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Abstract

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Keywords: Foreign aid, infrastructure, employment, China, Africa

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1. Introduction

The international community has used foreign aid as an important policy tool to support economic development in the developing world. While western donors have provided trillions of dollars in foreign aid, the evidence of its effectiveness remains mixed (Easterly 2003; Qian 2015; Galiani et al. 2017). Meanwhile, in recent decades, China has played an increasingly important role in this field. Between 2000 and 2014, China committed over 350 billion USD in official finance to 140 countries (Dreher et al. 2020). The amount of Chinese aid is also increasing tremendously. According to the State Council of China (2011; 2014), by the end of 2009, a total of 41 billion USD had been given as aid to foreign countries, whereas in the period 2010–12 alone China supplied about 15 billion USD in global aid. In the 2019–20 COVID-19 pandemic, China has pledged 2 billion USD in the next two years to support COVID-19 response efforts, particularly in developing countries.[2]

Chinese aid has drawn the attention of the recent literature not only due to its large amount and rapid increase, but also because of its major differences with the traditional donors.[3] Adhering to the principle of not interfering the internal affairs in the recipient countries and respecting their own paths of development, the allocation of Chinese aid projects is largely demand-driven, without imposing political conditions (The State Council 2014). But this may make it vulnerable to political capture (Dreher et al. 2019) and is also likely to be mixed with commercial interests (Brautigam 2010). In general, with an emphasis on infrastructure and the efficiency in implementing the large-scale infrastructure construction, Chinese aid projects in Africa are found to increase economic growth, as measured by GDP and night-time light density (Dreher et al. 2018, 2020, 2021). Besides the macro-economic effect, the literature has also shown that Chinese foreign aid can have a profound social impact. For example, it reduces

[2] Source: http://english.www.gov.cn/news/topnews/202006/07/content_WS5edc559ac6d066592a449030.html.
[3] From 2000 to 2014, the amount of financial assistance provided by the U.S. (the largest bilateral donor) to Africa increased from 2.11 to 9.33 billion, while the amount committed by China in the same period has increased from 0.67 to 6.19 billion. The figures are calculated by the authors based on World Development Indicators from the World Bank and Aiddata.

regional violence, increases social welfare, affects ideological alignment among the citizens of the recipient countries, changes local labor practices, and is likely to interact with local norms and increases local residents' corruption behaviors (Isaksson and Kotsadam 2018a, 2018b; Blair, Marty, and Roessler 2019; Gehring, Kaplan, and Wong 2019; Martorano, Metzger, and Sanfilippo 2020). However, how these profound impacts at individual level are generated remains unclear. To answer this question, it is natural to first investigate how individuals in the recipient countries are *involved* in Chinese aid projects. Our paper sheds light on this first-order question and studies the impact of Chinese aid projects on local employment in Africa. For locals, employment in relevant sectors creates exposure to Chinese aid projects. Therefore, understanding how Chinese aid affects individual employment could help explain its profound impacts on the ideology and norms of local populations. Also, employment is an important component of national economy. More knowledge about the impact of Chinese aid on local employment will help us to understand the aggregated effect of Chinese aid on economic growth.

This paper combines the 360 Chinese infrastructure aid projects in the category of Official Development Assistance (ODA-like) obtained from AidData during 2000–14 with multiple waves of Demographic and Health Survey (DHS) data across 10 sub-Saharan African (SSA) countries, covering a total of 559,724 individuals from 15,101 DHS clusters. We first exploit the geocoded locations of Chinese infrastructure aid projects and DHS clusters to measure whether individuals live close to any of the projects. We further focus on the timing of the projects and DHS surveys and identify the different ways in which local residents are exposed to nearby Chinese aid projects, e.g., whether individuals were surveyed before or after the local projects were implemented and for how long they had been exposed to them. Exploiting these spatial and temporal variations, we use a difference-in-differences type of identification building on the approach by Isaksson and Kotsadam (2018a, b) and estimate the changes in individual employment after the local infrastructure aid projects "switched" from “inactive” to “active,” compared with areas without any projects. This identification strategy relies on the plausibly exogenous nature of the timing of DHS surveys relative to the timing of Chinese projects in the local area.[4] Since the DHS data are repeated cross-sectional, to verify the validity of our strategy we conduct balance tests showing that the areas with active Chinese aid projects at the time of survey (“post-treatment”) are no different than the places where the projects are not yet implemented (“pre-treatment”), in terms of geography, pre-determined development indicators, and demographic characteristics of citizens after controlling for potential time trends and region-specific effects.

We find that the probability of an individual working or holding a job at the time of survey is two percentage points higher in the DHS clusters close to active aid projects than the places where the projects are not yet active, compared with the baseline group of places receiving no aid. Importantly, this probability is no different in the DHS clusters where aid projects are not yet implemented than the places with no aid whatsoever, reassuring us that in terms of local employment, there is no observed site selection of Chinese projects. In addition, we identify the dynamic effects based on the length of local residents’ exposure to Chinese projects. We find that while Chinese aid projects did not influence local individuals’ employment status before the projects started, they do increase the probability of working significantly, by two percentage points in the first year after the projects started and by three percentage points in the second year. Then, the difference becomes small and insignificant. In the longer term, the aggregated effect is much smaller and is not robust in some specifications. To the best of our knowledge, this is the first paper that provides the dynamic effects of Chinese aid projects on the local area based on micro-surveys. The short-term pattern of the impact we find is consistent with the recent study by Dreher et al. (2020), which reveals a short-run impact of Chinese aid on aggregated economic growth at the

[4] Similarly, Depetris-Chauvin, Durante, and Campante (2020) have relied on the plausibly exogenous nature of the Afrobarometer surveys relative to the timing of football matches in Africa, to identify the impact of national team victories on nation building.

recipient country level. Combined with information on the duration of these projects, this dynamic pattern suggests that Chinese aid projects increase local employment mostly during construction phases.

While there are no complete official employment data in African countries at disaggregated levels, by focusing on the individual employment data from DHS surveys, we find that, after they start, Chinese infrastructure aid projects are likely to create job opportunities for local residents both directly and indirectly in relevant sectors, as more employment is observed for skilled manual labor, professional, technical, and managerial positions, and also in the service sector. In addition, there are more year-round employment, rather than seasonal or occasional employment, and more cash-earning, rather than unpaid or in-kind earning, jobs, suggesting that Chinese aid projects make a contribution to formal rather than informal employment in Africa. Our results also shed light on employment inequality in Africa. We show that, across sub-samples, urban, female, and older workers benefit most from Chinese aid projects. Across a different educational attainment scale, employment of less educated individuals increases only in the short-term, during the construction of infrastructure, whereas employment of more educated workers is higher in the longer term, after local infrastructures are completed.

To address potential endogeneity issues, we have controlled for factors that might affect Chinese aid allocation—such as African countries' time-variant bilateral relations with China, economic and political status, local economic and social needs, natural resources, connection with political leaders, and local development level and potential—using covariates at DHS cluster level and fixed effects specific to county-year and second-level subnational regions.[5] We also consider carefully the potential bias that may arise from omitted variables relating to other local developmental resources, such as aid and investments from other sources. In particular, if various

[5] See Fuchs and Rudyak (2019) for example, for a review of China's foreign aid motives.

developmental resources exist intensively only in certain regions, the impact of Chinese aid projects could be overestimated and might capture the impact of other potential aid and investments that coincide with Chinese projects in time and location. We address this concern in the following ways. First, we collect data on other aid projects that have geocoded locations and timing of implementation, and show that the short-term impact of Chinese infrastructure aid projects is not confounded by projects from other sources. Second, we exclude the potential regions where African leaders may have interests to develop, conjecturing that if the impact of Chinese aid is driven by the cluster of other developmental resources in the same regions, this impact would disappear if these regions were excluded from the analysis. Third, we collect the geocoded data on roads, health facilities, and industrial companies, and control for their local densities as the proxy variables for the level of local developmental resources.

This paper contributes to several strands of literature. First, it complements the growing literature on the impact of Chinese aid. The literature has documented the effect of Chinese aid on economic growth and its social effects at local level. By investigating the impact on local employment, through which local residents may be exposed to Chinese aid, we contribute to a better understanding of the macro-economic and social impact of Chinese aid to Africa.

This paper also relates to research on the effect infrastructures have on employment in Africa. Dinkelman (2011) studies electrification infrastructures in South Africa, and Hjort and Poulsen (2019) examine the impact of fast Internet on employment exploiting the arrival of submarine Internet cables in Africa. They both find that the employment effects are largely heterogeneous. For example, the impact of fast Internet is local, driven by high-skill occupations and more educated individuals, whereas household electrification is more beneficial to female employment as women are likely to be released from home production with access to modern energy. Since the large-scale construction of infrastructure is a feature of Chinese aid projects in Africa, this paper casts light on the employment effect of infrastructure projects by focusing on those supported by Chinese aid. In particular, it provides a unique opportunity to compare the effects of different types of infrastructure within the same institutional context. We find that while all construction of different types of infrastructure increases local employment significantly in the short term, the effects of schools, hospitals, water programs, and power facilities are also greater over longer timeframes.

We also add to the discussion of how the Chinese involvement in Africa influences local labor markets. There have been anecdotal claims that Chinese firms and projects rely largely on Chinese expatriate workers and make little effort to develop local labor skills, which has a detrimental impact on employment in Africa (Adisu, Sharkey, and Okoroafo 2010; Zhao 2014; Wegenast et al. 2019). However, this perception has been challenged by several recent large-scale surveys of Chinese firms across Africa, which show that the proportion of local employees in Chinese firms is 74–85%, and in particular, the majority of Chinese firms provide skill training (Sautman and Yan 2015; Rounds and Huang 2017; Jayaram, Kassiri, and Sun 2017; Oya and Schaefer 2019).[6] In addition, the impact of Chinese involvement on African employment is not limited to Chinese firms. Chinese aid projects can also benefit employment among local residents by creating job opportunities in relevant industries. This paper takes the perspectives of local residents in over 15,000 locations across 10 SSA countries. By comparing places close to Chinese projects to areas with no Chinese projects, and changes in local employment before and after Chinese projects are implemented, we are able to identify empirically the extent to which local employment dynamics are

[6] Sautman and Yan (2015) interview 400 Chinese firms and projects across Africa and show that 85% of their workforce are African workers. Based on interviews with 11 Chinese firms in Kenya, Rounds and Huang (2017) document that the proportion of Kenyan employees is 78%, only slightly lower than the proportion among U.S. firms in the same region (82%). The survey of 1,073 Chinese firms in eight African countries conducted by Jayaram, Kassiri, and Sun (2017) from McKinsey & Company reveals that 89% of Chinese firm employees are African, providing a total of 300,000 jobs for African workers. This proportion of local employees is as high as 95% in the manufacturing sector. Skills training is provided by 64% of the Chinese firms, and 43% of the firms offer apprenticeship training. A recent field research by Oya and Schaefer (2019), who interviewed over 1,500 workers from 76 companies in Angola and Ethiopia, suggests that the average localization rate of Chinese companies is 74%, not largely different than non-Chinese companies.

associated with Chinese aid projects.

The rest of this paper proceeds as follows. In Section 2, we introduce our data and identification strategy. In Section 3, we present the baseline results on individual employment status, occupations, and the heterogeneous effects of different infrastructures across different sub-samples. In Section 4, we discuss the potential bias from other developmental resources in the area and the wider impacts of Chinese aid on household wealth and regional night light emission. Section 5 concludes.

2. Data and Identification

2.1. Data

We draw on two main sources of data to study the local impact of Chinese aid projects on individual employment in Africa. The data on Chinese aid projects are from AidData's Geocoded Global Chinese Official Finance (Version 1.1.1) for 2000–14 (Bluhm et al. 2018). Since there are no official data on Chinese aid, this dataset synthesizes the open source information and provides the most comprehensive records on Chinese aid projects so far.[7] We focus mainly on the projects classified as Official Development Assistance (ODA-like), which have development intent,[8] and in particular projects involving the construction of infrastructure, including roads, railways, schools, hospitals, water and power programs, and other government and social facilities.[9] The projects' locations and start dates are provided in the dataset, and we use those with precise locations in our study.[10] The Demographic and Health Survey (DHS) provides repeated cross-sectional data on households in African countries.[11]

[7] Please see Strange et al. (2017) for a detailed description of the data collection process.

[8] We also examine the impact of other types of Chinese aid projects in Section 4, including those coded as Other Official Flows (OOF-like) and Vague Flows (VF).

[9] We exclude projects involving grants, donation of materials, dispatch of medical teams and experts, and technical training, which involve no physical construction and limited involvement of local residents. In Appendix B, we show that the results are robust if we include such non-infrastructure aid projects in the sample.

[10] To guarantee the precision of the locations of aid projects, we only include those with a precision code equal to 1 or 2 in the AidData, i.e., within 25 km of an exact location.

[11] We exploit the standard DHS surveys with geocoded information on the survey clusters, so that we can measure households' proximity to Chinese aid projects. This information is missing for 253 DHS clusters (1.7%). We exclude them from the analyses.

With a lack of data on employment at disaggregated levels in Africa, combining the different waves of DHS surveys in African countries provides an opportunity to study the employment status and occupation of African citizens. Therefore, we combine these two sources of data based on (i) the proximity between aid projects and DHS clusters, and (ii) the timing of DHS surveys and aid projects in the area. Based on the distance between a given cluster and Chinese aid projects, we could measure whether a DHS cluster is close to and hence potentially affected by any Chinese infrastructure aid projects. Furthermore, we identify how the impact of Chinese aid projects on local employment evolves over time by exploiting the start year of projects and the time when the DHS surveys were conducted.

In order to estimate the dynamic effect of Chinese aid projects, we need to observe employment in multiple periods in the repeated cross-sectional data after Chinese aid projects in the area started. Therefore, we focus on the countries with numerous Chinese aid projects and DHS waves.[12] We select the top 10 African countries that observed most Chinese infrastructure aid projects during the period 2000–14, and which have at least two waves of DHS with geocoded data around this period.

In these 10 African countries, there were 360 Chinese ODA-like aid projects relating to infrastructure in 2000–14 and 29 DHS surveys around this period (1999–2016). These projects account for 54.63% of all the Chinese infrastructure aid projects in Africa. Among these 360 projects, 103 involve the construction of roads and railways, 69 relate to water and power facilities, 60 the construction of schools and hospitals, and 128 include other infrastructures, such as government buildings, stadiums, communication networks, etc. The multiple waves of DHS cover 559,724 individuals in 312,460 households from 15,101 clusters. Appendix A documents the details of the aid projects and DHS waves in our sample. The locations of Chinese aid projects in infrastructure and clusters covered by DHS are shown in Figure 1. The 10 countries

[12] For example, if there is only one aid project in a country in 2005, and two waves of DHS in 2005 and 2010, then we can only estimate the local impact of that aid project in the same year and five years later.

are Cameroon, DR Congo, Ethiopia, Ghana, Kenya, Namibia, Nigeria, Tanzania, Uganda, and Zambia. They cover about 57% of the population in sub-Saharan Africa, and 46% of its GDP (as of 2012).

[Figure 1 here]

2.2. Identification Strategy

Based on the location and timing of aid projects and DHS waves, the DHS clusters can be categorized into three groups. There are 9,236 clusters with no aid projects within a radius of 50 km during the whole sample period. We treat them as the comparison group in the main specification because of the absence of local aid projects.[13] In 4,331 DHS clusters, there had been active aid projects within 50 km before the surveys were conducted. Individuals in these clusters were exposed to the local aid projects at the time of the DHS surveys. They are included in the post-treatment group. For the remaining 1,534 clusters, aid projects were observed within 50 km only after DHS surveys; no projects existed in these clusters before the surveys were carried out. Hence, they form the pre-treatment group. With the following regression specification, we compare these three groups to identify the local impact of Chinese aid projects on employment.

$$Y_{ist} = \beta_0 Inactive_{st} + \beta_1 Active_{st} + \boldsymbol{X}_i \boldsymbol{\gamma} + u_z + v_{ct} + w_{ist} \qquad (1)$$

The main dependent variable Y_{ist} measures whether individual *i* in cluster *s* was working in year *t*. $Active_{st}$ is the dummy variable for the post-treatment group. It equals 1 if cluster *s* is within 50 km of any Chinese infrastructure aid projects that had been active before year *t*. $Inactive_{st}$ is the dummy variable for the pre-treatment group. It is equal to 1 if cluster *s* is within 50 km of aid projects that started only in or

[13] The radius of 50 km has been argued as an appropriate distance for commuting in an African context (Knutsen et al. 2017). In the robustness checks in Appendix B, we show that the results are not sensitive to this choice of radius.

after year *t* (i.e., no active projects had existed within 50 km before year *t*).[14] Hence, the comparison group includes the DHS clusters with no aid projects within 50 km in the sample period. In this way, β_1 measures the difference in individuals' employment status between a place close to active aid projects and a place with no aid projects nearby, whereas β_0 measures the difference between clusters with no aid projects and the clusters where aid projects had not yet become active. Therefore, the difference-in-differences estimator $\beta_1 - \beta_0$ measures how employment changes between places where projects have not yet been activated and places with active aid projects, compared to places with no aid projects. It identifies the causal impact of Chinese aid projects on local employment. It is also important to note that β_0 provides a test for the potential site selection of Chinese aid projects in terms of local employment. Since it measures the difference between unaided DHS clusters and clusters that are still to receive aid, the lack of site selection for Chinese aid projects would predict that β_0 would be insignificant.

Covariates at individual and cluster levels are included in $\boldsymbol{X}_i$. They include individual *i*'s gender, age, ethnicity, and years of education, which are likely to influence individuals' employment decisions.[15] We also control for the characteristics of every DHS cluster, including time-invariant geographical characteristics (rural/urban status, terrain roughness, travel time to nearest cities, distances to capitals, national borders, water bodies, and protected areas); ethnic diversity; natural resources (gold, copper, diamond, and petroleum deposits); and pre-determined socio-economic indicators (conflict intensity, population density, and night light density).[16] They measure the local

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[14] Since the exact start dates of most projects are missing, we are not aware whether the projects started before or after the DHS surveys, when they happened in the same year. To obtain a conservative result, we include the cases where DHS survey and local projects were observed in the same year (1.9% of observations) in the pre-treatment group. The results are robust if we exclude these observations.

[15] To control for ethnicities, we include 433 dummies for the different ethnic groups based on the digitized map provided by Nunn (2008) following Murdock's (1959) classification. The map is available at https://scholar.harvard.edu/nunn/pages/data-0.

[16] Most geographical characteristics of DHS clusters are provided in the DHS dataset. The distance from each DHS cluster to the national capital is calculated by the authors. Ethnic diversity is measured by the number of different ethnic groups within 50 km of a given DHS cluster, based on Murdock's (1959) classification. For natural resources, we include the number of gold, copper, and diamond deposits within 50 km of a given DHS cluster, respectively, using the data on Major Mineral Deposits of the World from the U.S. Geological Survey, available at https://mrdata.usgs.gov/major-deposits/. The dummy variable for

development and potential of each cluster, and may also influence the distribution of Chinese aid projects. The descriptive statistics for all these variables are reported in Table A4 in the Appendix. u_z is the region (second-level subnational administration, ADM2) fixed effect.[17] It controls for the structural differences across regions, including social and economic needs, connection with political leaders, ideology, etc. v_{ct} is the country-by-year fixed effect. It captures the African countries' time-variant bilateral relations with China (such as diplomatic and economic relations), political, and economic conditions. These fixed effects control for the factors that may affect Chinese aid allocation as found in the literature, and also the annual changes in employment in every country due to country-level shocks. Standard errors are clustered at the level of DHS clusters (primary sampling units of DHS).

Eq. (1) follows the specification of Knutsen et al. (2017) and Isaksson and Kotsadam (2018a, b). It reveals the overall impact of aid projects on employment by comparing the groups based on *whether* aid projects are active within 50 km. Building on it, we further exploit the information on *when* the projects become active relative to DHS surveys, and investigate the dynamic impact of aid projects by specifying the distributed lagged terms as follows.

$$Y_{is,t} = \alpha_0 Inactive_{s,t} + \sum_{\tau=1}^{T} \alpha_\tau Active_{s,t-\tau} + \alpha_{T+1} Active_{s,t-(T+1)} + \boldsymbol{X}_i \boldsymbol{\gamma}$$
$$+ u_s + v_{ct} + w_{ist} \qquad (2)$$

petroleum resource equals 1 if any (on- or off-shore) oil or gas fields were found within 50 km of a DHS cluster during 1946–2003. The data are obtained from the Petroleum Dataset (v.1.2), available at https://www.prio.org/Data/Geographical-and-Resource-Datasets/Petroleum-Dataset/. Conflict events are obtained from UCDP Georeferenced Event Dataset Global version 19.1, available at https://ucdp.uu.se/downloads/index.html#ged_global. A conflict event is defined as an incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least one direct death at a specific location and on a specific date. Since the data exist after 1989, we calculate the number of conflict events during 1989–99, the decade before our data were collected, in places within 50 km of a given DHS cluster. Population density and night light density are provided in the DHS dataset. We include the log population density and night light density for every DHS cluster in 2000 as covariates.

[17] There are 1,955 second-level subnational administrative regions in our sample. They are the ADM2 according to Global Administrative Areas, available at https://gadm.org/maps.html.

The lagged term $Active_{s,t-1}$ equals 1 if aid projects were implemented within 50 km of cluster s in the year *t-1*. Individuals in these DHS clusters had been exposed to Chinese aid projects for one year. $Active_{s,t-2}$ equals 1 if aid projects within 50 km started two years preceding the year of survey. Coefficient α_0 refers to the difference in employment between the areas with no aid projects and areas where projects had just been implemented or were not yet active. Therefore, $\alpha_1 - \alpha_0$, $\alpha_2 - \alpha_0$, and $\alpha_3 - \alpha_0$ measure how the local employment changes over time after Chinese aid projects "turned" from inactive to active (i.e., impact on employment one year, two years, and three years, respectively, after aid projects). $Active_{s,t-(T+1)}$ is a dummy variable equal to 1 if any aid projects occurred *T+1* or more years preceding *t*, and hence $\alpha_{T+1} - \alpha_0$ indicates the *aggregated* impact of aid projects after *T+1* years. Overall, these difference-in-differences estimators illustrate the dynamic effects of Chinese infrastructure aid on local employment. They also allow us to examine whether the observed dynamic pattern is reasonable and consistent with other evidence. The covariates and fixed effects are the same as Eq. (1).

The descriptive statistics are reported in Table A4. On average, 65% of the respondents were currently working at the time of DHS surveys. The mean age is 32 and mean years of education is six. Since women were emphasized in the DHS surveys in these African countries, only 32% of respondents in the sample are male. About 63% individuals live in rural areas. In the areas within 50 km of local DHS clusters, there were active Chinese aid projects in 27% of the clusters, while 9% of DHS clusters had aid projects pending and 64% of clusters had no aid projects within 50 km in the data period.

[Table 1 here]

As the literature has shown, the allocation of Chinese aid in Africa is influenced by many factors, including foreign policy considerations, connection with political leaders, and local economic needs (Dreher et al. 2018; Dreher et al. 2019; Guillon and Mathonnat 2020). In our sample, we also observe differences between the places that received Chinese aid and those that did not. In the balance checks in columns 1 and 2 of Table 1, we examine the differences between the individuals in aided DHS clusters (active or inactive) and those in the unaided clusters in terms of the important demographic characteristics and geographical and pre-determined characteristics of DHS clusters, unconditionally in column 1 and conditional on the ADM2 and country-year fixed effects in column 2. The two columns provide some qualitatively similar results. Chinese aid projects tend to target places with younger and more educated people, slightly less male, in or close to urban areas, with less terrain roughness, higher population density, and more night light emission, etc.

Hence, we do not rely on the direct comparison between places with aid projects and the areas with no aid projects to identify the impact of aid on local employment. Instead, we exploit a difference-in-differences comparison based on the spatial and temporal variations constructed using the repeated cross-sectional data, which identifies how employment changes from a place where the projects have yet to be active to a place with active aid projects, compared with places with no aid projects at all.

An important feature to note in this difference-in-differences type of estimation is that individuals in each cluster were only surveyed once, unlike a panel data structure where the same group of individuals would be observed both before and after treatment. That said, the people in the pre-treatment group were not the same as those in post-treatment group, so no one was observed both before and after the aid projects were implemented. Therefore, the exogenous timing of aid projects relative to DHS surveys is crucial in this setting. We check the balance of the sample between the post-treatment group (with active aid projects) and the pre-treatment group (with inactive projects) in columns 3 and 4 of Table 1. To guarantee that we are comparing individuals from the same region interviewed in the same year, we include the country-year and

ADM2 fixed effects in column 4. We find that there are no significant differences between these two groups of local residents in terms of the important demographic, geographical, or pre-determined characteristics. Within every country-year and each ADM2 region, the DHS clusters with active aid are similar to the clusters where aid projects were pending, in terms of local development indicators. This supports the exogenous nature in the timing of aid projects relative to DHS surveys.

3. Main Results

In this section we present the main results. In Section 3.1, we show the baseline evidence of the impact of Chinese infrastructure aid projects on employment across distance and over time. In Section 3.2, we examine the impact on local individuals' employment status more formally and illustrate the dynamic pattern of this impact. To obtain a better understanding of the local impact of Chinese aid, we also investigate the effects from different perspectives. We study the effects on different occupations, duration, and payment for work in Section 3.3, and the effects of different types of infrastructures in Section 3.4. We further study the impact of Chinese aid projects in relation to employment inequality in Africa in Section 3.5.

3.1. Baseline Evidence

Our identification exploits the geographical proximity of DHS clusters to Chinese infrastructure aid projects to estimate the local impact on employment. In Figure 2, we show how the employment rate of DHS clusters changes across distance from the closest Chinese project. The clusters are grouped into 20 equal-sized bins and the local average for each of them is plotted as one point, separately for those close to active projects (red points) and those close to inactive ones (blue points). The curves indicate the quadratic fits for them. It is clear that when DHS clusters are located closer to Chinese aid projects, the difference in employment rate between the active and inactive areas is more salient. For the places around active Chinese projects, moving closer is associated with an increase in employment rate, whereas in the regions where

Chinese projects are not yet implemented, the distance from these future projects does not correlate with employment, as expected. This confirms a positive and local impact of Chinese aid projects on employment. Over longer distances, this impact diminishes and rates of employment for active and inactive areas are close.

[Figure 2 here]

In Figure 3, we examine the impact on employment along the timing of Chinese aid projects. We plot the employment rate for the clusters that were surveyed by DHS in different years relative to the start year of Chinese aid projects nearby. It illustrates the trend in employment before and after Chinese aid projects were implemented, separately for the clusters within 50 km of the projects (red line) and for the areas more than 50 km away (blue line). In the years before Chinese aid projects started, rates of employment in the places within 50 km of these projects and in the areas further away were close and moved mostly in parallel over time. However, after the Chinese aid projects started, the areas within 50 km witnessed an immediate higher employment rate that remained higher for at least six consecutive years. This indicates a positive impact of Chinese aid on local employment in the short term. Employment in the places close to the Chinese projects increases again in the 9th–11th years, but then disappears.

[Figure 3 here]

3.2. Employment

We formally examine the impact of Chinese infrastructure aid projects on the employment status of local individuals (whether an individual was working at the time of DHS survey) in Table 2. In column 1, the fixed effects specific to each ADM2 region and every country-year grid are included. They control for African countries' time-variant economic and political status, bilateral relations with China, local ideology, natural resources, connection with political leaders, and economic and social needs for aid, all of which are likely to affect the allocation of Chinese aid. In columns 2 and 3, the covariates at the individual and DHS cluster levels are added, respectively. The variables at the DHS cluster level capture the local level of development and potential for it, as well as the factors that may affect Chinese aid allocation. Column 3 corresponds to Eq. (1), where all the covariates and fixed effects are included.

[Table 2 here]

In all the first three columns, the coefficient of “active” indicates that there is a significant difference in the share of individuals who were working between the areas with active aid projects within 50 km (post-treatment group) and the places with no nearby projects (comparison group). On average, the place with active Chinese infrastructure aid projects has an employment rate that is two percentage points higher. Importantly, the areas where aid projects were pending (pre-treatment group) are no different than the places with no aid projects, as indicated by the coefficient of “inactive.” This implies that there are unlikely any site selections of Chinese aid projects in terms of local employment. These findings are consistent with the pattern shown in Figure 2. The difference-in-differences estimators are reported at the bottom of Table 2. Overall, Chinese aid projects increase local employment by at least two percentage points, corresponding to 3% of the average employment rate (0.65).Columns 4–6 include the lagged terms for active aid projects within 50 km. Different sets of covariates are added in these columns and column 6 corresponds to Eq. (2). Before local aid projects become active, the employment rate is similar to that in the areas with no aid projects (coefficients of “Inactive” are from 0.007 to 0.010, insignificant); however, in the first year after the implementation of local projects, the employment rate rises significantly by about two percentage points, or 2% of the average employment rate. The employment rate is further increased in the second year by three percentage points, or 5% higher than the comparison areas with no nearby projects, as indicated by the difference-in-differences indicators in column 6. This effect, however, disappears in the third year in all these columns. In the longer term—for instance, aggregating the effects after the fourth year—Chinese aid projects increase local employment by only one percentage point, as indicated by “Active.Lag4+ – Inactive,” much smaller than the short-run effect. In Figure B1, where we employ different lagged terms, we find a consistent pattern of significant effects in the first two years, while in the longer term, the effects become significant only at least six years after local aid projects start. Overall, this short-run impact we find echoes the findings in Figure 3.

We further investigate the dynamic pattern of the impact using an event-study framework in Figure 4, where we plot the coefficients and the 99% confidence intervals for the dummy variables for the two-year periods before and after local Chinese aid projects start over longer time frames.[18] Figure 4 confirms that while Chinese infrastructure aid projects do not influence local employment in the years before the projects are constructed, they increase local employment significantly by three percentage points in the first two years, after which the effects diminish and become significant again six years after the start of local aid projects.

[Figure 4 here]

The short-run impact on local employment is robust in various cases, as reported in Appendix B. In terms of the geographical distance used to measure each DHS cluster's exposure to Chinese projects, the results are robust if we use the radii of 25, 75 or 100 km instead. The effects fade over distance, confirming that the short-run impact of Chinese aid projects on employment is mostly local and is unlikely to have large spatial spillover. Consistently, the impacts are greater if we only focus on the residents who

[18] We specify the lead and lagged terms for the periods within 10 years before and after the start of local Chinese aid projects, as Appendix B shows that 89% of the DHS surveys were carried out within 10 years from the start of local aid projects. The projects outside this time range are aggregated in the same way as in Eq. (2). In Figure 4, the lead and lagged terms cover all the cases where DHS surveys were carried out before and after the local Chinese infrastructure aid projects, respectively. The coefficient for the case where local aid projects and DHS surveys occurred in the same year is normalized to zero in this event-study approach.

lived in the area for at least 10 years. The short-term effects are not driven by potential migration into local areas. Regarding the sample used for analysis, the results are robust if we restrict the comparison group to the 2,621 DHS clusters that are 100–200 km from Chinese aid projects, which addresses the concern that places located too far away from any Chinese aid projects may be systematically different. The effects are also close to the baseline results if we restrict the sample to areas with nearby Chinese aid projects and only exploit the staggered timing of aid relative to DHS for identification. We also control for differential development in many flexible ways (e.g., by including trends specific to every ADM2 region and by interacting population density and night light density in the base year 2000 with year dummies), include project fixed effects for a smaller sample, include non-infrastructure aid projects, and employ Probit models. The short-run effects of Chinese aid projects on local employment are robust in all these cases.

Among the 360 Chinese aid projects, 115 have information on their end years. On average, these projects lasted for about 2.6 years. Therefore, our finding of the short-run impact on employment suggests an instantaneous effect during project construction. In the short term, Chinese aid projects may create job opportunities for local citizens either directly or indirectly in relevant sectors. But this effect diminishes once the projects are completed. The short-run pattern here is also consistent with the finding by Dreher et al. (2020) that at the aggregated country level, Chinese ODA-like projects increased economic growth significantly only in the first three years after aid was committed. Khomba and Trew (2019) also document that the impact of aid on disaggregated growth in Malawi peaked after two to three years and then diminished.

In the longer term, the impact on employment is likely to interact with many local factors and hence be confounded by them. For example, in the robustness checks in Table B1, we find that for residents who have lived in the area for more than 10 years, employment increases only in the short term and is not affected significantly after the fourth year. This implies that the employment effect in the longer term is likely to be driven by migrants into the regions after the Chinese infrastructure projects in the area are completed. In addition, in Section 4, after we include aid projects from other sources, we find that while the short-term impact is consistent, the impact on employment in the longer term is likely to be confounded by other types and sources of aid projects in the area. Since the existing data only cover Chinese aid projects during 2000–14, a precise examination of the long-term pattern is not feasible at this moment, as most projects occurred within 10 years around the DHS surveys in the area (see Figure B2). Therefore, we focus on the short-term pattern of the Chinese aid impact in this paper and estimate the long-term impact only aggregately for the period after the short-term effect disappears (i.e., from the fourth year).

3.3. Occupations

We further explore the occupations of individuals who were working at the time of the survey. We focus on the six major occupation categories provided by DHS: self-employed in agriculture, employee in agriculture, sales, service, professional work, and manual labor.[19] To study the sectoral composition of the impact of Chinese aid projects, we construct binary dependent variables indicating whether an individual was working in each of these six occupations, respectively, in columns 1–6 of Table 3. First, there is no large site selection of Chinese aid projects in terms of local occupation composition. If anything, there is only slightly more employment in the sales sector and fewer professional, technical, or managerial workers in the places where aid projects would be implemented. Given the lack of selection of Chinese aid projects, the difference-in-differences estimation at the bottom of Table 3 shows that Chinese aid projects reduce the employment in agriculture significantly by 0.9 percentage points (8%), increase employment in service sector by 0.3 percentage points (8%), increase professional, technical, and managerial employment by 0.4 percentage points (8%),

[19] The occupation categories grouped by DHS are based on the major occupation groups in the International Standard Classification of Occupations (http://www.ilo.org/public/english/bureau/stat/isco/isco08/).

and to a greater extent increase manual labor employment by 1.5 percentage points (14%). While detailed contracts of individual employment are unavailable, the local workforce employed in the construction of Chinese infrastructure projects is more likely to be manual labor. Therefore, these results suggest that Chinese infrastructure aid projects are likely to increase the employment of local residents both directly and indirectly by creating job opportunities in relevant sectors, such as the service sector.

[Table 3 here]

There has been criticism that Chinese companies in the mining sector in Africa rely largely on expatriate workers and fail to upskill local labor (Wegenast et al. 2019). However, it is unclear whether this holds for Chinese involvement in the form of development aid in Africa, in particular under China's Africa policy, which emphasizes the contribution to local employment (The State Council 2015). According to the State Council (2016), China has trained more than 12 million personnel from developing countries over the past 60 years. To shed light on this question, we further divide manual labor into skilled and unskilled in columns 7 and 8 of Table 3. While unskilled labor is not affected significantly by Chinese aid projects, skilled labor increases significantly by 1.7 percentage points (24%) after local Chinese infrastructure aid projects start. Alongside the fact that Chinese aid projects are more likely to be located in areas with less skilled manual labor but more unskilled labor (as indicated by the coefficient of "Inactive"), the result suggests that a skills transition is likely to happen with the Chinese aid projects in the area. The dynamic pattern shown in Table B3 reveals that the increase in skilled manual labor is persistent, lasting for about five years after Chinese projects start.

[Table 4 here]

In Table 4, we examine the impact on continuity of employment and type of earnings.

Columns 1 and 2 show that Chinese aid projects contribute to year-round employment (by two percentage points, or 5% of the mean), rather than seasonal or occasional employment. In terms of types of earnings, Chinese aid projects increase jobs with cash earnings by 3.9 percentage points (or 11%) and reduce jobs without earning or with in-kind earning. Overall, although Chinese infrastructure aid projects mostly increase short-term local employment, they contribute to formal employment in Africa, which provides year-round and cash-earning jobs.

As documented by Roubaud and Torelli (2013) and Golub and Hayat (2015), the predominance of informal employment in Africa has hindered structural transformation. In this respect, Chinese infrastructure projects, which are usually labor intensive, have created significant demand for local labor and are likely to contribute to the transition from informal to formal employment in Africa.

3.4. Infrastructure

We divide the Chinese aid projects into four main categories—roads and railways, water and power facilities, schools and hospitals, and other infrastructure, and construct the variables "Active," its lagged terms, and "Inactive," respectively, based on the projects in each category. We examine the impact of different infrastructures in Table 5 which reports the difference-in-differences estimation results. The full regression results are reported in Table B4 in the Appendix. In columns 1 and 2 of Table 5, we focus on the projects for transportation infrastructure, including roads and railways. There are 103 projects in this category (28.6% of all the Chinese infrastructure aid projects). "Active" is equal to 1 if there are active transportation infrastructure aid projects within 50 km of a given DHS cluster, and "Inactive" equals 1 for areas where transportation infrastructure projects within 50 km were not yet implemented. The comparison group consists of the DHS clusters with no transportation infrastructure projects within 50 km. The results indicate that road and railway projects increase employment by six percentage points in the second year. The aggregated impact after the fourth year is also significant but is only about one-third the magnitude of the short-term effect. Asher and Novosad (2020) study the rural roads construction program in India and also find that the impact on employment in local villages is limited when observed four years after construction.

[Table 5 here]

There are 19.2% infrastructure aid projects for water and power facilities, including water supply and treatment programs, power plants, and power transmission systems. As reported in column 4, these projects increase local employment by seven percentage points in the first year after the aid project is active, by eight percentage points in the second year, and by five percentage points from the fourth year. No significant impact was observed before the projects became active. This indicates that besides creating job opportunities directly during the construction of water and power facilities, the access to electricity and clean water also benefits local employment significantly in the longer term. This is consistent with the research on the impact of electrification in developing countries, which shows that having access to electricity has positive impacts on employment within five years (Dinkelman 2011) and after one decade (Lipscomb, Mobarak, and Barham 2013).

In columns 5 and 6, the projects relating to the construction of schools and hospitals are considered. These account for 16.7% of all infrastructure aid projects. The results show that there are significant increases in employment by three percentage points in the first year, by five percentage points in the second year, and by six percentage points after the fourth year. This indicates that these projects not only create immediate job opportunities, but also have greater positive impacts on employment over longer timeframes. It is plausible that, in the longer term, schools and hospitals help improve the human capital of local residents, which in turn benefits their employment. According to Duflo (2004), primary school construction in Indonesia has increased individuals' formal labor force participation in later life.

The rest of the projects (35.6%) include the construction of communications networks, government buildings, and other buildings such as stadiums, demonstration centers, etc. We examine the impact of these projects in columns 7 and 8. Their impact on local employment is relatively small and is only marginally significant in the first year and after the fourth year.

Another feature of Chinese aid is that it prioritizes the co-location of complementary projects to create a local economic agglomeration (Dreher et al. 2021). Therefore, besides using the dummy variables to measure whether a DHS cluster is exposed to active aid projects, we also rely on the number and total commitment of local Chinese aid projects to examine how the impact on local employment varies with the density of Chinese aid projects in the area (Table B5 in the Appendix). We find that the impact on local employment is much greater when there is a higher density of Chinese infrastructure aid projects in the area.

3.5. Inequality

We have also studied how Chinese infrastructure aid projects influence employment inequality in Africa. First, by dividing the sample into different sub-samples and examine the heterogeneous effects across them, we find that while women have a much lower employment rate than men in Africa, impact of Chinese aid projects on female employment is greater and more persistent. Also, employment in urban areas benefits more from Chinese aid projects, since infrastructure projects are more likely to be allocated to urban areas. Third, the increase in employment through Chinese aid is only observed among older workers.

Across educational attainment levels, employment of less educated individuals increases only in the short-term, during the construction of infrastructure. But for those with education above secondary level, they are not employed immediately at the start of Chinese projects, but are benefited in the longer term after local infrastructures are completed. The detailed results are reported in Table B6 and Figure B3 in the Appendix.

4. Discussion

4.1. Local Developmental Resources

While the local factors that influence Chinese aid allocation are unlikely to confound our results, the allocation of Chinese aid projects, as one potential tool for local development, may be jointly determined with the allocation of other developmental resources by African leaders. This potential bias from the omitted variables concerning other local developmental resources (e.g., aid from other sources, domestic investment, FDI, etc.) has not been discussed adequately in the literature. On the one hand, if policy makers allocate different types of development projects (which may also contribute to local employment) evenly across the country to balance regional development, the impact of Chinese aid projects on local employment found in this paper is likely to be underestimated. On the other hand, if policy makers aim to facilitate development in certain regions and allocate various developmental resources intensively there, the impact found in this paper could be overestimated.

The latter case imposes a particular challenge to the main finding of this paper. If the location and timing of Chinese aid projects coincide with other types of aid and investments, the impact of Chinese aid on local employment we find might be picking up the impact of other developmental resources in the area. We address this concern in the following ways.

First, we consider other aid projects in the area and isolate their potential impact on local employment, including other types of Chinese financial flows and World Bank infrastructure aid projects.

In the main analyses, we have focused on ODA-like projects that are intended to enable development. Besides these projects, there are 187 other Chinese projects coded as Other Official Flows (OOF-like) and Vague Flows (VF) in the 10 countries in our sample. OOF-like flows are more commercially-oriented, and VF projects include those that cannot be categorized as ODA- or OOF-like due to incomplete source material.[20] To study whether these less concessional financial flows from China also influence local employment in Africa, we construct the corresponding variables and the lagged terms to indicate whether a given DHS cluster is exposed to active OOF/VF infrastructure projects, following the same procedure as described in Section 2. As reported in Table C1, while less concessional OOF/VF projects only affect local employment to some extent aggregately, the short-term impact of ODA-like projects is still large and significant, increasing local employment by three percentage points in the second year, close to the baseline results.

Another important source of local development projects is aid from the World Bank. We obtain the data on World Bank aid projects from AidData's World Bank Geocoded Research Release (Version 1.4.2), including their timing and locations. We include aid projects implemented in the 10 countries in our sample during the same period (2000–14), and focus only on the projects involving infrastructure based on project names. Overall, there are 1,714 World Bank infrastructure aid projects in these countries. The correlation coefficient of the active projects between these two sources is 0.32. In Table C1, we show that the overall effect of World Bank infrastructure aid projects is insignificant, and they increase local employment only in the longer term, by 1.6–1.7 percentage points aggregately after the fourth year. Meanwhile, the short-term and overall impacts of Chinese aid projects stay the same as in the baseline results in Table 2.[21] In short, the short-run impact of Chinese infrastructure aid projects is robust after

[20] See Dreher et al. (2018) for comparisons of different types of financial flows from China to Africa.

[21] The difference in the temporal pattern between the impacts of Chinese and World Bank projects is likely due to differences in the timelines of infrastructure projects. Besides their efficiency in implementation, large-scale Chinese infrastructure aid projects are also demand-driven, and do not interfere in the internal affairs of the recipient countries (Dreher et al. 2019). In comparison, World Bank projects, which usually require standard cost-benefit screening and multiple rounds of involvement, last longer (Dreher et al. 2021). In our sample, the average duration of World Bank infrastructure projects is

considering other types of local projects, while their aggregated impact in the longer term is likely to be confounded by other local developmental resources.

Second, we examine areas that African leaders may have prioritized for development. If the impact of Chinese development aid projects is simply driven by the cluster of other developmental resources (e.g., aid from other sources, different types of investment, etc.) at the same time in the same regions, such an impact should disappear if these regions are excluded from the analysis. While there are no complete data on each country's priority development areas where the combination of different developmental projects are likely to exist to foster local development, we select approximate regions where development might be of interest to policy makers: their hometowns, populous areas, coastal areas, and capitals. To foster development in these regions, there is likely to be a cluster of various developmental resources. In Table C2 in the Appendix, we exclude these regions respectively and show that the short-run impact of Chinese infrastructure aid projects is still robust.

Third, we collect geocoded data on roads, health facilities, and industrial companies, and use their local densities as controls for the level of local developmental resources. We show in Table C3 that the results are robust after controlling for these local densities.

Fourth, to explore whether the impact on employment is driven by Chinese aid or other local factors, we randomly permute the Chinese aid projects among the DHS clusters in our sample and re-estimate the baseline results. Figure C1 in the Appendix shows that if the allocation of Chinese aid projects is randomly permuted, we are not able to find any significant impacts of the fake projects on local employment. In other words, the impact found in this paper is indeed driven by Chinese aid projects, rather than other local factors.

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about seven years, much longer than Chinese projects (three years). This might explain the lack of immediate effects of World Bank aid projects on employment.

4.2. Other Local Outcomes

To investigate the impact of Chinese aid projects on other local outcomes, we focus on household wealth and night light density at DHS cluster level. In columns 1 and 2 of Table 6, the dependent variable indicates the quintile of household wealth index calculated for each wave of DHS. As provided by the DHS dataset, this takes values from 1 to 5 representing the lowest to highest quintiles of household wealth. In columns 3 and 4, we calculate the average night light density of the pixels within 10 km of every DHS cluster in the year of survey, and take Log (1+Night light density) as the dependent variable. Data on nighttime lights are obtained from NOAA National Centers for Environmental Information.[22]

[Table 6 here]

The results show that the impact of Chinese infrastructure aid projects on household wealth is cumulative. Over time, household wealth increases significantly only from the third year after local Chinese projects start. The household wealth index increases by about 12 percentage points (4% of the mean) in the third year and by 7 percentage points (2%) aggregately from the fourth year. Night light emission, however, increases immediately with the start of Chinese aid projects, by 10 percentage points (11% of the mean) in the first year, 3 percentage points (4%) in the second year, and 6 percentage points (7%) aggregately from the fourth year. The impact on local night light density corresponds to the same pattern as the effects on local employment. The full regression results are present in Table C4 in the Appendix.

5. Conclusion

We use spatial and temporal variations in Chinese infrastructure aid projects and multiple waves of DHS surveys across 10 African countries during the period 2000–14,

[22] The data are available at https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html.

and identify changes in individual employment after the implementation of Chinese aid projects in the area. Our difference-in-differences estimation strategy with dynamic lags of local Chinese aid confirm the positive impact on local employment in the short run, suggesting that the overall employment rate is two percentage points higher in the first year after the arrival of Chinese infrastructure aid and three percentage points higher in the second year. This positive impact diminishes after the third year. This dynamic pattern indicates that Chinese projects increase local employment mostly during the construction phase. The short-run effect is robust in various cases. In the longer term, Chinese aid projects also increase local employment to some extent, but this impact is likely to be driven by migrants into regions with Chinese infrastructure projects and also seems to be confounded by other types and sources of aid projects.

Further investigation into occupations shows that Chinese aid projects are likely to create job opportunities for local residents both directly and indirectly through relevant sectors, as more employment is observed for manual labor, in particular for skilled manual labor, and also in the service sector after Chinese infrastructure aid projects begin. In addition, there is more year-round employment, rather than seasonal or occasional, and more cash-earning employment, rather than unpaid or in-kind earning jobs, suggesting a likely contribution to formal employment in Africa. Across sub-samples, urban, female, and older workers' employment are more benefited. There is also a heterogeneous effect across educational attainment. While there is only a short-term increase in employment for less educated individuals, the more educated benefit in the longer term.

Looking at different types of infrastructure, the impact of roads and railways is mostly short-term, while the impact of schools, hospitals, and water and electricity facilities is large and significant both in the short term and over longer timeframes. Furthermore, Chinese infrastructure aid projects increase local night light emission significantly and have cumulative effects on household wealth. Controlling for the confounding factors from other local development resources, such as Chinese financial flows, World Bank infrastructure projects, local development strategies, and the overall level of local infrastructure investment, our results on the short-run impact of Chinese aid on local employment still hold.

References

Adisu, Kinfu, Thomas Sharkey, and Sam C. Okoroafo. 2010. "The impact of Chinese investment in Africa." *International Journal of Business and Management*, 5(9), p.3.

AidData. 2017. "WorldBank_GeocodedResearchRelease_Level1_v1.4.2 geocoded dataset." Williamsburg, VA and Washington, DC: AidData. Accessed on [date]. http://aiddata.org/research-datasets.

Asher, Sam, and Paul Novosad. 2020. "Rural roads and local economic development." *American Economic Review*, 110(3).

Brautigam, D., 2010. "China, Africa and the international aid architecture." *African Development Bank Group Working Paper*, *107*.

Blair, R., R. Marty, and P. Roessler. "Foreign Aid and Soft Power: Great Power Competition in Africa in the Early 21st Century." AidData Working Paper #86. Williamsburg, VA: AidData at William & Mary.

Bluhm, Richard, Axel Dreher, Andreas Fuchs, Bradley Parks, Austin Strange, and Michael Tierney. 2018. "Connective Financing: Chinese Infrastructure Projects and the Diffusion of Economic Activity in Developing Countries." AidData Working Paper #64. Williamsburg, VA: AidData at William & Mary.

Depetris-Chauvin, Emilio, Ruben Durante, and Filipe Campante. 2020. "Building Nations through Shared Experiences: Evidence from African Football." *American Economic Review*, 110(5), pp.1572-1602.

Dinkelman, Taryn. 2011. "The effects of rural electrification on employment: New evidence from South Africa." *American Economic Review*, 101(7), pp.3078-3108.

Dreher, Axel, Andreas Fuchs, Brad Parks, Austin M. Strange, and Michael J. Tierney. 2018. "Apples and dragon fruits: the determinants of aid and other forms of state financing from China to Africa." *International Studies Quarterly*, 62(1), pp.182-194.

Dreher, Axel, Andreas Fuchs, Roland Hodler, Bradley C. Parks, Paul A. Raschky, and Michael J. Tierney. 2019. "African leaders and the geography of China's foreign assistance." *Journal of Development Economics*, 140, pp.44-71.

Dreher, Axel, Andreas Fuchs, Bradley Parks, Austin Strange, and Michael J. Tierney. 2020. “Aid, China, and growth: Evidence from a new global development finance dataset.” *American Economic Journal: Economic Policy*, forthcoming.

Dreher, Axel, Andreas Fuchs, Roland Hodler, Bradley C. Parks, Paul A. Raschky, and Michael J. Tierney. 2021. “Is favoritism a threat to Chinese aid effectiveness? A subnational analysis of Chinese development projects.” *World Development*, 139.

Easterly, William. 2003. “Can foreign aid buy growth?” *Journal of economic Perspectives*, 17(3), pp.23-48.

Duflo, Esther. 2004. “The medium run effects of educational expansion: Evidence from a large school construction program in Indonesia.” *Journal of Development Economics*, 74(1), pp.163-197.

Fuchs, Andreas, and Marina Rudyak. 2019. “The motives of China’s foreign aid.” In *Handbook on the International Political Economy of China*. Edward Elgar Publishing.

Galiani, Sebastian, Stephen Knack, Lixin Colin Xu, and Ben Zou. “The effect of aid on growth: Evidence from a quasi-experiment.” *Journal of Economic Growth*, 22(1), pp.1-33.

Gehring, Kai S., Melvin HL Wong, and Lennart Kaplan. 2018. “Aid and conflict at the subnational level: Evidence from World Bank and Chinese development projects in Africa.” (No. 657). Discussion Paper Series.

Golub, Stephen, and Faraz Hayat. 2015. “Employment, unemployment, and underemployment in Africa.” *The Oxford Handbook of Africa and Economics*, 1, pp.136-153.

Guillon, Marlène, and Jacky Mathonnat. 2020. “What can we learn on Chinese aid allocation motivations from available data? A sectorial analysis of Chinese aid to African countries.” *China Economic Review*, 60, p.101265.

Hjort, Jonas, and Jonas Poulsen. 2019. “The arrival of fast internet and employment in Africa.” *American Economic Review*, 109(3), pp.1032-79.

Isaksson, Ann-Sofie, and Andreas Kotsadam. 2018a. “Chinese aid and local corruption." *Journal of Public Economics*, 159, pp.146-159.

Isaksson, Ann-Sofie, and Andreas Kotsadam. 2018b. "Racing to the bottom? Chinese development projects and trade union involvement in Africa." *World Development*, 106, pp.284-298.

Jayaram, Kartik, Omid Kassiri, and Irene Yuan Sun. 2017. "Dance of the Lions and Dragons." McKinsey & Company.

Khomba, Daniel Chris, and Alex Trew. 2019. "Aid and growth in Malawi." Unpublished.

Knutsen, Carl Henrik, Andreas Kotsadam, Eivind Hammersmark Olsen, and Tore Wig. 2017. "Mining and local corruption in Africa." *American Journal of Political Science*, 61(2), pp.320-334.

Lipscomb, Molly, A. Mushfiq Mobarak, and Tania Barham. 2013. "Development effects of electrification: Evidence from the topographic placement of hydropower plants in Brazil." *American Economic Journal: Applied Economics*, 5(2), pp.200-231.

Martorano, Bruno, Laura Metzger, and Marco Sanfilippo. 2020. "Chinese development assistance and household welfare in sub-Saharan Africa." *World Development*, 129, p.104909.

Murdock, George Peter. 1959. *Africa Its Peoples and Their Culture History*. New York: McGraw-Hill Book Company.

Nunn, Nathan. 2008. "The long-term effects of Africa's slave trades." *The Quarterly Journal of Economic*s, 123(1), pp.139-176.

Oya, Carlos, and Florian Schaefer. 2019. "Chinese firms and employment dynamics in Africa: A comparative analysis." IDCEA Research Synthesis Report, SOAS, University of London.

Qian, Nancy. 2015. "Making progress on foreign aid." *Annu. Rev. Econ.*, 7(1), pp.277-308.

Roubaud, François, and Constance Torelli. 2013. "Employment, unemployment, and working conditions in the urban labor markets of sub-Saharan Africa: Main stylized facts." Urban Labor Markets in Sub-Saharan Africa, p.37.

Rounds, Zander, and Hongxiang Huang. "We are not so different: A comparative study of employment relations at Chinese and American firms in Kenya.” China-Africa Research Initiative Working Paper Series, 10.

Sautman, Barry, and Hairong Yan. 2015. “Localizing Chinese enterprises in Africa: From myths to policies.” Report No. 2015-05. HKUST Institute for Emerging Market Studies.

Strange, Austin M., Brian O’Donnell, Daniel Gamboa, Bradley Parks, and Charles Perla. “AidData’s methodology for tracking underreported financial flows.” Version 1.3. AidData, Williamsburg, VA.

The State Council, The People’s Republic of China. 2011. “China’s Foreign Aid.” http://english.www.gov.cn/archive/white_paper/2014/09/09/content_281474986284620.htm

The State Council, The People’s Republic of China. 2014. “China’s Foreign Aid.” http://english.www.gov.cn/archive/white_paper/2014/08/23/content_281474982986592.htm

The State Council, The People’s Republic of China. 2015. “China’s Africa Policy.” https://www.chinadaily.com.cn/world/XiattendsParisclimateconference/2015-12/05/content_22632874.htm

The State Council, The People’s Republic of China. 2016. “The Right to Development: China’s Philosophy, Practice and Contribution.” http://www.scio.gov.cn/zfbps/32832/Document/1534707/1534707.htm

Wegenast, Tim, Mario Krauser, Georg Strüver, and Juliane Giesen. 2019. “At Africa’s expense? Disaggregating the employment effects of Chinese mining operations in sub-Saharan Africa.” *World Development*, 118, pp.39-51.

Zhao, Suisheng. 2014. “A neo-colonialist predator or development partner? China’s engagement and rebalance in Africa.” *Journal of Contemporary China*, 23(90), pp.1033-1052.

Tables

Table 1. Balance Checks

Differences	DHS clusters with aid – clusters without aid		DHS clusters with active aid –	
	Uncondition	Condition	Uncondition	Conditional
	(1)	(2)	(3)	(4)
Male	-0.007***	-0.009***	-0.005	0.005
	(0.002)	(0.003)	(0.004)	(0.004)
Age	-0.290***	-0.071	-0.743***	-0.119
	(0.063)	(0.086)	(0.121)	(0.115)
Years of education	2.070***	0.448***	1.930***	0.007
	(0.056)	(0.088)	(0.090)	(0.118)
Ethnic diversity	-0.253***	0.099***	0.004	-0.010
	(0.026)	(0.033)	(0.044)	(0.027)
Rural	-0.260***	-0.051***	-0.116***	0.008
	(0.009)	(0.017)	(0.016)	(0.022)
Terrain roughness	-0.052*	-0.158**	-0.321***	-0.049
	(0.031)	(0.068)	(0.056)	(0.072)
Log travel time to nearest cities	-1.299***	-0.327***	-0.324***	-0.008
	(0.026)	(0.036)	(0.052)	(0.054)
Log distance to national	-0.060**	0.040*	0.110**	0.029
	(0.025)	(0.022)	(0.048)	(0.021)
Log distance to water bodies	-0.763***	-0.199***	-0.225***	0.021
	(0.026)	(0.026)	(0.050)	(0.029)
Log distance to protected	-0.160***	-0.13	-0.153***	0.009
	(0.019)	(0.025)	(0.032)	(0.020)
Log night light density in 2000	2.935***	0.781***	0.798***	0.113
	(0.057)	(0.101)	(0.104)	(0.114)
Log population density in 2000	1.881***	0.383***	0.778***	0.012
	(0.033)	(0.039)	(0.059)	(0.041)

Note: Columns 1 and 3 report the unconditional comparisons, while columns 2 and 4 present the comparisons after controlling for country-year and ADM2 fixed effects. The standard errors clustered at the DHS cluster level are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Impact of Chinese Aid Projects on Local Employment

Dependent variable	Whether an individual was currently working, mean = 0.65					
	(1)	(2)	(3)	(4)	(5)	(6)
Active	0.018***	0.021***	0.023***			
	(0.007)	(0.007)	(0.007)			
Active.Lag4+				0.020***	0.021***	0.022***
				(0.005)	(0.005)	(0.005)
Active.Lag3				0.010	0.004	0.004
				(0.007)	(0.006)	(0.006)
Active.Lag2				0.039***	0.040***	0.041***
				(0.006)	(0.006)	(0.005)
Active.Lag1				0.022***	0.024***	0.025***
				(0.007)	(0.007)	(0.007)
Inactive	-0.004	-0.000	0.001	0.007	0.009	0.010
	(0.007)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)
DHS cluster covariates			Yes			Yes
Individual covariates		Yes	Yes		Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	541,715	536,714	536,699	541,715	536,714	536,699
R-squared	0.084	0.220	0.220	0.084	0.220	0.220
Active – Inactive	0.022***	0.021***	0.022***			
	(0.006)	(0.006)	(0.006)			
Active.L4+ – Inactive				0.014**	0.011*	0.013**
				(0.006)	(0.006)	(0.006)
Active.L3 – Inactive				0.003	-0.005	-0.005
				(0.009)	(0.009)	(0.009)
Active.L2 – Inactive				0.032***	0.031***	0.031***
				(0.007)	(0.007)	(0.007)
Active.L1 – Inactive				0.016*	0.015*	0.015*
				(0.009)	(0.009)	(0.009)

Note: Columns 1–3 correspond to the regression specified in Eq. 1, while columns 4–6 correspond to the specification of Eq. 2. In columns 1 and 4, we include the fixed effects specific to each country-year grid and every second sub-national (ADM2) region. The individual covariates include gender, age, ethnicity, and years of education. The covariates at the DHS cluster level include rural/urban status, terrain roughness, travel time to nearest cities, and ethnic diversity; distances to capitals, national borders, water bodies, and protected areas; gold, copper, diamond, and petroleum deposits; conflict intensity, population density, and night light density before the sample period. Columns 3 and 6 include all the covariates and fixed effects specified in Eq. 1 and Eq. 2. The difference-in-differences type of estimators are reported at the bottom of the table. Standard errors clustered at the DHS cluster level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Impact on Different Occupations

Dependent variable	Agriculture self-employed	Agriculture employee	Sales	Service	Profession al	Manual	Skilled manual	Unskilled manual
Mean	0.18	0.11	0.13	0.04	0.05	0.11	0.07	0.04
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active	0.010	-0.009	0.006	0.001	-0.002	0.013***	0.009***	0.003
	(0.007)	(0.006)	(0.004)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
Inactive	0.006	-0.000	0.008*	-0.003	-0.006**	-0.002	-0.007**	0.005*
	(0.008)	(0.007)	(0.005)	(0.002)	(0.002)	(0.005)	(0.003)	(0.003)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	536,699	536,699	536,699	536,699	536,699	536,699	536,699	536,699
R-squared	0.400	0.285	0.130	0.060	0.160	0.091	0.071	0.095
Active – Inactive	0.004	-0.009**	-0.002	0.003*	0.004*	0.015***	0.017***	-0.002
	(0.006)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)

Note: The dependent variable indicates whether an individual was working in each main occupation category, respectively, in different columns. All the covariates and fixed effects specified in Eq. 1 are included. The difference-in-differences type of estimators are reported at the bottom of the table. Standard errors clustered at the DHS cluster level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Impact on Duration and Payment of Work

Dependent	Year-round	Seasonal or	Cash	Cash and kind	Not paid
Mean	0.37	0.22	0.35	0.14	0.13
	(1)	(2)	(3)	(4)	(5)
Active	0.012*	0.006	0.016**	0.003	-0.000
	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)
Inactive	-0.008	0.013**	-0.023***	0.012*	0.022***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)
Covariates	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	536,699	536,699	536,699	536,699	536,699
R-squared	0.181	0.166	0.202	0.190	0.152
Active – Inactive	0.020***	-0.007	0.039***	-0.009*	-0.022***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)

Note: The dependent variable indicates whether an individual was employed in work with different characteristics, respectively, in different columns. All the covariates and fixed effects specified in Eq. 1 are included. The difference-in-differences type of estimators are reported at the bottom of the table. Standard errors clustered at the DHS cluster level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Types of infrastructure aid projects

Dependent variable	Whether an individual was currently working, mean = 0.65							
Infrastructures	Road, railway (28.6%)		Water, power (19.2%)		School, hospital (16.7%)		Public building (35.6%)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active – Inactive	0.031***		0.064***		0.058***		0.009	
	(0.008)		(0.008)		(0.007)		(0.006)	
Active.L4+ – Inactive		0.021***		0.046***		0.056***		0.016**
		(0.008)		(0.008)		(0.009)		(0.008)
Active.L3 – Inactive		-0.007		0.056		0.010		-0.002
		(0.013)		(0.043)		(0.013)		(0.013)
Active.L2 – Inactive		0.063***		0.080***		0.051***		-0.006
		(0.011)		(0.011)		(0.008)		(0.008)
Active.L1 – Inactive		-0.006		0.070***		0.030**		0.027*
		(0.015)		(0.013)		(0.013)		(0.015)

Note: This table presents the difference-in-differences estimation results. The full regression results are reported in Table B4 in the Appendix. The regressions in odd columns are specified as Eq. 1 and those in the even columns correspond to Eq. 2. All the covariates and fixed effects specified in Eqs. 1 and 2 are included. Across different columns, the variables "Inactive," "Active," and its lagged terms are constructed based on local individuals' proximity to Chinese aid projects relating to different infrastructures, respectively. Standard errors clustered at the DHS cluster level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Impacts on Other Outcomes

Dependent variable	Wealth index		Night light index	
Mean	3.1		0.9	
	(1)	(2)	(3)	(4)
Active – Inactive	0.065**		0.051***	
	(0.025)		(0.014)	
Active.L4+ –		0.068**		0.059***
		(0.028)		(0.019)
Active.L3 – Inactive		0.121***		0.026
		(0.038)		(0.037)
Active.L2 – Inactive		0.021		0.031*
		(0.031)		(0.019)
Active.L1 – Inactive		0.022		0.096***
		(0.040)		(0.025)

Note: This table presents the difference-in-differences estimation results. The full regression results are reported in Table C4 in the Appendix. The dependent variable in columns 1 and 2 is the wealth index at the household level, representing the quintile of wealth distribution in which each household is located. All the covariates and fixed effects specified in Eqs. 1 and 2 are included in these two columns. The dependent variable in columns 3 and 4 is the logarithm of night light density at the DHS cluster level. The observations are the DHS clusters, hence individual-level covariates are not included in these two columns. Odd columns are specified as Eq. 1 and even columns are specified as Eq. 2. Standard errors are clustered at the DHS cluster level. *** p<0.01, ** p<0.05, * p<0.1.

Figures

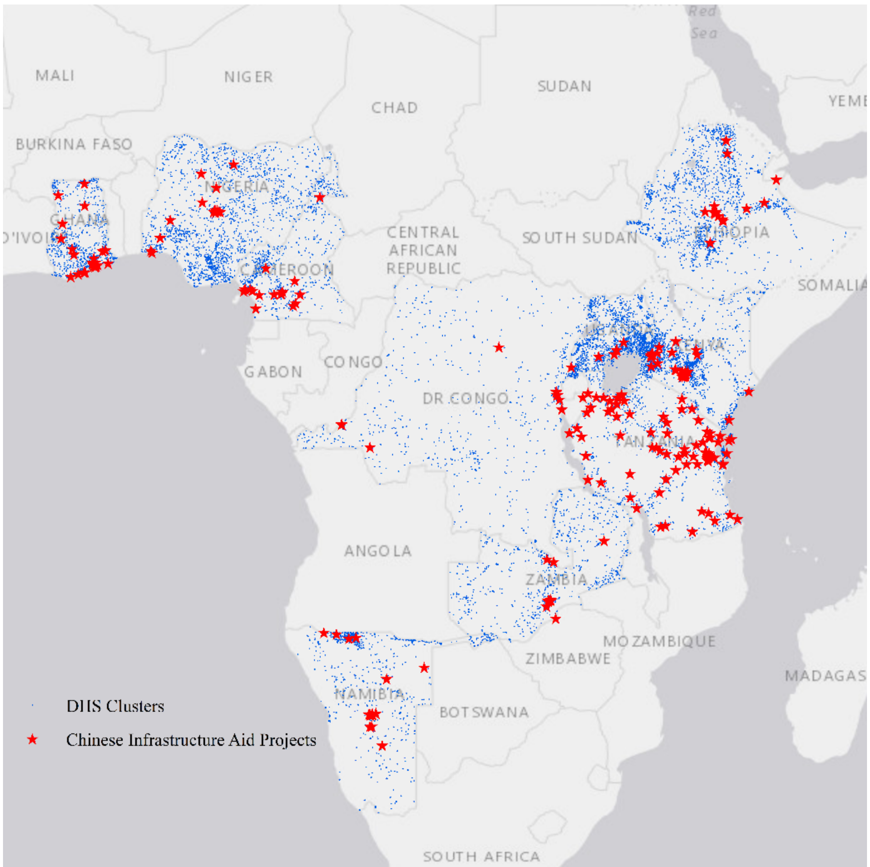

Figure 1. Locations of Chinese Aid Projects and DHS Clusters

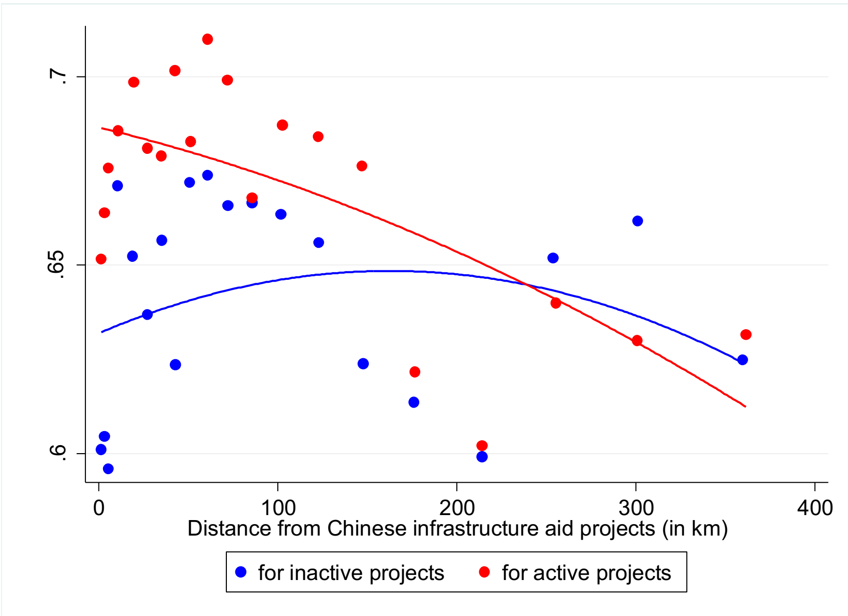

Figure 2. Employment and Distance from Chinese Projects

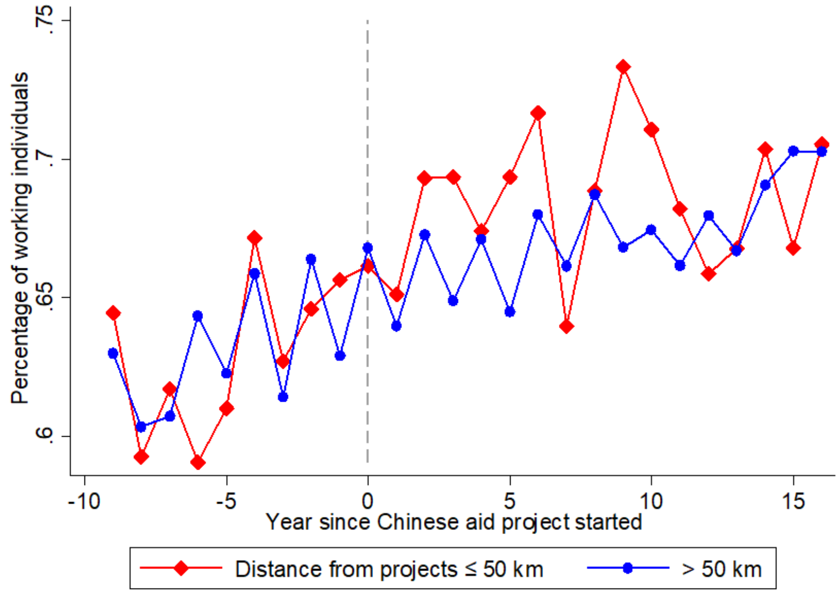

Figure 3. Trends in Local Employment

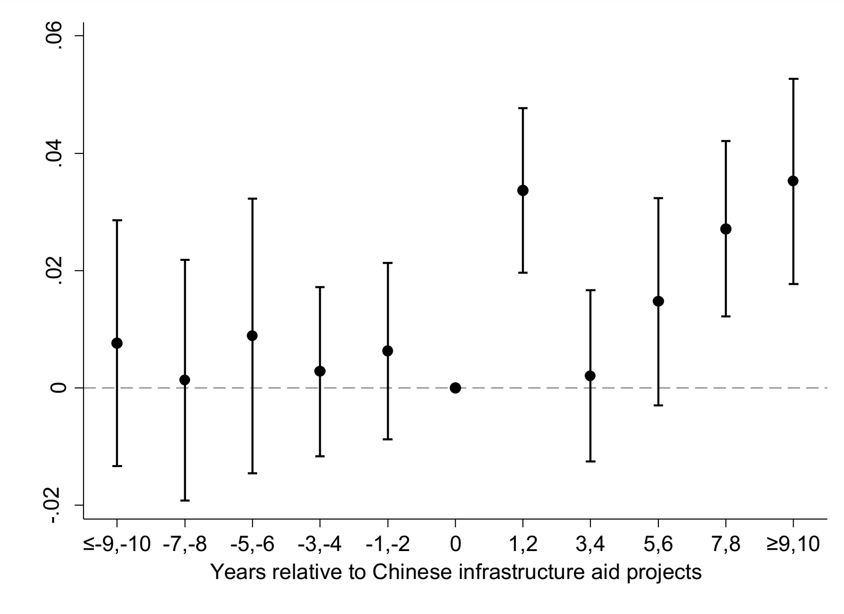

Figure 4. Impact of Chinese Aid Projects on Local Employment