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# Promoting pro-poor growth through infrastructure investment: Evidence from the Targeted Poverty Alleviation program in China

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ABSTRACT

This paper empirically estimates the effects of infrastructure investments on the level and distribution of impoverished households' income, utilizing the arguably exogenous investment shock from the Targeted Poverty Alleviation program in China. We focus on the agricultural income of poor rural households. We also examine whether these infrastructure investments increase or decrease income inequality within the impoverished group. We distinguish among different types of infrastructure investment, aiming to identify the investments effective in promoting growth in agricultural income, especially for the poorest. Based on a comprehensive household-level administrative dataset and econometric analysis, we find that electricity infrastructure significantly increases poor households' agricultural income and that the income benefit is equally distributed among the poor; agricultural irrigation infrastructure raises agricultural income significantly and delivers more benefit to the poorest households. An examination of the mechanism shows that both electricity and irrigation infrastructure increase the probability of participating in agricultural work and therefore increase agricultural income. These findings imply that, through increasing the utilization of agricultural land and the labor of impoverished households, electricity and irrigation infrastructure investments in rural impoverished areas are likely to lead to pro-poor and sustainable development.

## 1. Introduction

Infrastructure investment is a widely-adopted measure to battle against poverty, especially in developing countries. Examples include Nepal's Ninth Five Year Plan (Dillon, Sharma, & Zhang, 2011); the Rural Roads and Markets Improvement and Maintenance Project (RRMIMP) in Bangladesh funded by the World Bank (Khandker, Bakht, & Koolwal, 2009); and the Prime Minister's Village Road Program in India (Asher & Novosad, 2020). Although practitioners believe in the poverty alleviation effect of infrastructure investment, empirical evidence shows that the effect significantly varies across regions and projects. For example, studies show that RRMIMP in Bangladesh reduced poverty (Khandker, Bakht, & Koolwal, 2009), while rural roads in Philippines did not benefit the poor (Balisacan & Pernia, 2003). Given the large observable and unobservable differences in regions and projects, it is difficult to compare across these investments and reach a general conclusion on the effectiveness of investments. The Targeted Poverty Alleviation (TPA) program in China, started in 2013, provides an opportunity for a more comprehensive comparison, as this program invested in various kinds of infrastructure in a large number of impoverished villages during the same period. Therefore, in this paper, we utilize the infrastructure investment shock brought about by the TPA program in China, and investigate the effects of various infrastructure

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investments on agricultural income of impoverished households.

There has been a large literature studying the effect on income of infrastructure investments in rural areas, especially in developing countries. Theoretical literature generally agrees that infrastructure investment can stimulate economic growth by raising the productivity of the agricultural sector (e.g., Mamatzakis, 2003; Fan & Zhang, 2004; Teruel & Kuroda, 2005). However, empirical findings about the impact on the level and distribution of income are mixed. A large series of literature shows that improvement in infrastructure – such as construction of expressways, improving road quality, and equipping rural areas with irrigation and electrification – significantly increased agricultural production and agricultural income (e.g., Zhang and Fan, 2004a; Li, Yin, & Wu, 2015; Li, Cheng, & Zheng, 2017; Ding, Qin, & Shi, 2018), thereby narrowing the rural-urban income gap as well as income inequality within the agricultural sector (e.g., Banerjee, Duflo, & Qian, 2012; Charlery, Qaim, & Smith-Hall, 2016; Khandker, Bakht, & Koolwal, 2009; Zhang & Wan, 2016). In contrast, some literature has found the opposite. For example, Asher and Novosad (2020) found that India's national rural road construction program significantly reduced agricultural income by reallocating labor out of the agricultural sector; Charlery et al. (2016) found that rural road construction in Nepal increased income from sources such as forest products and grassland products, as well as remittances, wage income and other income, but not crop income or business income; Dillon et al. (2011) found that irrigation infrastructure in Nepal did not have a significant distributional effect; and Balisacan and Pernia (2003) showed that road construction in the Philippines significantly reduced poor people's average expenditure (a proxy for income) and expanded income inequality, while electricity access increased average expenditure but did not have a significant effect on the lowest-income group.

Mixed findings yield unclear implications for governments and institutions to choose among anti-poverty investments. Therefore, understanding the reasons behind the different findings is necessary for relevant policy making. We notice the following facts in the literature. First, the previous literature varies in investment types. Infrastructure investment studied in the literature includes investments in roads, electricity access, irrigation facilities, or other kinds of facilities. Given that types of investment vary, mechanisms to affect income and its distribution could also vary. Second, the previous literature varies by regions. Given that different regions have different institutional backgrounds, agricultural development levels, natural resources, etc., effects of infrastructure investment are likely to differ as well. In addition, previous studies use different methods or have different variables of interest, such as income, non-rural employment, benefit-cost ratio of infrastructure, etc. These differences may affect the conclusions as well.

Utilizing a comprehensive administrative dataset and the exogeneity provided by China's Targeted Poverty Alleviation (TPA) program, this paper investigates which type of infrastructure investments positively affect villagers' agricultural income and reduce inequality among the poor. We also investigate the potential mechanism of the effects. The findings shed light on the design and implementation of policies that aim for pro-poor development through infrastructure construction.

The Targeted Poverty Alleviation program was launched in 2014 in China. It is a set of policies and projects aiming to eradicate poverty through investing in infrastructure, education, technology, etc. in rural areas.[1] Infrastructure investment has concentrated on "within-village" investment to solve the problem of "last mile" connectivity. For example, electricity infrastructure such as transformers and distribution lines are constructed using TPA funds in order to improve rural power supply safety, increase power supply reliability, and increase power capacity. In addition, irrigation facilities are built in the TPA program to improve agricultural production; these include ponds, revetments, dams and weirs. During the period from 2014 to 2018, all funds invested in within-village infrastructure are from the TPA program. This makes the infrastructure investment data from TPA a good measurement for the infrastructure level of the village.

TPA has two critical features different from previous poverty reduction policies in China, which provide us the opportunity to identify the causal effects of infrastructure on agricultural income and inequality.

The first feature of the TPA program is that it targets the poor. The program puts great effort into precise identification of poor people and creates a list of Identified Poor Households (IPHs) all over China. Local governments are required to collect information for the households on the IPH list and to update the information annually. This provides researchers an opportunity to acquire panel data of IPHs since 2014.

The second feature is that it targets the needs of individual poor households and provides policy intervention accordingly. On the household level, the TPA program provides transfers directly from TPA funds to households to meet their livelihood needs, including agricultural development, to encourage IPHs to improve agricultural production. On the village level, the TPA program makes various investments, of which infrastructure is the largest. This includes investment in roads and bridges, educational infrastructure, communication infrastructure, irrigation facilities, electricity infrastructure, etc. Given the feature of targeting, the TPA program tailors the anti-poverty measures based on specific village characteristics, so the infrastructure investments differ across villages in terms of categories, amount, and construction time. In sum, the TPA program provides an opportunity to compare the effects of various infrastructure investments with the same background, because it invested in various infrastructure projects in a large number of similar villages during the same period. It also provides exogenous shocks to rural infrastructure, which make possible the identification of the causal effect of infrastructure on agricultural income.

We focus on agricultural income, the revenue from agricultural activity, of impoverished households, because agricultural income is one way for poor villagers to develop by utilizing local resources. Migration to urban areas is an effective way to increase total income, but it also faces many problems, such as unstable employment, left-behind children, etc (Shi, Yu, Shen, Kenny, & Rozelle, 2016; Van den Broeck & Kilic, 2019; Wang, 2011; Wang & Zuo, 1999; Ye & Pan, 2011). In addition, an increase in agricultural income

[1] The TPA program (referred as the 2014 program in this comment) is a package of polices and projects, which can be divided into the following main categories: (1) education policies, (2) medical policies, (3) the Moving to Opportunity (MTO) relocation program, (4) financial policies, (5) agricultural improvement policies, and (6) infrastructure programs.

is the key to the success of the Rural Revitalization Strategy of China.[2] The Rural Revitalization Strategy aims to stimulate the internal development of the rural areas (Liu, 2018) and the increase in agricultural income is expected to attract migrants back. With more labor and capital, it is hoped that this strategy will finally lead to the development of rural areas.

As we focus on agricultural income, we pay attention to two kinds of infrastructure investments that are important to agricultural production: electricity and irrigation infrastructure. Electricity infrastructure includes grid infrastructure (e.g., transmission lines) and substation infrastructure (e.g., transformers and switches). It is the key to electrification. Access to electricity and the use of high-quality power can promote the income level of rural residents (e.g., Chakravorty, Pelli, & Marchand, 2014; Rao, 2013). Dinkelman (2011) found that electrification in South Africa stimulates employment of people living in rural areas, which is a potential channel to influence households' income. Rathi and Vermaak (2018) found that the use of electricity can greatly improve agricultural production efficiency, thereby increasing agricultural income in developing countries. In addition to directly affecting income and agricultural production, rural electrification has more diverse and longer-term welfare impacts on socio-economic conditions in developing countries, including improving education (Khandker, Bakht, & Koolwal, 2009; Khandker, Barnes, & Samad, 2009; van de Walle, Ravallion, Mendiratta, & Koolwal, 2013), improving health (Chakrabarti & Chakrabarti, 2002; Kanagawa & Nakata, 2008), and reducing environmental pollution (Kanagawa & Nakata, 2008).

Irrigation facilities provide better water resources to agricultural production and reduce the dependence on local rainfall (Duflo & Pande, 2007; Fuglie & Rada, 2013). Irrigation therefore serves as an important poverty reduction tool (e.g., Rao, Ray and Subbarao, 1988; Lipton, Litchfield, & Faurès, 2003; Dillon, 2011; Burney & Naylor, 2012), through increasing agricultural productivity, decreasing the risk of crop failure, increasing farm employment, etc. (e.g., Hussain & Hanjra, 2004; Duflo & Pande, 2007). Moreover, because water is a key natural resource on which the rural poor heavily depend (Hussain & Hanjra, 2004), irrigation infrastructure may have the potential to improve income inequality.

Based on household- and village-level data on income and infrastructure investments through China's TPA, we find that total infrastructure investment does not increase the poor population's agricultural income but has a negative coefficient, although it is insignificant. This means infrastructure in general did not stimulate agricultural activities, consistent with the empirical results of Asher and Novosad (2020). However, we find that electricity and irrigation infrastructure investments increased agricultural income significantly. Moreover, we explore the distributional effect of different types of infrastructure and find that electricity infrastructure does not have a significant effect on the distribution of income, indicating that it benefits the poor evenly. By contrast, irrigation infrastructure reduced agricultural income inequality, indicating that investing in public irrigation facilities not only benefited the whole group of people, but benefited the poorest people most.

We then investigate the mechanisms through which infrastructure affects agricultural income. Different infrastructure may have different impacts on labor participation and the time spent working (Asher & Novosad, 2020; Köhlin, Sills, Pattanayak, & Wilfong, 2011; Lei, Desai, & Vanneman, 2019; Salmon & Tanguy, 2016). Previous literature has mainly focused on the potential impact of infrastructure on wage rates, amount of time worked at home and non-rural employment (Dinkelman, 2011; van de Walle, 2003; Lei et al., 2019), while we focus on the participation (*i.e.* extensive margin) and the working time spending in agricultural sector (*i.e.* intensive margin). We find that electricity and irrigation infrastructure investments have significant labor reallocation effects. Regarding the extensive margin, both types of infrastructure investments increase the probability of labor participation in the agricultural sector. This indicates that the willingness to participate in agricultural production is significantly stimulated by the provision of necessary agricultural infrastructure. Regarding the intensive margin, we do not find that the amount of time worked in the agricultural sector is significantly increased.

The first contribution of this paper is that we distinguish the effects of electricity and irrigation infrastructure from the total effect of general infrastructure categories. Isolating the effect of agricultural and electrical infrastructure helps explain the mixed findings of previous literature on infrastructure's effects and therefore assists in drawing clear policy implications. The second contribution is that, due to the detailed income data, we can distinguish infrastructure's impact on agricultural income from the impact on total income. The increase in agricultural income is the key for rural revitalization, so it is worthy of specific attention. The third contribution is that, besides the effects on income, we also study infrastructure's distributional effects, to call attention to the poorest people and inequality issues. The concern is that, due to limitations in human capital and resources, the poorest people may not have the ability to take advantage of and benefit from infrastructure investments. If not pro-poor, the growth cannot be inclusive and sustainable.

The remainder of the paper is organized as follows. Section 2 describes the datasets. Section 3 employs econometric models to conduct empirical analysis. Section 4 shows the empirical results regarding the effects on income and distribution. Section 5 explores the mechanism of the income increase. Section 6 concludes.

## 2. Data

The main datasets used in this paper are the TPA program infrastructure data and a panel of household administrative data of IPHs from the National Poverty Alleviation and Development Information System (NPADIS) of Xin County. Xin County is in Henan province of China. It is a typical impoverished county, representative of the counties in the middle region of China.

The TPA program data records village-level policies, including (1) village-level amounts of investment in different types of infrastructure, including transportation, communication, education, irrigation, electricity, etc.; and (2) village-level quantities of

[2] The Rural Revitalization Strategy was put forward by General Secretary Xi Jinping at the 19th CPC National Congress in 2017. In 2018, the State Council issued Document No. 1 of the "The State Council's Opinions on the Implementation of the Rural Revitalization Strategy".

various types of infrastructure. Table A1 in the appendix summarizes all types of infrastructure in which TPA invested during the period from 2014 to 2018. Table A2 summarizes the quantity of electricity and irrigation infrastructure.

The IPH administrative data includes (1) households' demographic characteristics; (2) household annual income from different sources, including work, agricultural activity, assets, and government transfer; and (3) the TPA policy intervention packages received by the IPHs.

Because the investments are recorded and IPHs are tracked annually, the above information forms village- and household-level annual panel data from 2014 to 2018 (data for more recent years are not available yet), covering about 43,000 registered poor individuals from about 12,000 IPHs in 206 villages in Xin County.[3] Both datasets include village identifiers that allow us to match the IPH panel to the TPA policy program panel.

### 2.1. Income

We calculate agricultural income per capita and a Gini coefficient that reflects the distribution of agricultural income within IPHs. The formula for the Gini coefficient of agricultural income is as follows.

$$Gini = \frac{1}{2\mu}\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \left|y_i - y_j\right| \tag{1}$$

where μ is the average agricultural income of the group of interest, which has $n$ households, $y_i$ is the agricultural income per capita of household $i$ in the group, and $w_i$ is the weight, which is the number of household members of household $i$ divided by the total population in the group. The Gini coefficient ranges from 0 to 1; when it equals 0, it indicates perfect equality. The larger the value of the Gini coefficient, the higher the level of inequality.

Fig. 1 shows that the agricultural income per capita increased significantly from 1183 Yuan in 2014 to 2170 Yuan in 2016 and remained stable afterward. The Gini coefficient of agricultural income for all years is high and increases from 0.69 to 0.87. Although agricultural income increases rapidly, the high values of the Gini coefficient imply that agricultural income is severely unequally distributed among the poor population, indicating that some poor households do not become better off through the high growth of average agricultural income. This phenomenon is in accordance with the fact that intra-regional and intra-rural inequality exists in China (Gustafsson & Li, 2002; Lee, 2000; Xing, Fan, Luo, & Zhang, 2009) and has been increasing, with agricultural income a major source of the increase in inequality (Adams & Richard, 2002).

### 2.2. Infrastructure stock and investment

Villagers' income is affected by infrastructure stock, not only newly-added infrastructure. We first calculate total infrastructure stock, then electrical infrastructure stock. Next, we calculate the pre-investment level of irrigation for the village. Then, we consider increases due to investment.

We calculate total infrastructure stock for each village before separately calculating electricity. We use the perpetual inventory method (Kohli, 1978; Fan & Chan-Kang, 2008) for the calculation:

$$K_t = (1-d)K_{t-1} + I_t, t = 2014, \ldots, 2018 \tag{2}$$

where $K_t$ is the infrastructure stock in year $t$ and $I_t$ is the real value of infrastructure investment of the TPA program; and $d$ is the depreciation rate, which we assume to be 10% (Teruel & Kuroda, 2005). When $t = 2014$, $K_{2014} = (1-d)K_{2013} + I_{2014}$. Since 2014 is the starting year of the data, $K_{2013}$ is unknown. We follow Griliches and Mairesse (1991) and assume the growth rate of infrastructure stock to be $g$, so infrastructure stock in 2014 can be presented as:

$$K_{2014} = (1+g)K_{2013} = (1-d)K_{2013} + I_{2014} \tag{3}$$

Solving the equation, we have:

$$K_{2014} = \frac{1+g}{g+d} I_{2014} \tag{4}$$

We take as the value of $g$ the compounded annual growth rate of the fiscal poverty alleviation investment plan from 2003 to 2007 of the prefecture-level city where Xin County is located.[4] We can do this because, before the TPA program, poverty-stricken counties made investment plans and implemented infrastructure investment according to the *National Program for Rural Poverty Alleviation (2001–2010)*. We also calculate electricity infrastructure stock according to this method.

Then we construct an irrigation indicator to measure the irrigation infrastructure level. We use effective irrigated farmland area divided by total farmland area, following Balisacan and Pernia (2003), Zhang and Fan (2004a, 2004b) and Teruel & Kuroda, 2005. The equation is shown as follows:

[3] One thing to notice is that IPHs are not removed from the list when they shake off poverty, so one might expect it to be a balanced panel.

[4] We do a sensitivity analysis to change the values of $g$ and $d$, shown in the appendix. The result is robust within a reasonable range of values.

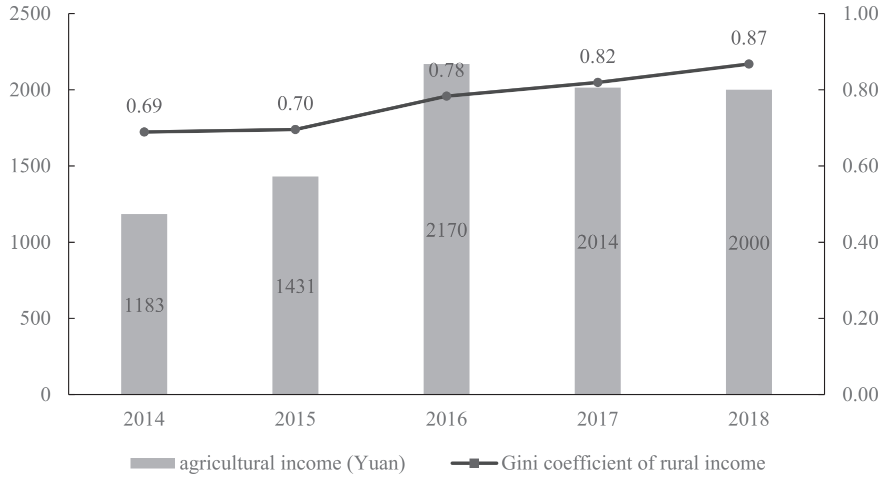



**Fig. 1.** Agricultural income and Gini coefficient from 2014 to 2018.
*Notes*: This figure plots agricultural income per capita and its Gini coefficient. Household's agricultural income is defined as gains or revenues from agricultural production. Agricultural income Gini coefficient is the Gini coefficient of household's agricultural income.

$$irrigation_{it} = \frac{effective\ irrigated\ farmland\ area_{it}}{farmland\ area_{it}} \times 100\% \tag{5}$$

where *effective irrigated area*$_{it}$ is the area of the relatively flat farmland that has certain water sources and supporting irrigation infrastructure owned by household $i$ in year $t$. *farmland area*$_{it}$ represents the total farmland area that household $i$ owned in year t. The value range of *irrigation* is 0% to 100% and a larger value of *irrigation* stands for a higher irrigation infrastructure level.

Fig. 2 summarizes the infrastructure conditions in Xin County in the studied period. Fig. 2.a illustrates the variation of infrastructure stock over the years. It shows that the infrastructure stock in Xin County increased rapidly from 242.73 million Yuan in 2014 to 584.64.50 million Yuan in 2018. Fig. 2.b shows that the stock of electricity infrastructure increased from 4.64 million Yuan in 2014 to 148.67 million Yuan in 2018, which also shows a rapidly rising trend. Fig. 2.c shows that the irrigation infrastructure level was 68.60% in 2014, indicating that about 31% of the cultivated land was not equipped with irrigation infrastructure. From 2014 to 2018, the irrigation infrastructure level increased from 68.60% to 70.43%.

## 3. Empirical strategy

Given that the previous section shows an increase of infrastructural stock during the TPA program as well as an increase in income level and inequality, we want to know whether the infrastructure investment increased the income level but worsened the income distribution. To answer this question, we adopt formal econometric models to investigate the impacts on agricultural income of total infrastructure investment and investments in electricity infrastructure and irrigation facilities.

### 3.1. Income effect

We explore infrastructure's impact on the poor's agricultural income, using the regression equation as follows:

$$ln(agri\_income_{ivt}) = \alpha_0 + \alpha_1 ln(infrastructure_{vt}) + \boldsymbol{X}'_{\boldsymbol{ivt}}\boldsymbol{\alpha_2} + \mu_i + \lambda_t + \varepsilon_{ivt} \tag{6}$$

where *infrastructure*$_{vt}$ is the total infrastructure stock of village $v$ in year $t$; and dependent variable *agri_income*$_{ivt}$ is the agricultural income of household $i$ in village $v$ in year $t$. $\boldsymbol{X}_{\boldsymbol{ivt}}$ is a vector of control variables added to control for the effects of observed factors.$\mu_i$ and $\lambda_t$ are household and time fixed effects, respectively; $\varepsilon_{ivt}$ is a time- and household-variant error term, which is assumed to be independent and identically distributed. This regression is a household-level regression and coefficient $\alpha_1$ captures the impact of infrastructure on households' agricultural income.

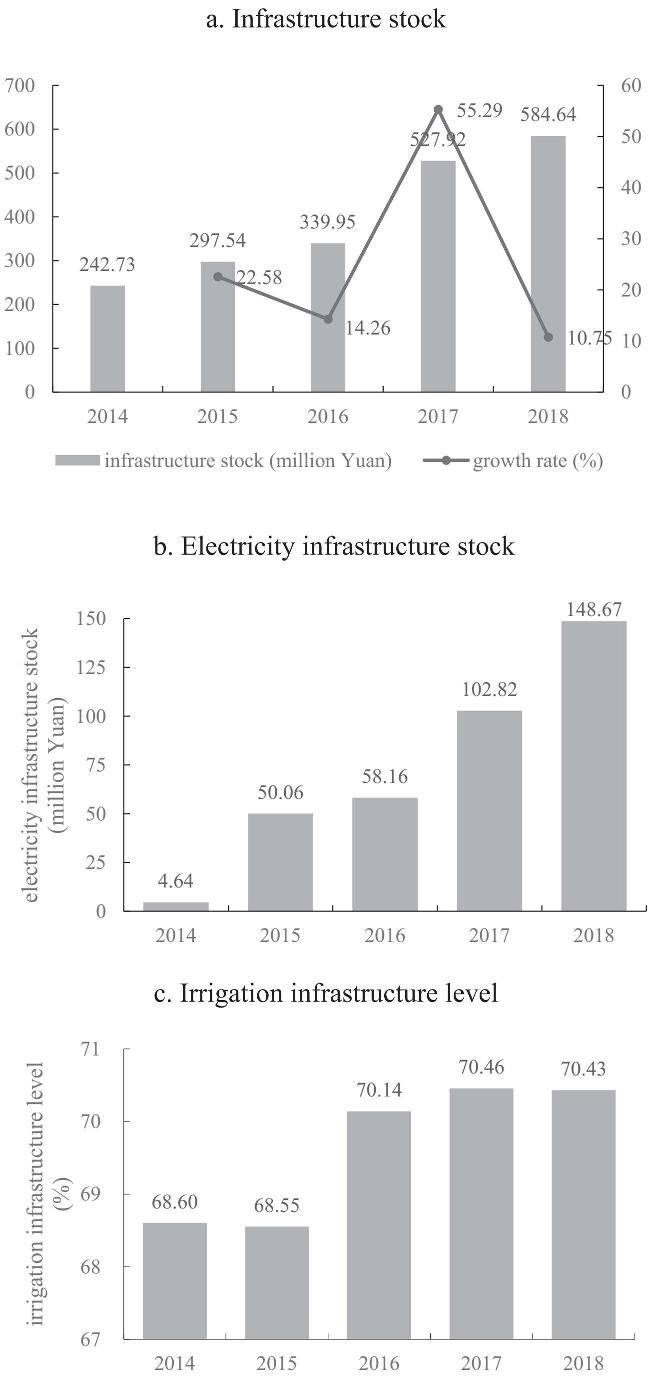



**Fig. 2.** Infrastructure in Xin County from 2014 to 2018.
*Notes*: Infrastructure stock and electricity infrastructure stock is calculated according to Eq. (3). Irrigation infrastructure level is calculated according to Eq. (5).

The control variable vector $\boldsymbol{X}_{ivt}$ includes (1) household's assets, including family's farmland area (*agriarea*) and woodland area (*woodarea*), which are the key assets directly related to agricultural production (Wan & Zhangyue, 2005); (2) household's demographic characteristics, including family size (*membernum*), human capital level of household head (*edu_head*), age (*age_head*) and age squared of household head ($age\_head^2$) (van de Walle, 2003; Wan & Zhangyue, 2005); and (3) log of household's cumulative investment in agricultural improvement projects (ln(*project_household*)).[5] The descriptive statistics of these variables are summarized in Table 1.

The household fixed effects $\mu_i$ absorb the effects of household characteristics that are time-invariant. For example, households' geographical location and natural resource endowments may simultaneously affect their agricultural income and the village's or local government's supply of infrastructure. Without dealing with this, the estimation could be biased. The two-way fixed effect model can solve this problem because households' geographical location and natural resource endowments are time-invariant, and their effects are therefore absorbed in the household fixed effects.

Because we control for a series of observables $\boldsymbol{X}_{ivt}$ and the household fixed effects $\mu_i$, the main remaining endogeneity could be due to selection. The concern is that, given the large cost and the high potential benefits of infrastructure investment, an investor is unlikely to make investment decisions randomly (Asher & Novosad, 2020; Shamdasani, 2021). Regions or villages that acquire infrastructure projects could be those that have the economic or political ability to raise funds. For political and economic concerns, infrastructure could be targeted to the areas with important roles (Dinkelman, 2011). In this way, the high level of infrastructure and high income only shows correlation but not causality. However, in the TPA program, this selection problem is alleviated due to the goal of the program and its process of investment decisions. In the program, the local government is responsible as a planner to allocate infrastructure funds and make investment decisions. The investment is made according to geographical characteristics and initial infrastructure levels; these are included in household fixed effects in the regression, which is a finer level of fixed effects than village-level fixed effects. Because the investments are provided by the TPA program, they are exogenous to villages' ability to attract investments. Given the program's goal of eradicating absolute poverty, the local government weighs the poorest people's welfare most, hence the government has no incentive to allocate investment funds to wealthy villages. That is, the effect is unlikely to be overestimated.

Besides total infrastructure investment, we are interested in electricity infrastructure and irrigation infrastructure for the reasons discussed previously. We expect positive effects of these two types of infrastructure on agricultural income, because electricity and irrigation are closely related to agricultural production and directly stimulate the output of agriculture. To do this, we run a regression as follows:

$$ln(agri\_income_{ivt}) = \theta_0 + \theta_1 ln(ele_{vt}) + \theta_2 ln(irrigation_{ivt}) + \theta_3 ln(village\_inv_{vt}) + \boldsymbol{X}^{'}_{ivt}\boldsymbol{\theta_4} + \mu_i + \lambda_t + \varepsilon_{ivt} \tag{7}$$

where the dependent variable $agri\_income_{ivt}$ is the agricultural income of household $i$ in village $v$ in year $t$; $ele_{vt}$ is the electricity infrastructure stock of village $v$ in year $t$; $irrigation_{ivt}$ is the irrigation infrastructure level of household $i$ in village $v$ at time $t$. We also control investment amount of other types of infrastructure of village $v$ at time $t$, denoted as $village\_inv_{vt}$, and a vector of control variables $X_{ivt}$, which is the same as the control in Eq. (6). $\mu_i$ and $\lambda_t$ are household and time fixed effects, respectively; $\varepsilon_{ivt}$ is a time- and household-variant error term which is assumed to be independent and identically distributed. If electricity and irrigation infrastructure improve agricultural income, we would expect $\theta_1 > 0$ and $\theta_2 > 0$.

### 3.2. Distributional effect

We further investigate how equitably the poor benefit from infrastructure investment. The direct way is to examine infrastructure's impact on the Gini coefficient, following Calderón and Chong (2004), Benerjee et al. (2012), Chen and Li (2020) and Xu, Wang, and Yang (2020). Therefore, we use the following village-level regression model:

$$Gini_{vt} = \beta_0 + \beta_1 ln(infrastructure_{vt}) + \boldsymbol{Z}_{vt}{'}\boldsymbol{\beta_2} + \delta_v + \sigma_t + \tau_{vt} \tag{8}$$

where $infrastructure_{vt}$ is the total infrastructure stock of village $v$ in year $t$; and independent variable $Gini_{vt}$ is the Gini coefficient of IPHs' agricultural income in village $v$ to measure the within-village distribution of IPHs. $\boldsymbol{Z}_{vt}$ is a vector of control variables at the village level. $\delta_v$ and $\sigma_t$ are village and time fixed effects, respectively; $\tau_{vt}$ is a time-variant and village-variant error term, which is assumed to be independent and identically distributed.

The control variable vector $\boldsymbol{Z}_{vt}$ includes (1) the inequality indicators of resources or capital, such as farmland area (*gini_agriarea*), wooded area (*gini_woodarea*) and human capital (*gini_eduyear*) (Tinbergen, 1972; Birdsall & Londoño, 1997;); (2) levels of different resources and capital, such as per capita farmland area (*agri_percap_village*), per capita wooded area (*wood_percap_village*), per capita agricultural income level (*aveincome*) and average education level (*edu_village*) of the identified poor households (Benjamin & Brandt, 1997; Wan, 2004; Wan & Zhangyue, 2005); (3) log of total investment in agricultural improvement projects of the village (ln

[5] An agricultural improvement project ("*chan ye fu pin*" in Chinese) is also one program in the TPA, which aims to provide private agricultural capital to encourage poor people develop agriculture, such as seeds and tools for planting and baby chickens, ducklings, etc., for animal cultivation. To make sure the IPHs fully take advantage of this agricultural capital, local governments buy and distribute them to IPHs, rather than giving them cash, to avoid the funds being spent for daily consumption. It is worth noting that the agricultural improvement project only provides private capital to the poor, so there is no overlap between the agricultural improvement project and infrastructure investment. Here we calculate cumulative investment of the agricultural improvement projects using the same method for calculating infrastructure stock as in Section 2.2.

**Table 1**
Summary statistics of variables.

| | Definition | Mean | Std Dev | Obs. |
|---|---|---|---|---|
| Panel A: dependent variables | | | | |
| *agri_income* | Income from agricultural production (Yuan) | 1775 | 8261 | 57623 |
| *wage* | Income from employment (Yuan) | 15336 | 16716 | 57932 |
| *Gini* | Gini coefficient of agriculture income | 0.739 | 0.141 | 882 |
| Panel B: key independent variables | | | | |
| *infrastructure* | Total infrastructure stock (million Yuan) | 1.908 | 3.036 | 57623 |
| *ele* | Electricity infrastructure stock (million Yuan) | 0.404 | 1.014 | 57623 |
| *irrigatin* | Ratio of irrigated land area to cultivated land | 69.88% | 34.66% | 57623 |
| Panel C: other variables | | | | |
| *household-level variables* | | | | |
| *agriarea* | Cultivated land of the household (Mu) | 2.27 | 1.46 | 57623 |
| *woodarea* | Woodland of the household (Mu) | 10.41 | 13.76 | 57623 |
| *membernum* | Family size (person) | 3.41 | 1.54 | 57623 |
| *edu_head* | Education level of head of the household (year) | 6.99 | 2.94 | 57623 |
| *age_head* | Age of the head (year) | 54.14 | 11.64 | 57623 |
| *project_household* | Household cumulative investment of the agricultural improvement projects (Yuan) | 15,570 | 28,743 | 57623 |
| *village-level variables* | | | | |
| *village_inv* | Infrastructure stock except for electricity (million Yuan) | 1.40 | 2.90 | 882 |
| *aveincome* | Average agricultural income of the poor | 5506 | 2913 | 882 |
| *agri_percap_village* | Average cultivated land of the poor (Mu) | 0.67 | 0.19 | 882 |
| *wood_percap_village* | Average wood land of the poor (Mu) | 3.49 | 4.15 | 882 |
| *edu_village* | Average education level of the poor (year) | 7.07 | 1.00 | 882 |
| *gini_agriarea* | Gini coefficient of cultivated land | 0.304 | 0.067 | 882 |
| *gini_woodarea* | Gini coefficient of woodland | 0.377 | 0.147 | 882 |
| *gini_eduyear* | Gini coefficient of human capital | 0.255 | 0.087 | 882 |
| *project_village* | Village cumulative investment of the agricultural improvement projects (Yuan) | 43.06 | 165.8 | 882 |
| *agri_ratio* | Ratio of agricultural income to total income | 10.23% | 7.42% | 882 |

*Notes*: "Mu" is a traditional Chinese unit of area. 1 mu = 666.67 square meters.

(*project_village*)), where *project_village* is the aggregation of households' *project_househehold* on village level; and (4) the ratio of agricultural income to total income (*agri_ratio*), considering that income structure also affects income inequality (Jiang & Liu, 2017).

In Eq. (8), if infrastructure construction improves the distribution of agricultural income, we would have $\beta_1 < 0$. Conversely, if infrastructure does not benefit the IPHs who have lower agricultural income, we will have $\beta_1 > 0$. Hence, combining estimations from Eqs. (6) and (8), we can learn about infrastructure's impact from both an average and distribution perspective.

We also investigate electricity and irrigation infrastructures' impact on agricultural income distribution, using the following regression:

$$Gini_{vt} = \omega_0 + \omega_1 ln(ele_{vt}) + \omega_2 irrigation_{vt} + \omega_3 ln\left(village\_inv_{vt}\right) + \mathbf{Z_{vt}}'\boldsymbol{\omega_4} + \delta_v + \sigma_t + \tau_{vt} \quad (9)$$

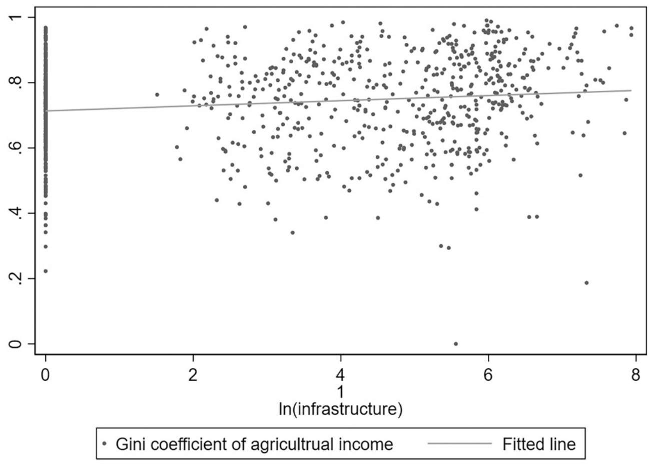



**Fig. 3.** Relationship between infrastructure and income distribution.
*Notes*: This figure plots the Gini coefficient of agricultural income among IPHs and the linearly fitted line. The slope of the linearly fitted line is 0.0078 and it's not statistically significant.

where $ele_{vt}$ represents electricity infrastructure stock of village $v$ in year $t$ and $irrigation_{vt}$ represents irrigation infrastructure level of village $v$ in year $t$. Dependent variable $Gini_{vt}$ denotes the Gini coefficient of agricultural income of all IPHs in village $v$ in year $t$. $village\_inv_{vt}$ is the investment amount of other types of infrastructure of village $v$ at time $t$. $\boldsymbol{Z_{vt}}$ is a vector of control variables, the same as the control in Eq. (8); $\delta_v$ and $\sigma_t$ are village and time fixed effects, respectively; and $\tau_{vt}$ is a time-variant and village-variant error term, which is assumed to be independent and identically distributed.

To interpret the estimates to be causal, the conditional zero mean assumption needs to be satisfied. One concern is that a reverse causality problem might exist if the government made infrastructure investments based on the degree of income inequality of the villages. However, to the best of our knowledge, the local government does not take into consideration within-village income distribution when they take measures to achieve the goal of the TPA program. As far as we know, the local government only acquired income information and calculated the mean of income and did not calculate the Gini coefficient or any other income distribution indicators. To verify this, we depict the village-level Gini coefficient before the TPA program and village-level total infrastructure investment in Fig. 3. It shows no correlation between the initial Gini coefficient and infrastructure investment. The slope of the linearly fitted line is 0.0078 and it's not statistically significant. The concern on reverse causality is therefore alleviated.

## 4. Estimation results

### 4.1. Effect on income

The regression results on the total effect of infrastructure on income are presented in Table 2. Column (1) is the basic model. Columns (2) to (4) add a series of control variables. All columns show that the estimated coefficient of *ln*(*infrastructure*) is not significantly different from zero but the sign is negative. This indicates that the overall infrastructure investment does not lead to a significant increase in poor households' agricultural gains, but may have a negative impact on agricultural income.

One possible reason for this result is that better transportation infrastructure such as rural roads and bridges encourages rural villagers to leave their villages to earn wages in the local downtown or in other cities, causing a crowding-out effect to the agricultural sector. To test this hypothesis, we substitute the dependent variable in regression Eq. (6) to be the wage income of a household (*ln* (*wage*)). *ln*(*wage*) refers to the total income from employment of a household. Because wage may be affected by last year's wage, which reflects the employer's expectation of wage and the value of work experience, we add a one-period lag of wage (*l. ln* (*wage*)) and adopt a Dynamic Panel Data model to estimate the coefficients. As shown in Table 3, infrastructure indeed increased the impoverished households' wage income. Our estimation is consistent with the empirical results from Dinkelman (2011) and Asher and Novosad (2020), which show that rural road construction stimulated workers to move out of agriculture, and did not bring agricultural investment or higher agricultural yields.

Table 4 summarized the estimation results of the effect of electricity and irrigation infrastructure on income. The estimated coefficients of *ln*(*ele*) and *irrigation* are significantly positive and remain stable in the four regressions. According to the estimates in Column (4), a 1% increase in electricity infrastructure stock increased agricultural income by 0.078%. Given that the investment

**Table 2**
Income effect of total infrastructure investment.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *ln*(*agri_income*) | *ln*(*agri_income*) | *ln*(*agri_income*) | *ln*(*agri_income*) |
| *ln*(*infrastructure*) | −0.00395 | −0.00360 | −0.00317 | −0.00160 |
| | (0.00963) | (0.00963) | (0.00967) | (0.00966) |
| *agriarea* | | 0.0309 | 0.0307 | 0.0305 |
| | | (0.0239) | (0.0231) | (0.0229) |
| *woodarea* | | 0.00748** | 0.00704* | 0.00683* |
| | | (0.00376) | (0.00377) | (0.00377) |
| *membernum* | | | 0.0552 | 0.0559 |
| | | | (0.0349) | (0.0349) |
| *edu_head* | | | 0.0182 | 0.0180 |
| | | | (0.0232) | (0.0232) |
| *age_head* | | | −0.134*** | −0.135*** |
| | | | (0.0313) | (0.0313) |
| *age_head_sq* | | | 0.00138*** | 0.00138*** |
| | | | (0.000286) | (0.000286) |
| *ln*(*project_household*) | | | | 0.0140*** |
| | | | | (0.00295) |
| Constant | 4.042*** | 3.891*** | 6.675*** | 6.686*** |
| | (0.0279) | (0.0749) | (0.924) | (0.922) |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Household fixed effect | Yes | Yes | Yes | Yes |
| observations | 57,779 | 57,777 | 57,268 | 57,268 |
| $R^2$ | 0.046 | 0.047 | 0.048 | 0.048 |

*Notes:* Two-way fixed effects model. Standard errors are clustered at household level. ***, **, and * indicate that the estimate is statistically significant at the 1%, 5%, and 10% significance level, respectively.

**Table 3**
Income effect of total infrastructure investment to wage.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *ln*(*wage*) | *ln*(*wage*) | *ln*(*wage*) | *ln*(*wage*) |
| *ln*(*infrastructure*) | 0.0545*** | 0.0520*** | 0.0257*** | 0.0257*** |
| | (0.00613) | (0.00611) | (0.00472) | (0.00472) |
| *l. ln* (*wage*) | 0.609*** | 0.603*** | 0.608*** | 0.607*** |
| | (0.0178) | (0.0180) | (0.0178) | (0.0178) |
| *agriarea* | | 0.134*** | 0.0501*** | 0.0498*** |
| | | (0.0357) | (0.0168) | (0.0167) |
| *woodarea* | | 0.00921*** | 0.00324*** | 0.00326*** |
| | | (0.00119) | (0.000792) | (0.000792) |
| *membernum* | | | 0.389*** | 0.390*** |
| | | | (0.0206) | (0.0206) |
| *edu_head* | | | 0.0579*** | 0.0581*** |
| | | | (0.00540) | (0.00540) |
| *age_head* | | | 0.0927*** | 0.0928*** |
| | | | (0.00887) | (0.00887) |
| $age\_head^2$ | | | −0.00112*** | −0.00112*** |
| | | | (8.60e-05) | (8.61e-05) |
| *ln*(*project_household*) | | | | 0.00457** |
| | | | | (0.00190) |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Household fixed effect | Yes | Yes | Yes | Yes |
| Observations | 45,695 | 45,693 | 45,351 | 45,351 |

*Notes*: Dynamic Panel Data model. Standard errors are clustered at household level. ***, **, and * indicate that the estimate is statistically significant at the 1%, 5%, and 10% significance level, respectively.

**Table 4**
Income effect of electricity and irrigation infrastructure.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *ln*(*agri_income*) | *ln*(*agri_income*) | *ln*(*agri_income*) | *ln*(*agri_income*) |
| *ln*(*ele*) | 0.0607*** | 0.0732*** | 0.0749*** | 0.0779*** |
| | (0.0108) | (0.0107) | (0.0108) | (0.0108) |
| *irrigation* | 0.851*** | 0.838*** | 0.851*** | 0.845*** |
| | (0.182) | (0.181) | (0.179) | (0.179) |
| *ln*(*village_inv*) | | −0.0681*** | −0.0672*** | −0.0674*** |
| | | (0.00975) | (0.00978) | (0.00979) |
| *agriarea* | | | 0.0350 | 0.0348 |
| | | | (0.0234) | (0.0232) |
| *woodarea* | | | 0.00481 | 0.00462 |
| | | | (0.00377) | (0.00378) |
| *membernum* | | | 0.0564 | 0.0572 |
| | | | (0.0348) | (0.0348) |
| *edu_head* | | | 0.0185 | 0.0184 |
| | | | (0.0231) | (0.0231) |
| *age_head* | | | −0.131*** | −0.132*** |
| | | | (0.0311) | (0.0311) |
| $age\_head^2$ | | | 0.00135*** | 0.00135*** |
| | | | (0.000285) | (0.000284) |
| *ln*(*project_household*) | | | | 0.0146*** |
| | | | | (0.00307) |
| Constant | 3.435*** | 3.503*** | 6.069*** | 6.088*** |
| | (0.128) | (0.128) | (0.929) | (0.927) |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Household fixed effect | Yes | Yes | Yes | Yes |
| Observations | 57,779 | 57,779 | 57,268 | 57,268 |
| $R^2$ | 0.048 | 0.050 | 0.051 | 0.051 |

*Notes:* Two way fixed-effect model. ***, **, and * indicate that the estimate is statistically significant at the 1%, 5%, and 10% significance level, respectively. Standard errors are clustered at household level.

covered all 12,000 poor households in Xin County, we calculate that a 10% increase of average electricity infrastructure stock (which is about 0.04 million Yuan increase) will increase the agricultural income of poor households by 0.16 million Yuan in a year. Considering that electricity infrastructure has an impact on agricultural income over a longer horizon, the overall benefit from electricity infrastructure is much larger in a lifespan of 18 to 24 years. We calculate that the total income increase would be about 2.99 to 3.99 million Yuan for the poor population in Xin County.

In terms of irrigation infrastructure, we find that a 10-percentage point increase of irrigation infrastructure level will raise agricultural income by 8.38% to 8.51%, corresponding to 148.74 Yuan to 151.05 Yuan per household on average and 1.78 to 1.81 million Yuan in total. When taking into consideration the lifespan of irrigation facilities (about 30–40 years), the total benefit of irrigation infrastructure would be 53.4 to 72.4 million Yuan.

### 4.2. Distributional effect

Table 5 shows the estimation results of total infrastructure's distributional effect. It shows that total infrastructure does not significantly change the Gini coefficient of agricultural income and the result remains stable to the control of village characteristics. Combining the result in Table 5 with that in Table 3, we find that overall infrastructure investment does not significantly affect poor households' agricultural income or its distribution.

Table 6 summarizes the estimation results of electricity and irrigation infrastructure's distributional effect. It shows that electricity infrastructure does not significantly affect agricultural income distribution. Combined with electricity infrastructure's income effect shown in Table 4, this indicates that poor households benefit equally from the investment in electricity facilities. As for irrigation infrastructure, Table 6 shows that the increase in irrigation facility coverage significantly decreases the Gini coefficient of agricultural income. This indicates that irrigation infrastructure benefits the poorest households more, leading to pro-poor growth.

For a robustness check, we utilize the following method to investigate the change of income distribution. We first divide the sample into five groups based on their income in 2014:

$$Group_i = \begin{cases} 1, if\ agri\_income_{i,2014} < 20\%quantile \\ 2, if\ 20\%quantile \leq agri\_income_{i,2014} < 40\%quantile \\ 3, if\ 40\%quantile \leq agri\_income_{i,2014} < 60\%quantile \\ 4, if\ 60\%quantile \leq agri\_income_{i,2014} < 80\%quantile \\ 5, if\ agri\_income_{i,2014} \geq 80\%quantile \end{cases}$$

We then run the regressions of Eqs. (6) and (7) on the five subsamples separately, and compare the effects of infrastructure investments across groups. As group 1 represents the households with the lowest agricultural income in 2014, a larger coefficient for group 1 indicates pro-poor growth, in that the poor with a lower level of agricultural income benefit more from the infrastructure investment.

Fig. 4 plots the estimated coefficients of *ln*(*infrastructure*), *ln*(*ele*), and *irrigation* in subsample regressions. We find that in the five subsamples, the coefficient of *ln*(*infrastructure*) is negative and statistically significant at the 5% significance level in the first group. Overall infrastructure obviously does not benefit the poorest households, consistent with our regression results in Table 5, in that both

**Table 5**
Distributional effect of total infrastructure investment.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *Gini* | *Gini* | *Gini* | *Gini* |
| *ln(infrastructure)* | 0.00243 | 0.00107 | 0.00104 | 0.000939 |
| | (0.00288) | (0.00272) | (0.00261) | (0.00265) |
| *gini_agriarea* | | −0.135 | −0.116 | −0.150 |
| | | (0.116) | (0.117) | (0.111) |
| *gini_woodarea* | | 0.151 | 0.125 | 0.165 |
| | | (0.110) | (0.105) | (0.104) |
| *gini_eduyear* | | 0.675** | 0.605** | 0.524* |
| | | (0.299) | (0.285) | (0.278) |
| *agri_percap_village* | | | −0.102 | −0.100 |
| | | | (0.0745) | (0.0731) |
| *wood_percap_village* | | | 0.0184*** | 0.0179*** |
| | | | (0.00584) | (0.00582) |
| *edu_village* | | | −0.0124 | −0.0153 |
| | | | (0.0225) | (0.0222) |
| *ln(aveincome)* | | | 0.0219 | 0.0243 |
| | | | (0.0178) | (0.0172) |
| *ln(project_village)* | | | 0.000256 | 0.000260 |
| | | | (0.00270) | (0.00265) |
| *agri_ratio* | | | | −0.246** |
| | | | | (0.121) |
| Constant | 0.675*** | 0.490*** | 0.429** | 0.480** |
| | (0.00506) | (0.0860) | (0.196) | (0.199) |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Village fixed effect | Yes | Yes | Yes | Yes |
| Observations | 893 | 882 | 882 | 882 |
| $R^2$ | 0.385 | 0.419 | 0.426 | 0.437 |

*Notes*: Two-way fixed effects model. ***, **, and * indicate that the estimate is statistically significant at the 1%, 5%, and 10% significance level, respectively. Standard errors are clustered at village level.

**Table 6**
Distributional effect of electricity and irrigation infrastructure.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *Gini* | *Gini* | *Gini* | *Gini* |
| *ln*(*ele*) | −0.000675 | −0.00159 | −0.00149 | −0.00126 |
| | (0.00266) | (0.00262) | (0.00262) | (0.00256) |
| *irrigation* | −0.132* | −0.129* | −0.141** | −0.143** |
| | (0.0711) | (0.0689) | (0.0703) | (0.0708) |
| *ln*(*village_inv*) | | 0.00429 | 0.00458* | 0.00511* |
| | | (0.00260) | (0.00254) | (0.00261) |
| *edu_village* | | | −0.0179 | −0.0175 |
| | | | (0.0217) | (0.0216) |
| *ln*(*aveincome*) | | | 0.0281 | 0.0271 |
| | | | (0.0174) | (0.0173) |
| *ln*(*project_village*) | | | | −0.00170 |
| | | | | (0.00261) |
| *gini_agriarea* | −0.203* | −0.187* | −0.173 | −0.171 |
| | (0.109) | (0.110) | (0.109) | (0.110) |
| *gini_woodarea* | 0.164 | 0.169 | 0.167 | 0.168 |
| | (0.104) | (0.103) | (0.103) | (0.104) |
| *gini_eduyear* | 0.606** | 0.608** | 0.489* | 0.492* |
| | (0.273) | (0.271) | (0.258) | (0.258) |
| *agri_percap_village* | −0.0957 | −0.0821 | −0.0849 | −0.0857 |
| | (0.0712) | (0.0717) | (0.0726) | (0.0726) |
| *wood_percap_village* | 0.0200*** | 0.0194*** | 0.0184*** | 0.0183*** |
| | (0.00617) | (0.00613) | (0.00609) | (0.00612) |
| *agri_ratio* | −0.225* | −0.224* | −0.231* | −0.231* |
| | (0.123) | (0.123) | (0.123) | (0.122) |
| Constant | 0.640*** | 0.620*** | 0.563*** | 0.569*** |
| | (0.105) | (0.105) | (0.191) | (0.192) |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Village fixed effect | Yes | Yes | Yes | Yes |
| Observations | 882 | 882 | 882 | 882 |
| $R^2$ | 0.438 | 0.441 | 0.444 | 0.445 |

*Notes*: Two-way fixed effects model. ***, **, and * indicate that the estimate is statistically significant at the 1%, 5%, and 10% significance level, respectively. Standard errors are clustered at village level.

of them indicate that income inequality is not improved by total infrastructure investment. For variable *ln*(*ele*), the coefficient of group one is 0.05, smaller than those of groups two to four (0.16, 0.23, 0.09 respectively), indicating that the poorest group does not benefit the most from electricity infrastructure. As for variable ***irrigation***, the coefficient of group one is 1.16 and is significantly positive, while the coefficients of groups two to four are insignificantly different from zero. Therefore, irrigation infrastructure benefits the poorest group most, leading to pro-poor income growth, consistent with the findings of the Gini regressions.

## 5. Mechanism: change of labor supply to agricultural sector

In this section we explore the mechanism of the infrastructure investment effect on agricultural income. Here we focus on one potential mechanism: the change of labor supply to the agricultural sector. The supply of electricity and irrigation affects labor allocation through changing relative labor productivity across economic sectors. For example, access to electricity that could be reliably used for powering agricultural machinery makes possible machine-intensive and large-scale agriculture, and therefore increase the relative labor productivity in the agricultural sector. Households would therefore participate or allocate more time working in the agricultural sector. Next, we distinguish the labor reallocation effect of infrastructure on both the extensive margin (participation in the agricultural sector) and the intensive margin (time spent working in the agricultural sector).

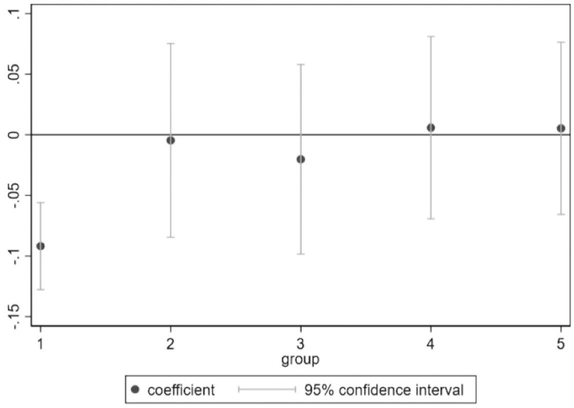
To empirically investigate electricity and irrigation infrastructure's impact on the probability of participating in agricultural work (i.e., the extensive margin of labor supply) and the time spent working in the agricultural sector (i.e., the intensive margin of labor supply), we model the relationship of the dependent variable, the mediator variables, and the independent variables as follows, according to MacKinnon, Lockwood, Hoffman, West, and Sheets (2002)'s mediating model:

$$ln(agri\_income_{ivt}) = \gamma_0 + \gamma_1 ln(ele_{vt}) + \gamma_2 irrigation_{ivt} + \boldsymbol{K}_{ivt}^{'}\boldsymbol{\gamma_3} + \mu_{1,i} + \lambda_{1,t} + e_{1,ivt} \tag{10}$$

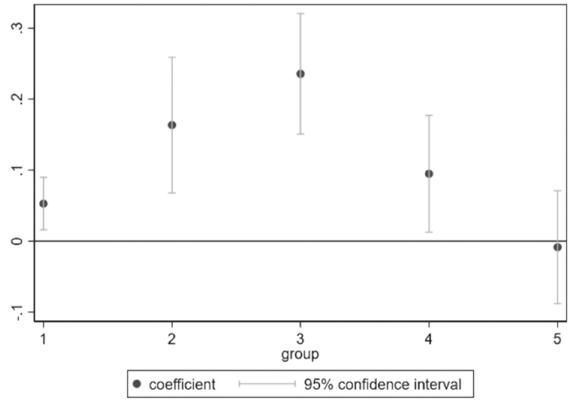
$$P(agriwork_{ivt} = 1|ln(ele_{vt}), irrigation_{ivt}, \boldsymbol{K}_{ivt}) = F\left(\gamma_4 + \gamma_5 ln(ele_{vt}) + \gamma_6 irrigation_{ivt} + \boldsymbol{K}_{ivt}{}^{'}\boldsymbol{\gamma_7} + \mu_{2,i} + \lambda_{2,t} + e_{2,ivt}\right) \tag{11}$$

$$rural\_month_{ivt} = \gamma_8 + \gamma_9 ln(ele_{vt}) + \gamma_{10} irrigation_{ivt} + \boldsymbol{K}_{ivt}^{'}\boldsymbol{\gamma_{11}} + \mu_{3,i} + \lambda_{3,t} + e_{3,ivt} \tag{12}$$

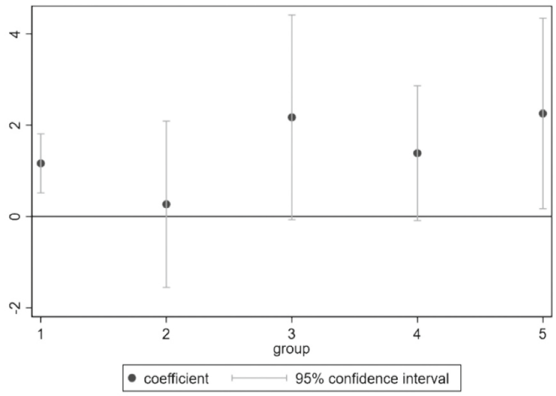
$$ln(agri\_income_{ivt}) = \gamma_{12} + \gamma_{13} ln(ele_{vt}) + \gamma_{14} irrigation_{ivt} + \gamma_{15} agriwork_{ivt} + \gamma_{16} rural\_month_{ivt} + \boldsymbol{K}_{ivt}^{'}\boldsymbol{\gamma_{17}} + \mu_{4,i} + \lambda_{4,t} + e_{4,ivt} \tag{13}$$




a. Coefficients of $ln(infrastructure)$ of five subsamples




b. Coefficients of $ln(ele)$ of five subsamples




c. Coefficients of $irrigation$ of five subsamples

**Fig. 4.** Regression coefficients of subsample groups.

where the dependent variable $agri\_income_{ivt}$ is the agricultural income of household $i$ in village $v$ in year $t$; the independent variable $ele_{vt}$ is the electricity infrastructure stock of village $v$ in year $t$; $irrigation_{ivt}$ is the irrigation infrastructure level of household $i$ in village $v$ at time $t$. The mediator variables are *agriwork* and *rural_month*. Variable $agriwork_{ivt}$ represents agricultural work participation of household $i$ in village $v$ in year $t$ and it represents the extensive margin of labor participating in agricultural production. Variable $rural\_month_{ivt}$ is the total months of rural work of household $i$ in year $t$, which represents the intensive margin of labor supply to agriculture. $F(\cdot)$ in Eq. (11) is the standard normal cumulative distribution function. To address the incidental parameter problem of using a Probit model for panel data in Eq. (11), we correct estimation bias following Cruz-Gonzalez, Fernández-Val, and Weidner (2017). $\boldsymbol{K_{ivt}}$ a vector of control variables, including $ln(village\_inv_{vt})$ and $\boldsymbol{X_{ivt}}$, the same as the controls in Eq. (6); $\mu_{j,\ i}$ and $\lambda_{j,\ t}$ ($j$=1,2,3,4) are household and time fixed effects, respectively; and $e_{j,\ ivt}$ ($j$=1,2,3,4) is a time-variant and individual-variant error term which is assumed to be independent and identically distributed.

If extensive margin and intensive margin of labor supply to agriculture are valid mechanisms, we expect the coefficients of ***ln*(*ele*)** and ***irrigation*** are significantly positive in Eqs. (11) and (12), suggesting that electricity and irrigation infrastructure increase the probability of participation and work intensity in agriculture. The coefficients of *agriwork* and *rural_month* are also expected to significantly positive in Eq. (13), suggesting that participating in agricultural production and raising work time leads to an increase of agricultural income. At the same time, the coefficient of independent variables *ln*(*ele*) and *irrigation* are expected to become smaller or insignificant comparing to those in Eq. (10), suggesting the impact of *ln*(*ele*) and *irrigation* is mediated by mediator variables.

Regression results are summarized in Table 7. Column (1) shows the regression result of Eq. (10), indicating that electricity and irrigation infrastructure increase agricultural income significantly, consistent with our previous results. Column (2) shows results of Eq. (11) that electricity and irrigation infrastructure significantly increase household's probability to participating in agricultural work. We also present Logit fixed effects model and a Linear Probability model respectively in Table A5, and the results remain robust.

Column (3) shows the regression result of Eq. (12) that electricity infrastructure does not increase the intensive margin of agricultural work but significantly decrease it. One possibility is that the mechanization level of agriculture increases due to the electricity infrastructure improvement in the village; as a result, the agricultural output and agricultural income increase although the intensive margin decreases. However, the dataset used in this article does not provide information about changes in the level of agricultural mechanization. Irrigation infrastructure does not have significant impact on intensive margin. In summary, extensive margin is a main mediator through which both electricity and irrigation infrastructure influence agricultural income.

Column (4) shows the result of Eq. (13) that mediator variable *agriwork* and *rural_month* has significant positive impact on *ln* (*agri_income*). We can also see that the coefficient of *ln*(*ele*) and *irrigation* become insignificant in Column (4), and the coefficient of *agriwork* is significantly positive, suggesting that the impact of electricity and irrigation infrastructure is mediated by the mediator. In summary, we see that infrastructure investments influence agricultural income mainly though raising households' participation in the agricultural sector.

To further test whether the mechanism differs across the whole distribution within the poor, we empirically investigate this question by applying a mediator model as follows:

$$Gini_{vt} = \eta_0 + \eta_1 ln(ele_{vt}) + \eta_2 irrigation_{vt} + \boldsymbol{H}'_{vt}\boldsymbol{\eta_3} + \delta_{1,v} + \sigma_{1,t} + \tau_{1,vt} \tag{14}$$

$$agriwork_{vt} = \eta_4 + \eta_5 ln(ele_{vt}) + \eta_6 irrigation_{vt} + \boldsymbol{H}'_{vt}\boldsymbol{\eta_7} + \delta_{2,v} + \sigma_{2,t} + \tau_{2,vt} \tag{15}$$

$$rural\_month_{vt} = \eta_8 + \eta_9 ln(ele_{vt}) + \eta_{10} irrigation_{vt} + \boldsymbol{H}'_{vt}\boldsymbol{\eta_{11}} + \delta_{3,v} + \sigma_{3,t} + \tau_{3,vt} \tag{16}$$

$$Gini_{vt} = \eta_{12} + \eta_{13} ln(ele_{vt}) + \eta_{14} irrigation_{vt} + \eta_{15} agriwork_{vt} + \eta_{16} rural\_month_{vt} + \boldsymbol{H}'_{vt}\boldsymbol{\eta_{17}} + \delta_{4,v} + \sigma_{4,t} + \tau_{4,vt} \tag{17}$$

where the dependent variable $Gini_{vt}$ is the Gini coefficient of agricultural income of the poor in village $v$ in year $t$; the independent variable $ele_{vt}$ is the electricity infrastructure stock of village $v$ in year $t$; $irrigation_{vt}$ is the village-level irrigation infrastructure of village $v$ in year $t$. The mediator variables are *agriwork* and *rural_month*. On village level, we define variable $agriwork_{vt}$ as the proportion of poor household participating in agricultural production in the poor population of village $v$ in year $t$, and define variable $rural\_month_{vt}$ as the average months of agricultural work in village $v$ in year $t$. $\boldsymbol{H_{vt}}$ a vector of control variables, including $ln(village\_inv_{vt})$ and $\boldsymbol{Z_{vt}}$, the same as the controls in Eq. (8); $\delta_{j,\ v}$ and $\sigma_{j,\ t}$ ($j$=1,2,3,4) are village and time fixed effects, respectively; and $\tau_{j,\ vt}$ ($j$=1,2,3,4) is a time-variant and village-variant error term which is assumed to be independent and identically distributed.

Regression results are summarized in Table 8. Column (1) shows the regression result of Eq. (14), indicating that irrigation infrastructure decreases agricultural income inequality significantly, but electricity does not have significant impact on income distribution, consistent with our previous results. Column (2) shows results of Eq. (15) that electricity and irrigation infrastructure significantly increase household's probability to participating in agricultural work on village level. It is also consistent with the household-level results shown in Column (2) of Table 7. Column (3) shows the regression result of Eq. (16) that both electricity and irrigation infrastructure do not increase the intensive margin of agricultural work.

Column (4) shows the result of Eq. (17) that mediator variables *agriwork* and *rural_month* significantly decrease Gini coefficient. We can also see that the coefficient of *irrigation* become insignificant from Column (1) to Column (4), and the sign of coefficient of *ln*(*ele*) become positive. Column (4) also shows that variable *agriwork* has a significant negative impact on Gini coefficient. This result suggests that the impact of electricity and irrigation infrastructure is mediated by *agriwork*. In conclusion, we see that infrastructure investments influence agricultural income distribution mainly though raising participation in the agricultural sector.

## 6. Conclusion

Infrastructure investment is critical to lift the poor out of poverty. However, the literature has shown that different infrastructure projects across countries have different effects on households' welfare. The heterogeneity of impacts indicates the importance of identifying the infrastructure type that could lead to pro-poor growth. This paper therefore investigates the effects on agricultural income level and distributional impacts of various infrastructure investments in the Targeted Poverty Alleviation (TPA) program in

**Table 7**
Mediator analysis for agricultural income.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *ln*(*agri_income*) | *P*(*agriwork* = 1) | *rural_month* | *ln*(*agri_income*) |
| ***Independent variables*** | | | | |
| *ln*(*ele*) | 0.0746*** | 0.0611*** | −0.919*** | −0.00358 |
| | (0.0107) | (0.0086) | (0.0269) | (0.0024) |
| *irrigation* | 0.853*** | 0.561*** | −0.199 | 0.0346 |
| | (0.1800) | (0.0974) | (0.3040) | (0.0336) |
| ***Mediator variables*** | | | | |
| *agriwork* | | | | 7.103*** |
| | | | | (0.0138) |
| *rural_month* | | | | 0.00320*** |
| | | | | (0.0007) |
| Control | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Household fixed effect | Yes | Yes | Yes | Yes |
| Observations | 57,267 | 24,182 | 57,267 | 57,267 |
| $R^2$ | 0.949 | / | 0.514 | 0.949 |

*Notes*: ***, **, and * indicate that the estimate is statistically significant at the 1%, 5%, and 10% significance level, respectively. Standard errors are clustered at household level.

**Table 8**
Mediator analysis for agricultural income distribution.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *Gini* | *agriwork* | *rural_month* | *Gini* |
| ***Independent variables*** | | | | |
| *ln*(*ele*) | −0.00126 | 0.00900*** | 0.00546 | 0.00374* |
| | (0.0026) | (0.0033) | (0.0534) | (0.0019) |
| *irrigation* | −0.143** | 0.202* | −3.082 | 0.0189 |
| | (0.0708) | (0.1050) | (3.7330) | (0.0488) |
| M***ediator variables*** | | | | |
| *agriwork* | | | | −0.485*** |
| | | | | (0.0246) |
| *rural_month* | | | | −0.000765 |
| | | | | (0.0016) |
| Control | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes |
| Village fixed effect | Yes | Yes | Yes | Yes |
| Observations | 882 | 882 | 882 | 882 |
| $R^2$ | 0.445 | 0.439 | 0.471 | 0.71 |

*Notes*: ***, **, and * indicate that the estimate is statistically significant at the 1%, 5%, and 10% significance level, respectively. Standard errors are clustered at village level.

China.

Based on data from the TPA program and econometric models, we find that infrastructure investment as a whole did not improve the agricultural income level or distribution; on the contrary, it crowded out labor from the agricultural sector. However, electricity infrastructure significantly increased agricultural income and the entire identified poor population equally shares benefits from electricity infrastructure. Irrigation infrastructure both increased agricultural income and reduced agricultural income inequality among all poor households, indicating that irrigation facility investment could lead to pro-poor growth.

Our calculation shows that electricity and irrigation infrastructure have high returns in terms of agricultural production: a 10% increase of average electricity infrastructure stock, which is about 0.04 million Yuan increase, will raise the total agricultural income of the poor population in Xin County by 0.16 million Yuan in one year and 2.99 to 3.99 million Yuan over the lifespan of the project. A 10-percentage point increase of irrigation level will bring 1.78 to 1.81 million Yuan a year, corresponding to 53.4 to 72.4 million Yuan for the poor over the project lifespan. In addition, irrigation investment decreases the Gini coefficient by 0.0143.

The findings in this paper provide governments and investment funders a comprehensive perspective to view infrastructure's effect on agricultural income. Since agricultural production is an important way to achieve rural development and rural revitalization, agricultural income is a key indicator of concern. Paying more attention to agricultural outcomes is a way to care about the most vulnerable poor people, because in China agricultural income is closely linked to the poorest people, especially those lacking labor force participation and human capital. Meanwhile, under the constraints of funding budgets, how to allocate investment among different types of infrastructure is an important question. Investing in those projects that can increase income as well as improve income distribution is the way to achieve efficiency and equity simultaneously.

Due to data limitations, this paper focuses on short-term income effects of infrastructure investment. We are very aware that infrastructure has more and longer-term impacts on the development of impoverished areas, including increasing job opportunities, improving technology access, inducing human capital investment, etc. These will be the directions of future research.

## Declaration of Competing Interest

None.

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## Appendix A. Appendix

**Table A1**
Types of infrastructure investment in Xin County from 2014 to 2018.

| Infrastructure type | Content | Percentage |
|---|---|---|
| Rural roads and bridges | Construction of rural road and bridges. | 31.64% |
| Education | Construction of school buildings and teaching facilities. | 19.36% |
| Communication | Construction of network. | 14.34% |
| Irrigation | Construction of irrigation facilities. | 12.95% |
| Rural neighborhood improvement | Facilities to improve rural neighborhood, such as horticultural planting, road beautification, etc. | 8.53% |
| Land consolidation | Comprehensive improvement of fields, water, roads, forests, and villages to improve the quality of cultivated land. | 5.32% |
| Electricity | Construction of power distribution network for rural area. | 3.84% |
| Water sanitation | Access to sanitized water. | 3.64% |
| Other fees | Supervision and survey costs for infrastructure investment. | 0.38% |

**Table A2**
Electricity and irrigation infrastructure construction in Xin County.

| Information on electricity infrastructure in rural area | | |
|---|---|---|
| | 2015 | 2018 |
| Power supply radius | 10.38 miles (10 kV)<br>0.67 miles (0.4 kV) | 9.50 miles (10 kV)<br>0.55 miles (0.4 kV) |
| The number of public distribution transformers | 1000 | 1400 |
| Capacity of public distribution transformers | 84,000 kVA | 191,000 kVA |
| Capacity of public distribution transformer per household | 0.82 kVA | 1.84 kVA |
| Household covered by power | 102,400 households | 103,900 households |

| Information of irrigation infrastructure in rural area | | |
|---|---|---|
| | 2014 | 2018 |
| Ponds | 81 | 40 |
| Revetment | 1601 m | 6346.6 m |
| Dams | 1 | 3 |
| Weirs | 10 | 32 |
| Total length of drainage | 1091 m | 4104 m |
| Total length of irrigation channels | 1234 m | 1481 m |

**Table A3**
Sensitivity analysis of: coefficients of ln(infrastructure) of Eq. (6).

| g\d | 10% | 11% | 12% | 13% | 14% | 15% |
|---|---|---|---|---|---|---|
| 10% | −0.00168 | −0.00197 | −0.00225 | −0.00252 | −0.00278 | −0.00303 |
| | (0.00996) | (0.00999) | (0.0100) | (0.0101) | (0.0101) | (0.0101) |
| 11% | −0.00193 | −0.00220 | −0.00247 | −0.00273 | −0.00298 | −0.00323 |
| | (0.00997) | (0.0100) | (0.0100) | (0.0101) | (0.0101) | (0.0101) |
| 12% | −0.00216 | −0.00243 | −0.00268 | −0.00294 | −0.00318 | −0.00342 |
| | (0.00998) | (0.0100) | (0.0100) | (0.0101) | (0.0101) | (0.0101) |
| 13% | −0.00238 | −0.00264 | −0.00289 | −0.00313 | −0.00337 | −0.00360 |
| | (0.00998) | (0.0100) | (0.0100) | (0.0101) | (0.0101) | (0.0101) |

(*continued on next page*)

**Table A3** (*continued*)

| g\d | 10% | 11% | 12% | 13% | 14% | 15% |
|---|---|---|---|---|---|---|
| 14% | −0.00259 | −0.00284 | −0.00309 | −0.00332 | −0.00355 | −0.00378 |
| | (0.00999) | (0.0100) | (0.0100) | (0.0101) | (0.0101) | (0.0101) |
| 15% | −0.00280 | −0.00304 | −0.00327 | −0.00351 | −0.00373 | −0.00395 |
| | (0.01000) | (0.0100) | (0.0101) | (0.0101) | (0.0101) | (0.0101) |

**Table A4**
Sensitivity analysis of: coefficients of ln(infrastructure) of Eq. (8).

| g\d | 10% | 11% | 12% | 13% | 14% | 15% |
|---|---|---|---|---|---|---|
| 10% | −0.00198 | −0.00196 | −0.00193 | −0.00191 | −0.00188 | −0.00186 |
| | (0.00251) | (0.00251) | (0.00252) | (0.00253) | (0.00254) | (0.00255) |
| 11% | −0.00196 | −0.00193 | −0.00191 | −0.00188 | −0.00186 | −0.00184 |
| | (0.00251) | (0.00252) | (0.00252) | (0.00253) | (0.00254) | (0.00255) |
| 12% | −0.00193 | −0.00191 | −0.00188 | −0.00186 | −0.00184 | −0.00182 |
| | (0.00251) | (0.00252) | (0.00253) | (0.00253) | (0.00254) | (0.00255) |
| 13% | −0.00191 | −0.00188 | −0.00186 | −0.00184 | −0.00182 | −0.00180 |
| | (0.00251) | (0.00252) | (0.00253) | (0.00254) | (0.00254) | (0.00255) |
| 14% | −0.00188 | −0.00186 | −0.00184 | −0.00182 | −0.00180 | −0.00178 |
| | (0.00252) | (0.00252) | (0.00253) | (0.00254) | (0.00255) | (0.00255) |
| 15% | −0.00186 | −0.00184 | −0.00182 | −0.00180 | −0.00178 | −0.00176 |
| | (0.00252) | (0.00252) | (0.00253) | (0.00254) | (0.00255) | (0.00256) |

**Table A5**
Electricity and irrigation infrastructure's impact on extensive margin of agricultural sector.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Probit | Logit | Linear Probability |
| | *agriwork* | *agriwork* | *agriwork* |
| ln(*ele*) | 0.0611*** | 0.100*** | 0.0110*** |
| | (0.00857) | (0.0159) | (0.00146) |
| *irrigation* | 0.561*** | 0.980*** | 0.115*** |
| | (0.0974) | (0.189) | (0.0253) |
| ln(*village_inv*) | −0.0280*** | −0.0497*** | −0.00415*** |
| | (0.00789) | (0.0164) | (0.00129) |
| *agriarea* | 0.0421 | 0.0716 | 0.00446 |
| | (0.0273) | (0.0853) | (0.00301) |
| *woodarea* | −8.86e-05 | −0.000352 | 6.33e-05 |
| | (0.00316) | (0.00697) | (0.000548) |
| *membernum* | 0.0516** | 0.0906* | 0.00680 |
| | (0.0241) | (0.0515) | (0.00472) |
| *edu_head* | −0.00553 | −0.00602 | 0.00123 |
| | (0.0143) | (0.0304) | (0.00321) |
| *age_head* | −0.120*** | −0.211*** | −0.0149*** |
| | (0.0232) | (0.0466) | (0.00419) |
| $age\_head^2$ | 0.00118*** | 0.00209*** | 0.000150*** |
| | (0.000216) | (0.000488) | (3.84e-05) |
| ln(*project_household*) | 0.0165*** | 0.0261*** | 0.00248*** |
| | (0.00268) | (0.00419) | (0.000404) |
| Constant | | | 0.795*** |
| | | | (0.125) |
| Year fixed effect | Yes | Yes | Yes |
| Household fixed effect | Yes | Yes | Yes |
| Observations | 24,182 | 24,182 | 57,267 |
| $R^2$ | / | / | 0.059 |

*Notes:* Probit two-way fixed effect model in Column (1), Logit two-way fixed effect model in Column (2) and Linear Probability model in Column (3). ***, **, and * indicate that the estimate is statistically significant at the 1%, 5%, and 10% significance level, respectively. Standard errors are clustered at household level.

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