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 25km 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., 2021). They are mainly directed towards “connective infrastructure” (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., 2021). “Connective infrastructure” (such as transportation, energy, telecommunications) 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 investigated whether Chinese foreign development assistance aimed at economic and social infrastructure can help improve agriculture productivity in Tanzania at the subnational level by combining 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.

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 used 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 exploit the cross-sectional variation in a village's likelihood to be allocated a Chinese aid project. I found 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 found 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 focused 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, and corruption(Brazys et al., 2017; Isaksson and Kotsadam, 2018a,b; BenYishay et al., 2016; Dreher et al., 2016, 2021; Martorano et al., 2020). My paper differs from the others because it examined the causal impact of Chinese aid on agricultural productivity. Also, in contrast to some of these papers, I made use of the natural path cost as the proxy of the probability of receiving aid as opposed to computing the probabilities using 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. I describe the main sources of data used in the study in section 2. The empirical strategy is presented in section 3 and the empirical results in section 4. Robustness checks are conducted in section 5 while section 6 explores the potential mechanisms. The conclusions are presented in section 7.

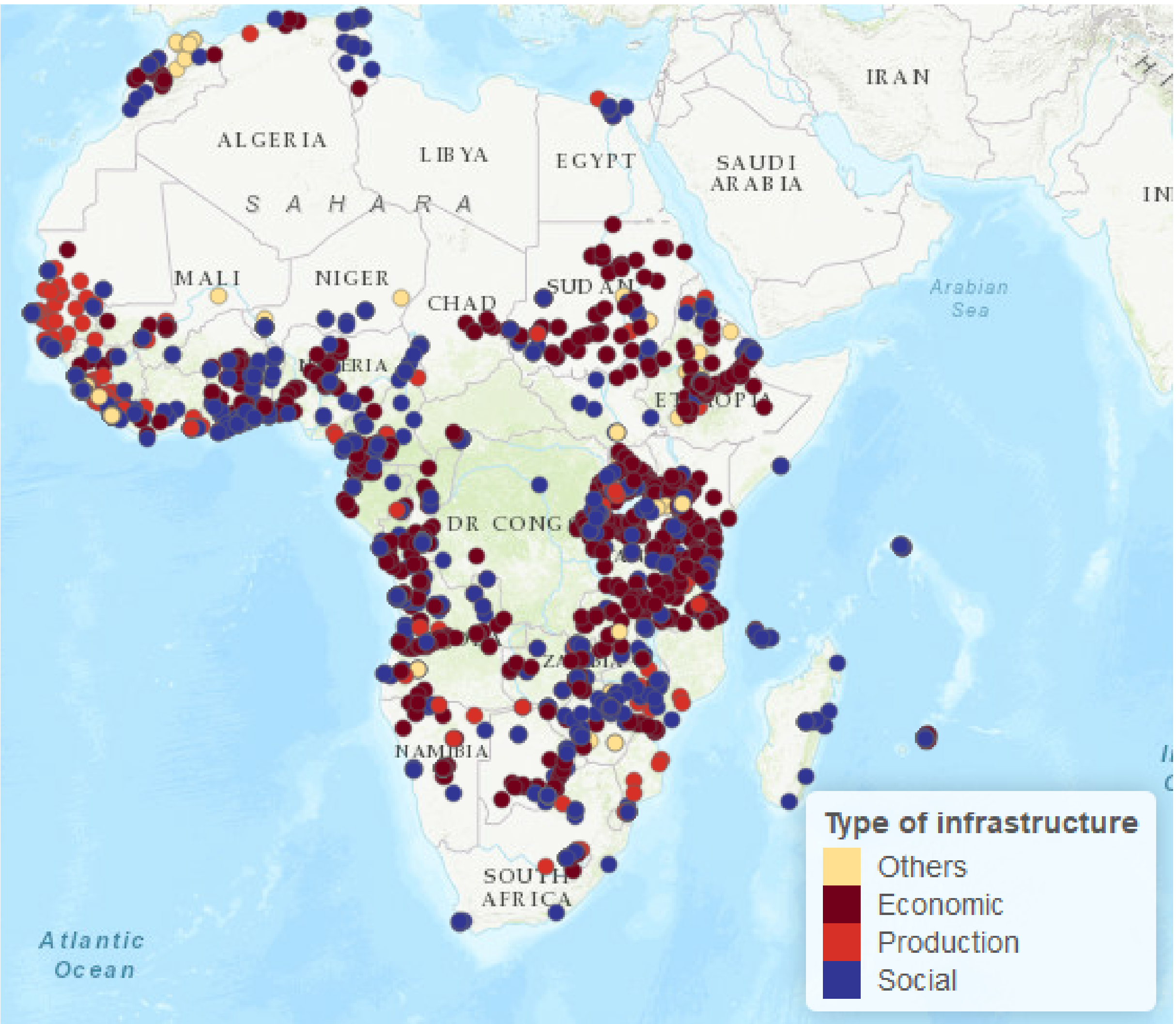

Figure 1: **Types of Chinese Financed Projects in Africa (2000 to 2014)**

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.

Figure 2: **Trend in Agriculture Labor Productivity**

Source: Author's construct using data from Expanded Africa Sector Database (Mensah et al., 2018)
Notes: Labor productivity is defined as agricultural real value added per number of employees in the agricultural sector. The values have been normalized to one in 1970.

2 Data

I provide a detailed description of the two main sources of data for the empirical analysis. 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)[1]. 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.). 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 & Animal husbandry. I was able to trace 1,907 and 1,892 of these sub-sample in the 2nd and 3rd rounds respectively. Summary statistics are provided in Table 1.

2.2 Geocoded Chinese official Finance Data

The data on Chinese development aid projects comes from AidData's Global Chinese Development Finance Dataset[2]. 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

[1] 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.

[2] Available at https://www.aiddata.org/data/geocoded-chinese-global-official-finance-dataset

flow (e.g., Official Development Assistance, ODA, or other Official Flows, OOF), start year of the project status (either completed or being implemented). I make the following adjustments to the data. Firstly, only projects classified as ODA are considered in this study[3]. Secondly, following the existing literature, I consider only projects with a precision code of up to 3 (analogous to the 2nd order administrative level). Thirdly, since most of the projects do not have a completion date, I only consider projects whose status indicated that they are completed. I therefore end up with 193 number of 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.

Table 1: Summary statistics of selected variables

	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 Characteristic			
Cultivated Area (has)	2.11	2.14	2.18
Family labor(person-days per has)	114.59	43.34	120.86
use organic fertlizer	0.18	0.18	0.20
use inorganic fertilizer	0.16	0.19	0.18
use pesticide	0.15	0.13	0.15
use improved seed	0.19	0.14	0.24
Hired labor(person-days per has)	12.18	9.15	10.53
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

Notes: HH stands for household, has for hectares and CHHs for crop production households i.e Agricultural households that engaged in crop production.

[3] According to the definition of 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.

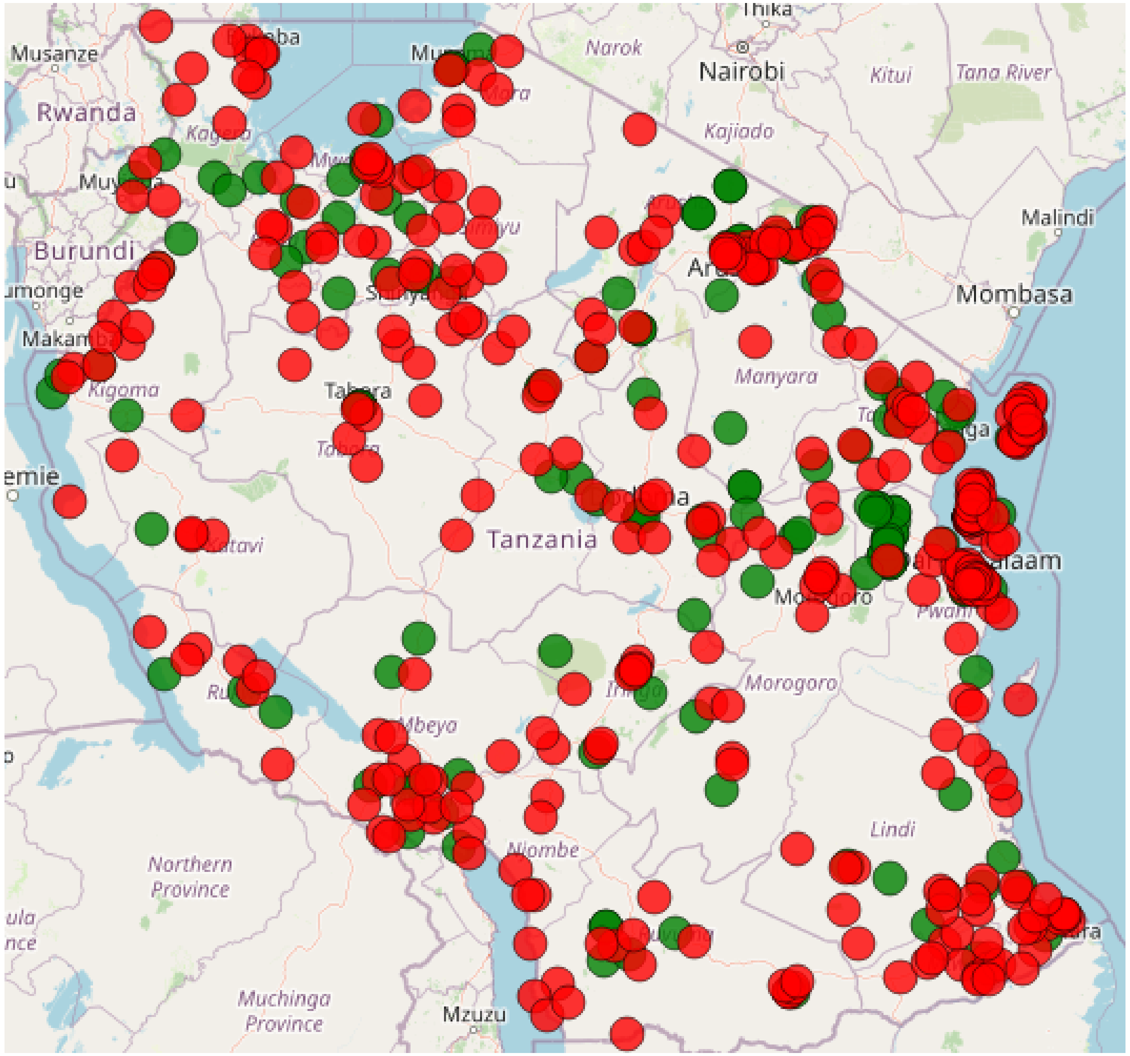

Figure 3: **Location of Villages (red dots) and Chinese Projects (green dots) in Tanzania**

Source: Author's construct using data from AidData and Tanzania National Bureau of Statistics.

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, α_h and ω_t are HH and season-year fixed effects respectively[4]. aid_{vt} is a measure of Chinese development aid. I make use of three alternative measures of Chinese development aid [5]. The first one is the cumulative number of active projects (from 2006 onwards) a village is near to, two years prior to the survey[6]. The second definition is a dummy variable which indicates whether if a village is near at least an additional active project, two years prior to the survey. The third definition is the additional number of active 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

[4]As explained in the data section, there are two agricultural seasons each year in Tanzania

[5]The data from AidData does not report actual disbursement but rather committed or budgeted amounts. This makes it difficult to use the project amount as actual disbursement will differ from the commitment figures.

[6]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.

conduct a robustness test to check the 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.

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The identifying assumption of model 3.1 is that within village variation in Chinese aid projects are 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 since some of the projects have started earlier and I am not able to fully account for the factors that determine their allocation. However, the identification assumption is likely to be valid in the case of the last 2 measures of Chinese aid. 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.

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

Where $steel_t$ is Chinese steel production and $\bar{P}_v$ is a village's probability to be allocated Chinese aid project. The use of China's steel production as an exogenous supply shock is since economic structure and political incentives lead to overproduction of steel in China. This is mainly done by, among other things, heavily subsidizing Chinese state-owned enterprises. China therefore commits to more aid projects overseas to clear markets (Dreher et al., 2016). These projects (see Figure 1) are infrastructure projects that often use these overproduced goods as inputs (Brautigam, 2011; Bluhm et al., 2018). Secondly, the probability of being allocated 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[7]. 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. On the other hand, villages that are closer to the main city may be the ones with highest potential for development, in this case they will have a higher probability to receive aid. It is therefore expected that the coefficient of the interaction to be negative in the latter case and positive in the former case.

[7] 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 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 of Table 2 may be biased.

I now turn to the two alternative measures in which the identification assumption is more likely to hold. The results for measure using a dummy for additional number of projects are presented in panel B while that of additional number of projects are presented in Table 2 and Table 3. 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 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, farm households living in villages near an additional number of Chinese development aid projects experienced a boost in agricultural land productivity by about 9% while that of agricultural labor productivity 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[8]. 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 suggest 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

[8]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.

productivity. The coefficient on the social sector projects on the other hand is negative although not different from zero. These results are consistent with empirical studies which suggest that improvements in economic infrastructure can help improve agricultural productivity.

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

	1	2	3
Panel A			
Cumulative num of projects	0.108**	0.098**	0.096**
	(0.048)	(0.045)	(0.045)
R-squared	0.623	0.637	0.638
Panel B			
Dummy for additional num of projects	0.145**	0.128**	0.126*
	(0.067)	(0.065)	(0.065)
R-squared	0.623	0.637	0.638
Panel C			
Additional num of projects	0.106**	0.091**	0.090**
	(0.044)	(0.043)	(0.043)
R-squared	0.623	0.637	0.638
HH FE	Yes	Yes	Yes
SeasonXYear FE	Yes	Yes	Yes
Control for inputs	No	Yes	Yes
Village characteristics x time trend	No	No	Yes
Observation	5133	5133	5133

*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.*

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

	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 num of 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
Observation	3580	3580	3580
HH FE	Yes	Yes	Yes
Season x Year FE	Yes	Yes	Yes
Control for inputs	No	Yes	Yes
Village characteristics x time trend	No	No	Yes

*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.*

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. As discussed in section 3, I instrument Chinese aid with the interaction between the probability to receive aid (log of natural cost path) and Chinese steel production. 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 result suggests that villages closer to a main city in 2002 are the ones more likely to be allocated aid projects. The 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 huge 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.

5 Robustness Checks

I have already shown in the previous section that the results are robust to the alternative definition of Chinese development projects. In this section I conduct two additional checks to demonstrate the robustness of the results. The first one has to with the choice of the proximity cut off. Secondly, I estimated 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 is stable 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) estimator. The results are shown in Tables B.2 and B.1. As can be seen the main results remain similar.

Table 4: OLS Estimates: Sectorial Analysis

	Land Productivity			Labor Productivity		
	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

*Notes: The table shows the sectorial 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.*

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

	1	2	3
Panel A: First Stage			
$\bar{P}_v * steel_t$	-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)
R-squared	-0.040	-0.009	-0.004
Observation	5133	5133	5133
HH FE	Yes	Yes	Yes
Season x Year FE	Yes	Yes	Yes
Control for inputs	No	Yes	Yes
Village characteristics x time trend	No	No	Yes

*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.*

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[9].

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.2 respectively. The estimates indicate a statistically insignificant effect of Chinese aid projects on land titling in Tanzania. Also, I investigated 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.2 respectively. Again, the estimates indicates that the total area cultivated is not statistically significantly affected by these aid projects.

[9] I only report the results of the IV estimates.

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 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.3 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[10]. The results are presented in Table C.3. 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. Farmers may now move away from subsistence production towards market production. 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 the value of 1 if the household had access to government extension services. The results are reported in Table C.1). I do find a

[10]There is no information available on the quantity of improved seed used in the survey.

positive effect on the share of harvested output that is sold in the market. This suggests that farmers now see agriculture as a way of business and now produce to sell in the market.

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 showed 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 suggest that economic sector projects mainly drive these results. This is 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 suggests 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 focused 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:

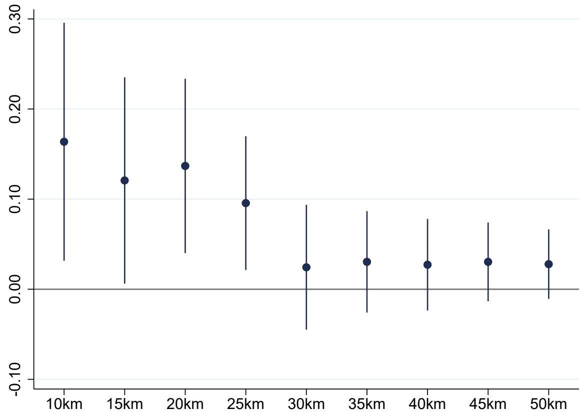
1. First, I calculated the slope gradients from a raster file using the Digital Elevation Model(DEM) of Tanzania,
2. I then compute a walking path friction surface raster by calculating for each pixel the estimated time to cross the pixel on foot with the hiking velocity function proposed by Tobler (1993) 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

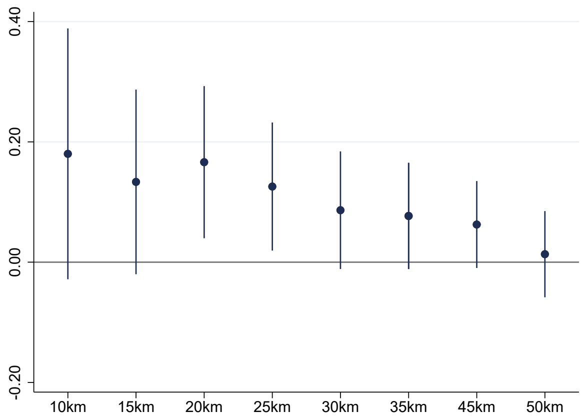
Table B.1: Sectoral analysis: PPMLE estimates

	Land Productivity			Labor Productivity		
	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

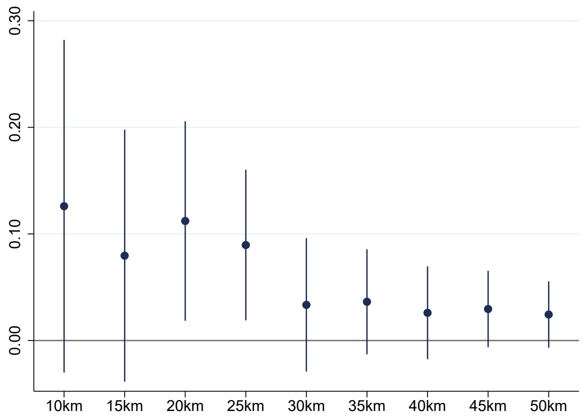
*Notes: The table shows the effects of Chinese aid projects on agricultural commercialization and extension. All regressions control for village-time trend, Household and season-year year fixed effects,village level time varying weather variables,age of household head, share of each main crop cultivated, share of farm land 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.*



(a) Cumulative number of projects



(b) dummy for additional number of projects



(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.

Table B.2: PPMLE estimates

	Land Productivity			Labor Productivity		
	1	2	3	4	5	6
Cumulative nos of projects	0.148**			0.019		
	(0.062)			(0.083)		
Additional number of projects		0.184***			0.142*	
		(0.056)			(0.085)	
Dummy for additional number of project			0.389***			0.295**
			(0.097)			(0.138)
Observation	5133.000	5133.000	5133.000	3598.000	3598.000	3598.000

*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.*

C Appendix C: Mechanisms

Table C.1: 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.*

Table C.2: Mechanisms:Land Titling and cultivated area (IV estimates)

	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

*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.*

Table C.3: Mechanisms:Access to labor and adoption of improved technologies (IV Estimates)

	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)
Observation	5133	5133	5133	5133	5133	5133	5133	5133

*Notes: The table shows the effects of Chinese aid projects on access to labor and adoption of improved technologies. 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. Total labor is the total labor used measured in person-days per hectare, hired is hired labor used measured in person-days per hectare, Family is family labor used measured in person-days per hectare. Organic means organic fertilizer, Inorganic means inorganic fertilizer. These two in addition to pesticide use is measured in kilograms per hectare. Irrigated area is the share of cultivated land irrigated by the household and improved seed is a dummy variable that takes the value of one if the household used an improved seed and zero otherwise. ***, **,* denotes 1%, 5% and 10% level of significance respectively.*