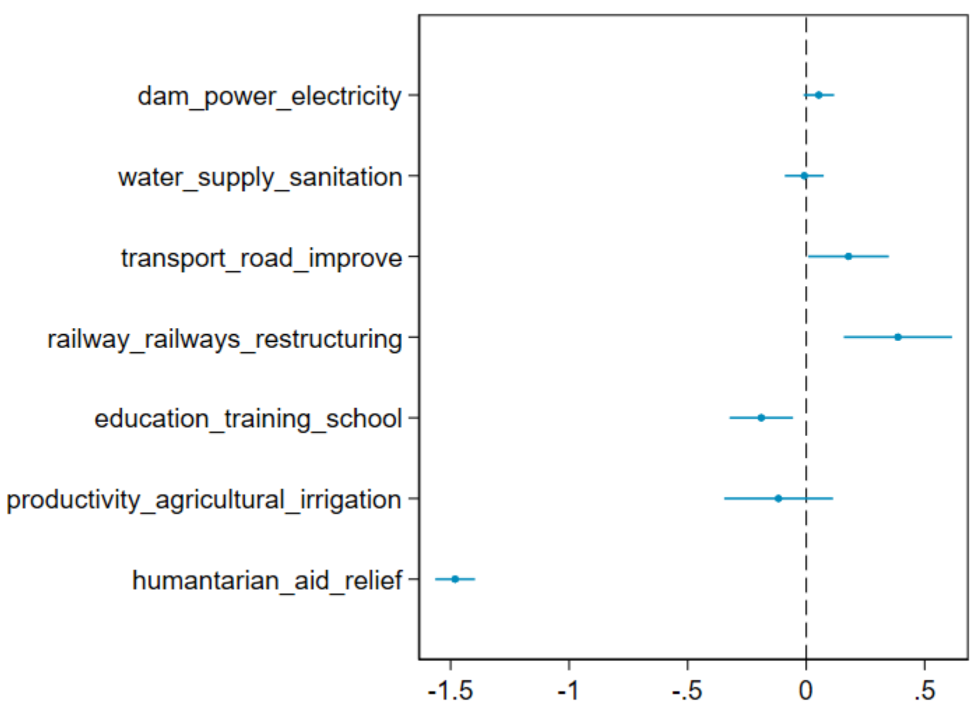


Table A.2: Controlling for location characteristics: Post0

	Infrastructure				Non-Infrastructure			
IHS(Nightlights)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treated \times Post$	-0.003	-0.004	-0.002	-0.001	-0.006	-0.002	-0.002	-0.003
	(0.011)	(0.010)	(0.010)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)
$Treated \times Post \times China$	0.048**	0.048**	0.042**	0.041**	0.046***	0.022	0.022	0.022
	(0.019)	(0.019)	(0.019)	(0.019)	(0.017)	(0.018)	(0.020)	(0.021)
Dist to Resources	-	Y	Y	Y	-	Y	Y	Y
Baseline NL & Land Suitability	-	-	Y	Y	-	-	Y	Y
Inst Qual, Democracy & Conflicts	-	-	-	Y	-	-	-	Y
Observations	147,848	147,848	145,208	144,730	128,593	128,593	125,506	124,885
Adjusted R^2	0.992	0.992	0.992	0.992	0.992	0.992	0.992	0.992
Mean of Dep. Var.	0.809	0.809	0.788	0.789	0.680	0.680	0.677	0.680
Treatment effect of Chinese project = 0	0.00368	0.00470	0.0105	0.00869	0.00594	0.186	0.243	0.270

Notes: This table corresponds to Table 3 in the main text, but here *Post* is an indicator for the project having started rather than having started for over 3 years as in the baseline. Standard errors presented in the paraphrases are clustered at the project level. ***: significant at 1%, **: significant at 5%, *: significant at 10%.

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