# Chinese Development Aid and Agricultural Productivity: Evidence from Tanzania \*

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#### Abstract

Improvement in agricultural productivity plays a key role in the process of economic development. Investment in critical infrastructure has been documented in the literature as one of the pathways to boost agricultural productivity. In this paper, I investigate whether foreign aid aimed at economic and social infrastructure can help improve agriculture productivity in Tanzania. I combine household panel data with rich farm level information with geocoded Chinese development projects. I then exploit the within village level variation in the total number of Chinese financed development projects in a panel fixed effects model to examine their effects on agricultural productivity. I find a positive effect on agricultural productivity in villages that are located within 25 km of these projects. This is largely driven by economic infrastructure. The results are robust to alternative definitions of Chinese financed development projects. I also find that the potential mechanisms driving the results are agricultural commercialization and access to improved seeds. This suggests that these projects connect farmers to input and output markets.

Keywords: Foreign Aid, Agricultural Productivity, China JEL classification codes: F35,013

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### 1 Introduction

Agricultural productivity is important for understanding international income differences. Agriculture GDP per worker for the richest countries is 71 times that of the poor countries compared to less than 4 times that of Non-agriculture GDP per worker between the 2 groups (Caselli, 2005; Restuccia et al., 2008). Therefore, improving agricultural productivity is a critical policy concern for most developing countries. Improvement in critical infrastructure has been documented as one of the pathways to boost agricultural productivity.

Since 2000, China has increased its footprint in terms of development finance and foreign direct investment on the African continent (Brautigam, 2011). African countries received a large proportion (59 percent) of the total number of projects financed by China between 2000 and 2014 (Dreher et al., 2021b). They are mainly directed towards "connective infrastructure" such as transportation, energy, telecommunications (see Figure 1) unlike other forms of development finance. This makes Chinese development aid a unique source of development finance that merits special attention (Dreher et al., 2021b). These kinds of infrastructure have the potential of improving agriculture productivity (Adamopoulos, 2011): stimulate access to and adoption of agricultural technology, provision of information on markets, prices, weather, among others.

In this paper, I empirically investigate the impact of Chinese development finance projects on agriculture productivity in Tanzania at the subnational level. To do so, I combine household panel data with rich farm level information with geocoded Chinese development projects. I focus on Tanzania because it is the largest receiver of the number of Chinese aid projects in Africa and one of the top growth performers in Sub-Saharan Africa (SSA). Also, the agricultural sector supports the livelihoods directly of about 55% of Tanzanians and 75% of the poor (World Bank, 2019). In addition, the country has witnessed some improvements in agriculture labor productivity since the 2000s (see Figure 2 ) which coincides with the onset of the inflows of Chinese development aid to SSA. Finally, just like Tanzania, agriculture sector is the main source

of livelihood in most countries in SSA (Shimeles et al., 2018; Jayne et al., 2017; Oecd, 2016). This implies that results of the study have implications for other countries in SSA whose structure is like that of Tanzania.

The main challenge in identifying the causal effect of Chinese development aid is that they are not randomly allocated across villages. Villages with the highest potential for development may be given preference, or those lagging furthest behind to obtain priority. I therefore exploit the within village variation in the number of projects in a panel fixed effect model. Furthermore, to deal with the fact that the allocation of these projects could be determined by unobservable time variant factors, I use an instrumental variable (IV) strategy that is based on the interaction of two elements to isolate the exogenous component of variation in the number of these projects. The first element exploits the arguably exogenous time variation in China´s steel production and the second element exploits the cross-sectional variation in a village's likelihood to be allocated a Chinese aid project.

I find a positive effect of Chinese development projects on agricultural productivity in villages near these projects. This effect is robust to alternative definitions of Chinese aid projects and largely driven by economic sector projects. I also find that farmers in villages near to these projects are more likely to have access to improved seeds compared to others. They also sell a higher share of their produce in the market.

My paper contributes to our understanding of the relationship between development aid and economic development. One strand of this literature is focus on the country level impact of aid on economic growth (Doucouliagos and Paldam, 2010; Galiani et al., 2017; Rajan and Subramanian, 2008; Dreher and Langlotz, 2017; Clemens et al., 2012). The effectiveness and the extent to which foreign aid fosters economic development is largely inconclusive in this literature and depends on varied factors. In addition to the inconclusiveness of this strand of literature, analysis at the macro-level suffer from problems of endogeneity issues related to the aggregation of foreign aid, reverse causality and unobserved heterogeneity underlying the allocation of bilateral aid flows from donor to recipient countries. I depart from these papers by focusing on the sub-national level instead of the national level.

An increasing number of studies examined the effectiveness of Chinese aid both at the macro and subnational level by examining their impact on: economic activity, literacy, environmental degradation, trade union participation, corruption and household welfare (Brazys et al., 2017; Isaksson and Kotsadam, 2018a,b; BenYishay et al., 2016; Dreher et al., 2016, 2021b; Martorano et al., 2020). My paper differs from the others because it examines the causal impact of Chinese aid on agricultural productivity. Also, in contrast to some of these papers, I make use of the natural path cost which is the time in hours it takes to walk from a village to the nearest city in the absence of any transportation infrastructure as the proxy of the probability of receiving aid as opposed to computing the probabilities using the share of aid received in the past.

Finally, the paper is closely related to the literature that investigated the determinants of agricultural productivity (Yamamoto et al., 2019; Gottlieb and Grobovšek, 2019; Abman and Carney, 2020; Goldstein and Udry, 2008; Chen, 2017). I provide further evidence that foreign aid aimed at improving infrastructure can help increase agricultural productivity.

The rest of the paper is structured as follows. Section 2 discusses the main sources of data and descriptive statistics. Section 3 lays out the empirical strategy while section 4 reports the empirical results. Section 5 presents the robustness checks. Section 6 explores the potential mechanisms driving the results. The paper concludes in section 7.



Figure 1: Types of Chinese Financed Projects in Africa (2000 to 2014)

#### Source: Author's construct using data from AidData

Notes: The projects are grouped based on their Creditor Report System (CRS). Economic projects include Transport and Storage (210); Communications (220); Energy Generation and Supply (230), Social projects include: Education (110); Health (120); Population Policies (130); Water Supply and Sanitation (140); Government and Civil Society (150); Other Social Infrastructure and Services (160). CRS codes are provided in parentheses. The economic projects are mainly aimed at roads, ports, railways and bridges. These kind of infrastructure are collectively known as "connective infrastructure" because they facilitate the mobility of goods, labor and capital.







#### 2 Data

I provide a detailed description of the two main sources of data in this section. These are the Living Standards Measurement Study - Integrated Surveys on Agriculture and the AidData's Global Chinese Development Finance Dataset (Version 1.1.1).

# 2.1 Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA)

The LSMS-ISA for Tanzania is a panel of three rounds of a nationally representative household sample, collected by the Tanzania's National Bureau of Statistics (NBS).<sup>1</sup> The first 3 rounds were collected in 2008/2009, 2010/2011 and 2012/2013. They have very detailed information on the household agricultural activities (detailed plot level information on cultivation, input use, land quality, etc.). Each round has information on two agricultural seasons, the long and short rainy seasons. 3,265 unique households were interviewed in the first round clustered in 409 enumeration areas. Out of this number, 2,429 (74.4%) are Agricultural households (AgHH). A sub-sample of AgHH (2,080) engage in crop husbandry, or both crop husbandry and animal husbandry. I refer to this sub-sample as crop production households (CHHs).<sup>2</sup> The rest of the AgHH are engaged in only animal husbandry. I was able to trace 1,907 and 1,892 of the CHHs in the 2nd and 3rd rounds respectively.

Summary statistics are provided in Table 1. About 80% of the CHHs are males with an average household size of 6 across the 3 waves. The average years of schooling is about 12 in the first 2 waves and 13 in the third wave. This means, a typical farm household member has attended school up to the ordinary secondary level.<sup>3</sup> On average, the farmers cultivate small plots of land and tend to use more family labor

<sup>&</sup>lt;sup>1</sup>Technically, there are 4 rounds of the data but only the first 3 can be considered a panel. The last round collected in 2014/2015 draws on 3,352 new households keeping at least half of the original sample. The last round is excluded from this study due to this reason but also because there are several key variables relevant for my study that are missing in the last round.

<sup>&</sup>lt;sup>2</sup>I use CHHs and farm households interchangeably.

<sup>&</sup>lt;sup>3</sup>The system of education in Tanzania comprises a 2-7-4-2-3+ structure. Two years of pre-primary school, seven years of primary school, four years of ordinary secondary school, two years of advanced secondary school and at least 3 years of higher education.

than hired labor. The average farm size cultivated by the households in the 3 waves is about 2 hectares. This suggest that the farm households are on average smallholder farmers.

Farm labor, especially family labor declined on average in the 2nd wave but increased in the 3rd wave. The decline of family labor in the 2nd wave is because a relatively small share of the farm households used family labor compared to the other two waves. This is likely due to the drought experienced in East Africa in 2011. The use of fertilizer, pesticides and improved seeds is also low among the farm households. In the last wave, 20% of the farm households used organic fertilizer, 18% used inorganic fertilizer, 15% used pesticide and 24% used improved seeds.

Finally, the farmers have a title to, and irrigate a small share of land that they cultivate. The small share of cultivated area that is irrigated reflects the dominance of rainfed agriculture in most countries in SSA.

#### 2.2 Geocoded Chinese official Finance Data

The data on Chinese development aid projects comes from AidData's Global Chinese Development Finance Dataset.<sup>4</sup> AidData reports geocoded information on Chinese official finance projects from 2000 to 2014. For each project, the database provides detailed information on its precise location, the sector it belongs to classified following the OECD Creditor Report System (CSR) purpose codes, financial volume, the type of flow (e.g., Official Development Assistance, ODA, or other Official Flows, OOF), start year and the project status (either completed or being implemented). A main limitation of the data is that, AidData collates project information from numerous sources including the media, government, among others (Strange et al., 2013). This is because the Chinese government does not officially report information on foreign assistance.

I make the following adjustments to the data. First, only projects classified as ODA are considered in this study. This is because ODA projects are primarily aimed

<sup>&</sup>lt;sup>4</sup>Available at https://www.aiddata.org/data/geocoded-chinese-global-official-finance-dataset

at fostering development goals while OOF projects are primarily aimed at commercial activities.<sup>5</sup>

Secondly, following the existing literature, I restrict the sample to projects with a precision code of up to 3. AidData classifies the precision of the location of the projects on a scale of 1 to 7. The higher the number, the less precise the location. A precision code of 3 is analogous to the 2nd order administrative level. This means, I consider only projects whose location are relatively more precise.

Thirdly, while all the projects have a start date, most of them do not have a completion date. Therefore, I only consider projects whose status indicated that they are completed. I end up with 193 projects in Tanzania of which 60% of them are economic infrastructure. For the sample of projects that have both start and completion dates, it takes on average 1.8 years to complete them. The location of these projects and the villages are shown in Figure 3. It can be seen that most of the projects (green dots) are concentrated in villages closer to the major cities such as the capital city Dar es Salaam (center right) and Mwanza (top left).

<sup>&</sup>lt;sup>5</sup>According to the OECD Development Assistance Committee (DAC) definition, ODA is (a) provided by official agencies to developing countries, (b) aimed at promoting economic development and welfare, and (c) contains a grant element of at least 25 percent.

	2008/2009	2010/2011	2012/2013
Demographics			
(HH head(male=1))	0.76	0.76	0.77
HH size	5.41	5.70	5.62
HH average years of education	11.72	11.94	12.93
Farm Characteristics			
Cultivated Area (has)	2.11	2.14	2.18
Family labor (person-days per has)	114.59	43.34	120.86
Hired labor (person-days per has)	12.18	9.15	10.53
Use hired labor (Yes $=1$ )	0.45	0.38	0.43
Use family labor (Yes =1)	0.95	0.34	0.65
Use organic fertilizer (Yes =1)	0.18	0.18	0.20
Use inorganic fertilizer (Yes =1)	0.16	0.19	0.18
Use pesticide (Yes =1)	0.15	0.13	0.15
Use improved seed (Yes =1)	0.19	0.14	0.24
Others (share of farm land)			
Sandy	0.17	0.17	0.16
Loamy	0.58	0.56	0.56
Intercropped	0.54	0.49	0.57
Irrigated	0.03	0.02	0.03
HH has title	0.07	0.10	0.14
Number of CHHs	2080	1907	1892

Table 1: Summary statistics of selected variables

Notes: HH stands for household, has for hectares and CHHs for crop production households i.e agricultural households that engaged in crop production. A typical person-day is about eight hours per day. The harvest values are in 2009 constant prices.



Source: Author's construct using data from AidData and Tanzania National Bureau of Statistics. Figure 3: Location of Villages (red dots) and Chinese Projects (green dots) in Tanzania

### **3** Empirical model and identification strategy

I estimate the effect of Chinese development aid on agricultural productivity in a panel fixed effect model using the following specification.

$$Y_{hvt} = \beta_0 + \alpha_h + \omega_t + \delta aid_{vt} + \eta H_{hvt} + \gamma W_{vt} + \theta S_v t + \epsilon_{hvt} \quad (3.1)$$

Where  $Y_{hvt}$  denotes a measure of productivity of farm cultivated by household (HH) h, in village v, in period t, where t is a season-year pair,  $\alpha_h$  and  $\omega_t$  are HH and season-year fixed effects respectively.<sup>6</sup> aid is a measure of Chinese development aid. I make use of three alternative measures of Chinese development aid.<sup>7</sup> The first one is the cumulative number of projects a village is near to, two years prior to the survey.<sup>8</sup> The second definition is a dummy variable which indicates whether if a village is near to at least an additional project, two years prior to the survey. The third definition is the additional number of projects a village is near to, two years prior to the survey. In specifications that made use of the last two definitions, I control for the historical number of projects. It is worthy to mention at this juncture that the preferred measure of Chinese aid in this study is the third definition since it considers the intensity of treatment. Also, I restrict the proximity of a village to a Chinese development aid project to 25 km in the main analysis. This is because the Tanzania LSMS GPS coordinates have been randomly displaced to preserve the anonymity of the households. Specifically, urban areas are randomly offset by a maximum of 2 km while rural areas are randomly displaced within a range of 0 to 5 km. In addition, some of the rural clusters are randomly displaced by a maximum of 10 km. The arbitrary choice of 25 km is to compromise between not being too close or far away from the maximum random displacement. I conduct a robustness test to check the

<sup>&</sup>lt;sup>6</sup>As indicated in the data section, there are two agricultural seasons each year in Tanzania

<sup>&</sup>lt;sup>7</sup>AidData provides information on the commitment amounts but not actual disbursements. Apart from the fact that commitment figures can significantly differ from actual disbursement, the commitment figures are available at the overall project level but not at the project site level.

<sup>&</sup>lt;sup>8</sup>Since the data on the dependent variable starts from 2008/2009 while the Chinese projects start from 2000, I decided to take into account all the projects by computing the cumulative number of project 2 years prior to the survey year. 2 years was chosen because it takes on average 1.8 years from start to completion for the sample projects that have both a start and a completion date.

sensitivity of the results to alternative distance buffers in section 5.1.

Model 3.1 also includes a set of control variables:  $H_{hvt}$  is a vector of household time varying variables which includes age of HH head, labor inputs use, share of each main crop cultivated, share of farmland quality, among others.  $W_{vt}$  is a vector of village level time varying weather variables (temperature and precipitation) and the log of population. Finally,  $S_v t$  is a set of interactions between a common linear time trend t, and fixed village level characteristics such as distance to major road, distance to district headquarters. This interaction absorbs time varying heterogeneity in agricultural productivity across factors correlated with the likelihood of being allocated a Chinese aid project in lieu of the time trends.

The identifying assumption of model 3.1 is that within village variation in Chinese aid projects are as good as randomly assigned, conditional on observable characteristics and fixed effects. For the first measure of Chinese aid project, this assumption may not be valid. This is because this measure considers projects that have started in 2000. Therefore, any time varying factor that may have influenced the allocation of the aid projects in the very past is not accounted for in the model. However, the identification assumption is more likely to be valid in the case of the last 2 measures of Chinese aid as they consider only recent aid projects. Another concern is that the variation in Chinese aid projects could still be endogenous: determined by unobservable time variant factors. In that case, OLS estimates of model 3.1 may not be interpreted as causal effects.

To deal with the above concern, I make use of an instrumental variable (IV) approach to isolate the arguably exogenous part of the variation. The IV approach exploits the exogenous time variation in China's steel production and cross-sectional variation in the likelihood of a village to be allocated a Chinese aid project. Specifically, the first stage regression is estimated as follows.

$$aid_{vt} = \delta(\bar{P}_v * steel_{3t}) + \alpha_h + \omega_t + \eta H_{hvt} + \gamma W_{vt} + \theta S_v t + \nu_{vt} \quad (3.2)$$

Where *steel*<sub>3t</sub> is Chinese annual steel production (in logs and detrended) three years prior to the survey and  $\bar{P}_v$  is a village's probability to be allocated Chinese aid project. I use the amount of steel produced three years prior to the survey to allow for a year lag between steel production and the financing of the aid projects.<sup>9</sup> As demonstrated by the existing literature (Bluhm et al., 2020; Dreher et al., 2021a,b), the annual production of steel in China, is a key determinant of the number of Chinese financed infrastructure projects. The authors showed that the number of projects financed tend to increase with China's steel production. They argue that China produces steel at levels that considerably surpasses domestic demand because the country consider steel to be a strategic commodity. This is mainly done by, among other things, heavily subsidizing Chinese state-owned enterprises. China then commits to more aid projects that often use these overproduced goods as inputs (Brautigam, 2011; Bluhm et al., 2020), i.e. the excess supply is used to subsidize infrastructure projects abroad by making their financing conditional on the purchase of steel and other inputs from China.

Secondly, the probability of being allocated a Chinese aid project is proxied with a natural path cost which is the time in hours it takes to walk from a village to the nearest city in 2002 in the absence of any transportation infrastructure.<sup>10</sup> This measure considers the effect of geography, i.e., travel speed adjusted by slope and other topographical characteristics. It provides the most efficient, i.e., the least costly in terms of hiking time that it would take farmers to transport their produce on foot to the nearest city or to purchase inputs on foot from the nearest city. The argument is that villages that are remote may be the ones in need for development and hence have a higher probability of being allocated these development projects. The interaction term, therefore allows the positive effect of steel production on the number of Chinese financed infrastructure projects to depend on the probability of being allocated an aid project.

<sup>&</sup>lt;sup>9</sup>The data on China's steel production is from the statistical yearbook of the World steel association. https://worldsteel.org/steel-by-topic/statistics/steel-statistical-yearbook

<sup>&</sup>lt;sup>10</sup>see Appendix A for a description of how the natural path cost is constructed

### 4 Empirical Results

In this section, I present and discuss the empirical results. I start by presenting and discussing the OLS estimates of 3.1 in section 4.1 followed by a sectoral analysis of the different projects in 4.2. I end the section with the IV results in section 4.3.

#### 4.1 OLS Estimates

In this section, the results of the OLS estimate of equation 3.1 are presented and discussed. The results for land productivity (log of real value of agricultural output per hectare) are presented in Table 2 while that of labor productivity (log of real value of household farm output per person-days) are presented in Table 3. There are three panels, each corresponds to each measure of Chinese aid. Also, there are three columns, column 1 omits the controls for input usage and the interaction between a linear time trend and village characteristics. These controls are added in columns 2 and 3 respectively.

First, I focus on the first measure of Chinese aid, the cumulative number of projects (panel A). One can observe a positive and significant effect of Chinese aid on agricultural productivity (see column 1 of Panel A) from the baseline estimates. The results suggests that an additional increase in the cumulative number of Chinese aid projects leads to an increase in both land and labor productivity by about 10% (see column 3 of Panel A). As already pointed out in section 3, the identification assumption that within village variation in Chinese aid projects are as good as randomly assigned, conditional on observable characteristics and fixed effects is unlikely to hold for the first measure Chinese development aid. Therefore the results in Panel A may be biased.

I now turn to the two alternative measures in which the identification assumption is more likely to hold. The results for the measure using a dummy for additional number of projects are presented in Panel B while that of additional number of projects are presented in Panel C. The results in general point towards a positive and statistically significant effect on agricultural productivity. Controlling for input usage and the interaction between a linear time trend and village characteristics slightly reduces the magnitude of the effect for land productivity while that of labor productivity slightly increases (see columns 2 and 3).

Specifically, farm households living in villages near to at least one additional Chinese development aid project experienced an increase in agricultural land productivity by about 12.6% while that of agricultural labor productivity increases by 17.7%. On the other hand, each additional project boost the productivity of agricultural land by about 9% while that of agricultural labor increases by about 12%.

Although, the magnitudes of the three measures are not directly comparable, they all point to a statistically significant positive effect of Chinese development aid on agricultural productivity in Tanzania.

#### 4.2 Sectoral Analysis

To further understand the above results, I conduct a sectoral analysis using the preferred measure of Chinese development aid projects i.e., additional number of Chinese development aid projects. The projects are grouped based on their Creditor Report System (CRS) sectoral codes to make a distinction between social and economic sector projects.<sup>11</sup> The results are shown in Table 4. Economic and social infrastructure projects are included separately (columns 1, 2,4 and 5) and then together in the same model (columns 3 and 6). The inclusion of both sectors in the same model allows one to investigate the heterogeneity of the effect of the different types of aid project. Also, according to Chin and Gallagher (2019), Chinese aid projects seek to achieve interlinkages between different sectors. This suggests that the decision to provide both types of projects may not be mutually independent. The results as shown in Table 4 suggest that economic projects have a positive effect on agricultural land and labor productivity. The coefficient on the social sector projects on the other hand is negative

<sup>&</sup>lt;sup>11</sup>Economic projects include: Transport and Storage (210); Communications (220); Energy Generation and Supply (230), Social projects include: Education (110); Health (120); Population Policies (130); Water Supply and Sanitation (140); Government and Civil Society (150); Other Social Infrastructure and Services (160). CRS codes are provided in parentheses.

although not different from zero. These results are consistent with empirical studies which suggest that improvements in economic infrastructure can help improve agricultural productivity Adamopoulos (2011).

#### 4.3 IV Estimates

As mentioned earlier, the OLS estimates presented in the previous sections may not be interpreted as causal effects due to endogeneity concerns. This section therefore presents the IV estimates of models 3.1 and 3.2. I show here the results for the additional number of projects which is my preferred measure of Chinese aid project. The results are shown in Table 5.

The first stage results indicate a strongly negative and statistically significant effect of the instrumental variable on Chinese aid allocation. This means that more of the additional aid projects created by the increase in steel production are allocated to villages closer to the main cities. As can be seen from Figure 3, most of these projects are concentrated in villages closer to the major cities in Tanzania. A likely explanation for this is that these are the villages with the potential for development. Secondly, the Kleibergen-Paap F statistic is well above the threshold value of 10. This suggests that the instrument passes the weak instrument test.

The second stage results largely confirm the OLS estimates. The results point towards a positive and statistically significant effect on agricultural productivity in all specifications. The magnitude and standard errors (SE) of the IV estimates are larger than that of the OLS. The large IV SE implies that one cannot reject the fact that this effect is just the original OLS effect. This implies that the estimates may not be fraught with endogeneity issues. A possible explanation for the different magnitudes is that the OLS is estimating the average treatment effect (ATE) while the IV is estimating the local average treatment effect (LATE) i.e., the effect of the agricultural productivity increase for the sub population whose choice of treatment was affected by the instrument. However, taken together, the OLS and IV estimates suggest that villages near an additional Chinese aid project experience an increase in agricultural productivity.

Panel ACumulative num of projects0.108**0.098**0.096**		1	2	3
Cumulative num of projects 0.108** 0.098** 0.096**	Panel A			
	Cumulative num of projects	0.108**	0.098**	0.096**
(0.048) $(0.045)$ $(0.045)$		(0.048)	(0.045)	(0.045)
R-squared 0.623 0.637 0.638	R-squared	0.623	0.637	0.638
Panel B	Panel B			
Dummy for additional projects $0.145^{**}$ $0.128^{**}$ $0.126^{*}$	Dummy for additional projects	0.145**	0.128**	$0.126^{*}$
(0.067) $(0.065)$ $(0.065)$		(0.067)	(0.065)	(0.065)
R-squared 0.623 0.637 0.638	R-squared	0.623	0.637	0.638
Panel C	Panel C			
Additional num of projects 0.106** 0.091** 0.090**	Additional num of projects	0.106**	0.091**	0.090**
(0.044) $(0.043)$ $(0.043)$		(0.044)	(0.043)	(0.043)
R-squared 0.623 0.637 0.638	R-squared	0.623	0.637	0.638
HH FE $\checkmark$ $\checkmark$ $\checkmark$	HH FE	$\checkmark$	$\checkmark$	$\checkmark$
SeasonXYear FE 🗸 🗸 🗸	SeasonXYear FE	$\checkmark$	$\checkmark$	$\checkmark$
Control for inputs $\checkmark$ $\checkmark$	Control for inputs		$\checkmark$	$\checkmark$
Village characteristics x time trend $\checkmark$	Village characteristics x time trend			$\checkmark$
Observation 5133 5133 5133	Observation	5133	5133	5133

Table 2: OLS Estimates of the effects of Chinese aid on agricultural land productivity (within 25km)

Notes: The table shows the FE estimates of Chinese development aid project on the log of real value of household farm output per hectare. All regressions control for soil type, main crop grown by the the households, temperature, rainfall and population. Panel B and C also control for the historical number of projects. Robust standard errors clustered at the village level are reported in parentheses. \*\*\*, \*\*,\* denotes 1%, 5% and 10% level of significance respectively.

	1	2	3
Panel A			
Cumulative num of projects	0.094**	0.101**	0.099**
	(0.041)	(0.041)	(0.041)
R-squared	0.788	0.791	0.791
Panel B			
Dummy for additional projects	0.172**	0.176**	0.177***
	(0.071)	(0.068)	(0.068)
R-squared	0.788	0.791	0.791
Panel C Additional num of projects	0.118***	0.117***	0.118***
	(0.045)	(0.043)	(0.043)
R-squared	0.788	0.791	0.791
1			
Observation	3580	3580	3580
HH FE	$\checkmark$	$\checkmark$	$\checkmark$
Season x Year FE	$\checkmark$	$\checkmark$	$\checkmark$
Control for inputs		$\checkmark$	$\checkmark$
Village characteristics x time trend			$\checkmark$

Table 3: OLS Estimates of the effect of Chinese Aid on Agricultural Labor Productivity (within 25km)

Notes: The table shows the FE estimates of Chinese development aid project on the log of real value of household farm output per person-days. All regressions control for soil type, main crop grown by the the households, temperature, rainfall and population. Panel B and C also control for the historical number of projects. Robust standard errors clustered at the village level are reported in parenthesis. \*\*\*, \*\*,\* denotes 1%, 5% and 10% level of significance respectively.

	Land	l Product	tivity	Labo	r Produc	tivity
	1	2	3	4	5	6
Economic	0.0920**		0.0882**	0.115***		0.112**
	(0.0413)		(0.0425)	(0.0428)		(0.0434)
Social		-0.146	-0.110		-0.113	-0.0726
		(0.123)	(0.123)		(0.107)	(0.110)
R-squared	0.642	0.641	0.642	0.791	0.790	0.791
Observation	5114	5114	5114	3580	3580	3580

Table 4: OLS Estimates: Sectorial Analysis

Notes: The table shows the sectoral effects of Chinese aid projects on land and labor productivity. All regressions control for the use of inputs, village-time trend, Household and season-year year fixed effects. Robust standard errors clustered at the village level are reported in parentheses. \*\*\*, \*\*,\* denotes 1%, 5% and 10% level of significance respectively.

	1	2	3
Panel A: First Stage			
$\bar{P_v} * steel_{3t}$	-0.318***	-0.316***	-0.318***
	(0.055)	(0.055)	(0.056)
R-squared	0.619	0.622	0.622
Kleibergen – Paap F statistic	33.0	32.7	32.8
Panel B: IV Estimates			
Additional num of projects	0.639**	0.640**	0.630**
	(0.317)	(0.313)	(0.309)
Observation	5133	5133	5133
HH FE	$\checkmark$	$\checkmark$	$\checkmark$
Season x Year FE	$\checkmark$	$\checkmark$	$\checkmark$
Control for inputs		$\checkmark$	$\checkmark$
Village characteristics x time trend			$\checkmark$

Table 5: IV estimates of the effects of Chinese Aid on Agricultural Productivity (within 25km)

Notes: The table shows the IV estimates of Chinese development aid project on the log of real value of household farm output per hectare. Robust standard errors clustered at the village level are reported in parenthesis. \*\*\*, \*\*, \* denotes 1%, 5% and 10% level of significance respectively.

### 5 Robustness Checks

I have already shown in the previous section that the results are robust to alternative definitions of Chinese development projects. In this section, I conduct two additional checks to demonstrate the robustness of the results. The first has to do with the choice of the proximity cut off. Secondly, I estimate the main equations with the dependent variable in levels rather than in logs. All the results are shown in Appendix B.

#### 5.1 Proximity to Chinese development aid projects

As explained in section 3, a proximity of 25 km was arbitrary chosen due to the random displacement of the household GPS coordinates. I test the robustness of the results to alternative distance buffer by estimating equation 3.1 for different levels of proximity,  $d \in [10,50]$ . The point estimates and the confidence intervals are shown in Figure B.1. It can be observed that the coefficients are similar for distance values ranging from 10 to 25 km but the confidence intervals are high. The effect seems to be lower for higher distance buffers but with a lower confidence intervals.

#### 5.2 Dependent variable in levels

In this section I estimate equation 3.1 with the dependent variable in levels instead of logs using the Poisson Pseudo Maximum Likelihood (PPML) as proposed by Silva and Tenreyro (2006, 2011). The authors note that the PPML estimator leads to more robust and consistent coefficient estimates than the standard log-linear ordinary least squares (OLS) method in the presence of heteroskedasticity. The results are shown in Tables B.1 and B.2. As can be seen the main results remain similar.

### 6 Potential Mechanisms

The results so far have demonstrated that Chinese aid have been beneficial for agricultural productivity in Tanzania. The question then arises: what are the mechanisms through which these projects affect agricultural productivity? The section aims to provide further insights that can answer this question. I estimate a model like model 3.1 with the dependent variables defined in the subsections below. The independent variable of interest is the preferred measure of aid projects, i.e., the additional number of Chinese aid projects. The results are shown in Appendix C.<sup>12</sup>

#### 6.1 Land Titling and Cultivated Area

Land titling, i.e., secure ownership of land greatly affect the investment in the land and thus improve agricultural productivity (Abman and Carney, 2020; Gottlieb and Grobovšek, 2019; Chen, 2017; Chen et al., 2017). Could the improvement in productivity observed in this paper be due to increase in the share of titled land? I use two measures to proxy for land titling. The first one is the share of cultivated land that the household has secured title to. The second measure is a dummy variable that takes the value of 1 if the household has a secured title to at least one of the cultivated plots and zero otherwise. The results for these two measures are reported in columns 1 and 2 of Table C.1 respectively. The estimates indicate a statistically insignificant effect of Chinese aid projects on land titling in Tanzania. Also, I investigate the effect of the Chinese development aid projects on total cultivated area. Total cultivated area is defined as the area (both titled and non-titled) in hectares cultivated by the household. The results for total cultivated area in levels and in logs are shown in columns 3 and 4 of Table C.1 respectively. Again, the estimates indicate that the total area cultivated is not statistically significantly affected by these aid projects.

### 6.2 Access to labor and adoption of improved technologies

The literature has emphasized the importance of labor availability in the adoption of improved technologies. The low rate of adoption of productivity enhancing technologies has been partly attributable to the seasonality and the inadequate supply of agricultural labor. Improvement in economic infrastructure such as road can facilitate

<sup>&</sup>lt;sup>12</sup>I only report the results of the IV estimates.

the mobility of labor and thus make labor available.

To examine the labor mechanism, I define farm labor as the total labor used on the farm measured in person-days per hectare. I then decompose total farm labor use into hired and family labor. The results are presented in columns 1,2 and 3 of Table C.2 respectively. These results are not statistically significant.

Secondly, I use several measures to investigate the improved technology usage mechanisms. These are the use of organic and inorganic fertilizer measured in kilograms per hectare, pesticides (in kilograms per hectare), the share of cultivated land under irrigation and dummy variable which indicates whether the household used an improved seed.<sup>13</sup> The results are presented in Table C.2. The results point toward a positive and significant effect of these aid projects on the likelihood of using an improved seed. All the other measures are not statistically different from zero. This result is not surprising because the use of such inputs is still very low, and agriculture is largely rain-fed in developing countries including Tanzania.

#### 6.3 Agricultural Commercialization and Extension

Improvement in infrastructure can also increase access to agricultural extension agents and connect farmers to output markets. The extension agents normally visit the farmers to provide information on improved agricultural technologies, best farming practices, among others. The improvement in infrastructure can facilitate the mobility of these agents and technology transfer, which in turn enhances agricultural productivity (Maertens et al., 2021; Ragasa and Mazunda, 2018; Dercon et al., 2009). Also, most agricultural areas in SSA are engaged in subsistence farming because of poor market access (Bank, 2007). Farmers may now move away from subsistence production towards market production due to the improvement in infrastructure.

To operationalize this mechanism, I define agricultural commercialization as the percentage of output harvested by the household that has been sold in the market. Agricultural extension on the other hand is defined as a dummy variable that takes

<sup>&</sup>lt;sup>13</sup>There is no information available on the quantity of improved seed used in the survey.

the value of 1 if the household had access to government extension services. The results are reported in Table C.3. I do find a positive effect on the share of harvested output that is sold in the market. The positive effect of these projects on agriculture commercialization suggests that the projects link farmers to output markets. In addition, it is likely that farmers now see agriculture as a way of business and now produce to sell in the market due to the improvement in market access (Dercon et al., 2009).

### 7 Conclusion

I contribute to the growing literature on the effectiveness and allocation of Chinese development aid projects by examining their impact on agricultural productivity in Tanzania. To make a causal claim, I employed a panel fixed effects and instrumental variable strategy to isolate the exogenous variation in the allocation of these projects. I show that Chinese development projects have a positive effect on agricultural productivity in villages close to these projects. The effect decreases with distance and does not go beyond villages that are located farther than 25 km from these projects. Sectoral level analysis suggests that economic sector projects mainly drive these results. This is in line with economic theory which suggests that improvement in economic infrastructure can help improve agricultural productivity. The main mechanisms through which these projects affect agricultural productivity are the use of improved seed and agricultural commercialization. These suggest that these aid projects link farmers to both input and output markets. While the within single country analysis helps overcome endogeneity issues fraught with country level studies, the results may not be generalized to other countries whose structure differ significantly from that of Tanzania.

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# A Appendix A

#### Measures of output and inputs

**Output**: I focus on the farm as the production unit so the unit of observation is a household farm h . This is mainly due to 2 reasons. First, developing country agriculture is characterized by shifting cultivation. This a practice whereby farmers cultivate plots of land temporarily and then allow the plots to rest in order regain their fertility. Therefore, it is unlikely to trace the plots over time. Second, there are measurement issues in attributing output and inputs to each plot since a farmer may operate one or several parcels (or plots) of land. To measure real agricultural output at the farm level, I construct a Laspeyres index of production that aggregates the quantity produced of each crop by the household farm using proxies of prices in the first year as weights. Prices are proxied with unit prices: the value of sales is divided by the quantity sold of each crop and the median unit value of each crop is computed at the national level as standard in the literature.

**Cultivated land area and other inputs**: Farm area cultivated is obtained by adding up the size of the plots cultivated by the household. The survey provides information on input use such family labor, hired labor, pesticides, organic and inorganic fertilizers among others. Just like the output, I aggregated the information on input use to the household farm level. Labor input is measured as the number of person-days used on the farm for both family and hired labor. Inputs usage such as pesticide, fertilizer is measured in kgs per hectare(ha). Furthermore, a farm implements index is constructed using Principal Component Analysis (PCA) to proxy for use of farm implements.

**Other variables** : The survey also provides information on the crop type cultivated by the household, soil characteristics and other cultural practices by the household such as intercropping, irrigation, etc. The shares of each main crop type cultivated on the household farmland area under irrigation, intercropping, rent, etc. were computed. With respect to soil characteristics, the survey asks farmers to classify each parcel according to soil type (sandy, loam, clay), quality (good, fair, or poor) and topography (hilly, flat, gentle slope, valley or other). The parcel-level indicators were aggregated to the farm level to compute the share of each category.

#### Natural Path Measure

The natural path distance is calculated in line with Damania et al. (2016) and Faber (2014) as follows:

- First, I calculated the slope gradients from a raster file using the Digital Elevation Model(DEM) of Tanzania,
- 2. I then compute a walking path friction surface raster by calculating for each pixel the estimated time to cross the pixel on foot with the hiking velocity function proposed by Tobler (1993) to calculate the hiking velocity (V in km per hour) based on the slope (S in gradients) of the terrain.
- 3. Next, I calculate the accumulated cost for each pixel to walk on foot from the village centroids to the cities.
- 4. Finally, the least cost path is calculated using the matrix obtained above.

# **B** Appendix B: Robustness check results

	Lanc	l Product	tivity	Labo	r Produc	tivity
	1	2	3	4	5	6
Economic	0.177***		0.174***	0.154*		0.150*
	(0.0590)		(0.0567)	(0.0853)		(0.0852)
Social		-0.194	-0.0665		-0.237	-0.160
		(0.201)	(0.208)		(0.248)	(0.252)
Observation	5133	5133	5133	3598	3598	3598

Table B.1: Sectoral analysis: PPMLE estimates

Notes: The table shows the PPML estimates of sectoral effects of Chinese aid projects on land and labor productivity. All regressions control for the use of inputs, village-time trend, Household and season-year year fixed effects. Robust standard errors clustered at the village level are reported in parentheses. \*\*\*, \*\*,\* denotes 1%, 5% and 10% level of significance respectively.



(c) Additional number of projects

Figure B.1: Effect of Chinese aid on land productivity

**Notes**: The figure shows the FE estimates of Chinese development aid project on the log of real value of household farm output per hectare for different distances d. The dots show the point estimates, and the bars indicate 90% confidence intervals.

	Lan	d Producti	vity	Labo	or Producti	ivity
	1	7	3	4	ß	6
Cumulative number of projects	0.148** (0.062)			0.019 (0.083)		
Additional number of projects		0.184*** (0.056)		~	0.142* (0.085)	
Dummy for additional projects			0.389*** (0.097)			0.295** (0.138)
Observation	5133.000	5133.000	5133.000	3598.000	3598.000	3598.000
Notes: The table shows the PPML es	stimates of ti	he effects of	Chinese aid	projects on	land and la	bor produc-

Table B.2: PPMLE estimates

tivity. All regressions control for village-time trend, Household and season-year year fixed effects, village level time varying weather variables, age of household head, share of each main crop cultivated, share of farmland quality. Robust standard errors clustered at the village level are reported in parenthesis. \*\*\*, \*\*, denotes 1%, 5% and 10% level of significance respectively.

## C Appendix C: Mechanisms

	Titled Area	Title Area (dummy)	Area Cultivated	Area Cultivated(logs)
Additional num of projects	0.290	0.0193	-1.771	-0.0876
	(0.382)	(0.0743)	(1.868)	(0.183)
Observation	5129	5129	5129	5129

Table C.1: Mechanisms: Land Titling and cultivated area (IV estimates)

Notes: The table shows the effects of Chinese aid projects on Land Titling and cultivated area. All regressions control for village-time trend, Household and season-year year fixed effects, village level time varying weather variables, age of household head, share of each main crop cultivated, share of farmland quality. Robust standard errors clustered at the village level are reported in parenthesis. Titled Area is the share of cultivated land that the household has secured title to, Titled Area (dummy) is a dummy variable that takes the value of 1 if the household has a secured title to at least one of the cultivated plots and zero otherwise. Area cultivated is defined as the total area (both titled and non-titled) in hectares cultivated by the household. \*\*\*, \*\*, \* denotes 1%, 5% and 10% level of significance respectively.

							)	
		Labor use				Input	Usage	
	Total	Hired	Family	Organic	Inorganic	Pesticide	Irrigated Area	Improved Seed
Additional num of projects	-51.65	-10.69	-40.97	262.3	-469.9	0.195	0.00385	$^{-}0.246^{*}$
	(81.52)	(22.57)	(72.56)	(217.8)	(321.6)	(4.499)	(0.0315)	(0.126)
bservation	5133	5133	5133	5133	5133	5133	5133	5133

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trol for village-time trend, household and season-year year fixed effects, village level time varying weather variables, age of household parenthesis. Total labor is the total labor used measured in person-days per hectare, hired is hired labor used measured in person-days irrigated by the household and improved seed is a dummy variable that takes the value of one if the household used an improved seed Notes: The table shows the effects of Chinese aid projects on access to labor and adoption of improved technologies. All regressions conhead, share of each main crop cultivated, share of farmland quality. Robust standard errors clustered at the village level are reported in ganic fertilizer. These two in addition to pesticide use is measured in kilograms per hectare. Irrigated area is the share of cultivated land per hectare, Family is family labor used measured in person-days per hectare. Organic means organic fertilizer, Inorganic means inorand zero otherwise. \*\*\*, \*\*,\* denotes 1%, 5% and 10% level of significance respectively.

Table C.3: Mechanisms: Agricultural commercialization and extension (IV Estimates)

	Commercialization	Extension
Additional num of projects	0.790*	0.0174
	(0.414)	(0.0790)
Observation	5045	5072

Notes: The table shows the effects of Chinese aid projects on agricultural commercialization and extension. All regressions control for village-time trend, Household and season-year year fixed effects, village level time varying weather variables, age of household head, share of each main crop cultivated, share of farmland quality. Robust standard errors clustered at the village level are reported in parenthesis. Commercialization is the percentage of output harvested by the household that has been sold in the market. Extension is a dummy variable that takes the value of 1 if the household had access to government extension services. \*\*\*, \*\*,\* denotes 1%, 5% and 10% level of significance respectively.