Journal of Asian Economics 84 (2023) 101573

Contents lists available at ScienceDirect

Journal of Asian Economics

journal homepage: www.elsevier.com/locate/asieco

Infrastructure and poverty reduction: Assessing the dynamic impact of Chinese infrastructure investment in sub-Saharan Africa☆

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ARTICLE INFO

JEL classification:
F35
I3
O18
O55

Keywords:
Chinese infrastructure investment
Sub-Saharan Africa
Multidimensional poverty
Spatial-temporal estimation

ABSTRACT

Infrastructure investment is essential for African countries to enhance economic activities and reduce poverty; however, the conclusions from national-level studies remain ambiguous. Combining geo-coded Chinese infrastructure project data from 2000 to 2014 and Demographic and Health Surveys information, we employ a spatiotemporal estimation strategy and explore the dynamic effectiveness of Chinese infrastructure investment on local multidimensional poverty in sub-Saharan Africa and its mechanisms. Our findings demonstrate that infrastructure projects can continuously alleviate local multidimensional poverty following project completion, primarily by improving living standards through local industrialization and increasing individual employment stability. Further investigating heterogeneities, we determine that Chinese infrastructure projects are more effective for self-dependent recipients, in rural areas, and when overseen by state-owned enterprises. Our findings provide insights into the long-term effectiveness for underdeveloped countries to reduce local poverty with Chinese infrastructure investment.

1. Introduction

The COVID-19 pandemic and the impact of climate change have interrupted 4.381% of the average annual economic growth rate in

☆ We would like to thank the Editor, the Associate Editor, and the two anonymous reviewers for their insightful and constructive comments and suggestions that substantially improved our paper. We also acknowledge the comments of He Li, Hongyuan Zhang, and all other participants in the seminar at Jilin University and Michael Darko from the University of Leicester. We are solely responsible for any error that might yet remain.

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https://doi.org/10.1016/j.asieco.2022.101573

Available online 19 December 2022

sub-Saharan Africa (SSA) since the 21st century.[2] The global level of extreme poverty also rose for the first time in the past 20 years, of which SSA accounts for more than half of the global total population in poverty.[3] Although the overall poverty rate of SSA has declined slowly over the years since the 1990s, apparent differentiation remains among countries, and some have not fundamentally improved.[4]

In contrast, total development assistance and investment to SSA in the past few decades have been rising. Since 2000, about 32% of the development funds from the United States went to Africa, and 33% for the same period from the World Bank.[5] Unfortunately, the provision of substantial funds has not led to universal poverty reduction, but resulted in heavy dependence (Qian, 2015). The considerable capital gap in infrastructure construction has heavily stagnated African economic development and poverty reduction (Lin & Wang, 2017).

Unlike traditional donors, China's infrastructure-led approach has placed competitive pressure on them and provided alternative sources of development finance under the "Belt and Road" initiative.[6] According to Timetric's Infrastructure Intelligence Center (IIC), China accounted for 31% of the global infrastructure investment in 2017, of which 40% were railway infrastructure projects. Moreover, foreign direct investment (including infrastructure investment) by Chinese companies grew by an average 11% from 2008 to 2018, according to Moody's Investors Service.[7] With its experience and advantages in infrastructure development, China has spread infrastructure investment worldwide. However, whether China's costly development investments can continuously help SSA countries alleviate poverty, especially those in the infrastructure sector, remains unanswered. Through an empirical analysis of the dynamic impact of Chinese infrastructure projects on local multidimensional poverty and its mechanisms, we enhance the understanding of these effects.

To the best of our knowledge, this study is the first to investigate the relationship between China's infrastructure investment and local multidimensional poverty at the project level. As with the uncertainty regarding whether development investment can bring economic growth to recipients (Burke & Ahmadi-Esfahani, 2006; Burnside & Dollar, 2000; Galiani et al., 2017; Hansen & Tarp, 2001; Rajan & Subramanian, 2008; Xu et al., 2019), the conclusions on poverty reduction are also ambiguous. Some literature has found that development projects significantly reduce poverty (Alvi & Senbeta, 2012; Arndt et al., 2015; Mahembe & Odhiambo, 2021). Infrastructure projects in particular effectively improve recipient countries' endowment (Donaubauer et al., 2016). Yang et al. (2020) demonstrated that most Asian nations' infrastructure investment promoted economic growth, welfare, foreign trade, and trade terms. In contrast, some studies assert that the over-reliance of African countries on foreign investment is not conducive to sustainable development and poverty reduction, criticizing the hindering effects of aid on poverty reduction in terms of debt, project purpose, and interest group involvement (Azam et al., 2016; Balla & Reinhardt, 2008; Collier & Dollar, 2002; Easterly, 2002).

We contend that noise at the national-level data is the main reason for these diverging conclusions. Due to the uneven distribution of poverty and aid flows within countries, studies at the national level are inevitably disturbed by unobservable factors.[8] Macro-level estimation biases caused by micro-level resource allocation confuse the conclusions. Since all aid projects are implemented at subnational levels, economic impacts should also be investigated in respective areas (Tierney et al., 2011). Our contributions are primarily reflected in three aspects. First, we analyze the relationship between Chinese infrastructure investment and local multidimensional poverty from a micro-level perspective to avoid spatial mismatches. Second, we introduce a dynamic regression model to analyze the evolving impacts of project implementation over time. Third, we explore the micro-mechanisms of infrastructure aid in poverty reduction.

Due to the release of geo-coded China development assistance projects by the AidData database, a small but growing body of literature on Chinese aid has developed over the past few years. Research evaluating China's aid is also increasing (Dreher et al., 2016, 2019; Eichenauer et al., 2021; Isaksson & Kotsadam, 2018). The study closest to ours is Martorano et al. (2020). With the help of Chinese aid projects in 13 SSA countries, and constructing areas sharing the first decimal place for both latitude and longitude coordinates and a panel difference-in-differences (DID) model, the authors compared the changes in respondents' education, child health, and nutrition before and after the projects' construction of the projects, demonstrating that Chinese aid improved education and child mortality in the treatment areas. Nevertheless, this study does not explore the impact on household poverty and its mechanisms. Moreover, due to methodological limitations, it cannot accurately capture the dynamic effects after the project completion, which is crucial for assessing infrastructure investment and determining whether the "illusion of sustainability" exists

[2] The average economic growth rate in SSA was 3.244% in 2019 and dropped to − 1.953% in 2020. (Data source: World Bank database at https://databank.worldbank.org/reports.aspx?source=world-development-indicators).

[3] See poverty overview from the World Bank at https://www.worldbank.org/en/topic/poverty/overview.

[4] For example, the poverty rates of Angola, Benin, Côte d'Ivoire, Madagascar, Malawi, Sao Meido, South Africa, South Sudan, Togo, Uganda, Zambia, and Zimbabwe fluctuated or even increased during this period. See the World Bank database at https://datacatalog.worldbank.org/search/dataset/0037712/World-Development-Indicators.

[5] Source: OECD Statistics at https://stats.oecd.org/.

[6] According to the Chinese government's white books, China's development finance was about 41.5 billion US dollars from 2013 to 2018, of which 44.65% went to Africa and 45.73% went to the least developed countries. From 2016–2020, the total amount of infrastructure projects under construction in Africa was valued at nearly 200 billion US dollars, and the proportion of projects implemented by Chinese enterprises reached 31.4% in 2020. See white books *China's International Development Cooperation in the New Era* at http://www.scio.gov.cn/zfbps/32832/Document/1696686/1696686.htm and *China and Africa in the New Era: A Partnership of Equals* at http://www.scio.gov.cn/zfbps/ndhf/44691/Document/1717829/1717829.htm.

[7] See Moodys' 2019 Report at https://www.moodys.com/chinainfrastructure/.

[8] For example, most of the development resources may go to affluent areas such as urban areas and effectively mitigate local poverty, but the poverty in the more expansive rural areas may be worsened, which will then affect the average poverty level of the entire country.

(Kremer & Miguel, 2007).

To avoid endogeneity problems in the regression results, we geographically matched Chinese infrastructure project data in SSA from 2000 to 2014 and waves 4–7 of Demographic and Health Surveys (DHS) data for a total of 778,240 respondents. Comparing the poverty of individuals living near infrastructure projects and those living near projects in the pipeline, we can control for unobserved variables to some extent and obtain a DID estimation. The results show that the difference between the poverty of respondents living near infrastructure projects and those without any project is significantly larger than the difference between the poverty level of the respondents living near projects in the pipeline and people living in the areas without any project, implying the effectiveness of poverty reduction from Chinese infrastructure projects.

It is also necessary to understand the mechanisms of poverty reduction from infrastructure projects. To this end, we explored the heterogeneity of projects on different dimensions of poverty, determining that improved living standards are the primary mechanism of poverty reduction. We further demonstrate that infrastructure projects can promote local industrialization, improving individual employment stability nearby and alleviating poverty. Theoretically, infrastructure investment can effectively promote the continuous development of local factories and enterprises and provide more stable employment opportunities from the demand side. In addition, infrastructure improvement also encourages people to seek more stable jobs from the supply side.

Finally, we analyzed the poverty reduction effects of different project types in different countries and regions, finding that only self-dependent countries can achieve poverty reduction with Chinese infrastructure investment. Infrastructure projects have a more significant effect on poverty reduction in rural areas than in urban areas. And projects undertaken by state-owned agencies have more significant effects than those undertaken by private agencies.

The next section presents the theoretical nexus between infrastructure projects and poverty reduction. We introduce the data and estimation strategy in Section 3 and detail the case study in Section 4. Section 5 shows the benchmark regression results and robustness tests. Section 6 is the mechanism analysis. Section 7 provides the extensions on heterogeneity analysis. Section 8 concludes.

2. Infrastructure investment and poverty

We propose a principal chain channel through which infrastructure investment can impact local poverty. Infrastructure projects can solve the inadequate transportation, communications, and warehousing that can bottleneck the development of local industrialization, establishing additional non-agricultural jobs and enhancing employment stability, thereby alleviating multidimensional poverty.

First, infrastructure construction is conducive to improving the local business environment, cultivating the development of factories and enterprises. The literature emphasizes the importance of a high-quality business environment for enterprises' production and operations (Moyo, 2013). According to the transportation-inventory model, enterprises' inventory of raw materials and semi-finished products have constant or decreasing marginal costs, and production activities consume inventory at a stable rate (Tyworth & Zeng, 1998). Consequently, enterprises must determine the "lead time" to reorder before materials are exhausted. Infrastructure projects, such as those related to transportation and communications, can unblock the channels of information, human capital, and intermediate goods by connecting enterprises in the same or different but interrelated industries and regions, shortening the lead time, reducing transport costs and production uncertainty, and promoting capital inflows and enterprise agglomeration. Moreover, improving the business environment can increase the probability of potential enterprises entering the market and reduce the probability of others withdrawing from the market. More convenient infrastructural facilities expand enterprises' potential market, promote technological progress, and enable enterprises on the verge of exit to survive (Wu et al., 2021).

Production efficiency is the fundamental impetus for the continuous development of regional industrialization, and can be promoted by infrastructure construction (Bonaglia et al., 2000). Investigating the influence of the Indian expressway on the efficiency of manufacturing enterprises, Ghani et al. (2016) determined that the expressway network construction improved the efficiency, survival probability, and scale of enterprises along the route. The expansion of enterprise size correlated with a high-quality business environment will attract more homogeneous or related enterprises to a region, deepening the division of labor and improving productivity, which is evident in service industries with tremendous potential for division of labor and higher economic agglomeration effects (Vijverberg et al., 2011).

Second, China's infrastructure projects can encourage nearby residents to engage in non-agricultural work, receiving higher wages than agricultural production, which reduces poverty (Dethier & Effenberger, 2012; Winters et al., 2009). Specifically, it operates through "push" and "resistance" mechanisms. According to the dual economic theory, the more significant the gap between industrial and agricultural labor productivity, the faster the speed of rural labor migration into industry and the greater the probability residents will engage in non-agricultural work (Ranis & Fei, 1961). The construction of infrastructure projects and resulting economic agglomeration effects provide non-agricultural employment opportunities with higher returns than agricultural production.

In addition, infrastructure has a critical influence on reducing labor-transfer resistance. In contrast to the contentions of the dual economic theory, which emphasizes the driving factors of labor mobility, rural infrastructure construction partially eliminates the obstacles of labor mobility costs and surplus labor. For example, improved transportation, communication, and water and power supply capacity can increase labor productivity and remuneration (Pinstrup-Andersen & Shimokawa, 2006). At the same time, it may also reduce the cost of nearby agricultural production, help to release additional labor for non-agricultural employment, and resolve the stock of the rural surplus labor force.

Therefore, industrialization and employment stability arguably speak in favor of China's infrastructure investment and local multidimensional poverty. In Section 6, we discuss how to approach this question empirically.

3. Data and methodology

3.1. Dependent variable

Previous studies have employed direct and indirect methods to measure poverty (Alvi & Senbeta, 2012; Dhahri & Omri, 2020; Kosack, 2003). The former seeks to observe whether people's lives meet basic needs or standards, and the latter determines whether people's incomes are below the poverty line. However, there are many limitations in applying the indirect method, such as the delimitation of the poverty line being affected by price levels in different regions. In addition, due to differing consumption behavior, even an income above the poverty line cannot guarantee that individuals' primary living conditions are met (Sen, 1982). While the direct method measures "permanent income" or long-term residents' welfare, rather than short-term monetary income (Rutstein & Johnson, 2004), which will largely avoid the measurement error caused by the indirect method.

Unfortunately, the typical problems of the wealth indicators that are measured using the direct method in standard DHS datasets include intertemporal and transnational incomparability.[9] Thus, we reference Alkire and Foster (2011) and construct the multidimensional poverty index (MPI) based on capability theory.[10] The index directly identifies deprived people unable to meet the minimum transnationally comparable living standards, thus complementing the indirect approach based on income and poverty lines. Table 1 presents the dimensions, weights, and thresholds of the MPI.

3.2. Variable of interest

As the Chinese government does not disclose detailed information on its development investment projects, we collect China's infrastructure project data from the Global Chinese Official Finance Dataset, Version 1.1.1, in the AidData database released by Bluhm et al. (2018).[11] According to the definition of official development assistance (ODA), other official flows (OOF), and vague projects in the database, China's infrastructure funds are divided by purpose, including development, commercial, and representative purposes. Considering its unique donor system from traditional aid, we select the projects that belong to social and economic infrastructure sectors, including OOF and vague projects in the empirical analysis.

The database assigns longitudes, latitudes, and related location information to infrastructure projects, divided into eight grades according to precision.[12] Since we are focusing on the respondents in specific areas near infrastructure projects, we select those with a precision of 1 and 2 as the sample, corresponding to a specific location or within 25 km at most. In addition, we choose the transaction start year as the project implementation year, representing earlier timing between the project start time and the last transfer record time. Fig. 1 shows the location of China's infrastructure projects and DHS clusters in SSA. The DHS waves and observations for each country are presented in Appendix Table A1.

3.3. Control variables

We include control variables both at individual and regional levels. At the individual level, we account for a set of variables commonly employed in analyses of individual perceptions (Isaksson & Kotsadam, 2018; Xu & Zhang, 2020), including gender, age, the square of age, and race. Moreover, we include five characteristic variables. First, we control the individual's religion, such as Catholic, Assembly of God, and Methodist, since different religions may lead to different living habits and consumption tendencies (Minton et al., 2018). Second, considering that the urban respondents may have higher income levels, we generate a dummy variable of whether an individual lives in the urban area. In addition, we also control the education level and occupation of the individual by dividing the education level into four levels: no education or preschool, primary, secondary and higher. Occupations are classified into 11 categories: not working, sales, services and clerical, etc. These individual characteristics are closely related to their income and

[9] WI construction is based on samples from a particular country and survey wave. Each wave is based on a principal component analysis of different households, meaning that it is a relative rather than an absolute value, with an average value of 0 in each wave. With the refinement of the survey and changes in social lives, the number of indicators selected for the construction from waves 4–7 gradually increased, which may result in households with higher wealth scores in wave 4 scoring lower in wave 7. It is counterintuitive that individual poverty levels have changed due to changes in waves.

[10] We construct an indicator to equalize the scores of households with the same wealth in different waves. The composite indicator must include the same indicators and weights in various countries and surveys to ensure intertemporal and transnational comparability. For the principles of constructing the MPI, please see Alkire and Santos (2014).

[11] For the detailed data collection and processing process, please see Strange et al. (2017). Tracking Underreported Financial Flows (TUFF) Methodology, Version 1.3. *Williamsburg, VA: AidData*.

[12] According to the AidData precision system, precision is an ordinal scale that captures how precisely a record has been geocoded, wherein 1 is the highest level of spatial precision and 8 is the lowest spatial precision. Specifically, 1 = The coordinates correspond to an exact location; 2 = The location is mentioned in the source as being "near," in the "area" of, or up to 25 km away from an exact location; 3 = The location is, or is analogous to, a second-order administrative division (ADM2); 4 = The location is, or is analogous to, a first-order administrative division (ADM1); 5 = The location can only be related to estimated coordinates; 6 = The location can only be related to an independent political entity, but is expected to be disbursed locally; 7 = The location is unclear; 8 = The location can only be related to an independent political entity, but the central government will be the only direct beneficiary. For detailed information, see Geocoding Methodology, Version 2.0.2 at: https://www.aiddata.org/publications/geocoding-methodology-version-2–0.

Table 1
Dimensions, indicators, cut-offs, and weights of MPI.

Dimension	Code	Indicator	Deprivation cut-offs	Destitution cut-offs	Weight
Education	1	Years of Schooling	No household member has completed five years of schooling.	No household member has completed one year of schooling.	1/6
	2	Child Attendance to School	Any school-aged child is not attending school in years 1–8*.	Any school-aged child is not attending school in years 1–6.	1/6
Health	3	Child Mortality	Any child has died in the household.	More than one child has died in the household.	1/6
	4	Nutrition	Any adult to a child with nutritional information is malnourished**.	Any adult to a child for whom there is nutritional information is malnourished.	1/6
Living Standard	5	Electricity	No electricity.	No electricity.	1/18
	6	Sanitation	Not improved or improved but shared with others***.	No sanitation facility.	1/18
	7	Water	No safe drinking water or it is more than 30 min' walk****.	No safe drinking water, or it is more than 45 min' walk.	1/18
	8	Floor	Dirt, sand, or dung floor.	Dirt, sand, or dung floor.	1/18
	9	Cooking Fuel	Dung, wood, or carbon.	Dung or wood.	1/18
	10	Assets	No more than one of the following assets: radio, television, telephone, bicycle, scooter, or refrigerator, and no cars or trucks.	No assets and vehicles.	1/18

Notes: * Data source of official entrance age to primary education is from the UNESCO Institute for Statistics (UIS): http://data.uis.unesco.org/?ReportId=163. ** Deprivation: BMI is below 18.5 for adults, z-score of weight-for-age for children is below − 2 standard deviations from the median of the reference population; Destitution: BMI is below 17 for adults, z-score of weight-for-age for children is below − 3 standard deviations from the median of the reference population. *** Improved sanitation facility: non-shared flush toilet, ventilated improved pit latrine (VIP), and composting toilet. **** Safe drinking water: piped water, tube well water, protected well, protected spring, and rainwater.

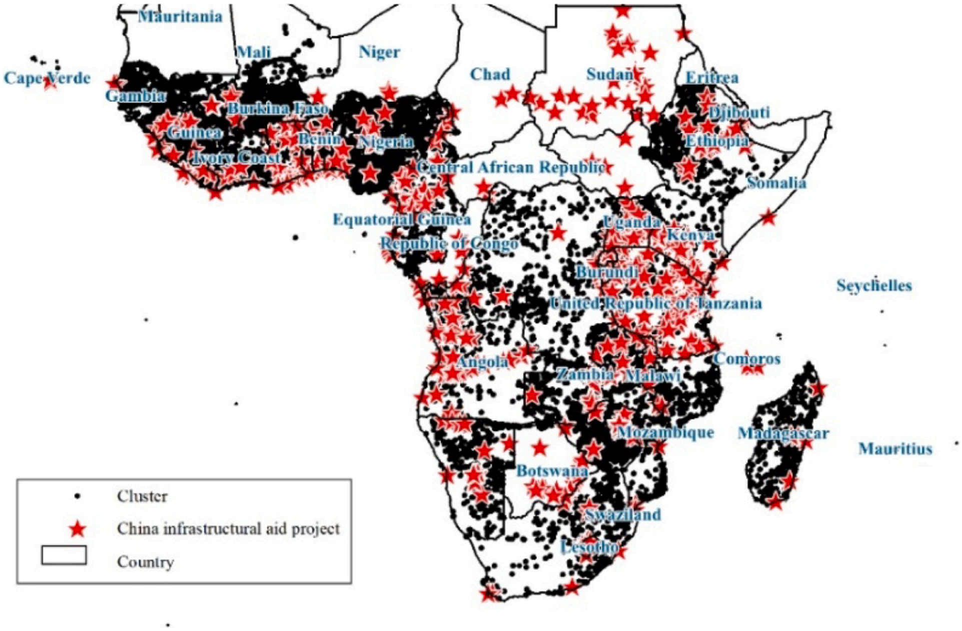


Fig. 1. Location of Chinese infrastructure projects and DHS clusters. Notes: Since the Global Chinese Official Finance Dataset only releases geographical information, including the longitude and latitude, for project centroids, all projects are considered to be approximate points.

Table 2
Descriptive Statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
deprivation	778,240	0.359	0.225	0	1.389
destitution	778,240	0.224	0.176	0	1.167
*active*50	778,240	0.338	0.473	0	1
*inactive*50	778,240	0.102	0.303	0	1
sex	778,240	1.605	0.489	1	2
age	778,240	29.348	10.491	15	64
*age*2	778,240	971.374	686.578	2.250	40.960
religion	778,240	1.548	3.181	0	96
urban	778,240	1.368	0.482	1	2
sex hhh	778,240	1.230	0.421	1	2
edu	778,240	0.274	0.678	0	3
occu	778,240	3.354	2.901	0	11
time2cities	778,240	2.103	2.190	0.009	33.083
dis2border	778,240	0.080	0.086	0	0.594
dis2water	778,240	0.110	0.110	0	0.697
dis2proareas	778,240	0.071	0.063	0	0.769
lansuit	778,240	0.386	0.220	0	0.999
popden	778,240	0.001	0.002	0	0.041
nightlight	778,240	0.076	0.297	0	9.286
ethdiversity	778,240	1.337	1.763	0	13.155
conflict	778,240	0.519	1.673	0	14.740
mineral	778,240	0.295	0.456	0	1

poverty. Last, we add a dummy variable of whether the household leader is female or not, which may lead to different households' consumption behaviors (Turner et al., 2021).

At the regional level, we include ethnic diversity. When there is a more significant overlap between ethnicities and cultures, various political and economic outcomes (such as internal conflicts and the provision of public goods) may worsen (Desmet et al., 2017), which may harm economic activities, and thereby poverty reduction becomes more difficult. We further control the distance from the nearest national boundary, water body and nature reserves, land suitability for agricultural production, and mineral resources such as gold, copper, and diamond. These variables determine the degree of local resource endowments. In addition, considering that local preliminary development conditions may also have an impact on subsequent development and poverty, we control the economic and social indicators of these areas for the year 2000, including distance from the nearest city, population density, nightlight intensity, and the total number of conflicts during 1989–1999. The sources of control variables are shown in Appendix Table A2.

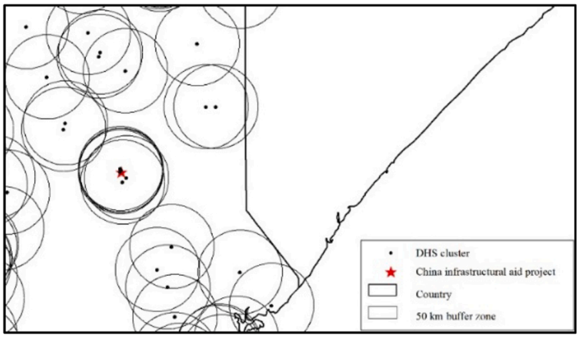


Fig. 2. Clusters with 50 km buffer zones. Notes: This figure shows the sampling process when grouping.

The resulting sample includes up to 778,240 observations. Table 2 provides the corresponding descriptive statistics. The average respondent is 29 years old, female (60.462%), lives in a rural area (63.191%), has no education or only preschool (84.815%), has a male household leader (77.038%), and is most likely not working (30.114%). His or her deprivation score is 0.359.

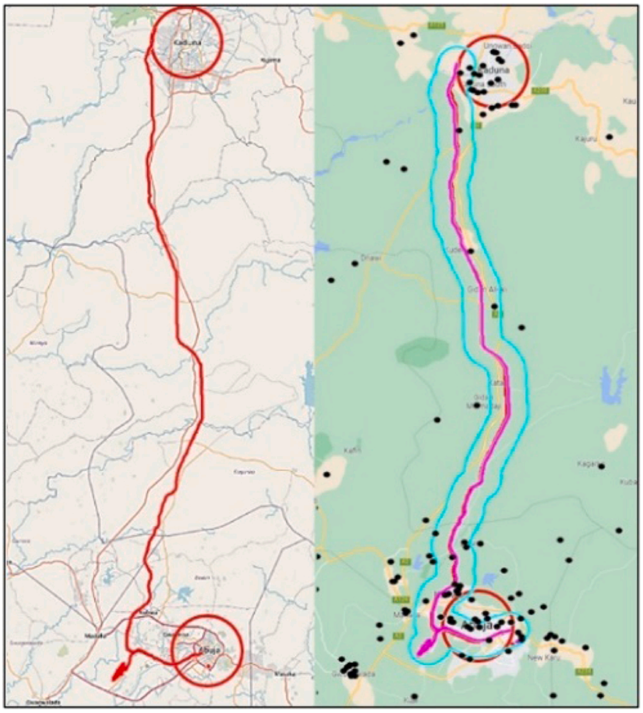
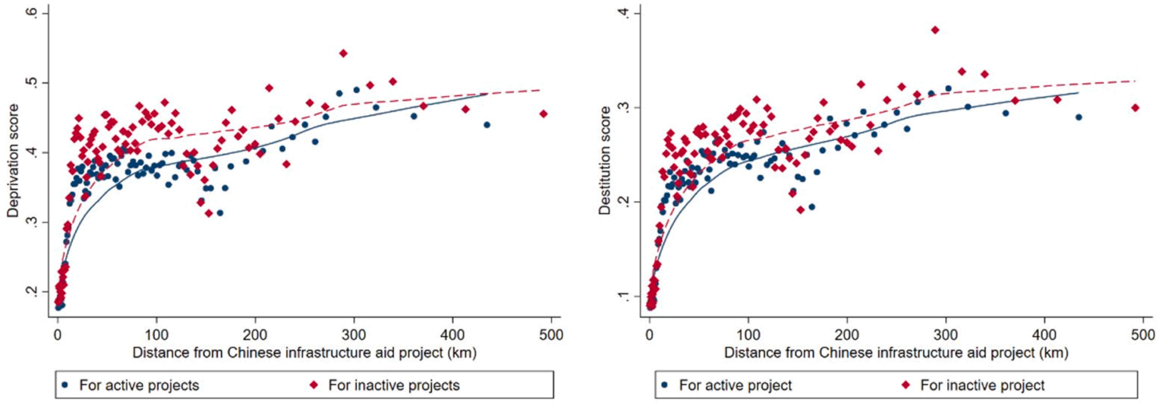


Fig. 3. Railway modernization project in Nigeria (Abuja-Kaduna section). Notes: Maps are from Google Maps and OpenStreetMap, and the figure is made by authors.

3.4. Methodology

Endogeneity is the most critical challenge when examining the causal effect between Chinese infrastructure investment and local poverty. Most Chinese infrastructure projects are implemented through bidding; therefore, the non-randomness of site selection will affect the robustness of our empirical results. To ensure that infrastructure projects can pass the internal review and be implemented as scheduled, projects may preference affluent areas (Briggs, 2017, 2018a, 2018b; Custer et al., 2017; Marty et al., 2017; Oeehler & Nunnenkamp, 2014; Ohler et al., 2019; Zhang et al., 2022). Thus, we use the spatiotemporal estimation strategy first introduced by Kotsadam and Tolonen (2016), comparing the poverty level between respondents close to the infrastructure projects and those living close to sites where a project is planned but not yet started at the time of the survey. The difference reflects the causal effect of Chinese



(1)   (2)

Fig. 4. Distance to nearest active or inactive projects and poverty. Notes: This figure illustrates the common trend test results with the lowest fitting method, revealing that the poverty reduction effect initially rises, then diminishes as distance increases.

Table 3
Impact of Chinese infrastructure investment on local poverty.

	(1) Deprivation	(2)	(3)	(4) Destitution	(5)	(6)
Panel A: Regression results with lagged Chinese infrastructure projects						
*active*50	-0.027***			-0.024***		
	(0.002)			(0.002)		
*active*50_*L*1		-0.044***	-0.012**		-0.030***	-0.010**
		(0.007)	(0.006)		(0.005)	(0.005)
*active*50_*L*2		-0.049***	-0.027***		-0.047***	-0.024***
		(0.005)	(0.006)		(0.004)	(0.005)
*active*50_*L*3		-0.071***	-0.039***		-0.060***	-0.038***
		(0.007)	(0.007)		(0.005)	(0.005)
*active*50_*L*4		-0.057***	-0.023***		-0.053***	-0.022***
		(0.004)	(0.004)		(0.003)	(0.003)
*active*50_*L*5		-0.052***	-0.029***		-0.045***	-0.024***
		(0.002)	(0.002)		(0.001)	(0.002)
*inactive*50	-0.020***	-0.016***	-0.020***	-0.014***	-0.026***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Panel B: Spatial-temporal estimation results						
*active*50 −*inactive*50	-0.007**			-0.010***		
	(4.997)			(12.094)		
*active*50_*L*1 −*inactive*50		-0.028***	0.008		-0.004	0.004
		(14.603)	(1.542)		(0.389)	(0.904)
*active*50_*L*2 −*inactive*50		-0.033***	-0.007		-0.021***	-0.010**
		(36.207)	(1.639)		(23.154)	(3.974)
*active*50_*L*3 −*inactive*50		-0.055***	-0.019***		-0.034***	-0.024***
		(63.352)	(7.235)		(49.374)	(18.356)
*active*50_*L*4 −*inactive*50		-0.041***	-0.003		-0.027***	-0.008**
		(76.867)	(0.359)		(55.920)	(4.088)
*active*50_*L*5 −*inactive*50		-0.036***	-0.009***		-0.019***	-0.010***
		(161.323)	(7.635)		(76.866)	(13.516)
region FE	Y	N	Y	Y	N	Y
country FE	Y	N	Y	Y	N	Y
year FE	Y	N	Y	Y	N	Y
adj. R^2	0.437	0.299	0.438	0.398	0.274	0.398
N	778,240	778,240	778,240	778,240	778,240	778,240

Note: Robust standard errors (clustered by the survey clusters) in parentheses for Panel A and F-values in parentheses for Panel B. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Control variables are included in all regressions, and their estimates are not reported here for brevity.

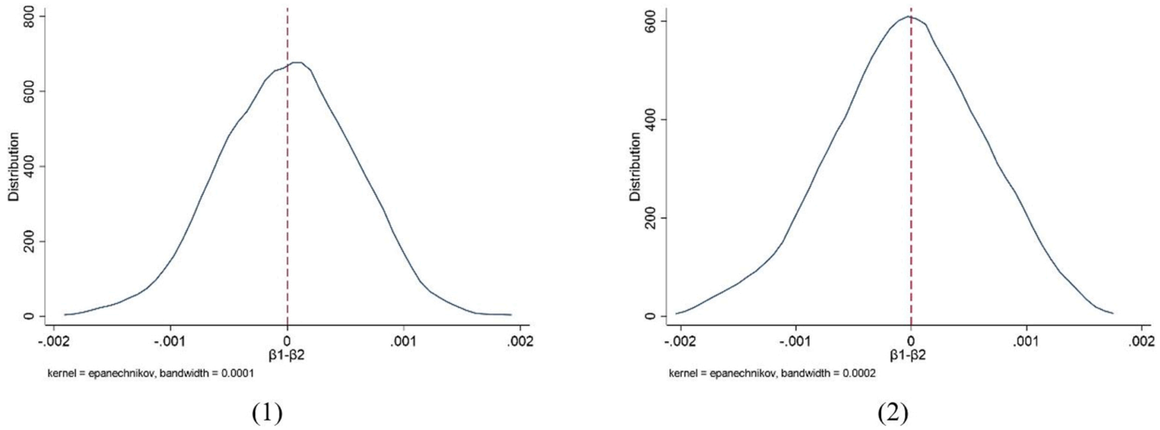


Fig. 5. Placebo tests (Based on 500 simulations). Notes: The left figure shows the result of random projects location, and the right figure represents the result of individuals' random interview time.

infrastructure projects on local poverty, solving the estimation error caused by the non-random location of the projects to some extent.

Assuming that the impact of projects on local poverty decreases with distance (Briggs, 2018b), we need to determine an appropriate buffer zone indicating that projects have impacted an area. We choose 50 km as the buffer zone of benchmark regression based on four applicable principles. (1) To protect the privacy of individuals' information, the DHS randomly moved geographic information by up to 5 km, of which 1% was moved by 10 km. (2) The coordinate project information with a precision of 1 and 2 reflect the exact centroid coordinates of the projects or a geographical location of up to 25 km around the projects. If the zone is too small, we cannot capture accurate information effectively. (3) The sample size significantly increases with an increase in the buffer zone, and large samples will improve the credibility of the regression results. (4) According to Bluhm et al. (2018), China's transport infrastructure projects diverge economic activities in developing African countries within regions, but the expansion is relatively insignificant across regions. Therefore, a buffer zone that is too large cannot accurately capture the impact of Chinese infrastructure projects. We contend that 50 km is a reasonable buffer zone based on the above arguments. The robustness test reveals that the robustness of the benchmark regression results is not sensitive to buffer zones.

Since the DHS waves are not tracking surveys, we cannot analyze the local poverty using panel data; however, we are able to group the samples according to the order of respondents' interview time and the projects' active time. Specifically, we can determine whether there is a project around the geo-coded respondents in each country and each wave of the survey, and whether the interview took place after the projects' active time, obtaining a group of individuals with infrastructure projects around them to compare this with the sample close to projects in the pipeline. As shown in Fig. 2, we divide the sample into three groups: (1) those with at least one active project (active) within 50 km, (2) those with at least one project within 50 km that has been planned but not yet implemented at the time of the interview and there is no active project (inactive), and (3) those with no project within 50 km, revealing that 37.808% of the respondents belong to the active group and 10.557% belong to the inactive group. To avoid the dummy trap problem, we exclude the variable of the third group in the regression model. The benchmark regression is presented as model (1).

$$Y_{i,v,t} = \beta_1 \cdot active_{i,v,t} + \beta_2 \cdot inactive_{i,v,t} + \alpha \cdot X_{i,v,t} + \gamma \cdot Z_v + \varphi_s + \rho_c + \delta_t + \varepsilon_{i,v,t} \tag{1}$$

$$Y_{i,v,t} = \beta_0 \cdot inactive_{i,v,t} + \beta_\tau \cdot \sum_{\tau=1}^{T} active_{i,v,t-\tau} + \beta_{T+1} \cdot active_{i,v,t-(T+1)} + \alpha \cdot X_{i,v,t} + \gamma \cdot Z_v + \varphi_s + \rho_c + \delta_t + \varepsilon_{i,v,t} \tag{2}$$

In model (1), $Y_{i,v,t}$ represents the deprivation or destitution score of individual i in cluster v and year t, and the dummy variables, $active_{i,v,t}$ and $inactive_{i,v,t}$, represent the samples of group (1) and group (2), respectively. To explore the dynamic effects of infrastructure projects on poverty reduction, we establish model (2). The lagging terms $active_{i,v,t-\tau}$ indicate that the respondents with infrastructure projects within 50 km have been exposed to the projects for τ years. $active_{i,v,t-(T+1)}$ indicates that individuals living around projects within 50 km have been exposed for at least T years. By comparing the difference of coefficient β_0 and β_τ, we can reflect the dynamic changes in local poverty after projects' implementation. $X_{i,v,t}$ in both models represents individual characteristics. Z_v controls the regional geographical features of the 50 km buffer zone. Considering that different regions within the same country may have heterogeneous characteristics, we introduce φ_s and ρ_c to control regional and country fixed effects, respectively. δ_t is the year fixed effect, and $\varepsilon_{i,v,t}$ is the standard error clustered by the survey clusters.

Table 4
Robustness to alternative cut-offs.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Excluding child school attendance		Using under-5 mortality (not at any age)		Using higher living standards deprive cut-offs		Poverty score
	Deprivation	Destitution	Deprivation	Destitution	Deprivation	Destitution	
Panel A: Regression results with lagged Chinese infrastructure projects							
*active*50_*L1*	-0.015**	-0.010**	-0.011*	-0.009*	-0.011*	-0.009**	-0.030**
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.004)	(0.013)
*active*50_*L2*	-0.027***	-0.027***	-0.027***	-0.024***	-0.027***	-0.025***	-0.054***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.013)
*active*50_*L3*	-0.045***	-0.042***	-0.039***	-0.038***	-0.036***	-0.035***	-0.091***
	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.016)
*active*50_*L4*	-0.025***	-0.024***	-0.023***	-0.022***	-0.023***	-0.023***	-0.055***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.009)
*active*50_*L5*	-0.028***	-0.024***	-0.029***	-0.024***	-0.029***	-0.024***	-0.063***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)
*inactive*50	-0.021***	-0.014***	-0.020***	-0.014***	-0.019***	-0.014***	-0.036***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
Panel B: Spatial-temporal estimation results							
*active*50_*L1* −*inactive*50	0.006	0.004	0.009	0.005	0.008	0.005	0.006
	(1.006)	(0.595)	(1.771)	(1.125)	(1.935)	(1.243)	(0.162)
*active*50_*L2* −*inactive*50	-0.006	-0.013**	-0.007	-0.010*	-0.008	-0.011**	-0.018
	(0.786)	(6.374)	(1.551)	(3.827)	(1.490)	(4.453)	(1.951)
*active*50_*L3* −*inactive*50	-0.024***	-0.028***	-0.019***	-0.024***	-0.017**	-0.021***	-0.055***
	(9.700)	(23.766)	(7.044)	(17.953)	(5.380)	(13.974)	(10.855)
*active*50_*L4* −*inactive*50	-0.004	-0.010**	-0.003	-0.008**	-0.004	-0.009**	-0.019*
	(0.533)	(6.284)	(0.359)	(4.092)	(0.565)	(4.706)	(3.140)
*active*50_*L5* −*inactive*50	-0.007*	-0.010***	-0.009***	-0.010***	-0.010***	-0.010***	-0.027***
	(3.609)	(12.647)	(7.325)	(13.003)	(7.576)	(12.946)	(13.780)
adj. R^2	0.426	0.387	0.437	0.397	0.450	0.413	0.488
N	778,240	778,240	778,240	778,240	778,240	778,240	775,361

Notes: Robust standard errors (clustered by the survey clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The region, country, year fixed effects, and control variables are included in all regressions, and their estimates are not reported here for brevity.

(2) Alternative weights

4. Stylized fact: Abuja-Kaduna railway project in Nigeria

Before the empirical analysis, we show the stylized facts of China's infrastructure projects on poverty reduction through a case study. We chose the Abuja-Kaduna railway project in Nigeria based on the following principles.[13] (1) The project cannot be located entirely in the capital cities or urban areas. It may lead to the overestimation of the economic and social outcomes. (2) A scattered distribution of a certain number of respondents near the project exists. The sampling method of the DHS database ensures that samples are randomly sampled according to population density and distribution. (3) There are respondents interviewed both earlier and later than the project's active, making it easier to compare the outcome changes.

The implementation of the Abuja-Kaduna railway began in February 2011 and promoted local employment, migration, and the flow of commodities during construction and operation. CCECC was in charge of mandating a ten-to-one ratio of local employees to Chinese workers, which favored hiring local workers in Nigeria (Chen, 2018). It has created 150,000 local jobs and trained more than 300 railway operators.[14] Since it was completed in 2014, the number of passengers choosing to travel by road has decreased from 1, 554,360 in 2015 to 52,503 in 2018 because of traffic safety and time costs.[15] On the contrary, the Abuja-Kaduna railway sent 733,400

[13] The Nigerian railway modernization project is the government's initiative to restore the railway network during the British colonial period. The Abuja-Kaduna Rail Line project, which is part of it, is the first overseas standard railway invested by the Chinese government, adopting China's first-class railway standards with standard gauges and a maximum 150 km per hour speed. In this project, the Export-Import Bank of China (China Eximbank) provided the Nigerian government with 500 million dollars preferential buyer's credit at an interest rate of 2.5% for 20 years, while the Nigerian government contributed 374 million dollars. The China Civil Engineering Construction Corporation (CCECC) was in charge of the project's construction, the procurement of building materials and workers, and the operations and maintenance of the line upon completion. This project is a single passenger and freight railway linking the Nigerian capital Abuja and the commercial center Kaduna. It is also a sea route for goods and products in northern Nigeria and the main transport route to extend its inland hinterland. The railway has 186.5 km, shortening the original six-hour travel time to about two hours, providing a faster, more comfortable, and safer driving environment than the existing narrow-gauge railways and roads. See the report from Railway Technology at https://www.railway-technology.com/projects/abuja-kaduna-rail-line/.

[14] See the Chinese CCTV report at http://news.cctv.com/2019/04/21/ARTIkKN6e17ejZ4NyS67zuU1190421.shtml?spm=C94212. PxBacx-QyDqwK.S95581.89.

[15] See Statistical Digest of Federal Road Safety Corps at https://frsc.gov.ng/statistical-digest/.

Table 5
Robustness to alternative weights.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	50% Health		50% Education		50% Living standard		PCA	
	Deprivation	Destitution	Deprivation	Destitution	Deprivation	Destitution	Deprivation	Destitution
Panel A: Regression results with lagged Chinese infrastructure projects								
*active*50_*L*1	-0.014**	-0.011**	-0.009	-0.006	-0.013**	-0.012**	-0.033**	-0.021**
	(0.006)	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)	(0.015)	(0.010)
*active*50_*L*2	-0.023***	-0.022***	-0.028***	-0.024***	-0.030***	-0.027***	-0.067***	-0.053***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.014)	(0.011)
*active*50_*L*3	-0.035***	-0.034***	-0.036***	-0.035***	-0.045***	-0.046***	-0.112***	-0.088***
	(0.006)	(0.005)	(0.007)	(0.005)	(0.008)	(0.006)	(0.018)	(0.012)
*active*50_*L*4	-0.018***	-0.018***	-0.022***	-0.021***	-0.028***	-0.028***	-0.067***	-0.053***
	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)	(0.011)	(0.007)
*active*50_*L*5	-0.025***	-0.021***	-0.029***	-0.023***	-0.034***	-0.030***	-0.082***	-0.058***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.004)
*inactive*50	-0.018***	-0.013***	-0.020***	-0.014***	-0.021***	-0.016***	-0.048***	-0.031***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.005)
Panel B: Spatial-temporal estimation results								
*active*50_*L*1 −*inactive*50	0.004	0.002	0.011*	0.008	0.008	0.004	0.015	0.010
	(0.399)	(0.245)	(3.271)	(2.271)	(1.314)	(0.582)	(0.868)	(0.850)
*active*50_*L*2 −*inactive*50	-0.005	-0.009*	-0.008	-0.010**	-0.009	-0.011*	-0.019	-0.022*
	(0.954)	(3.311)	(1.676)	(4.271)	(2.088)	(3.786)	(1.692)	(3.822)
*active*50_*L*3 −*inactive*50	-0.017***	-0.021***	-0.016**	-0.021***	-0.024***	-0.030***	-0.064***	-0.057***
	(6.831)	(15.960)	(4.640)	(15.607)	(9.516)	(20.563)	(11.862)	(20.294)
*active*50_*L*4 −*inactive*50	-0.000	-0.005	-0.002	-0.007*	-0.007	-0.012***	-0.019	-0.022***
	(0.000)	(1.519)	(0.150)	(3.448)	(1.669)	(7.098)	(2.585)	(7.083)
*active*50_*L*5 −*inactive*50	-0.007**	-0.008***	-0.009**	-0.009***	-0.013***	-0.014***	-0.034***	-0.027***
	(4.943)	(8.495)	(5.066)	(10.494)	(12.533)	(19.354)	(16.394)	(21.326)
adj. R^2	0.354	0.315	0.419	0.361	0.495	0.474	0.536	0.478
N	778,240	778,240	778,240	778,240	778,240	778,240	778,240	778,240

Notes: Robust standard errors (clustered by the survey clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The region, country, year fixed effects, and control variables are included in all regressions, and their estimates are not reported here for brevity.

passengers in 2018, an increase of about 128% over the previous year, with an average of 61,100 passengers per month and a maximum of 85,800 passengers per month, making it the first choice for residents of the two places.[16] In addition, it has led to a 35% increase in trade in goods and services and generated a monthly income of 300 million nairas for state finance.[17]

To test the poverty reduction effect of the Abuja-Kaduna railway project, Fig. 3 shows a schematic map of the railway from Abuja (the lower red circle) to Kaduna (the upper red circle). In addition to the departure and terminal station, most of the seven stops along the way are in rural areas. The figure on the right shows a buffer zone of 5 km along the railway (blue line) and the clusters (black dots) within this range. We found 259 respondents within the buffer zone, and the average deprivation score fell from 0.200 in year 2008 to 0.135 in year 2013. We conclude that the railway project promotes the development of central cities and has a positive economic impact on the vast rural areas along the route.

5. Results

5.1. Baseline result

Before reporting the results of benchmark regression, we examine how the poverty of groups 1 and 2 changes with the geographical distance from projects before and after the implementation. The sample is divided into active and inactive project groups by calculating the distance from the nearest project to the clusters and discerning whether the project is active. We then divide them into 100 groups according to the order of distance. The average poverty score in each group and the distance from the nearest projects are calculated to determine whether residents' multidimensional poverty degree changed with the distance from the projects.

As demonstrated in Fig. 4, the average level of deprivation and destitution gradually rises with increased distance, suggesting that Chinese infrastructure projects preference affluent areas, and the poverty level of the two groups shows a common trend. Moreover, the poverty of respondents in group 1 is always lower than the control group within 500 km for both deprivation and destitution, indicating that active projects have a significant effect on local poverty reduction compared with the residents located around projects in the pipeline. It is also notable that the results reveal an inverted U-shape in respondents' gaps. The divergence becomes larger as

16 See the Chinese government report at http://www.gov.cn/xinwen/2019–01/13/content_5357539.htm.
17 See the report at https://www.channelstv.com/2021/12/19/revenue-generation-abuja-kaduna-rail-line-makes-n300m-a-month-amaechi/.

Table 6
Robustness to the buffer zone.

	(1) 25 km	(2)	(3) 50 km	(4)
	Deprivation	Destitution	Deprivation	Destitution
Panel A: Regression results with lagged Chinese infrastructure projects				
active_L1	-0.019***	-0.015***	-0.012**	-0.010**
	(0.005)	(0.004)	(0.006)	(0.005)
active_L2	-0.028***	-0.024***	-0.027***	-0.024***
	(0.005)	(0.004)	(0.006)	(0.005)
active_L3	-0.035***	-0.026***	-0.039***	-0.038***
	(0.006)	(0.004)	(0.007)	(0.005)
active_L4	-0.032***	-0.022***	-0.023***	-0.022***
	(0.004)	(0.003)	(0.004)	(0.003)
active_L5	-0.030***	-0.023***	-0.029***	-0.024***
	(0.002)	(0.002)	(0.002)	(0.002)
inactive	-0.023***	-0.015***	-0.020***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)
Panel B: Spatial-temporal estimation results				
active_L1 −inactive	0.004	0.000	0.008	0.004
	(0.340)	(0.007)	(1.542)	(0.904)
active_L2 −inactive	-0.005	-0.009*	-0.007	-0.010**
	(1.005)	(3.351)	(1.639)	(3.974)
active_L3 −inactive	-0.012*	-0.011**	-0.019***	-0.024***
	(3.532)	(4.430)	(7.235)	(18.356)
active_L4 −inactive	-0.009*	-0.007*	-0.003	-0.008**
	(3.202)	(2.910)	(0.359)	(4.088)
active_L5 −inactive	-0.007*	-0.008**	-0.009***	-0.010***
	(3.326)	(5.492)	(7.635)	(13.516)
adj. R^2	0.438	0.398	0.438	0.398
N	778,240	778,240	778,240	778,240

Notes: Robust standard errors (clustered by the survey clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The region, country, year fixed effects, and control variables are included in all regressions, and their estimates are not reported here for brevity.

distance increases but diminishes when individuals live too far away from projects.[18]

We next conduct a regression based on the data of China's infrastructure projects from 2000 to 2014 and waves 4–7 waves of DHS information, presenting the benchmark regression results in Table 3, which indicate that Chinese infrastructure projects to SSA generally alleviate local deprivation (*active*50–*inactive*50 is significantly negative) and have a substantial effect on reducing destitution. This conclusion remains robust when controlling individual characteristics, geographical characteristics, and regional-, country-, and year-fixed effects.

Column (1) presents the benchmark regression results of model (1). The coefficient of *active*50 represents the difference in deprivation between individuals living around projects within 50 km and those living far away. The results show that implementing projects can reduce deprivation by 2.7%. At the same time, the coefficient of *inactive*50 is significantly negative, which must be interpreted very carefully. It indicates the presence of a corresponding improvement in deprivation among those living within 50 km around the projects in the pipeline in comparison to those far away from any projects. Its significance suggests that introducing region-, country-, and year-fixed effects into the model cannot control the non-randomness of the Chinese infrastructure project locations. The poverty reduction effects before the implementation might be due to other development resources or the resulting agglomeration effect leading to an early increase in job opportunities.

Therefore, only focusing on the significance of the *active*50 would lead to a misunderstanding. To avoid the sample self-selection problem, we use the F-test to determine whether there is a significant difference between β_1 and β_2 ($\beta_1 - \beta_2 = 0$). The results in Panel B indicate that the coefficient of (*active*50 −*inactive*50) is significantly negative, meaning that the projects' implementation helps reduce poverty within 50 km compared with the areas with projects in the pipeline.

Column (2) shows the dynamic regression result of model (2). Comparing the significance between the lag items of *active*50 and *inactive*50 reveals that projects already had a poverty reduction effect at the beginning of construction. Since changes in poverty

[18] The potential reasons that the gaps are small when individuals are close to projects could be: (a) The steep rise in poverty from 0 to 100 km is one of the reasons for the small visual difference between the two groups. The difference between the two groups remains within 20 km. Observing the sample within 50 km separately, we determined that the active project group is always below the inactive project group, indicating effectiveness in poverty mitigation (see Appendix Fig. A1). (b) The favoritism of Chinese projects toward affluent regions (Xu et al., 2016; Zhang et al., 2019) (see Appendix Fig. A2). For any group, distance is positively related to poverty in Fig. 4. Moreover, the poverty reduction effect in rich areas has thresholds, and Appendix Table A3 suggests that the marginal increment of poverty reduction in rich areas is smaller. (c) Measurement error. To protect respondents' privacy, DHS data applies a random position offset of up to10 km of the cluster locations. In addition, China's project data also contains measurement errors of up to 25 km. Therefore, focusing on the differences between the two groups within a small range will produce greater errors.

Table 7
Excluding outliers and African leader birth places.

	(1)	(2)	(3)	(4)	(5)	(6)
	Excluding outliers		Excluding ADM1		Excluding ADM2	
	Deprivation	Destitution	Deprivation	Destitution	Deprivation	Destitution
Panel A: Regression results with lagged Chinese infrastructure projects						
*active*50_*L*1	-0.012**	-0.010**	-0.015**	-0.013***	-0.011*	-0.009**
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
*active*50_*L*2	-0.028***	-0.025***	-0.030***	-0.027***	-0.028***	-0.025***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
*active*50_*L*3	-0.039***	-0.038***	-0.034***	-0.033***	-0.039***	-0.039***
	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)
*active*50_*L*4	-0.023***	-0.023***	-0.023***	-0.022***	-0.022***	-0.022***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
*active*50_*L*5	-0.028***	-0.024***	-0.030***	-0.024***	-0.028***	-0.024***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
*inactive*50	-0.020***	-0.014***	-0.022***	-0.015***	-0.020***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Panel B: Spatial-temporal estimation results						
*active*50_*L*1 −*inactive*50	0.008	0.004	0.007	0.002	0.009	0.005
	(1.352)	(0.784)	(1.164)	(0.298)	(1.821)	(0.958)
*active*50_*L*2 −*inactive*50	-0.008	-0.011**	-0.008	-0.012**	-0.008	-0.011**
	(1.858)	(4.216)	(1.568)	(4.524)	(1.957)	(4.468)
*active*50_*L*3 −*inactive*50	-0.019***	-0.024***	-0.012	-0.018***	-0.019***	-0.025***
	(7.137)	(18.317)	(2.554)	(9.447)	(7.285)	(18.639)
*active*50_*L*4 −*inactive*50	-0.003	-0.009**	-0.001	-0.007	-0.002	-0.008*
	(0.398)	(4.235)	(0.015)	(2.608)	(0.217)	(3.812)
*active*50_*L*5 −*inactive*50	-0.008**	-0.010***	-0.008**	-0.009***	-0.008**	-0.010***
	(6.638)	(12.366)	(4.599)	(9.580)	(5.790)	(11.825)
adj. R^2	0.434	0.395	0.432	0.394	0.432	0.393
N	767,169	767,169	700,843	700,843	749,711	749,711

Notes: Robust standard errors (clustered by the survey clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The region, country, year fixed effects, and control variables are included in all regressions, and their estimates are not reported here for brevity.

between different countries or regions may affect the location of Chinese projects,[19] we add region-, country-, and year-fixed effects in column (3). The result shows that the fixed effects do not affect the robustness of the baseline result. However, the poverty reduction effect did not appear until 2–3 years after the start of the projects. Since the average construction cycle was 1.384 years for projects' completion (the soonest is one year and the latest is 8 years), a certain lag in poverty reduction should be expected. It is also notable that the effect peaked in period 3, which might be due to an improvement in local non-agricultural employment.[20]

Columns (4), (5), and (6) give the impact on the local destitution and show that compared with the individuals living near the projects that have not yet started within 50 km, the destitution around the started projects has been significantly alleviated. From the results of columns (3) and (6), it can be found that the projects have a more significant effect on alleviating destitution than deprivation.

5.2. Robustness

5.2.1. Placebo tests

To show that other local development factors do not determine the causal effects of Chinese infrastructure projects and local poverty reduction, we randomly allocate the location of projects in SSA 500 times. Suppose the random selection of the projects' sites does not change the significance of the regression results. It indicates that the projects are not conducive to improving the poverty of the residents. If randomly located infrastructure projects do not significantly reduce poverty, other development sources are not the main factors that cause the local poverty reduction. In addition, to prove that the poverty reduction effect occurs after the start of the projects, rather than driven by the non-randomness of the location of the project, we randomly allocate the sequence of individuals' interview time and the projects' implementation time 500 times for those who live close to the projects.

The kernel density distributions of randomly simulated coefficients of model (1) are shown in Fig. 5. The actual coefficient of benchmark regression was − 0.007 and − 0.010, as shown above. The left figure shows that the coefficient of $\beta_1 - \beta_2$ of the random project address is not significantly different from "0", indicating that there is no significant difference between the regression coefficient β_1 and β_2, which means that the randomly located projects cannot significantly change the local poverty. Similarly, the right

[19] For example, China may tend to increase investment in poorer countries because governments' economic or financial conditions cannot meet OECD or the World Bank requirements.

[20] We explored the impact of China's infrastructure aid projects on non-agricultural employment. Appendix Table A4 shows that Chinese infrastructure aid can significantly improve local non-agricultural employment, with the effect peaking in the lag 3 period.

Table 8
Controlling other development projects.

	(1) Deprivation	(2) Destitution	(3) Deprivation	(4) Destitution
Panel A: Regression results with lagged Chinese infrastructure projects				
*active*50_*L*1	-0.011*	-0.009*	-0.010*	-0.008
	(0.006)	(0.005)	(0.006)	(0.005)
*active*50_*L*2	-0.025***	-0.022***	-0.026***	-0.023***
	(0.006)	(0.005)	(0.006)	(0.005)
*active*50_*L*3	-0.034***	-0.034***	-0.033***	-0.032***
	(0.007)	(0.005)	(0.007)	(0.005)
*active*50_*L*4	-0.019***	-0.019***	-0.018***	-0.018***
	(0.004)	(0.003)	(0.004)	(0.004)
*active*50_*L*5	-0.027***	-0.022***	-0.026***	-0.021***
	(0.002)	(0.002)	(0.002)	(0.002)
*inactive*50	-0.018***	-0.013***	-0.018***	-0.013***
	(0.003)	(0.003)	(0.003)	(0.003)
wbproject	-0.017***	-0.017***	-0.016***	-0.016***
	(0.002)	(0.002)	(0.002)	(0.002)
otherproject			-0.014***	-0.015***
			(0.003)	(0.002)
Panel B: Spatial-temporal estimation results				
*active*50_*L*1 −*inactive*50	0.007	0.004	0.008	0.005
	(1.373)	(0.744)	(1.601)	(0.969)
*active*50_*L*2 −*inactive*50	-0.007	-0.009*	-0.008	-0.010**
	(1.233)	(3.225)	(1.645)	(4.022)
*active*50_*L*3 −*inactive*50	-0.016**	-0.021***	-0.015**	-0.019***
	(5.286)	(14.403)	(4.380)	(12.454)
*active*50_*L*4 −*inactive*50	-0.001	-0.006	-0.000	-0.005
	(0.042)	(2.300)	(0.004)	(1.767)
*active*50_*L*5 −*inactive*50	-0.009**	-0.009***	-0.008**	-0.008***
	(6.298)	(11.255)	(4.907)	(8.829)
adj. R^2	0.438	0.399	0.438	0.400
N	778,240	778,240	778,240	778,240

Notes: Robust standard errors (clustered by the survey clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The region, country, year fixed effects, and control variables are included in all regressions, and their estimates are not reported here for brevity.

figure shows that the $\beta_1 - \beta_2$ after the randomization of interview time is also close to 0. Thus, the original hypothesis of $\beta_1 - \beta_2$ cannot be rejected, indicating that the randomly generated individuals' interview time does not affect local poverty reduction. The results reflect that the actual Chinese infrastructure projects and their implementation can reduce local poverty and eliminate the interference of other regional development resources on the robustness of the benchmark regression results.

5.2.2. Robustness to MPI

(1) Alternative cut-offs

The altering of cut-offs may impact our empirical results. Thus, we attempt to test the robustness by changing the cut-offs of some key indicators.[21] In addition, to avoid the subjectivity of indicator selection, we introduce the scoring method similar to the construction of WI in DHS datasets, and the assigned values to the items and give corresponding scores to indicators to represent the deprivation degree of each household. Same with the hypothesis of WI, we argue that members have the same degree of poverty in one household. See Table A5 for detailed indicators and scores.

The result is shown in Table 4. Columns (1)-(6) are the results under the composition of altered indicators or more stringent poverty cut-offs. The significance of the difference between lagged *active*50 and *inactive*50 showed that the selection of MPI composition indicators or the changes of cut-offs does not affect the robustness of its poverty reduction effect. Column (7) gives the regression results of the scoring method. The coefficient in Panel B is significantly larger than that of the benchmark regression in magnitude, indicating that the regression result of the poverty threshold dichotomy is more conservative than the scoring method.

To test the robustness of the benchmark regression within a specific range of weights, we adopt the method of alternately assigning

[21] Referencing Alkire and Santos (2014), we exclude child attendance to school and only consider the year of schooling. With regards to health, the previous practice covered three types of situations in which a household was not deprived: (1) no children died, (2) children died but more than five years from the survey, and (3) household members aged more than 18 and died within five years. We now exclude the third hypothetical condition to get stricter restrictions and define that a household is deprived of mortality when members die within five years before the survey without limiting the age of under 18. In terms of living standards, stricter thresholds are adopted for household water use (the need for pipe water), sanitation (the need for flushing toilets), and floor materials (households with palm, bamboo, and wood floors are considered to be deprived).

Table 9
Dimensional analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
	Deprivation			Destitution		
	Health	Education	Living standard	Health	Education	Living standard
Panel A: Regression results with lagged Chinese infrastructure projects						
*active*50_*L1*	-0.020***	0.001	-0.017*	-0.014***	0.004	-0.019**
	(0.007)	(0.008)	(0.010)	(0.005)	(0.007)	(0.008)
*active*50_*L2*	-0.011*	-0.031***	-0.039***	-0.013***	-0.024***	-0.036***
	(0.006)	(0.007)	(0.009)	(0.005)	(0.006)	(0.008)
*active*50_*L3*	-0.023***	-0.027***	-0.066***	-0.021***	-0.024***	-0.071***
	(0.006)	(0.009)	(0.011)	(0.005)	(0.006)	(0.010)
*active*50_*L4*	-0.003	-0.022***	-0.043***	-0.004	-0.018***	-0.045***
	(0.005)	(0.007)	(0.007)	(0.004)	(0.005)	(0.006)
*active*50_*L5*	-0.012***	-0.027***	-0.049***	-0.009***	-0.018***	-0.047***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)
*inactive*50	-0.012***	-0.022***	-0.025***	-0.009***	-0.012***	-0.022***
	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)
Panel B: Spatial-temporal estimation results						
*active*50_*L1* −*inactive*50	-0.008	0.023***	0.008	-0.005	0.016**	0.003
	(1.445)	(7.134)	(0.659)	(0.727)	(5.463)	(0.123)
*active*50_*L2* −*inactive*50	0.001	-0.009	-0.014	-0.004	-0.012*	-0.014
	(0.017)	(1.254)	(2.462)	(0.603)	(3.468)	(2.690)
*active*50_*L3* −*inactive*50	-0.011*	-0.005	-0.041***	-0.012**	-0.012*	-0.049***
	(2.992)	(0.286)	(11.949)	(4.473)	(3.578)	(20.655)
*active*50_*L4* −*inactive*50	0.009*	-0.000	-0.018**	0.005	-0.006	-0.023***
	(2.800)	(0.007)	(5.779)	(1.488)	(1.241)	(11.364)
*active*50_*L5* −*inactive*50	0.000	-0.005	-0.024***	0.000	-0.006	-0.025***
	(0.000)	(0.768)	(20.199)	(0.012)	(2.338)	(25.322)
adj. R^2	0.109	0.321	0.516	0.096	0.229	0.525
N	778,240	778,240	778,240	778,240	778,240	778,240

Notes: Robust standard errors (clustered by the survey clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The region, country, year fixed effects, and control variables are included in all regressions, and their estimates are not reported here for brevity.

50% weight to health, education, and living standards and 25% to the other two.[22] In addition, we use principal component analysis for cross-testing to avoid the arbitrariness of subjective weighting. Table 5 shows that the difference between lagged *active*50 and *inactive*50 coefficients obtained by dimension alternating weighting and principal component analysis are significantly negative, and the coefficients in Panel B of column (7) (8) are considerably more significant than those of benchmark regression and columns (1)-(6). It still reflects that the benchmark regression results are robust and conservative.

5.2.3. Robustness to buffer zones

The empirical analysis uses the buffer zone to determine the sample size and individuals' characteristics. Hence, it is necessary to test the robustness of alternative buffer zones. Although we have previously explained the rationality of choosing 50 km as the buffer zone in the benchmark regression, we still adjust the size to 25 km. Table 6 shows that the benchmark regression maintains good robustness under 25 km. However, the magnitudes and significance of the coefficients in Panel B under 25 km are smaller than those under 50 km but are still significantly negative, indicating that Chinese infrastructure projects may benefit poverty reduction in a broader range. It might be because we cannot precisely capture the full effects when the buffer zone is too small, as described above. Nevertheless, we still use 50 km as a buffer zone in the benchmark regression to ensure the accurate capture of projects.

5.2.4. Excluding outliers and African leader birth regions

Chinese infrastructure projects may be excessively distributed in some areas with extraordinary resources, resulting in biases in the benchmark regression. We find that the number of projects around respondents shows uneven distribution through the statistical analysis. The average number of projects around the respondents is 9.246, and the standard deviation is 10.051. Thus, we exclude the sample out of the 95th quartile and find that 11,071 individuals have 30 projects within 50 km, accounting for 4.210% of the total sample. The regression results are shown in Table 7. The difference between lagged *active*50 and *inactive*50 in columns (1) and (2) is significantly negative, indicating that the poverty reduction effect still exists after excluding outliers.

In addition, as the "on-demand" projects are vulnerable to being captured by recipients' politics, the birthplaces of African leaders are more likely to be the areas with access to external development resources (Dreher et al., 2019). After matching whether the projects

[22] In model (1), the weight of health is 50%, education is 25%, and living standards is 25%, whose weight is 4.16% for each indicator. In model (2), the weight of health is 25%, education is 50%, and living standards is 25%, whose weight is 4.16% for each indicator. In model (3), the weight of health is 25%, education is 25%, and living standards is 50%, whose weight is 4.16% for each indicator. Model (4) is the weight determined by principal component analysis.

Table 10
Mechanism analysis.

	(1) Deprivation	(2) Industry	(3) Employment stability	(4) Deprivation
Panel A: Regression results with lagged Chinese infrastructure projects				
*active*50_*L*1	-0.012**	0.049	0.028*	-0.003
	(0.006)	(0.090)	(0.015)	(0.006)
*active*50_*L*2	-0.027***	0.787***	0.053***	-0.020***
	(0.006)	(0.094)	(0.013)	(0.006)
*active*50_*L*3	-0.039***	0.355***	0.028	-0.033***
	(0.007)	(0.122)	(0.017)	(0.007)
*active*50_*L*4	-0.023***	0.550***	0.016	-0.016***
	(0.004)	(0.066)	(0.013)	(0.005)
*active*50_*L*5	-0.029***	0.813***	0.011*	-0.024***
	(0.002)	(0.047)	(0.006)	(0.002)
*inactive*50	-0.020***	0.554***	-0.009	-0.015***
	(0.003)	(0.042)	(0.008)	(0.003)
industry			0.006***	-0.005***
			(0.001)	(0.000)
emplsta				-0.020***
				(0.001)
Panel B: Spatial-temporal estimation results				
*active*50_*L*1 −*inactive*50	0.008	-0.505***	0.037*	0.012
	(1.542)	(28.374)	(5.214)	(2.704)
*active*50_*L*2 −*inactive*50	-0.007	0.233**	0.062***	-0.005
	(1.639)	(5.756)	(19.617)	(0.757)
*active*50_*L*3 −*inactive*50	-0.019***	-0.199	0.037*	-0.018**
	(7.235)	(2.400)	(4.105)	(6.219)
*active*50_*L*4 −*inactive*50	-0.003	-0.004	0.025*	-0.001
	(0.359)	(0.002)	(3.340)	(0.092)
*active*50_*L*5 −*inactive*50	-0.009***	0.259***	0.020**	-0.009**
	(7.635)	(20.685)	(5.262)	(6.468)
adj. R^2	0.438	0.671	0.149	0.432
N	778,240	778,240	521,333	521,333

Notes: Robust standard errors (clustered by the survey clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The region, country, year fixed effects, and control variables are included in all regressions, and their estimates are not reported here for brevity.

were implemented in the leader's birthplaces during their term of office, we find that there were 199 projects in first-level administrative regions (ADM1), accounting for 12.261% of the sample, and 72 in second-level administrative regions (ADM2), accounting for 4.436%. We exclude the projects located in the African leaders' birthplaces in ADM1 and ADM2 regions during their tenures.[23] The regression results are shown in columns (3) (4) and (5) (6) of Table 7, respectively. The results show that the difference between lagged *active*50 and *inactive*50 is still significantly negative, indicating that excluding the birthplace of African leaders does not affect the robustness of the regression results.

5.2.5. Control other development projects

We control projects from World Bank in 2000–2014, from the African Development Bank in 2009–2010, from the United States, the United Kingdom, Canada, Australia, Japan, and the European Union during 2000–2014 to Burundi, Sierra Leone, DRC, Nigeria, Senegal, Uganda, and Somalia, as well as to Malawi in 2000–2011, and the Central African Republic in 2013. Columns (1) and (2) in Table 8 list the regression results after controlling the active World Bank projects, and columns (3) and (4) report the results of controlling both active World Bank projects and other projects. The results show that implementing World Bank and other projects negatively correlates with local poverty. The difference between lagged *active*50 and *inactive*50 in all columns is still significantly negative, proving the robustness of the benchmark regression results after controlling other multi-bilateral projects.

6. Mechanism analysis

6.1. Dimensional analysis

To explore the mechanisms of infrastructure projects, we regress on the three dimensions of the MPI. Columns (1) and (4) and (2) and (5) in Table 9 show the deprivation and destitution results for health and education, respectively. The difference between lagged 2 or 3 terms of *active*50 and *inactive*50 is significant, indicating that the poverty reduction effect is only evident in the second or third year after implementation. Columns (3) and (6) are the results on living standards, revealing that significant differences between lagged

[23] Data on the tenure and birthplace of African leaders come from Dreher, A., Fuchs, A., Hodler, R., Parks, B. C., Raschky, P. A., & Tierney, M. J. (2019). African leaders and the geography of China's foreign assistance. *Journal of Development Economics, 140*, 44–71.

Table 11
Poverty reduction effectiveness in aid-dependence and self-dependence recipients.

	(1)	(2)	(3)	(4)
	Deprivation		Destitution	
	Aid-dependent	Self-dependent	Aid-dependent	Self-dependent
Panel A: Regression results with lagged Chinese infrastructure projects				
*active*50_*L1*	-0.007	-0.012	-0.009	-0.007
	(0.009)	(0.008)	(0.007)	(0.007)
*active*50_*L2*	-0.016**	-0.032***	-0.013**	-0.028***
	(0.008)	(0.007)	(0.006)	(0.006)
*active*50_*L3*	-0.013	-0.044***	-0.007	-0.047***
	(0.009)	(0.009)	(0.007)	(0.007)
*active*50_*L4*	-0.019***	-0.024***	-0.020***	-0.018***
	(0.006)	(0.006)	(0.005)	(0.005)
*active*50_*L5*	-0.025***	-0.029***	-0.020***	-0.026***
	(0.003)	(0.003)	(0.002)	(0.003)
*inactive*50	-0.023***	-0.017***	-0.019***	-0.012***
	(0.005)	(0.004)	(0.004)	(0.003)
Panel B: Spatial-temporal estimation results				
*active*50_*L1* −*inactive*50	0.016	0.005	0.010	0.005
	(2.423)	(0.405)	(1.533)	(0.468)
*active*50_*L2* −*inactive*50	0.007	-0.015**	0.006	-0.016**
	(0.692)	(4.128)	(0.779)	(6.090)
*active*50_*L3* −*inactive*50	0.010	-0.027***	0.012	-0.035***
	(0.958)	(8.611)	(2.339)	(24.057)
*active*50_*L4* −*inactive*50	0.004	-0.007	-0.001	-0.006
	(0.260)	(0.910)	(0.024)	(1.301)
*active*50_*L5* −*inactive*50	-0.002	-0.012***	0.000	-0.014***
	(0.166)	(6.835)	(0.033)	(16.039)
adj. R^2	0.405	0.453	0.374	0.420
N	375,944	402,296	375,944	402,296

Notes: Robust standard errors (clustered by the survey clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The region, country, year fixed effects, and control variables are included in all regressions, and their estimates are not reported here for brevity.

*active*50 and *inactive*50 are evident in the third year. Therefore, we conclude that China's infrastructure projects in SSA have a short-term effect on health and education, and poverty reduction is primarily achieved by improving individual living standards, which seems reasonable. China's infrastructure projects directly affect local mortality and education through the provision of water supplies and medical equipment; however, such projects face high maintenance costs and require further investments. Examining a large water project in Kenya, Miguel and Gugerty (2005) found that 43% of borehole wells were abandoned after being transferred from donors to local maintenance committees. It is extremely challenging to promote the sustainable provision of local public goods through external intervention. Improved living standards may increase household assets by raising the local employment rate and providing stable income sources for local respondents. Thus, we further explore whether China's infrastructure projects can reduce poverty by improving the development of industrialization and individual employment stability.

6.2. Industrialization and employment stability

To further explore the mechanisms of infrastructure projects on poverty reduction, we introduce two variables, industrialization (*industry*) and employment stability (*emplsta*). Stepwise regressions employ the following models. First, model (3) regresses the basic independent variables on the dependent variable to reflect the total effect of local poverty reduction. Second, models (4) and (5) regress the independent variables on *industry* and *emplsta* to analyze the promotional impact on industrialization and employment stability, respectively. Finally, model (6) regresses the benchmark independent and intermediary variables simultaneously on the dependent variable to reveal the relationship between industrialization, employment stability, and poverty. Industrialization (*industry*) is measured by the number of factories and enterprises within 50 km of the community,[24] and employment stability is measured by whether respondents' occupation is year-round, quarterly, occasional, or temporary.[25]

$$Y_{i,v,t} = \beta_\tau \cdot \sum_{\tau=1}^{T} active_{i,v,t-\tau} + \beta_{T+1} \cdot active_{i,v,t-(T+1)} + \beta_2 \cdot inactive_{i,v,t} + \alpha \cdot X_{i,v,t} + \gamma \cdot Z_v + \varphi_s + \rho_c + \delta_t + \varepsilon_{i,v,t} \tag{3}$$

[24] Data on the number of industrial enterprises are obtained from the Industrial Atlas of Africa at https://www.industryabout.com/new-africa-industrial-map.
[25] The data on respondents' occupation duration are obtained from the standard DHS database.

Table 12
Poverty reduction effectiveness in rural and urban areas.

	(1)	(2)	(3)	(4)
	Deprivation		Destitution	
	Rural	Urban	Rural	Urban
Panel A: Regression results with lagged Chinese infrastructure projects				
*active*50_*L*1	0.002	-0.033***	-0.003	-0.022***
	(0.006)	(0.010)	(0.006)	(0.007)
*active*50_*L*2	-0.013**	-0.022***	-0.014**	-0.017***
	(0.006)	(0.008)	(0.006)	(0.006)
*active*50_*L*3	-0.033***	-0.049***	-0.030***	-0.044***
	(0.008)	(0.010)	(0.007)	(0.008)
*active*50_*L*4	-0.016***	-0.016**	-0.018***	-0.012**
	(0.005)	(0.007)	(0.005)	(0.005)
*active*50_*L*5	-0.021***	-0.028***	-0.019***	-0.021***
	(0.003)	(0.004)	(0.002)	(0.003)
*inactive*50	-0.012***	-0.023***	-0.009***	-0.017***
	(0.004)	(0.006)	(0.003)	(0.004)
Panel B: Spatial-temporal estimation results				
*active*50_*L*1 −*inactive*50	0.014**	-0.010	0.006	-0.005
	(3.959)	(0.872)	(1.075)	(0.492)
*active*50_*L*2 −*inactive*50	-0.001	0.001	-0.005	0.000
	(0.025)	(0.016)	(0.610)	(0.012)
*active*50_*L*3 −*inactive*50	-0.021**	-0.026**	-0.021***	-0.027***
	(5.787)	(5.173)	(8.488)	(9.608)
*active*50_*L*4 −*inactive*50	-0.004	0.007	-0.009*	0.005
	(0.533)	(0.771)	(3.090)	(0.628)
*active*50_*L*5 −*inactive*50	-0.009**	-0.005	-0.010***	-0.004
	(5.459)	(0.656)	(8.417)	(0.883)
adj. R^2	0.313	0.277	0.278	0.266
N	491,780	286,460	491,780	286,460

Notes: Robust standard errors (clustered by the survey clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The region, country, year fixed effects, and control variables are included in all regressions, and their estimates are not reported here for brevity.

$$industry_{i,v,t} = \pi_\tau \cdot \sum_{\tau=1}^{T} active_{i,v,t-\tau} + \pi_{T+1} \cdot active_{i,v,t-(T+1)} + \pi_2 \cdot inactive_{i,v,t} + \alpha \cdot X_{i,v,t} + \gamma \cdot Z_v + \varphi_s + \rho_c + \delta_t + \varepsilon_{i,v,t} \tag{4}$$

$$worsta_{i,v,t} = \partial_\tau \cdot \sum_{\tau=1}^{T} active_{i,v,t-\tau} + \partial_{T+1} \cdot active_{i,v,t-(T+1)} + \tau_2 \cdot inactive_{i,v,t} + \tau_3 \cdot industry_{i,v,t} + \alpha \cdot X_{i,v,t} + \gamma \cdot Z_v + \varphi_s + \rho_c + \delta_t + \varepsilon_{i,v,t} \tag{5}$$

$$Y_{i,v,t} = \theta_1 \cdot \sum_{\tau=1}^{T} active_{i,v,t-\tau} + \theta_{T+1} \cdot active_{i,v,t-(T+1)} + \theta_2 \cdot inactive_{i,v,t} + \theta_3 \cdot industry_{i,v,t} + \theta_4 \cdot worsta_{i,v,t} + \alpha \cdot X_{i,v,t} + \gamma \cdot Z_v + \varphi_s + \rho_c + \delta_t + \varepsilon_{i,v,t} \tag{6}$$

The results are presented in Table 10, where columns (1)–(4) correspond to models (3)–(6), respectively. Column (1) shows the benchmark regression results of the poverty reduction effect of infrastructure projects. A significant difference between lagged *active*50 and *inactive*50 appears in column (2) 5 years after project implementation, indicating that the number of factories and enterprises only increases when the infrastructure construction is relatively completed. Column (3) shows a significant difference between lagged *active*50 and *inactive*50 from the second year, indicating that infrastructure projects increase local employment stability. Moreover, the *industry* coefficient is significantly positive, indicating that the increase in industrial enterprises has improved employment stability. Column (4) demonstrates that the coefficients of *industry* and *emplsta* are significantly negative, indicating that improving industrialization and employment stability is conducive to poverty reduction. Hence, we conclude that China's infrastructure projects can reduce poverty by promoting the development of local industrialization and individual employment stability.

Table 13
Poverty reduction effectiveness of Chinese infrastructure projects by state-owned and private agencies.

	(1)	(2)	(3)	(4)
	Deprivation		Destitution	
	State sector	Private sector	State sector	Private sector
Panel A: Regression results with lagged Chinese infrastructure projects				
*active*50_*L*1	-0.007	-0.016	0.003	-0.011
	(0.012)	(0.013)	(0.009)	(0.009)
*active*50_*L*2	-0.029***	-0.003	-0.027***	-0.009
	(0.008)	(0.012)	(0.008)	(0.009)
*active*50_*L*3	-0.047***	0.017	-0.045***	0.017
	(0.009)	(0.023)	(0.007)	(0.018)
*active*50_*L*4	-0.030***	-0.014	-0.029***	-0.022**
	(0.007)	(0.012)	(0.005)	(0.009)
*active*50_*L*5	-0.038***	-0.004	-0.032***	-0.005
	(0.004)	(0.007)	(0.003)	(0.005)
*inactive*50	-0.022***	-0.005	-0.014***	-0.006
	(0.006)	(0.009)	(0.005)	(0.007)
Panel B: Spatial-temporal estimation results				
*active*50_*L*1 −*inactive*50	0.015	-0.011	0.017*	-0.005
	(1.473)	(0.665)	(3.004)	(0.214)
*active*50_*L*2 −*inactive*50	-0.007	0.002	-0.013	-0.003
	(0.619)	(0.028)	(2.060)	(0.047)
*active*50_*L*3 −*inactive*50	-0.025**	0.022	-0.031***	0.023
	(6.573)	(0.836)	(13.798)	(1.648)
*active*50_*L*4 −*inactive*50	-0.008	-0.009	-0.015**	-0.016
	(0.900)	(0.493)	(5.309)	(2.207)
*active*50_*L*5 −*inactive*50	-0.016***	0.001	-0.018***	0.001
	(6.795)	(0.014)	(12.923)	(0.044)
adj. R^2	0.424	0.481	0.398	0.438
N	317,981	72,101	317,981	72,101

Notes: Robust standard errors (clustered by the survey clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The region, country, year fixed effects, and control variables are included in all regressions, and their estimates are not reported here for brevity.

7. Extensions

7.1. Aid-dependence and self-dependence

SSA has attracted a large number of aid investments since the 1960s. Most of the recipients' public finance cannot be sustained without continuous inflows of foreign aid. In 1965, 15 African countries had an ODA-GNI ratio of more than 10%; the number was 29 in 2012.[26] Countries long heavily dependent on aid have reached a considerable number. The loss of viability caused by aid addiction may impact the country's macroeconomic stability, economic and social development, infrastructure availability, and investment environment quality. Hence, we use whether the average ODA-GNI ratio of 31 African countries from 1960 to 2010 is lower than the sample's median to determine whether the country is self-dependent and divide the sample into aid-dependent and self-dependent countries.[27]

Columns (1) and (3) in Table 11 report the poverty reduction effects of aid projects in aid-dependent countries, and columns (2) and (4) on the effects in self-dependent countries. The results in Panel A show that the lag terms of *active*50 in columns (1) and (3) are significant, indicating that the poverty in the project sites is relatively low after several years. However, the coefficient of *inactive*50 was also significantly negative, and the lag terms of *active*50 were not significantly different from that of *inactive*50 in Panel B. It indicates that the projects' location may be in affluent areas of these countries, and the projects' implementation is not the main reason for improving poverty in aid-dependent countries. On the contrary, the results in columns (2) and (4) show that the differences between *active*50 lags and *inactive*50 are significantly negative after 2, 3, and 5 years, indicating that aid programs can significantly improve local poverty in self-dependent countries. Thus, we argue that only if SSA countries have found ways to develop can they effectively utilize foreign investment for poverty reduction.

7.2. Rural and urban areas

We divide the individuals having projects into urban and rural areas and compare the significance of *active*50 lag terms and *inactive*50 in Table 12. It is found that China infrastructure projects can effectively alleviate poverty in rural areas, but it is only significant in the third phase and does not exist for the long term in urban areas. Considering areas may be suitable for different types,

[26] Source: World Bank statistics.
[27] For data related to classification standards, see Lin and Monga (2017). Beating the odds: Princeton University Press.

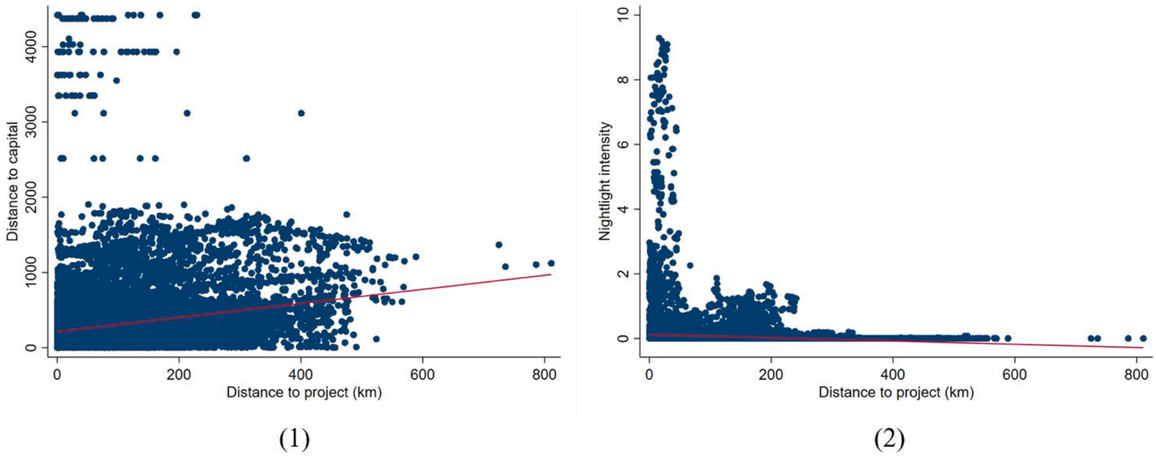


Fig. A1. Distance to capital, nightlight intensity, and distance to project.

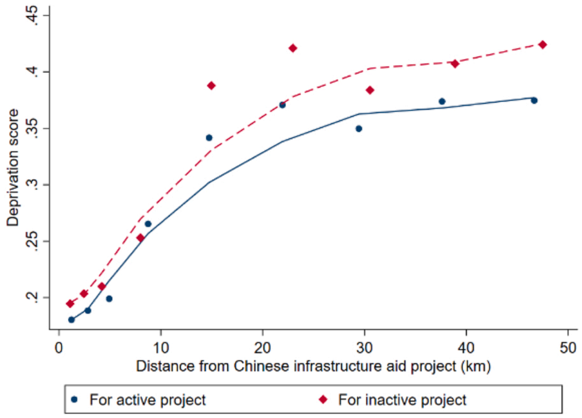


Fig. A2. Distance to nearest projects within 50 km and poverty.

we find no significant difference in the project types between urban and rural areas, mainly transport and storage projects. However, urban respondents have significantly higher scores than rural ones in education, occupation, and household wealth,[28] and urban areas' initial economic development conditions are significantly superior.[29] It indicates that the heterogeneity is not caused by types but by the specificities of the samples and regions so that the elasticity in the areas with higher initial development basics is smaller than that in the backward areas. This conclusion is consistent with Briggs (2021), suggesting that projects can play a more significant role in poorer areas. Meanwhile, it also supports the "diminishing marginal effects" of infrastructure projects. Therefore, for the vast rural areas where development resources are scarce (the rural sample accounts for 66.420%, about 1.980 times that of the urban sample), Chinese infrastructure projects are more crucial to local poverty reduction.

7.3. State-owned and private agency

Due to the heterogeneous performance of state-owned and private agencies,[30] we analyze whether there is any difference in poverty reduction effects between the two agencies. According to the keyword "implementing agency" in the database, all projects except missing values are divided into the state sector and the private sector according to whether they are "state-owned" or

[28] The average education level, occupation, and household wealth of rural residents were 0.301, 4.620, and 2.375, respectively, while those of urban residents were 0.435, 5.125, and 4.037, respectively.

[29] The average value of initial economic development level in rural areas is 0.023, the average distance from water sources is 1.100, and the average value of mineral resources is 0.233, while in urban areas, the average values are 0.142, 9.800, and 0.325, respectively.

[30] Malik et al. (2021) argued that 35% of the Belt and Road Initiative (BRI) infrastructure projects have experienced corruption scandals, labor violations, environmental hazards, and public protests, but infrastructure projects undertaken by the governments have encountered fewer implementation problems.

Table A1
Sample descriptions.

Country	Wave	Observation	Country	Wave	Observation
Angola	7	6,749	Madagascar	5	16,029
Benin	4, 6, 7	26,151	Malawi	4, 7	32,965
Burkina Faso	4, 6	17,697	Mali	5, 6, 7	29,458
Burundi	6, 7	23,831	Mozambique	6	17,199
Cameroon	4, 6, 7	22,436	Namibia	4, 5, 6	28,740
Comoros	6	6,556	Nigeria	4, 5, 6, 7	88,656
Congo, DR	5, 6	15,998	Rwanda	5, 6, 7	50,717
Cote d'Ivoire	6	8,174	Senegal	6, 7	49,778
Eswatini	5	8,508	Sierra Leone	5, 6, 7	35,013
Ethiopia	4, 6, 7	60,991	South Africa	7	4,540
Gabon	6	10,358	Tanzania	4, 7	12,105
Ghana	4, 5	14,352	Togo	6	8,865
Guinea	6, 7	17,168	Uganda	4, 5, 6, 7	16,709
Kenya	4, 5	13,736	Zambia	5, 6, 7	64,387
Lesotho	4, 6	4,643	Zimbabwe	4, 5, 6, 7	49,889
Liberia	6, 7	15,842			

"government agency". 577 (39.278%) were state-owned projects of the 1469 project sites, and private agencies undertook 148 (10.075%).

Table 13 reports that only the differences between lagged *active*50 and *inactive*50 in columns (1) and (3) are significantly negative from the third year, indicating that compared with the projects implemented by private agencies, the poverty reduction effect undertaken by state-owned enterprises and the government is more significant. It might be because projects undertaken by the private agencies may face greater external incentives to pursue profits or subject to their financial constraints, the scales of the projects are smaller than those of state-owned agencies (the average amount undertaken by state-owned agencies is 4.383 billion USD, while that of the private agencies is 1.444 billion USD). Private projects are also more likely to be interrupted, resulting in less effective poverty reduction than those undertaken by state-owned enterprises and governments.

8. Conclusion

China's infrastructure investments in developing countries have recently been rising, providing opportunities to break development bottlenecks. Abundant empirical research has examined the impact of Chinese projects on recipient countries (Dreher et al., 2016, 2019; Eichenauer et al., 2021; Isaksson & Kotsadam, 2018). However, considering the severe poverty faced by SSA and the 2030 MDGs, the effects and mechanisms of Chinese infrastructure projects on local multidimensional poverty must be further investigated.

This study first provides evidence of Chinese infrastructure projects' dynamic impact on local multidimensional poverty in 31 SSA countries from a micro perspective, remedying the spatial mismatch caused by uneven distribution at the national level. Our study combines geo-coded Chinese infrastructure projects from 2000 to 2014 and information from DHS waves 4–7, applying a spatio-temporal estimation strategy to compare the difference between respondents living within 50 km near projects and those living within 50 km of a project that had not been started at the time of the survey, which solves the endogenous problem to a certain extent. The results indicate that Chinese infrastructure projects generally alleviate the local multidimensional poverty within 50 km, although this effect does not appear until 3 years following implementation. This conclusion remains robust after changing the index definition and weights, buffer zone, and randomly assigning project locations or survey time.

Exploring the mechanisms of infrastructure projects for poverty reduction, we determine that it is mainly achieved through improvement in living standards, while improvement in health and education is only effective in the short term 2–3 years after implementation. Furthermore, we find that promoting local industrialization and respondents' work stability is the key to improving living standards and reducing poverty. Infrastructure projects can influence both supply and demand sides in the non-agricultural labor market, wherein people become motivated to choose non-agricultural jobs with higher incomes, and more non-agricultural employment opportunities are provided for residents by promoting the development of local factories and enterprises, which improves employment stability and reducing poverty.

Table A2
Variable descriptions.

Variable	Description	Source
Individual-level controls	See Section 2.3.	Standard DHS data.
lansuit	Use the raster data with 0.5 precision introduced by Ramankutty et al. (2002), and calculate the average for the applicability of agricultural land in the 50 km buffer zone of the cluster.	Center for Sustainability and the Global Environment: https://sage.nelson.wisc.edu/data-and-models/atlas-of-the-biosphere/?datasetid= 19andincluderelatedlinks= 1anddataset= 19.
ethdiversity	Calculate the proportion sum of ethnicities in the 50 km buffer zone of the clusters.	ETH Zurich database: https://icr.ethz.ch/data/greg/.
mineral	Calculate the number of precious metals, industrial minerals (copper, lead, iron, etc.) and diamond deposits in the 50 km buffer zone of the cluster to generate virtual variables of oil or gas within the sample range.	USGS database: https://mrdata.usgs.gov/major-deposits/; PRIO database: https://www.prio.org/data/geographical-and-resource-datasets/petroleum-dataset/.
conflict	Calculate the number of 1989–1999 conflict events in the 50 km buffer zone of the clusters.	UCDP database: https://ucdp.uu.se/downloads/indicator.html#ged_global.
nightlight	Since that DMSP-OLS light data can only observe night lights from 1992 to 2013, and there are some problems such as lack of in-orbit radiation calibration and saturation, NPP-VIIRS-NTL data has high resolution and efficient detection ability, but the period is short, so Chen et al. (2021) is adopted. It provides NPP-VIIRS-like night light intensity within the cluster 50 km buffers.	Earth System Science Data: https://doi.org/10.5194/essd-13–889–2021.
Pre-determinators	The distance to national boundaries, water bodies and protected areas, the time to the nearest city, and population density.	Standard DHS data.

Table A3
Chinese infrastructure investment effectiveness in poverty reduction and nightlight.

	(1)	(2)
	Deprivation	Destitution
*active*50	-0.026***	-0.023***
	(0.002)	(0.002)
*active*50 ×*nightlight*	0.042***	0.034***
	(0.008)	(0.006)
nightlight	-0.057***	-0.046***
	(0.007)	(0.006)
region FE	Y	Y
country FE	Y	Y
year FE	Y	Y
adj. R^2	0.437	0.398
N	778,240	778,240

Notes: Robust standard errors (clustered by the survey clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The region, country, year fixed effects, and control variables are included in all regressions, and their estimates are not reported here for brevity.

Table A4
Chinese infrastructure investment and non-agricultural employment.

Dependent variable: *non-agricultural employment*	(1)	(2)
Panel A: Regression results with lagged Chinese infrastructure projects		
*active*50	0.036***	
	(0.004)	
*active*50_*L*1		0.036***
		(0.012)
*active*50_*L*2		0.035***
		(0.010)
*active*50_*L*3		0.041***
		(0.014)
*active*50_*L*4		0.013
		(0.009)
*active*50_*L*5		0.039***
		(0.004)
*inactive*50	0.012**	0.011**
	(0.005)	(0.005)
Panel B: Spatial-temporal estimation results		
*active*50 −*inactive*50	0.024***	
	(16.500)	
*active*50_*L*1 −*inactive*50		0.025*
		(3.721)
*active*50_*L*2 −*inactive*50		0.024**
		(5.061)
*active*50_*L*3 −*inactive*50		0.030**
		(4.425)
*active*50_*L*4 −*inactive*50		0.002
		(0.028)
*active*50_*L*5 −*inactive*50		0.028***
		(19.584)
adj. R^2	0.340	0.340
N	778,240	778,240

Notes: Robust standard errors (clustered by the survey clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The region, country, year fixed effects, and control variables are included in all regressions, and their estimates are not reported here for brevity.

Table A5
Items and scores.

Indicator	(Score) Item
Education	(3) No Education/ Preschool; (2) Primary; (1) Secondary; (0) Higher
School Attendance	(2) Any school-aged child is not attending school up to class 6; (1) Any school-aged child is not attending school up to class 8; (0) Other
Child Mortality	Sum of deaths of children under 18 in the past five years till the interview.
Nutrition	Nourishment for children (Karlsson et al., 2020): (2) Severely malnourished children; (1) Children who are malnourished but not severely malnourished at home; (0) Other
	Nourishment for adults (BMI): (2) Severely malnourished adults; (1) Adults who are malnourished but not severely malnourished at home; (0) Other
Electricity	(1) No; (0) Yes
Sanitation	(4) Composting toilet; (3) No facility; (2) Pit Toilet; (1) Flush toilet; (0) Private flush toilet
Water	(7) Bottle water; (6) Tanker truck; (5) Rainwater; (4) Surface water; (3) Dug well; (2) Tube well water; (1) Piped water; (0) Piped water within 30 min' walk
Floor	(3) Natural; (2) Rudimentary; (1) Finished
Cooking Fuel	(3) Natural ; (2) Fossil fuel ; (1) Natural gas ; (0) Electricity
Assets (Sum Score)	(−1) Telephone; (−1) Radio; (−2) Television; (−2) Refrigerator; (−2) Bicycle; (−3) Motorcycle/scooter; (−4) Car/truck

The listed entries represent all items with the same first-bit code in the DHS Recode Manual. See https://dhsprogram.com/publications/publication-dhsg4-dhs-questionnaires-and-manuals.cfm.

Table A6
Infrastructure project sectors.

Sector	Code	Name (Number)
Social infrastructure	110	Education (176)
	120	Health (397)
	130	Population Policies / Programmes and Reproductive Health (1)
	140	Water Supply and Sanitation (74)
	150	Government and Civil Society (130)
	160	Other Social infrastructure and services (100)
Economic infrastructure	210	Transport and Storage (318)
	220	Communications (156)
	230	Energy Generation and Supply (115)
	250	Business and Other Services (2)

We further analyze the heterogeneous effects of infrastructure projects on poverty reduction, finding that the viability of recipients is the key to determining the effectiveness of development investment. Infrastructure projects do not significantly alleviate poverty in aid-dependent countries, as aid dependence leads to insufficient public expenditure and limited policy space, and has long been associated with heavy debt burden. More importantly, it reflects the fact that only if a country has found ways to independently develop can it effectively use foreign investment for poverty reduction. Moreover, recipient areas' initial economic basics are also influential to projects' effectiveness. We find that education level, occupation, and household wealth in rural areas are lower than those in urban areas, and water, minerals, and other resources are relatively scarce in rural areas; therefore, infrastructure projects can significantly alleviate poverty in rural areas but are only effective in urban areas in the short term. In addition, projects undertaken by state-owned agencies receive a larger scale of funding and are more effective in poverty reduction than those undertaken by private agencies.

Overall, after illustrating the positive impact of the Chinese infrastructure investment on poverty reduction in SSA, we propose that both donor and recipient governments prioritize improving business environments around infrastructure projects, which is essential to promoting local industrialization and improving individual employment stability. Moreover, recipients should pay ongoing attention to developing existing viabilities, eliminating aid dependence, and considering the contributions of rural areas.

Finally, we would like to highlight some critical limitations of this study. Although the AidData database reveals relatively long-term geo-coded Chinese infrastructure project data, which allow us to study project implementation and effects at the micro-level, insufficient information from other investors limits our investigation of interaction effects. Subsequent studies should focus on the impact of different donors and provide a more comprehensive assessment of projects' effectiveness on poverty reduction combined with case studies. However, this remains a challenging task due to data limitations at the micro-level in SSA.

Funding

This work was supported by the National Natural Science Foundation of China [No. 71972063]; and the National Social Science Fund of China [No. 18ZDA095].

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper, and all authors have read and agreed to the published version.

Data availability

Data will be made available on request.

Acknowledgements

We would like to thank the Editor, the Associate Editor, and the two anonymous reviewers for their insightful and constructive comments and suggestions that substantially improved our paper. We also acknowledge the comments of He Li, Hongyuan Zhang, and all other participants in the seminar at Jilin University and Michael Darko from the University of Leicester. We are solely responsible for any error that might yet remain.

Appendix

See in Figs. A1 and A2.
See in Tables A1–A6.

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