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 investigated whether foreign aid aimed at economic and social infrastructure can help improve agriculture productivity in Tanzania. I combined 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 found that the mechanisms driving the results are 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., 2017) . 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., 2017). These kinds of infrastructure have the potential of improving agricultural productivity. However, the effectiveness and the extent to which foreign aid fosters economic development is largely inconclusive in the literature and depends on varied factors.

I empirically investigated whether foreign aid aimed at economic and social infrastructure can help improve agriculture productivity in Tanzania at the subnational level. 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. To examine the causal effect of Chinese development aid on agricultural productivity, the paper combined household panel data with rich farm level information with geocoded Chinese development projects. The main challenge in identifying the causal effect of Chinese 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 exploit the exogenous time variation in China 's steel production and cross-sectional variation in a village 's likelihood to be allocated a Chinese aid project to isolate the exogenous component of variation. I focus on Tanzania because it is the largest receiver of the number of Chinese aid projects in Africa. Tanzania is one of the top growth performers in Sub-Saharan Africa (SSA). Agriculture supports the livelihoods directly of about 55% of Tanzanians and 75% of the poor (World Bank, 2019). The country has witnessed some improvements in agriculture labor productivity since the 2000s (see Figure 2).The paper finds a positive effect of Chinese development projects on agricultural productivity. This effect is robust to alternative definitions of Chinese aid projects and largely driven by economic sector projects.

The present paper is related to the literature on development aid and economic development (Doucouliagos and Paldam, 2010; Galiani et al., 2017; Rajan and Subramanian, 2008; Dreher and Langlotz, 2017; Clemens et al., 2012). This strand of literature is focused on the country level impact of aid on economic growth and is largely inconclusive. In addition to the inconclusiveness of the existing literature, analysis at the macro-level suffer from problems of endogeneity: aggregation issues associated with the foreign aid measure, unobserved heterogeneity underlying the allocation of bilateral aid flows from donor to recipient and reverse causality. The present paper departs from these papers by focusing on the sub-national level. This paper is also closely related to the increasing number of recent studies that 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, 2017; Martorano et al., 2020). The present paper is different from these papers in the sense it examined the causal impact of Chinese aid on the productivity of the livelihoods of most of the poor. Also, the paper made use of the natural path cost as the measure of the probability of receiving aid as opposed to computing the probabilities using share of aid received in the past as done in some of the above-mentioned papers. Finally, the paper is closely related to the determinants of agricultural productivity. I provide further evidence that foreign aimed at improving infrastructure can help improve agricultural productivity.

The rest of the paper is structured as follows; In section 2 the main sources of data used in the study are presented. The empirical strategy is then presented in section 3 and the empirical results in section 4.

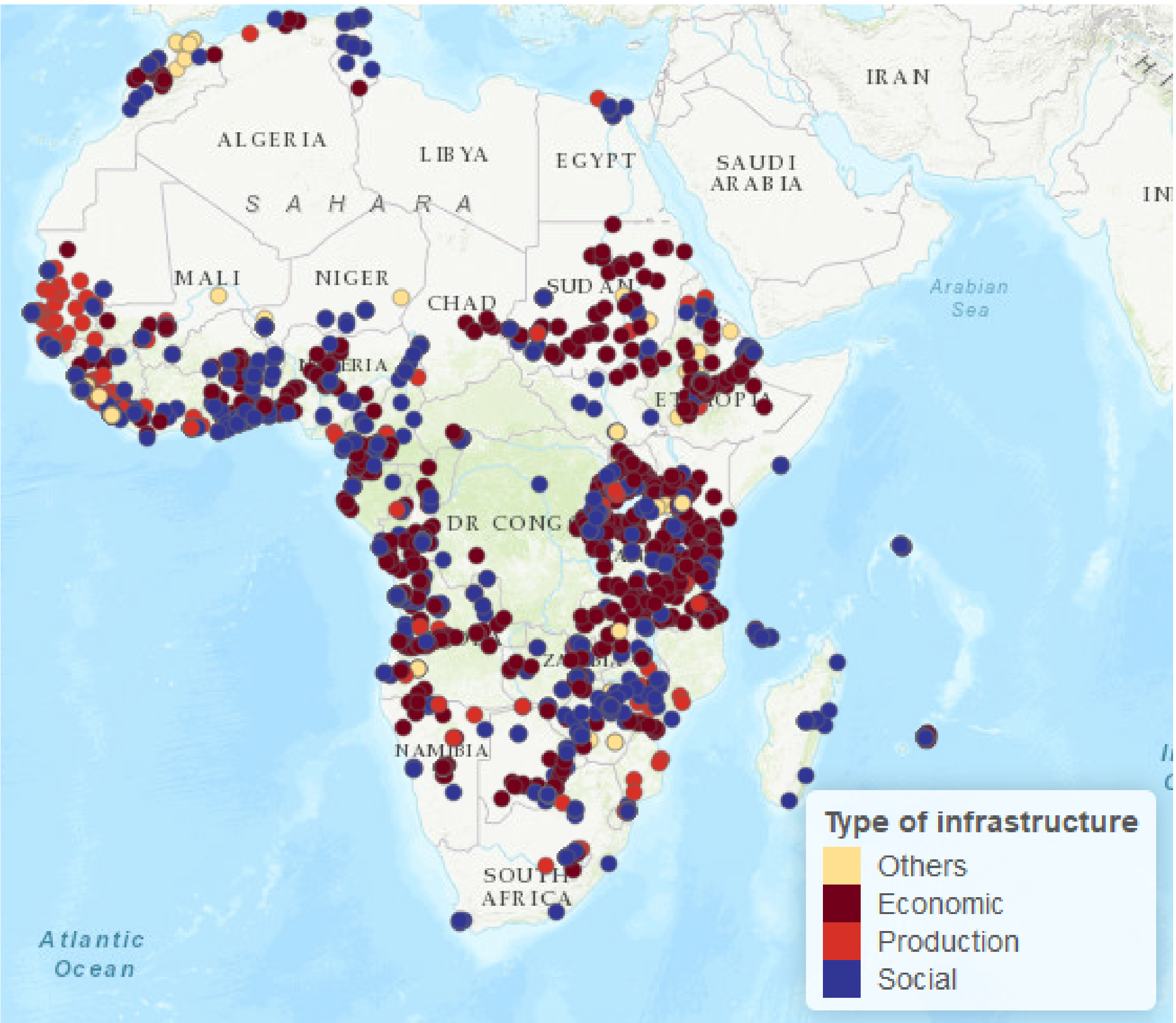


Figure 1: **Types of Chinese Financed Projects in Africa (2000 to 2014)**

Source: Author's construct from AidData

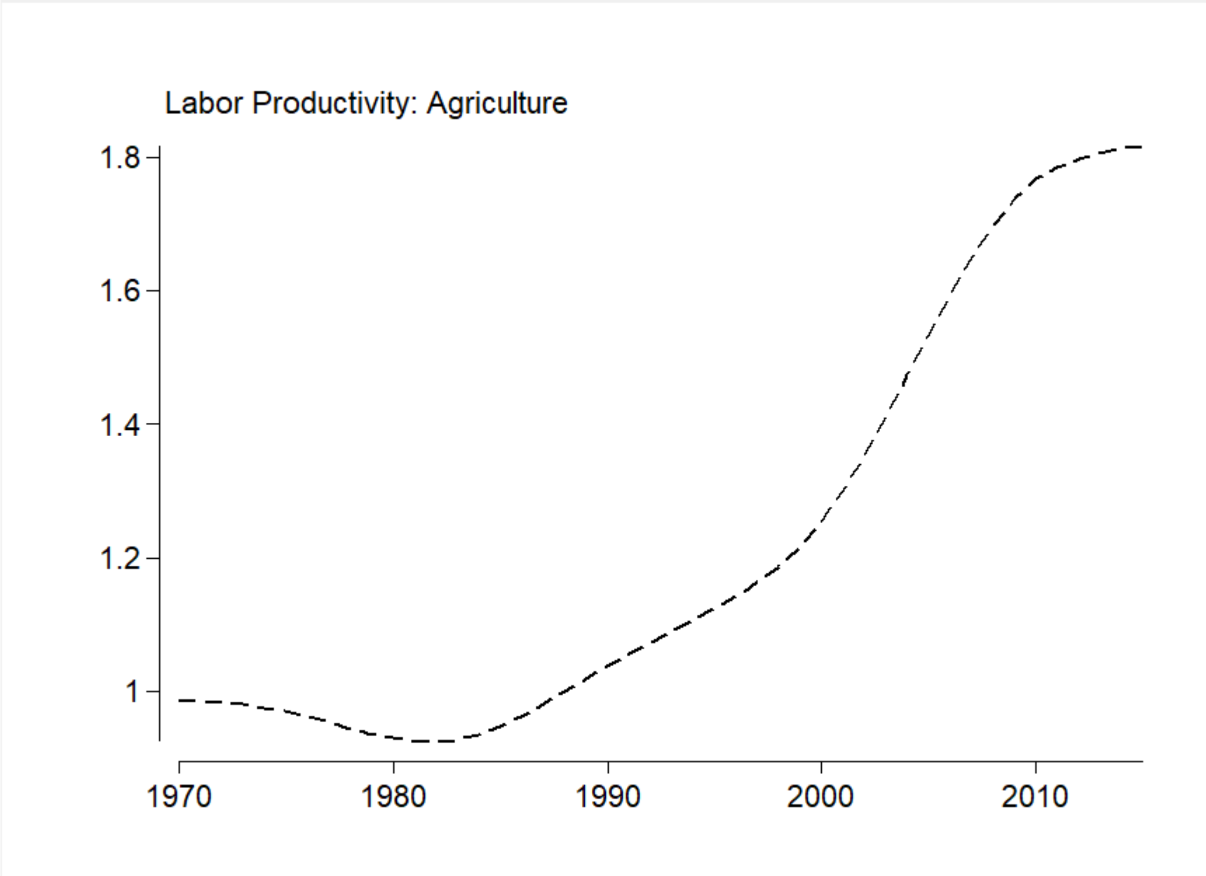


Figure 2: **Trend in Agric Labor Productivity**

Source: Author's construct from Expanded Africa Sector Database (EASD)

2 Data

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

The LSMS-ISA for Tanzania is a panel of three [1] rounds of a nationally representative household sample, collected by the Tanzania's National Bureau of Statistics (NBS). 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. 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 of the project status (either completed or being implemented). I make the following adjustments to the data. Firstly, only projects classified as ODA[2] are considered in this study. Secondly, following the existing literature, I restrict ourselves to projects with a precision code of up to 3

[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 but also because there are several key variables relevant for this study that are missing in the last round

[2] 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.

(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

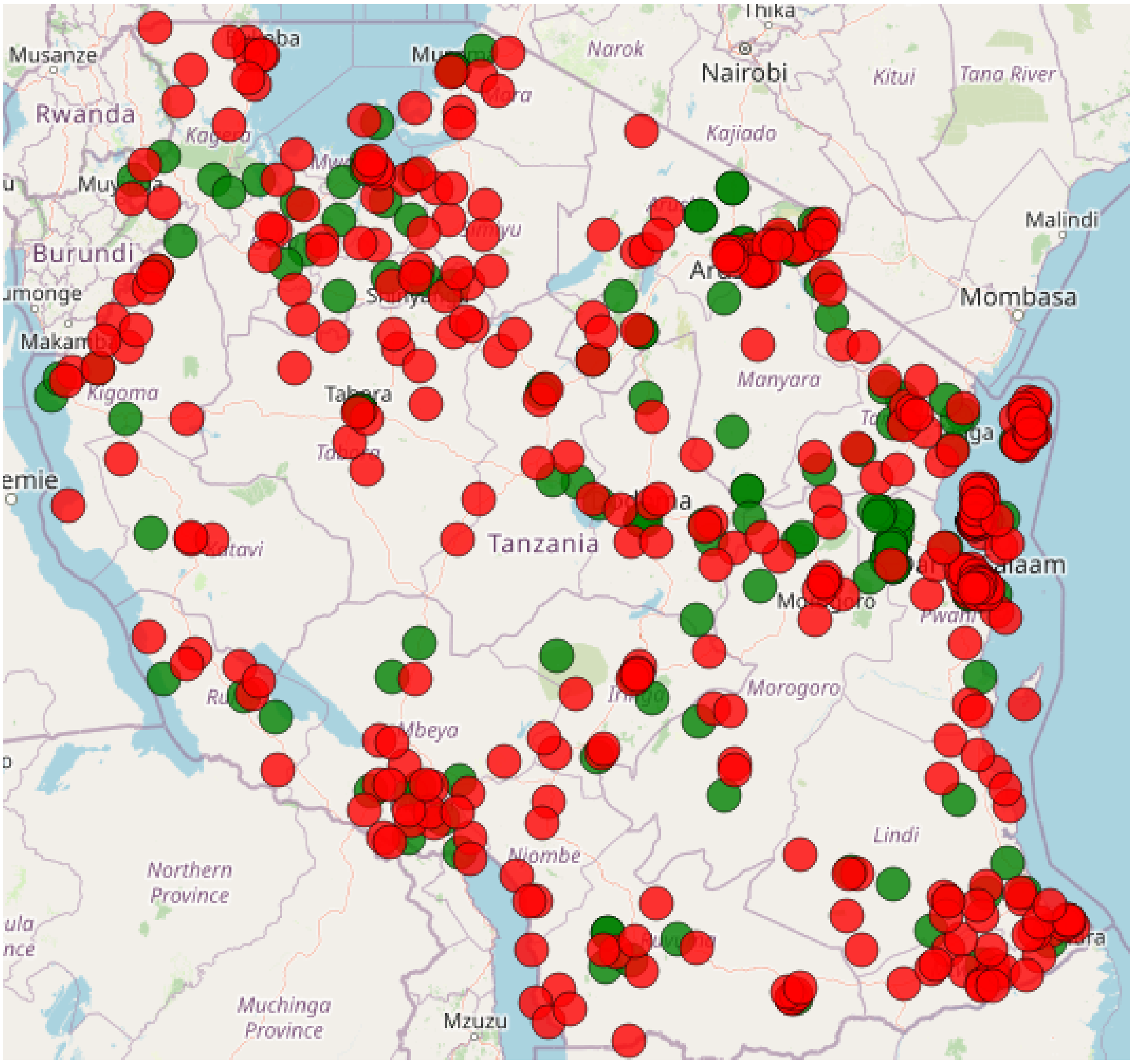


Figure 3: **Location of Villages(red dots) and Chinese Projects (green dots) in Tanzania**

Source: Author′s construct from AidData and NBS

3 Empirical 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; aid_{vt} is a measure of Chinese aid project a village is d km close to, $d \in$[10,50]. α_h and ω_t are HH and season-year fixed effects respectively. I make use of three measures[3] of Chinese aid projects; Cumulative [4] number of active projects (from 2006 onwards) a village is close to 2 years prior to the survey; a dummy variable indicating if a village is close to at least an additional active project 2 years prior to the survey and the additional number of active projects a village is close to 2 years prior to the survey. In the last 2 cases 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 last one since it takes into account the intensity of treatment. The model 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, etc. W_{vt} is a vector of village level time varying weather variables 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 Chi-

[3]The data from AidData does not report actual disbursement but rather committed or budgeted amounts. This makes it difficult to use the project amount

[4]Since the data on our 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.

nese 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. The identification assumption is likely to be valid in the case of the last 2 measures of Chinese aid. However, 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 based on the fact that 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[5] 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. 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

[5] see Appendix A for a description of how the natural path cost is constructed

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.

4 Empirical Results

4.1 Baseline Estimates

In this section, the results of the OLS estimates of equation 2 are presented and discussed. Table 5 presents the results for a proximity of 25km and the dependent variable is real agricultural output per hectare. There are 3 panels, each corresponds to each measure of Chinese aid. Also, there are 3 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. Firstly, 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. Controlling for input usage and the interaction between a linear time trend and village characteristics slightly reduces the magnitude of the effect (see columns 2 and 3) which points towards the robustness of the results. Secondly, using dummy for additional number of projects (see panel B) also indicates a positive and statistically significant effect. The magnitudes of the estimates are somehow higher than the first measure. Finally, using the additional number of projects also shows a positive and statistically significant effect. In general, the results shown in Figure 5 point towards a positive effect of Chinese aid on agricultural land productivity for all 3 measures of Chinese aid projects. Specifically, I find that being close to Chinese project increases agricultural productivity between

9% to 12.6% (see column 3).

Next, I explored if these projects affect labor productivity i.e real agricultural output per unit labor instead of land productivity. The results are shown in Table 3. The same pattern is observed for labor productivity as well. I find a positive and significant effect of Chinese aid on labor productivity in all the specifications.

An interesting question that arises is the choice of distance buffer. Why did I make use of a proximity of 25km? To answer this question, I estimate equation 3.1 for different levels of proximity, $d \in [10,50]$. The point estimates and the confidence intervals are shown in Figure 4. First, it can be observed that the effect decreases with distance in all three cases. Secondly, the estimates are not statistically different from zero beyond a proximity of 25km. This provides the rationale for using a proximity of at most 25km. Furthermore, a proximity of 25km considers spillover effects as the effects are not statistically from zero beyond this threshold.

Table 2: OLS Estimates of the effects of Chinese Aid on Land Productivity (within 25km)

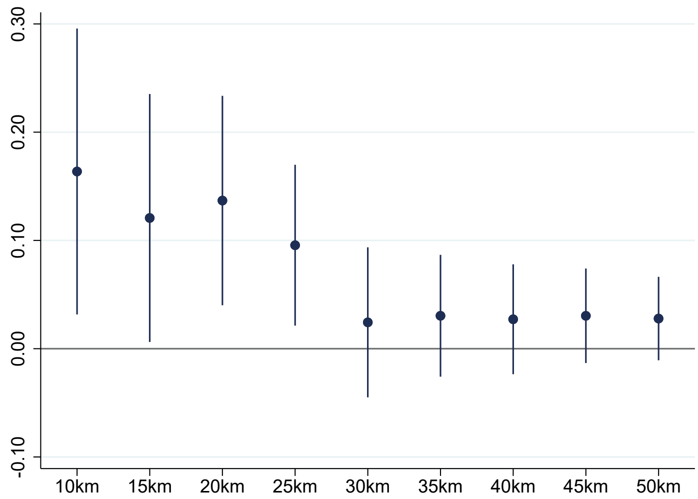
	1	2	3
Panel A			
Cumulative nos of projects	0.108**	0.098**	0.096**
	(0.048)	(0.045)	(0.045)
R-squared	0.623	0.637	0.638
Panel B			
Dummy for additional nos of projects	0.145**	0.128**	0.126*
	(0.067)	(0.065)	(0.065)
R-squared	0.623	0.637	0.638
Panel C			
Additional nos of projects	0.106**	0.091**	0.090**
	(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 x'ticsXtrend	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 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.*

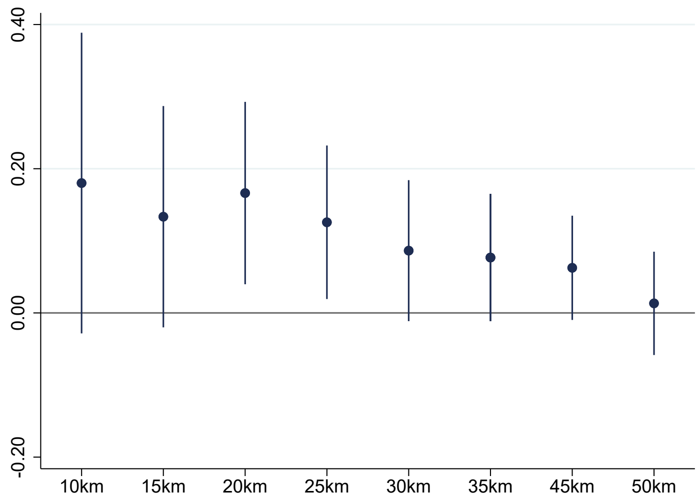
Table 3: OLS Estimates of the effect of Chinese Aid on Labor Productivity (within 25km)

	1	2	3
Panel A			
Cumulative nos 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 nos 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 nos of projects	0.118***	0.117***	0.118***
	(0.045)	(0.043)	(0.043)
R-squared	0.788	0.791	0.791
HH FE	Yes	Yes	Yes
SeasonXYear FE	Yes	Yes	Yes
Control for inputs	No	Yes	Yes
Village x'ticsXtrend	No	No	Yes
Observation	3580	3580	3580

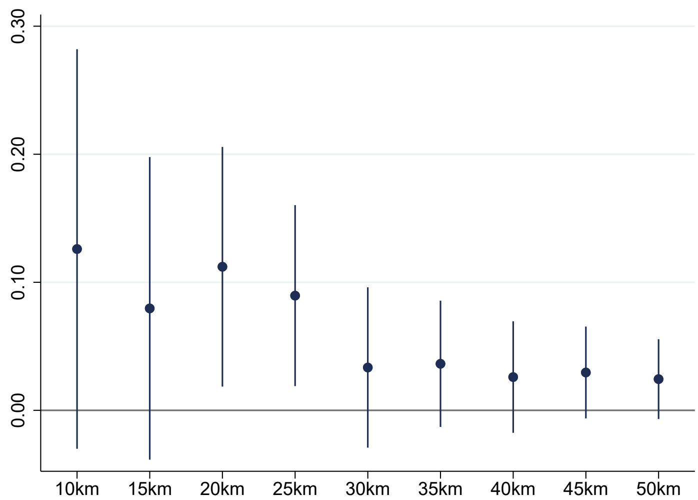
*Notes: The table shows the FE estimates of Chinese development aid project on the log of real value of household farm output per person-days .All regressions control for soil type, main crop grown by the the households, temperature, rainfall and population. Panel B and C also control for the historical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



(a) Cumulative nos of projects



(b) dummy for additional number of projects



(c) Additional number of projects

Figure 4: **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.

4.2 Sectorial Analysis

To further understand the above results, I conduct a sectorial analysis. The projects are grouped based on their Creditor Report System (CRS) sectoral codes to make a distinction between social and economic sector projects[6]. 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 inter-linkages between different sectors. This suggest that the decision to provide both types of projects may not be mutually independent. The results presented in 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 although not different from zero. These results are consistent with empirical studies which suggest that improvements in economic infrastructure can help improve agricultural productivity.

[6]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.

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.*

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 model 3.1. I show here the results for the additional number of projects. As discussed above, 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 potential 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. However, the IV estimates suggest a higher effect of Chinese aid on agricultural productivity. This result shows that the OLS estimates are biased downward likely due to endogeneity. The value of the coefficient in column 3 of panel B is 0.630 and statistically significant at the 1% level. This suggests that an increase in the number of Chinese projects village is close to leads to 63% increase agricultural productivity. Taken together, the OLS and IV estimates suggest that villages near a Chinese aid project experience an increase in agricultural productivity.

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
$Kleibergen - PaapF$ statistic	33.0	32.7	32.8
Panel B: IV Estimates			
Additional number of project	0.639**	0.640**	0.630**
	(0.317)	(0.313)	(0.309)
R-squared	-0.040	-0.009	-0.004
HH FE	Yes	Yes	Yes
SeasonXYear FE	Yes	Yes	Yes
Control for inputs	No	Yes	Yes
Village x'ticsXtrend	No	No	Yes
Observation	5133	5133	5133

*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.*

4.4 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 into the potential mechanisms grouped as follows:

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? The result shows a positive effect on titled area (see columns 1 and 2 of Table 6) although not statistically significant. Also, I investigated the effect of these projects on cultivated area. The results are shown in columns 3 and 4. A negative effect is observed although not statistically significant. This suggest that neither the area cultivated nor the share of titled is significantly affected by these aid projects.

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. In Table 7, I present the results of these potential mechanisms. One can observe a negative effect on total labor use per hectare. When I decompose labor use into hired and family labor, a negative effect on hired labor but a positive effect on family labor use is observed. These results are however not statistically significant. Secondly, I did not find a statistically significant effect on the use of fertilizer (organic and inorganic) and pesticides. This result is not surprising because the use of such inputs is still very low in developing countries. Thirdly, I find a positive and significant effect on the use of improved seeds. Lastly, I find a positive effect on the share of cultivated land under irrigation (see Column 5 of 7) although statistically insignificant. Again, this result is not surprising because developing country agriculture is largely rain-fed.

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. I do find a positive effect on agricultural commercialization (see Table 8). This suggests that farmers now see agriculture as a way of business and now produce to sell in the market.

Table 6: Mechanisms:Land Titling and cultivated area

	Titled Area	Title Area (dummy)	Area Cultivated	Area Cultivated(logs)
		Panel A: OLS Estimates		
Additional nos of projects	-0.0591	-0.0142	0.115	-0.00739
	(0.0489)	(0.00989)	(0.163)	(0.0239)
R-squared	0.347	0.460	0.616	0.786
		Panel B: IV Estimates		
Additional nos 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) takes the value of 1 if the household has title to at least one of the plots cultivated and zero otherwise, Area Cultivated is the area in hectares cultivated by the household. ***, **,* denotes 1%, 5% and 10% level of significance respectively.*

Table 7: Mechanisms:Access to labor and adoption of improved technologies

	Labor use			Input Usage				
	Total	Hired	Family	Organic	Inorganic	Pesticide	Irrigated Area	Improved Seed
Panel A: OLS Estimates								
Additional nos of projects	10.83	-1.027	11.86*	142.0*	11.56	-2.200	-0.00109	-0.0112
	(8.168)	(2.806)	(6.806)	(73.15)	(51.60)	(1.710)	(0.00436)	(0.0157)
R-squared	0.444	0.358	0.474	0.434	0.310	0.477	0.701	0.547
Panel B: IV Estimates								
Additional nos 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.*

Table 8: Mechanisms:Agricultural commercialization and extension

	OLS		IV	
	Commercialization	Extension	Commercialization	Extension
Additional nos of projects	0.00958	0.00584	0.790*	0.0174
	(0.0842)	(0.0119)	(0.414)	(0.0790)
Observation	5045	5072	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.*

5 Conclusion

I contribute to the growing literature on the effectiveness and allocation of Chinese aid by examining their impact on agricultural productivity in Tanzania. To make a causal claim the paper employed a panel fixed effects and instrumental variable strategy. I showed that Chinese development projects have a positive effect on agricultural productivity. The effect decreases with distance and does not go beyond villages that are located farther than 25km from these projects. Sectorial 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.

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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; 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. Secondary, 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 ouput, 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.