Economics Development Analysis Journal Vol (1) (2022)

Economics Development Analysis Journal

http://journal.unnes.ac.id/sju/index.php/edaj

Impact of Agricultural Infrastructure Exposure on Inequality and Social Capital

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Article Information

History of Article
Received October 2021
Accepted December 2021
Pusblished February 2022

Keywords:
infrastructure, agriculture, inequality, social capital

Abstract

Infrastructure is expected as one of the engines of growth. However, there are also concerns about infrastructure externalities, such as inequality, social capital, and environmental issues. This study aims to clarify these unintended consequences of infrastructure, focusing on inequality and social capital. The research method of this study employs one of quasi-experimental methods, namely Instrumental Variables (IV) to address the endogeneity issues between infrastructure exposure, inequality, and social capital. Using PODES and SUSENAS data, the instrumental variable estimation shows that that the district with high exposure to integrated agricultural infrastructure negatively associates with inequality and positively corresponds to social capital. This result is consistent in direction with the Ordinary Least Square (OLS) estimation. One of the mechanisms behind it is increased farming productivity. This result also implies that the complementarity aspect between infrastructure types should be considered in the infrastructure development plan and execution.

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ISSN 2252-6560

INTRODUCTION

Infrastructure is one of the engines of growth that is expected to systematically drive economic efficiency and equity through reduced transactional cost, increased economic activities, and improved equity in public goods access. However, there is also a concern about the negative externalities of infrastructure, such as inequality (Chatterjee & Turnovsky, 2012), environmental issues (Doyle & Havlick, 2009), and socio-cultural disruption as an effect of displacement and resettlement (Aiken & Leigh, 2015).

This study explores these unintended issues focusing on the inequality aspect and social implication of agricultural infrastructure in Indonesia. The study does not include the environmental issue due to the data limitation. I also specifically use the infrastructure related to the agriculture sector for some reasons. Firstly, there is growing evidence that the agricultural infrastructure, such as dams, has an uneven distributional issue between the upstream and downstream areas. The displacement and resettlement during the construction also become another concern, especially in the socio-cultural aspect. Secondly, Indonesia is a developing country that relies on the agricultural sector as the third biggest GDP contributor after services and manufactures (Oberman et al., 2012). This condition makes the need and priority for agricultural infrastructures, such as water reservoirs and irrigation, becomes the necessity.

As a developing country, Indonesia has been progressively expanding the budget allocation for the infrastructure development, including agricultural infrastructure. The total spending on infrastructure was approximately $57.3 billion in 2014 (6.4% of GDP) and estimated to increase to $138.6 billion in 2025 (PwC, 2017). In the context of the agricultural sector, since 2014, the development of new large dams was prioritized as the national strategic program or PSN (Program Strategis Nasional). There are 65 dams built over the last six years (Purnamasari, 2021). This policy mainly aims to reduce the vulnerability of rainfall shock, mitigate floods, develop hydropower energy, enhance the livelihood alternative (fishery and tourism), and other benefits.

Nevertheless, agricultural infrastructure might imply distributional issues, such as income inequality. The seminal work about large dams in India by Duflo & Pande (2007) point out that the dams have a favorable impact on the downstream area, such as increased agricultural production, lowered rainfall shock vulnerability, and decreased rural poverty, but the area where the dams located to experience the opposite effects. In the Indonesian context, this phenomenon is also found by Aribowo & Yudhistira (2021). They reveal that every additional large dam in the district is associated with decreased household consumption living around the dams by 2.4-3.1%. This effect is likely caused by the change in agricultural and work activity. However, whether this local effect systematically stimulates aggregate district inequality remains ambiguous. Besides that, other agricultural infrastructure, such as small dams and irrigation, might affect household welfare. Therefore, this study extends Aribowo & Yudhistira (2021) 's study by exploiting the broader agricultural infrastructure scope and its implication on district inequality. This study also becomes the complement of Makmuri (2017) that explores the heterogeneous impact of infrastructure type on Indonesia's inequality but does not accommodate the agricultural infrastructure yet.

The infrastructure also seems to associate with the social fabric due to development, displacement, and resettlement. Aiken & Leigh (2015) find that several dams construction in Malaysia induces the frilled social relationship, high unemployment, and increased poverty because of the bad governance during the project. In the Indonesian context, the qualitative studies show the mixture result of the social implication of dams during and after the construction (Fadli et al., 2019; Surjono, 2015).

The various impact is also highlighted by Ward et al. (2020). They find that the infrastructure positively influences bonding and bridging but has no effect on linking aspects in the refugee camp context. In the irrigation project in Sri Lanka, Aoyagi et al. (2014) conclude that the infrastructure project, in particular irrigation, affects the social capital through the years of access, not merely by the repeated interaction. This result indicates that the infrastructure is likely to connect the individuals institutionally.

In short, these mixture results indicate that the contextual aspect might matter. These issues also remain an open question for Indonesia. In conducting the analysis, I utilize and combine several district-level datasets. Firstly, I employ the potential village survey in 2014 or PODES (Survei Potensi Desa) to measure the agricultural infrastructure exposure in the district. The agricultural infrastructures include irrigation and water reservoirs, such as large dams, small dams, lakes. Secondly, I calculate the district income inequality or Gini index using National Socioeconomic Survey in 2015-2017 or SUSENAS (Survei Sosial dan Ekonomi Nasional). Lastly, the social capital data is estimated by the gotong-royong (cooperation) practice from PODES 2018 and the composite index from the socio-cultural survey module in SUSENAS 2018. The effect of infrastructure might not simultaneously occur in the same year. Hence, I evaluate the impact in the subsequent years.

The main issue of infrastructure on inequality and social capital regression is the endogeneity bias from omitted variable bias and reverse causality. Therefore, I employ an instrumental variable approach to handle it. The instrument variable is the river exposure in the district. The river is likely to become the main supporting factor of agriculture infrastructure development that arguably possesses a random variation or an exogenous characteristic. At the same time, this variable might indirectly affect inequality and social capital.

However, another potential channel might link river exposure to inequality and social capital, such as farming productivity and inland fishery. However, I argue that the dynamic of farming productivity is more likely to be affected by the quality of agricultural infrastructure rather than directly driven by river exposure. Therefore, the farming aspect is expected to be a potential mediator variable in this study. The fishery might also be less problematic because the magnitude and productivity of inland fishery in Indonesia are relatively smaller than those of the agricultural sector or marine fishery. The fishery contribution (all sector) is about 2% in 2016, while the agriculture sector is about 11% in 2016 (Ministry of Marine and Fisheries of Indonesia, 2018)

The result of this study is appealing. By aggregate, the higher agricultural infrastructure exposure in the district negatively corresponds to inequality. Every 1 unit increase in agricultural infrastructure exposure is associated with lower inequality in 2015 by 0.000292 (OLS) - 0.001451 (IV). Due to the remaining OVB and imperfect instrumental variable, the OLS result is likely to represent the lower bound, while the IV is the upper bound estimation. Compared to the inequality mean in 2015, this magnitude is relatively low in the range of 0.08% - 0.41%. This finding contradicts prior literature showing the problematic distributional issue for households residing around the infrastructure (Aribowo & Yudhistira, 2021; Duflo & Pande, 2007). However, this result also aligns with some Makmuri (2017) conclusions that reveal the favorable effect of some infrastructure types in reducing inequality, such as electricity quantity, airport quantity, and airport quality.

Meanwhile, in terms of social capital, agricultural infrastructure exposure in the district positively affects social capital in the medium run. By magnitude, every 1 unit increase in agricultural infrastructure associates with rising gotong royong habit (in helping community member-SOCA Type II) by 0.05% (OLS) - 0.18% (IV). Meanwhile, in terms of the broader social capital aspect (SOCA Type III), the effect reaches 0.07% (OLS) - 0.23% (IV). These findings might complement the previous literature. The infrastructure construction is likely to distract socio-cultural habits in the short term, but this impact might be dissipating in the longer period by social life adaptation.

This study contributes to the literature in two aspects. Firstly, this study fills the gap by examining the aggregate impact of agriculture infrastructure on inequality and social capital to see whether the negative externalities of infrastructure emerge during rapid infrastructure development in Indonesia. Secondly, instead of analyzing the single infrastructure type, this study accommodates the complementary effect of related infrastructure types, such as water reservoirs and irrigation, as an integrated infrastructure. Thirdly, this study also concerns the endogeneity issue by introducing an instrumental variable approach.

The structure of the paper is as follows. The following section elaborates on data, empirical model, and identification strategy. Then, it is followed by the result section that discusses the main empirical result of this study. The last section is a conclusion, policy implication, and limitation of the study.

RESEARCH METHODS

The infrastructure might boost the economic activity and then increase the community welfare. In the agricultural context, these rising economic activities are most likely represented by improved agricultural productivity. The increasing opportunity and economic access, especially for the deprived group, is likely to stimulate the reduced income gap. However, this condition potentially does not occur when the project design promotes uneven benefit distribution (Aribowo & Yudhistira, 2021; Duflo & Pande, 2007). In the end, it implies a larger inequality. In contrast, the well-design project, such as a better water reservoir-irrigation system between upstream and downstream and livelihood change management, probably can mitigate or reduce this distributional problem. In short, the net impact of the agricultural infrastructure in affecting inequality is likely to depend on the project governance. Due to this heterogeneous channeling mechanism, it is crucial to ensure that the positive side of infrastructure outweighs its adverse impact (Srinivasan, 2001).

This situation also applies in the context of the social implication of infrastructure. During displacement and resettlement, the uncareful project execution might stimulate negative externalities, such as destroyed socio-cultural habits and jobs or business loss. In contrast, the well-design project might enhance the social cohesion through the appearance of similar feelings and responsibility to maintain the infrastructure as a public goods (Aoyagi et al., 2014). In the actual example, the repeated interaction when utilizing an irrigation system or water reservoir during the farming period might also encourage more social relationships. It means that the infrastructure has the potency to connect the people institutionally. Besides that, the positive externalities of agricultural infrastructures, such as increased tourism and controlled flood probably also associate with improved area amenity that affects social life.

Estimating the impact of agricultural infrastructure on inequality and social capital is challenging due to the possibility of join endogeneity from omitted variable bias and reverse causality. The infrastructure development as government decision might not be purely random. The most potential confounders are the past inequality and past social capital that might matter in simultaneously comprehending the future infrastructure, inequality, and social capital. Hence, I add the past district inequality and the past social capital in 2009 in the model. Why do I use 2009 data? As we know, the social, political, and economic downturn in Indonesia occurred in 1997 – 2009. The fluctuations during this period are likely to massively change many development aspects in Indonesia, such as inequality level and social capital profile. Therefore, the variation of social capital profile and inequality level in 2009 might be the starting point of Indonesian development in the subsequent periods.

The identified confounder will be used as the control variable in the model to reduce the bias from omitted-third factors and improve the comparability across the district. However, other potential confounders might remain unobserved, such as heterogeneity in leadership, political, and policy aspect, and unmeasurable, such as accurate rainfall intensity. Therefore, the dummy province, which might still be insufficient, will be added as a control to capture it.

To handle the possibility of reverse causality, I employ the lagged infrastructure exposure to predict the inequality and social capital in the subsequent periods. Besides that, I also use the instrumental variable approach to elicit the exogenous variation of infrastructure exposure at the district level. The instrument variable is river exposure. Explicitly, the empirical models of the study are as follows.

The Ordinary Least Square (OLS) estimation:

$$INEQ_d = \alpha + \beta_1 INFRA_d + \beta_2 IN09_d + \pi_{p(d)} + \varepsilon_d \quad (1)$$

$$SOCA_d = \alpha + \delta_1 INFRA_d + \delta_2 SC09_d + \pi_{p(d)} + \varepsilon_d \quad (2)$$

The Instrumental Variable (IV) estimation:

$$INEQ_d = \alpha + \theta_1 \widehat{INFRA}_d + \theta_2 IN09_d + \pi_{p(d)} + \varepsilon_d \quad (3a)$$

$$INFRA_d = \alpha + \rho_1 RIVER_d + \rho_2 IN09_d + \pi_{p(d)} + \varepsilon_d \quad (3b)$$

$$SOCA_d = \alpha + \gamma_1 \widehat{INFRA}_d + \gamma_2 SC09_d + \pi_{p(d)} + \varepsilon_d \quad (4a)$$

$$INFRA_d = \alpha + \vartheta_1 RIVER_d + \vartheta_2 SC09_d + \pi_{p(d)} + \varepsilon_d \quad (4b)$$

Model (3) and (4) are utilized to estimate the impact of agricultural infrastructure on inequality and social capital using the conditioning strategy in the OLS regression. This strategy relies on the conditional independence assumption between INFRA and error terms (Angrist & Pischke, 2008). Meanwhile, the equation (3a), (3b), (4a), and (4b) are the models for instrumental variables estimation. Model (3b) and (4b) is the first-stage regression, while the model (3a) and (4a) are the second-stage regression by using the predicted value of agriculture infrastructure exposure, $\widehat{INFRA}$ from model (3b) and (4b). This predicted value is expected to represent the exogenous variation of agricultural infrastructure exposure.

The income inequality, INEQ, is measured by the Gini coefficient at the district level. The Gini coefficient is calculated in the Stata by using the command ineqdeco. This command is developed by Jenkins (2006). The Gini coefficient formula is as follows:

$$G(S) = \frac{1}{n-1}(n + 1 - 2\frac{\sum_{i=1}^{n}(n+1-i)y_i}{\sum_{i=1}^{n} y_i} \quad (5)$$

Where $G(S)$ denotes Gini coefficient for a random sample S consisting of income y_i, $i = 1$ to n. The social capital, SOCA, use several proxies. Due to the data limitation, I only estimate the social capital in 2018 using PODES 2018 and Socio-cultural Module in the SUSENAS 2018. The social capital in PODES is defined by the share of the village with *gotong-royong* (cooperation) habit at the district level. The *gotong-royong* is also divided into cooperation in public goods provisions and helping community members. Meanwhile, the social capital in the SUSENAS is measured by the share of the individuals with a high social capital index. Firstly, to calculate the social capital index, I estimate the individual social capital using latent variable estimator within the class estimator of IRT (Item Response Theory); specifically, we use the Rasch Model (Baker & Kim, 2004; Fischer & Molenaar, 2012). I assume that the difficulty and ability to answer in the social capital survey vary. Hence, we employ the Rasch Model to accommodate these latent factors and then use it as the indexing factor. Secondly, I utilize a national mean of individual social capital as the bottom-line threshold for estimating the share of individuals with high social capital in the district. The estimating equation of the Rasch model for individual n with item j from 1 to 14 is as follows:

$$\Pr(X_{nj} = x_{nj} | \theta_n, \delta_j) = \frac{\exp(x_{nj}(\theta_n - \delta_j))}{1+\exp(\theta_n - \delta_j)} \quad (6)$$

In which θ_n is the so-called difficulty level captured by each item or question and δ_j is the parameter measuring the level of social capital of individual n. $X_{nj}$is a random variable representing the response of the nth individual (n = 1,…, N) to the j-th item (j = 1,…, J), x_{nj} is the realization of response for each item of an individual. The social capital index, thus, represents the individual (household head) perception or answer of several statements/questions in the Socio-cultural Module SUSENAS 2018. Table 1 depicts the detail of statements/questions about social capital aspect in the SUSENAS 2018.

Table 1. Social Capital Questionnaire in Socio-cultural Module SUSENAS 2018

No.	Dummy Variable from the Statements/Questions
1.	Do you participate in RT/RW/Ward/Village meeting?
2.	Do you share the opinion in that meeting?
3.	Do you participate in religion activities?
4.	Do you participate in skill development activities?
5.	Do you participate in sport/hobby activities?
6.	Do you participate in gotong royong activities?
7.	Do you participate in *arisan* activities?
8.	Do you participate in funeral?
9.	Do you participate in other social activities?
10.	Response to other race activities
11.	Response to other religion activities
12.	Response if one of household member has a friend from another race
13.	Response if one of household member has a friend from other religion
14.	Election participation

Source: SUSENAS 2018 - Social and Cultural Module

The variable of interest, agricultural exposure or $INFRA$ is estimated by the number of villages exposed by the complete set of agricultural infrastructure, namely the irrigation and water reservoir. Hence, the interest parameters of this study are $\beta_1, \delta_1, \theta_1, \rho_1$.

Due to limited data, I cannot use the accurate proxy of infrastructure exposure, such as the water reservoir area or the length/area of irrigation in the district. Therefore, instead of utilizing the number of infrastructures as used by Duflo & Pande (2007) and Aribowo & Yudhistira (2021), I prefer to use the exposure level to represent the coverage scale of infrastructure (Approach 2 in Figure 1).

Besides that, the complete infrastructure set might also reflect how the complementarity of infrastructure type works. The data for agricultural infrastructural exposure is generated from PODES 2014.

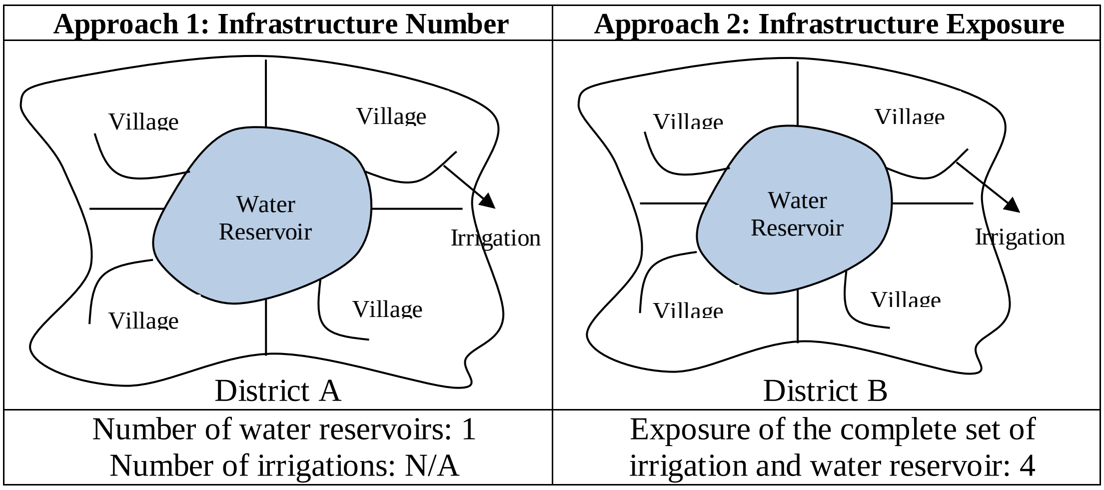

Figure 1. Agricultural Infrastructure Measures in the Hypothetical Map

The control variables, $IN09$ and $SC09$, represent the past inequality and social capital in 2009, respectively. Both variables are estimated by using SUSENAS 2009. Lastly, π is the dummy province to capture the province heterogeneity in leadership, politic, government policy, and other unobserved aspects.

To scrutinize how the agriculture infrastructure affects inequality and social capital, I also estimate the mediation analysis using farming productivity as a potential mediator. The rising farming productivity is likely to promote welfare enhancement and reduce aggregate inequality. Besides that, the repeated cooperation during the farming period might also potentially drive the social capital in the community.

The estimation employs an instrumental variable approach using river exposure as a single instrument to obtain the causal mediation effect. This method was introduced by Dippel et al. (2020). I assume that river exposure is also a valid instrument for farming productivity. Explicitly, the empirical models are as follows:

$$INEQ_d = \alpha + \theta_1 \widehat{FARM}_p + \varepsilon_d \qquad (7a)$$

$$FARM_p = \alpha + \rho_1 RIVER_d + \rho_2 INFRA_d + \varepsilon_d \qquad (7b)$$

$$SOCA_d = \alpha + \gamma_1 FARM_p + \varepsilon_d \qquad (8a)$$

$$FARM_p = \alpha + \vartheta_1 RIVER_d + \vartheta_2 INFRA_d + \varepsilon_d \qquad (8b)$$

Model (7b) and (8b) are the first stage regression utilizing the river exposure as an instrumental variable for farming productivity. These models are also conditional on the agricultural infrastructure. Meanwhile, the model (7a) and (7b) are the second stage regression estimating the indirect effect of farming productivity, FARM, on inequality and social capital. The farming productivity data is from the Ministry of Agriculture of Indonesia and represents the rice harvest at the province level.

RESULTS AND DISCUSSION

This Figure 2 exhibits the agriculture infrastructure exposure at the province level. The highest exposure is East Java, Central Java, and West Java. These provinces are also well-known as the top three contributors of rice production in Indonesia, reaching approximately 13, 11, and 12 million tons in 2018, respectively. Interestingly, the map also shows the divergence condition in the sector of agriculture infrastructure in Indonesia that is mainly concentrated in Java Island.

Notes: The map shows number of villages exposed by agricultural infrastructure at the province level.

Figure 2. Agriculture Infrastructure Exposure in Indonesia (Province Level)

Moreover, the summaries of each variable are illustrated in Table 2. The outcome variable, inequality, and social capital show a positive trend. The inequality decreased from 0.35 in 2015 to 0.34 in 2017, but this value trend is higher than the inequality level in 2009. The gotong-royong habit in 2018 is also high. Above 80% of the village in the district still maintains the gotong-royong value activity. However, in terms of the social capital index that employs a broader aspect of social capital, it shows a moderate level. The individual with high social capital in a district is only approximately 53.74% on average. This value was smaller than the social capital in 2009.

Table 2. Summary Statistic

	N	Mean	St. Dev	Min	Max
Interest Variables					
INFRA	511	7.585127	11.38214	0	99
Outcome Variables					
INEQ 2015	510	.3515882	.0517312	.181	.675
INEQ 2016	511	.3394227	.0463018	.155	.483
INEQ 2017	511	.3364266	.0473175	.181	.505
SOCA Type I	511	80.67485	13.75635	22.64151	100
SOCA Type II	511	88.70682	10.14785	24.74227	100
SOCA Type III	511	53.7392	11.04811	35.91333	84.35695
Instrumental Variable					
RIVER	511	123.7886	92.09853	0	407
Mediator Variables					
FARM 2015	511	48.82043	9.465652	22.85	62.14
FARM 2016	511	47.75039	9.560248	22.79	60.6
FARM 2017	511	47.65867	8.827201	23.09	59.09
FARM 2018	511	47.26865	9.149649	26.53	72.76
Control Variables					
SC09	466	.5660628	.1421449	.0259474	.8999058
IN09	466	.2909226	.0421884	.07575	.44257

Source: PODES 2014 & 2018, SUSENAS 2009, 2015-2018, Ministry of Agriculture

The river exposure in Indonesia is relatively high. The number of villages crossed by a river in a district is about 123 on average. However, at the same time, the farming productivity of rice is stagnant at 47-48 quintals per hectare during 2015 - 2018.

I use the river exposure variable as the instrumental variable for the agricultural infrastructure exposure. Table 3 illustrates the first-stage regression result delineating the relationship of both variables.

Table 3. The First-Stage Regression Result

	(1) INFRA	(2) INFRA (Inequality Context)	(3) INFRA (Social Capital Context)
RIVER	0.058557***	0.056320***	0.057679***
	(0.006717)	(0.006756)	(0.006331)
IN09		-24.895208**	
		(9.654785)	
SC09			13.247608***
			(4.574347)
Observation	511	466	466
R-square	0.224498	0.413084	0.420567
F-Stat	75.996234	11.067253	11.481988
Dummy Province	NO	YES	YES

Robust standard errors in parentheses with ***, **, and * indicate 1, 5, and 10% significance levels, respectively. The estimation employs OLS. The INFRA is agricultural infrastructure exposure at the district level. The instrumental variable is RIVER or river exposure at the district level.

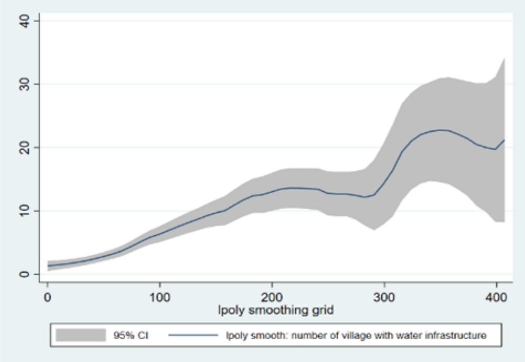

Figure 3. Monotonicity Graph between River and Agricultural Infrastructure Exposure

Table 3 shows that the river exposure significantly affects the agricultural infrastructure exposure by approximately 0.05-0.06. Every 20 unit (or 16%) increase in river exposure is associated with increased agricultural infrastructure exposure by 1-1.2 or about 13-15.78% compared to the mean of INFRA. It indirectly exhibits that the higher number of villages crossed by a river in the district corresponds to the higher probability of agricultural infrastructure development. The instrument is also quite strong, with F-stat value more than 10. In short, the first-stage regression shows that the instrument is strong and relevant.

Apart from the strong and relevant assumption, the other aspect that needs to be verified is monotonicity. This aspect is used to show whether each observation instrument's direction in predicting the endogenous variable (INFRA) is monotonic or uniform. Figure 3 illustrates that the river exposure as an instrument might be imperfect due to the monotonicity issue. Overall, the trend is validly upward sloping, but there are fluctuated trends in the range of 200-300 and above 350.

The lack of monotonicity indicates that the instrumental variable estimation might still be biased. Therefore, the IV result is more likely to represent an upper bound estimation. This condition also becomes the limitation of this study that needs to be concerned in future works.

The relationship between agricultural infrastructure, inequality, and social capital are ambiguous due to the various channels. The prior studies found that the welfare gap between the area around the water reservoir (upstream) and other areas might boost a larger inequality level in the district. Nevertheless, this hypothesis is not proven in this study. Surprisingly, the district with high infrastructure exposure negatively corresponds to inequality (see Table 4). This result is consistent in the context of the short (effect in 2015) and mid-term (effect in 2017). For example, every 1 unit increase in agricultural infrastructure exposure corresponds with lower inequality in 2015 by 0.000292 (OLS) - 0.001451 (IV) (See Appendix 1). Due to the remaining OVB and imperfect instrumental variable, the OLS result is likely to represent the lower bound, while the IV is the upper bound estimation. Compared to the inequality mean in 2015, this effect is relatively low in the range of 0.08% - 0.41%.

This result contradicts the existing literature, such as Aiken & Leigh (2015), Aoyagi et al. (2014), Aribowo & Yudhistira (2021), Duflo & Pande (2007). Two conditions can comprehend it. Firstly, this study employs a complete set of agricultural infrastructure, namely the integrated water reservoir-irrigation exposure in the village. In other words, this result also indirectly shows the impact of infrastructure under complementarity feature, while the previous study specifically examines the dams as a single infrastructure. This study finds that the integrated water reservoir and irrigation system is proven to reduce inequality, while the prior studies reveal that the dams reduce the welfare of households living around the dams.

Therefore, this welfare loss might be due to the absence of an integrated irrigation system connecting upstream and downstream areas. Both findings also indicate that the policymaking might need to be emphasized in the specific location, especially the community residing around the dams. One of the ways is probably by developing or improving irrigation systems in that area. Secondly, the welfare loss might occur for the household living around the water reservoir, but by aggregate, the magnitude of loss does not systemically stimulate larger inequality in the district, or the loss is still lower than the positive impact of infrastructure.

In the literature, the social consequences of infrastructure are limited and show the mixture results. The empirical estimation in Appendix 2 exhibits that the agricultural infrastructure exposure positively corresponds to the various social capital type. Nevertheless, the effect on SOCA Type I or gotong royong in public goods provision is likely to be trivial. Explicitly, every 1 unit increase in agricultural infrastructure associates with rising gotong royong habit (in helping community member or SOCA Type II) by 0.05% (OLS) - 0.18% (IV). Meanwhile, in terms of the broader social capital aspect (SOCA Type III), the effect reaches 0.07% (OLS) - 0.23% (IV).

Compared to the social capital mean, this range of effect is feeble. However, this positive sign might confirm the hesitation of the prior mixture result about displacement and resettlement issues. Besides that, these results also represent the medium run implication of infrastructure development that might be different in the short-term context. The socio-cultural disruption during and soon after the construction might be gradually recovered by the social life adaptation over time.

One potential mediator between agricultural infrastructure, inequality, and social capital might be farming productivity. The high infrastructure exposure is likely to boost the farming activity and productivity that enhances the welfare of the agricultural household. This condition might reduce the income gap between the deprived group (mainly from the agricultural household) and the rich group (relatively from non-agricultural households). Besides that, the collective movement during the farming period might induce positive externalities in forming social cohesion. The increased tourism and amenity from the water reservoir might also stimulate a stronger social interaction, especially for the local people.

The mediation analysis in Appendix 3 shows that the effect of agricultural infrastructure is dominantly through farming productivity by approximately 140%. Interestingly, the direct impact shows a positive sign indicating the potential negative externalities if there is no farming impact of infrastructure. This result indirectly provides another vital insight into the infrastructure effectiveness, namely utilization. Beyond the issue of public goods provision, the government should also ensure whether the infrastructure is optimally utilized or not.

In terms of social capital, the decomposed effect of agricultural infrastructure is varied (see Appendix 4). The direct effect is positive in all social capital types, but the indirect effect shows a different pattern. The impact of farming productivity on SOCA Type I is trivial and negative, but positive for SOCA Type II and III. During the farming period, the agricultural community might concentrate more on farming than other activities (such as gotong royong in public goods provision). Meanwhile, the farming productivity positively corresponds to SOCA Type II and III due to the positive side impact of collective action and repeated interaction during the harvest time. This condition might drive mutual help, trust, and networking.

The mediation effect also signifies that the farming productivity is not the full mediator for agricultural infrastructure and social capital nexus. The share of mediation path is 45% and 73% for SOCA Type II and III, respectively. This result delineates that there are other potential mediators, such as the tourism or amenity aspect. These variables might matter to be considered in future studies.

Overall, the results suggest that the agricultural infrastructure exposure in Indonesia does not drive the negative impact on equality and social capital. These findings might imply that the aggregate and mid-term benefit of infrastructure is greater than its unintended impact, as found in the prior literature. This study also elaborates the complementarity of infrastructure (water reservoir-irrigation) as a variable measurement. Hence, the results also represent the complementarity effect of infrastructure that might be important to be considered during infrastructure plan dan development.

Moreover, this finding also complement the literature by evaluating the unintended consequences of infrastructure in the context of aggregate and mid-term impact, while the prior literatur focus on spatial heterogeneity impact between areas surrounding the infrastructure (e.g. upstream and downstream) such as in Duflo & Pande (2007) and Aribowo & Yudhistira (2021). The previous studies found that the unintended consequences of infrastructure such as rising inequality occured between the upstream and downstream area, but in the aggregate and mid-term context, the infrastructure exposure still promote the beneficial impact for inequality and social capital.

This study is undoubtedly limited. Firstly, some confounders remain excluded in the models, such as rainfall intensity, district leader capacity, and public governance. Secondly, the river exposure as an instrument might be imperfect due to the monotonicity issue. Thirdly, the infrastructure proxy might not be precise because it does not represent the actual measurement, such as area or length. Future work probably needs to concern these issues by developing a panel or longitudinal data set, using an exact proxy, or finding more valid instruments, such as river gradient (Duflo & Pande 2007).

CONCLUSION

The infrastructure development aims to improve the economic access of everyone. Sometimes, this goal is partly violated due to poor project governance, such as found by Duflo & Pande (2007), Makmuri (2017), Ward et al. (2020), and Aribowo & Yudhistira (2021) that reveal the uneven welfare distribution and the distraction of some social aspects during and after infrastructure construction. However, the well-design project might be beneficial for socio-economic conditions. This study confirms it by estimating agricultural infrastructure exposure on inequity and social capital under the complementarity feature. The agricultural infrastructure is defined by the complete set of the village's water reservoir and irrigation system.

The estimation result shows that the district with high exposure to agricultural infrastructure negatively associates with inequity and positively corresponds to social capital. The integrated water reservoir and irrigation system might reduce the vulnerability of uneven income distribution in the district. For example, the irrigation system that connects the upstream and downstream areas probably drive water access equity during the farming period. Moreover, the repeated interaction during infrastructure utilization is also likely to bolster the social capital. It means that the infrastructure potentially connects the people. By mechanism, the effect of agricultural infrastructure on inequality and social capital is more likely to be mediated by farming productivity.

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APPENDIX

Appendix 1. Regression Result of Agricultural Infrastructure Exposure and Inequality

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS						
	Inequality 2015	Inequality 2016	Inequality 2017	Inequality 2015	Inequality 2016	Inequality 2017
INFRA	-0.000112	0.000011	-0.000004	-0.000292**	-0.000315***	-0.000407***
	(0.000157)	(0.000132)	(0.000132)	(0.000141)	(0.000120)	(0.000140)
IN09				0.485055***	0.287387***	0.324440***
				(0.054045)	(0.054299)	(0.056597)
Observation	510	511	511	465	466	466
R-square	0.000605	0.000008	0.000001	0.510645	0.473431	0.491446
Dummy Province	NO	NO	NO	YES	YES	YES
Outcome Mean	0.351588	0.339423	0.336427	0.353022	0.341034	0.338236
Panel B: Instrumental Variable						
	(1)	(2)	(3)	(4)	(5)	(6)
	Inequality 2015	Inequality 2016	Inequality 2017	Inequality 2015	Inequality 2016	Inequality 2017
INFRA	-0.000890**	-0.001046***	-0.000815**	-0.001451***	-0.001841***	-0.001294***
	(0.000424)	(0.000404)	(0.000381)	(0.000422)	(0.000443)	(0.000403)
IN09				0.413526***	0.201164***	0.274336***
				(0.062246)	(0.066379)	(0.066123)
Observation	510	511	511	465	466	466
R-square	-0.028730	-0.067495	-0.037997	0.455811	0.364018	0.456646
Dummy Province	NO	NO	NO	YES	YES	YES
Outcome Mean	0.351588	0.339423	0.336427	0.353022	0.341034	0.338236
Wald F-Stat	76.353770	75.996234	75.996234	69.069282	69.492933	69.492933

Robust standard errors in parentheses, with ***, **, and * indicate 1, 5, and 10% significance levels, respectively. INFRA represents the agricultural infrastructure exposure. IN09 is the district inequality in 2009. The instrumental variable is river exposure.

Appendix 2. Regression Result of Agricultural Infrastructure Exposure and Social Capital

	(1) SOCA Type I	(2) SOCA Type II	(3) SOCA Type III	(4) SOCA Type I	(5) SOCA Type II	(6) SOCA Type III
Panel A: OLS						
INFRA	0.193669***	0.155531***	0.124147***	0.084889**	0.051596*	0.075893*
	(0.039009)	(0.030123)	(0.037993)	(0.040512)	(0.027166)	(0.040041)
SC09				14.032582**	19.964477***	13.591136***
				(5.740559)	(4.000722)	(3.511443)
Observation	511	511	511	466	466	466
R-square	0.025678	0.030432	0.016358	0.360861	0.339735	0.042797
Outcome Mean	80.674847	88.706817	53.739202	80.711242	88.929011	53.802376
Dummy Province	NO	NO	NO	YES	YES	NO
Panel B: Instrumental Variable						
	(1) SOCA Type I	(2) SOCA Type II	(3) SOCA Type III	(4) SOCA Type I	(5) SOCA Type II	(6) SOCA Type III
INFRA	0.190486*	0.219852***	0.237840**	0.176290	0.183525**	0.234872**
	(0.105040)	(0.073088)	(0.103083)	(0.108992)	(0.079405)	(0.112109)
SC09				12.349144**	17.534585***	10.029026**
				(5.645139)	(4.071706)	(4.184100)
Observation	511	511	511	466	466	466
R-square	0.025671	0.025228	0.002639	0.356172	0.320207	0.017481
Outcome Mean	80.674847	88.706817	53.739202	80.711242	88.929011	53.802376
Dummy Province	NO	NO	NO	YES	YES	NO
Wald F-Stat	75.996234	75.996234	75.996234	83.000516	83.000516	71.196275

Robust standard errors in parentheses, with ***, **, and * indicate 1, 5, and 10% significance levels, respectively. Type I is the share of the village with *gotong-royong* in public goods provision habit. SOCA Type I is the share of the village with *gotong-royong* in helping community member habit. SOCA Type III shows the share of the individual with the high social capital index at the province level.

Appendix 3. Mediation Analysis on Agricultural Infrastructure and Inequality

	(1) Inequality 2015	(2) Inequality 2016	(3) Inequality 2017
total effect	-0.000890**	-0.001046***	-0.000815**
	(0.000424)	(0.000404)	(0.000381)
direct effect	0.000377	0.000500*	0.000339*
	(0.000296)	(0.000255)	(0.000205)
indirect effect	-0.001267*	-0.001545**	-0.001153**
	(0.000736)	(0.000690)	(0.000585)
Observation	510.000000	511.000000	511.000000
F-Stat (Infra on River)	76.353770	75.996233	75.996233
F-Stat (Farm on River | Infra)	20.763303	32.013661	32.818926
Mediation effect/Total effect (%)	142.381784	147.794805	141.580431

Robust standard errors in parentheses, with ***, **, and * indicate 1, 5, and 10% significance levels, respectively. The total effect is the total of direct and indirect effect of agricultural infrastructure exposure on inequality. The indirect effect is the agricultural infrastructure exposure through farming productivity.

Appendix 4. Mediation Analysis on Agricultural Infrastructure and Social Capital

	(1) SOCA Type I	(2) SOCA Type II	(3) SOCA Type III
total effect	0.190486*	0.219852***	0.237840**
	(0.105040)	(0.073088)	(0.103083)
direct effect	0.195383***	0.120885***	0.062905
	(0.057799)	(0.039390)	(0.053437)
indirect effect	-0.004897	0.098967	0.174935
	(0.141095)	(0.092756)	(0.134517)
Observation	511.000000	511.000000	511.000000
F-Stat (Infra on River)	75.996233	75.996233	75.996233
F-Stat (Farm on River | Infra)	27.298351	27.298351	27.298351
Mediation effect/Total effect (%)	-2.570982	45.015213	73.551351

Robust standard errors in parentheses, with ***, **, and * indicate 1, 5, and 10% significance levels, respectively. The total effect is the total of the direct and indirect effect of agricultural infrastructure exposure on inequality. The indirect effect is the agricultural infrastructure exposure through farming productivity. SOCA Type I is the share of the village with gotong-royong in public goods provision habit. SOCA Type I is the share of the village with gotong-royong in helping community member habit. SOCA Type III shows the share of the individual with the high social capital index at the province level.