JICA Research Institute

JICA-RI Working Paper

Impact Assessment of Infrastructure Projects on Poverty Reduction

The Role of Infrastructure in Mitigating Poverty Dynamics: The Case of an Irrigation Project in Sri Lanka

Yasuyuki Sawada, Masahiro Shoji, Shinya Sugawara, and Naoko Shinkai

No. 4 (Revised)

June 2013

JICA Research Institute

JICA Research Institute
10-5 Ichigaya Honmura-cho
Shinjuku-ku
Tokyo 162-8433, JAPAN
TEL: +81-3-3269-3374
FAX: +81-3-3269-2054

The Role of Infrastructure in Mitigating Poverty Dynamics:

The Case of an Irrigation Project in Sri Lanka

Yasuyuki Sawada[*], Masahiro Shoji[†], Shinya Sugawara[‡], and Naoko Shinkai[§]

Abstract

While it is known that access to physical infrastructure enhances household welfare, there are very few micro-econometric studies that analyze its role in mitigating chronic and transient poverty. This paper aims to bridge this gap in the existing literature by evaluating the impact of a large-scale irrigation infrastructure project implemented in Sri Lanka. It identifies the treatment effect of irrigation access by exploiting a natural experimental situation where the government used lotteries to randomly distribute irrigated plots. We extend the seasonal consumption smoothing model of Paxson (1993) by introducing endogenous credit constraints. By using unique household level monthly panel data over a period of two years, it is shown that the average income increases, and the probability of binding credit constraint declines with irrigation accessibility through which transient poverty is mitigated. These empirical results suggest that irrigation infrastructure has a positive impact on reducing both chronic and transient poverty directly and indirectly by improving income and relaxing credit constraints. The structural estimation results support the validity of our theoretical framework.

Keywords: poverty reduction, role of infrastructure, monthly panel data

[*] Corresponding author, Visiting Fellow, JICA Research Institute and Faculty of Economics, University of Tokyo, Tokyo, Japan (sawada@e.u-tokyo.ac.jp)

[†] Department of Economics, Seijo University, Tokyo, Japan

[‡] Faculty of Economics, University of Tokyo, Tokyo, Japan

[§] Graduate School of International Development, Nagoya University, Nagoya, Japan

This paper forms part of a research project titled “Impact Assessment of Infrastructure Projects on Poverty Reduction” conducted by the former Japan Bank for International Cooperation (JBIC) Institute which was integrated into the Japan International Cooperation Agency (JICA) Research Institute. We would like to thank Masahito Aoki, and Taro Katsurai for their collaboration in the project design, survey implementation, and data processing. We also acknowledge the efforts of field survey supervisors Intizar Hussain, Fuard Marikar, and Sunil Thrikawala, and we thank the enumerators of the International Water Management Institute (IWMI). We acknowledge the helpful comments and suggestions from Ousmane Badiane, Marcel Fafchamps, Yujiro Hayami, Hidehiko Ichimura, Masahiro Kawai, Carol A. Litwin, Megumi Muto, Takashi Kurosaki, Keijiro Otsuka, Ryuhei Wakasugi, and the participants of a wide range of seminars and conferences, including the Annual Bank Conference on Development Economics (ABCDE) Tokyo, the FASID Hakone Conference, Asian Development Bank Institute (ADBI) Conference on Infrastructure and Poverty, the Global Development Network Rio de Janeiro Conference, and the Japanese Economic Association. Needless to say, we are responsible for any remaining errors.

1. Introduction

Our aim in this paper is to evaluate the role of irrigation infrastructure in mitigating the negative impact of poverty dynamics using household panel data from Sri Lanka. Such research and analysis is largely missing from the literature, although development economists consider physical infrastructure to be an indispensable precondition of industrialization and economic development (Murphy, Shleifer, and Vishny 1989).[1] Many empirical studies demonstrate that the development of physical infrastructure improves an economy's long-term production and income levels (Canning and Bennathan 2000; Esfahani and Ramirez 2003; Lipton and Ravallion 1995; Jimenez 1995). For instance, Hulten, Bennathan, and Srinivasan (2006) find that in India, from 1972 to 1992, highways and electricity accounted for almost half the growth of the Solow residuals of manufacturing industries. The positive productivity effects of physical infrastructure development can be found even in rural areas and agricultural sectors (Jimenez 1995; Fan and Zhang 2004; Zhang and Fan 2004). From these findings, it is evident that infrastructure is likely to reduce poverty by enhancing growth, because a strong positive correlation between income growth and poverty reduction has repeatedly been found in studies such as Besley and Burgess (2003), Dollar and Kraay (2000), and Ravallion (2001).

In fact, an increasing amount of empirical literature has started to focus on the role of infrastructure in reducing poverty directly. Existing studies include Datt and Ravallion (1998) on state level poverty in India, Van de Walle (1996) on the poverty reduction effect of irrigation infrastructure in Vietnam, Jalan and Ravallion (2003) on water supply systems, and Lokshin and Yemtsov (2004, 2005) on the poverty reduction effect of community level infrastructure improvement projects on water supply systems in Georgia. In addition, Brockerhoff and Derose (1996) and Jalan and Ravallion (2003) investigated the role of water supply and public health

1. Physical infrastructure in general consists of two parts; namely, economic infrastructure such as roads, irrigation, and electricity; and social infrastructure such as water supply, sewer systems, hospitals, and school facilities.

systems; and Jacoby (2000), Gibson and Rozelle (2003), and Jacoby and Minten (2008) investigated the effectiveness of road and transportation infrastructure.

While these micro-econometric studies are insightful in uncovering the role of infrastructure in reducing poverty, two important issues remain unaddressed. The first issue is a proper identification of the causal impact of irrigation infrastructure on poverty reduction (Duflo and Pande 2007). This issue may have remained unaddressed because randomized evaluation, which has been increasing rapidly (Duflo, Glennerster, and Kremer 2008), is difficult to implement in the context of large scale infrastructure development. The second remaining issue is that to the best of our knowledge all the preceding micro studies of the nexus between infrastructure and poverty reduction employ a static concept of poverty even though most recent poverty studies have started focusing on its dynamic and stochastic nature (Dercon, ed. 2005; Fafchamps 2003).[2] It has been established that policy analyses based on static poverty can yield substantial inefficiencies in policy interventions (Jalan and Ravallion 1998).

This paper aims to close these gaps in the literature by evaluating the role of irrigation infrastructure in mitigating the negative impact of poverty dynamics; that is, in reducing chronic and transient poverty by regulating water availability across seasons. The government constructed a large scale irrigation system and allocated plots to farmers in southern Sri Lanka. We use a unique monthly household panel dataset collected in the area through extensive field surveys. The data is based on questionnaires modified by us specifically for this study.

Our study area has two preferable features that enable us to identify the causal impact of infrastructure. First, the government used lotteries to randomly allocate irrigated plots to farmers. Second, the irrigation construction began in the north and gradually extended southward. Therefore, the farmers who received the plot in the north could have access to irrigation at the earlier stage. Furthermore, the construction was not started at all in the southern areas at the time

2. Using district level data from India, Duflo and Pande (2007) find that constructing a dam upstream reduced the adverse effect of variability in rainfall, possibly through improved irrigation accessibility.

of data survey. Thus, households in the south did not have access to irrigation for an exogenous reason. These distinctions allow us to test the conditional independency of irrigation treatment.

With regard to the methodological framework, we extend the model of the life-cycle permanent income hypothesis for a seasonal expenditure decision, similar to Paxson (1993), by including the differences in irrigation accessibility and endogenous credit constraints. Then, we evaluate the impact of irrigation infrastructure in reducing poverty dynamics. We also perform statistical testing for conditional independency of irrigation accessibility on household expenditures, which suggests randomized irrigation placement. In addition, we conduct a wide variety of robustness tests, such as relaxing the assumptions of econometric models and addressing the possibility of nonrandom irrigation allocation.

The rest of the paper is organized as follows: in Section 2, we describe our data collection procedure in the field and the basic descriptive and poverty statistics data employed in this paper. Section 3 explains our theoretical framework, and in Section 4, we present the regression strategy and results. Section 5 concludes the paper.

2. Study site

Natural experiment

For the sample of our evaluation study, we selected the Walawe Left Bank (hereafter, WLB) irrigation system in the underdeveloped area of southern Sri Lanka (Mahaweli Authority of Sri Lanka 2002). The WLB Irrigation Upgrading and Extension Project for this system was initiated in 1997 with the help of concessional loans from the Japan Bank for International Cooperation (JBIC), formerly the Overseas Economic Cooperation Fund (OECF).[3] The type of farming in the study area varies, ranging from irrigated to rainfed and *chena* (slash and burn) cultivation, and the project area exhibits considerable variability in cropping patterns. The main crops grown

3. JBIC, formerly OECF, provided a total of ¥2.57 billion (approximately US$ 25 million) for five years starting from 1997. This covered about 85% of the total irrigation development cost in this region. The government of Sri Lanka provided ¥0.45 billion (US$ 4.4 million).

include paddy, sugarcane, banana, and other upland crops. This situation is suitable for evaluating the role of infrastructure in reducing poverty.

Figure 1 depicts the study site which consists of four strata: Sevanagala, Kiriibbanwewa, Sooriyawewa, and Extension Area. The irrigation construction was implemented in the north first and then gradually extended to the south. When the survey data was collected, these areas were divided into three regions depending on the irrigation accessibility. The first region is Sevanagala where both irrigated and rainfed plots are included. In the second region of Sooriyawewa and Kiriibbanwewa, the construction or irrigation was completed and all households had access to irrigation. Finally, in the third region in the south known as Extension Area, the construction was not yet started at the time of survey. Therefore, farmers in this region had no access to irrigation for an exogenous reason.

Intriguingly, the government used lotteries in each stratum to distribute land randomly for some one third of the farmers. Based on the lottery results and without regard to their own wishes, these households were allotted plots for certain crops (Aoyagi et al. 2010). Therefore, the households who obtained plots in the north in the strata were able to have access to irrigation at an earlier stage. This establishes a natural experimental situation of exogenously given irrigation placements even in Sevanagala, where there were both irrigated and unirrigated plots available for farmers. This situation helps us identify the causal impact of irrigation construction.

Data survey

Approximately 75,000 people reside in the WLB, including government allottees, encroachers, and nonfarm households, i.e., landless people. In order to select representative sample households, we adopted a multistage stratified random sampling strategy using a complete list of all the households, which is summarized in Table 1. The actual samples consist of 712 households, including 548 farm and 164 nonfarm households. The *Yala* (dry) season begins in

February and ends in September and the *Maha* (rainy) season begins in October and extends up to January in the WLB area. Therefore, household surveys were conducted five times in 2001 and 2002 to capture the seasonal effects. The first, second, and third surveys took place in June, August, and October 2001, respectively. The first was conducted specifically to obtain monthly data for the previous *Maha* season while the second and third were designed to gather data for the *Yala* season. The fourth and fifth surveys were conducted in June and October 2002, respectively, to capture information on the 2002 *Maha* and *Yala* seasons.

Descriptive statistics

Figure 2 depicts the dynamics of food and nonfood monthly consumption relative to the irrigation accessibility.[4] The "unirrigated" category includes farmers with rainfed plots or plots with primitive water control such as traditional tanks and reservoirs. Firstly, it is evident that households in unirrigated areas have systematically lower consumption throughout the year than those in the irrigated areas. The incidence of chronic poverty may be more serious in the unirrigated areas than in the irrigated areas.[5] Secondly, while the consumption levels vary depending on the accessibility of irrigation infrastructure, the pattern of monthly fluctuations appears to be similar across areas; consumption levels are stable from October through February, increasing in April immediately after the *Maha* harvesting, decreasing during May and June, and increasing slightly in September after the *Yala* harvesting.

A similar pattern is found in Figure 3 illustrating the pattern of monthly income fluctuations. It shows a marked increase in income in April and September, following the

4. Nonfood consumption broadly defined includes nondurable expenditures comprising such items as medical care and education. We employ the age-sex weights used by Townsend (1994) in the context of Southern India.
5. We also calculate the head count ratio by using the poverty line of $2.00 per day, converted by the PPP. The overall incidence of poverty is approximately 12%. The highest head count ratio is observed in Extension Area with 14% and the lowest poverty rate is found in Kiriibbanwewa with 8%. These figures indicate that accessibility to irrigation infrastructure is systematically related to the incidence of poverty.

harvests.[6] Our data include information on monthly income only for the latter twelve months, i.e., from October 2001 to September 2002, while on monthly consumption we have information for twenty-four months, from October 2000 to September 2002. For the purposes of our econometric analysis, we use the data pertaining to the congruent twelve months. While these figures are insightful, further careful investigation is, however, necessary to identify a causal effect of this infrastructure on chronic and transient poverty.

In Table 2 we provide decomposition results of an expenditure-based poverty index using the framework of Ravallion (1988) and Kurosaki (2006). We can define aggregate measures of total poverty, P, chronic poverty, P^C, and transient poverty, P^T, for a population of N households: $P \equiv (1/N)\sum_N E[1 - (E_i/z)]^{\alpha}$, $P^C \equiv (1/N)\sum_N [1 - E(E_i/z)]^{\alpha}$ and $P^T \equiv (1/N)\sum_N \{E[1 - (E_i/z)]^{\alpha} - [1 - E(E_i/z)]^{\alpha}\}$ where E_i is the consumption level of individual i and z is a poverty line. We use total expenditure data for the consumption level, E_i, and calculate the expected values by computing sample averages for the twelve months October 2001-September 2002. We utilize the poverty gap measure by setting that α=2. The poverty line is set at 1.25 US dollars based on the World Bank's purchasing power parity adjusted by the local consumer price index (Chen and Ravallion 2008). The table shows that households without irrigation are more likely to suffer from both transient and chronic poverty than households with irrigation. Also, the impact of irrigation infrastructure on reducing chronic poverty may be more significant than its impact on transient poverty.

An important characteristic to understand the poverty dynamics is the irrigation impact on access to credit; yet regular household surveys do not include credit information that directly enables an identification of the prevailing credit conditions (Scott 2000). To deal with this issue, we carefully designed a special credit module in our questionnaire to directly identify credit-constrained households. In particular, we asked two related questions. First, we queried

6. The income data is calculated by aggregating income from the sale of crops, the imputed value of self-production, income from noncrop agriculture such as livestock, and wages from agricultural and nonagricultural sources.

the amount of credit a household obtained in a particular period; then, among those who had not obtained credit, we asked the reasons for not having borrowed. Households responding that they did not need to borrow are labeled noncredit constrained, while households listing such reasons as fear of default or impossibility of borrowing are identified as credit constrained. Of the households that had borrowed, those able to borrow as much as they wanted are considered unconstrained while the others are considered constrained.

Table 3 summarizes the other household characteristics used in the study relative to access to irrigation infrastructure and the credit market.[7]

3. Modeling the role of infrastructure in poverty reduction dynamics

We aim in this section to formalize the channels through which irrigation reduces poverty. Accessibility to irrigation has a potential impact on consumption mainly by changing income dynamics and access to credit. To incorporate these features, we extend Paxson's (1993) seasonal consumption model by introducing endogenous credit constraints. Each household determines seasonal consumption by maximizing its lifetime utility subject to its intertemporal budget constraints. Here we assume tentatively that all of the households have perfect credit market accessibility. A household has a time-separable constant relative risk aversion (CRRA) utility function, $U(C_{st}) = \alpha_s(C_{st})^{1-a}(1-a)^{-1}$, of the household consumption, C_{st}, in season s in year t. For purposes of exposition, we exclude the year subscript in the following presentation. α_s represents a taste parameter, and a is the coefficient of relative risk aversion. The household's decision problem is to choose C_{st} that maximizes the discounted lifetime utility with a seasonal discount factor, β, subject to an intertemporal budget constraint with seasonal income, Y_{st}; household assets at the beginning of the period, W; and an exogenous seasonal interest rate, $r \equiv$

7. JBIC and IWMI (2002) summarize the basic household characteristics in the area.

R–1. Assuming no consumption tilting, i.e., $\beta R = 1$, we have the following optimal expenditure for season s:

(1) $$E_s{}^* = \omega_s R\Pi,$$

where $E_s{}^* = P_s C_s$ with P_j representing the price of consumption in season s; ω and Π are utility weights assigned to consumption in season s and total household assets, respectively; i.e., they correspond to the sum of human and initial physical assets. Note that Equation (1) is an extended version of the life-cycle permanent income hypothesis. The utility weight involves the taste parameter in the utility function and the relative consumption prices in the two periods. Defining Y as the sum of expenditures in different periods, we have $Y = R\Pi$ because $\sum_s \omega_s = 1$. Note that Y measures the total annual income, inclusive of net annual interest earnings for the year.

Thus far we have assumed perfect credit market accessibility. In order to introduce the possibility of binding credit constraints captured by income volatility, we follow Flavin (1981) and Paxson (1993) and assume that the expenditure at s is a weighted average of the optimal expenditure at s and income in that season:

(2) $$E_s = (1-\pi)E_s{}^* + \pi Y_s$$

where π represents the degree of credit constraint. If $\pi = 0$, then the credit constraint is not binding, and if $\pi = 1$, it is perfectly binding. Recalling that $Y = R\Pi$, Equation (2) can be rewritten as $E_s = Y[\omega_s(1-\pi) + \pi A_s]$, where $A_s \equiv Y_s/Y$; i.e., the fraction of annual income earned in season s. By log-linearizing this equation, we obtain the structural form of the seasonal expenditure model:

(3) $$\ln E_s = \ln Y + \omega_s(1-\pi) + \pi A_s - 1$$

Irrigation increases consumption and reduces chronic and transient poverty through multiple paths. Conceptually, we consider four channels for evaluating the role of irrigation infrastructure: first, impact on permanent income, Y; second, demand for credit by changing income fluctuation patterns, A_s; third, supply of credit through changes in creditworthiness; and, finally, other channels such as preferences and time allocation. To quantify the relative importance of the different channels, we consider the following estimation equation:

(4) $$\ln E_s = \gamma^Y \ln Y_s + X_s \gamma^X + \gamma^Z Z_s + \gamma_s^0 + \gamma_k^Z H_k Z_s + u_s$$

where, X_s includes demographics, household head characteristics, geographic characteristics and the unirrigated land holdings such as the rainfed land and land with primitive water controls; Z_s is the size of irrigated land allocated by the government and its coefficient; γ^Z, represents a time-invariant premium of irrigated lands through non-income channels, presumably such as changes in preferences; and, following Paxson (1993), γ_s^0 denotes common month-specific fixed effects, reflecting month-specific preferences and prices. The three terms, $X_s \gamma^X$, $\gamma^Z Z_s$, and γ_s^0, on the right-hand side of Equation (4) correspond to the second term on the right-hand side of Equation (3). The fifth term on the right-hand side of Equation (4), $\gamma_k^Z H_k Z_s$, captures the income fluctuation term in Equation (3), i.e., πA_S, where H_k (k = 1, 2, 3) are the binary variables representing the harvest period of the rainy season (March and April), planting period of the dry season (May and June), and harvest period of the dry season (July to September), respectively. The remaining season (October to February) is the planting period of the rainy season which is used as the reference season. Hence, the coefficients, γ_k^Z, on the interaction term of the binary variables, H_k, and irrigated land size, Z_s, capture the remaining time-dependent impact of irrigation which mainly includes changes in income fluctuation patterns. In other words, as can be seen in the fifth term on the right-hand side of Equation (4), we take the interaction term, $H_k Z_S$, as the instrument for the endogenous variable A_s. Following the theoretical implications, if the credit constraint is not binding, i.e., $\pi = 0$, then the parameters

γ_k^Z should jointly be zero. This is a joint test for credit accessibility and effectiveness of irrigation on increasing income.

Endogenous credit constraints

In the development literature, it is commonly accepted that poor households in developing countries, which typically are comprised of landless farmers, have only limited access to credit. While irrigation accessibility potentially affects the demand for credit by changing income fluctuation patterns, it could also influence on the supply of credit as determined by creditworthiness. This study examines the overall impact of irrigation on the credit constraint.

A conventional empirical approach for incorporating credit constraints into estimation models ignores the endogeneity of the constraints and exogenously splits the sample into those constituents likely to be credit constrained and those not likely to be so (Foster 1995). In contrast, following Jappelli (1990), we introduce an empirical model of endogenous credit constraint. Recall that *E** represents the optimal LC-PIH consumption in the absence of current credit constraints. Then, $E^* = E$ holds if the credit constraint is not binding, while $E^* > E$ holds if the credit constraint is binding. A discrete model of credit constraint is obtained as follows:

$$cc_s = 1[X_s\beta_1 + Z_s\beta_2 + S_s\beta_3 + \varepsilon_s > 0] \tag{5}$$

where $1[\cdot]$ denotes an indicator function for a discrete variable of credit constraint, *cc*; *S* includes binary variables to represent unanticipated water shortages in the rainy and dry seasons; and ε denotes an error term that captures unobserved elements and a measurement error.

Conditional independency of the irrigation treatment

Note that Equation (4) can be viewed as a linear program evaluation equation (Lee 2005). The parameters, γ_k^Z, capture the extra amount of expenditure that farmers can achieve with irrigation access; these are expenditures that are enabled by the irrigation infrastructure, or simply by the season-specific treatment effect of irrigation infrastructure. However, an endogeneity issue remains to be addressed. The correlation between consumption and unobserved determinants of irrigation accessibility has the potential to generate the omitted variable bias in the estimated coefficients.

In order to avoid the bias, the estimation specification has to satisfy the conditional independency between the irrigation accessibility and the household expenditure, given the other control variables. The conditional independency implies that, if the irrigated households had not had access to irrigation, the consumption level of such hypothetical households would have been comparable with that of actually unirrigated farmers, conditional on observed household characteristics. It is, however, known to be difficult to test this condition directly, because normally we cannot observe the counterfactual outcomes.

Alternatively, we employ an indirect testing procedure which was originally proposed by Heckman, Ichimura and Todd (1997) and recently formulated by Imbens and Wooldridge (2009, 46-50). A key requirement for this approach is existence of households which do not have irrigation accessibility for an exogenous reason. If such households exist, then we can utilize the testable implication that the consumption level should not significantly differ between those without irrigation exogenously and those without irrigation endogenously.[8]

As described in Section 2, the irrigation construction was not started in Extension Area at the time of data survey. We exploit the observations in this area as the unirrigated farmers for the exogenous reason. On the other hand, Sevanagala includes both unirrigated and irrigated farmers. The irrigation accessibility in the area might or might not have been determined exogenously, despite the fact that the government used lotteries to allocate the irrigated plots to them.

We compare the consumption of unirrigated households in Sevanagala and Extension Area, given the other observed household characteristics equal in the next section, and find supporting results. The use of such a geographically separated area is also encouraged by Imbens

8. Note, however, that this is not a direct test for the conditional independence. See Imbens and Wooldridge (2009) for the details.

and Wooldridge (2009, 47). Furthermore, the next section also attempts to address the potential endogeneity without the conditional independency by using the fixed effect models.

4. Regression analysis

Our main econometric analysis is comprised of the following five models: first, we estimate the impact on the permanent income; second, we conduct reduced form estimation for the seasonal expenditure based on Equation (4); third, to test the validity of our model framework, we estimate the structural model of Equation (3); fourth, we also test the conditional independency; and finally, we conduct a wide range of tests for robustness.

Estimation result 1: Permanent income

While irrigation accessibility affects consumption through multiple paths, one of the most important channels is likely to be an increase in annual income overall; not only will irrigation allow farmers to grow more valuable crops in the dry season, but it may also allow more intensive cultivation in the rainy season. Therefore, we regress the permanent income, which is approximated by the average household income per adult equivalent scale over twelve months, on a set of household human and physical asset variables.

Table 4 reports the estimation results. Irrigated land size has positive and statistically significant coefficients on permanent income. For farmers with average sized irrigated plots (0.5 acre per adult equivalent scale), addition of one acre plots increases the permanent income by approximately 21.1%. Human and physical asset variables, such as the age of the head of household, number of adult male members, and ownership of sewing machines and tractors are also positively related to the level of permanent income. The negative coefficients of females and children are presumably caused by the use of an adult equivalent scale.

Estimation result 2: Reduced form estimation

We attempt to estimate Equation (4) by addressing two endogeneity problems: first, we mitigate the endogeneity of the permanent income variable using the instrumental variable method. After careful investigation of sixteen types of agricultural assets and eighteen types of nonagricultural assets, we decide to employ the holding of sewing machines and small tractors as our instruments.[9] As shown below, these instruments satisfy the condition in the over-identification tests.

Secondly, in order to cope with the sample selection bias arising from endogenous credit constraints, we combine the dummy endogenous variable specification for credit constraint in Equation (5) with the seasonal expenditure model in Equation (4). Accordingly, we have the following econometric models of expenditure with and without endogenous credit constraints in which sample selection correction terms are included under joint normality of the error terms (Lee 1978; Amemiya 1985):

(6)
$$\begin{aligned}\ln E_s = &\gamma^{Y,C} \ln Y_s + X_s\gamma^{X,C} + \gamma^{Z,C} Z_s + \gamma_s^{0,C} + \gamma_k^{Z,C} H_k Z_s \\ &+ \gamma^C \frac{\varphi(X_s\beta_1 + Z_s\beta_2 + S_s\beta_3)}{\Phi(X_s\beta_1 + Z_s\beta_2 + S_s\beta_3)} + u_s^C \qquad \text{if } cc_s = 1\end{aligned}$$

(7)
$$\begin{aligned}\ln E_s = &\gamma^{Y,N} \ln Y_s + X_s\gamma^{X,N} + \gamma^{Z,N} Z_s + \gamma_s^{0,N} + \gamma_k^{Z,N} H_k Z_s \\ &+ \gamma^N \frac{\varphi(X_s\beta_1 + Z_s\beta_2 + S_s\beta_3)}{1 - \Phi(X_s\beta_1 + Z_s\beta_2 + S_s\beta_3)} + u_s^N \qquad \text{if } cc_s = 0\end{aligned}$$

where superscripts *C* and *N* denote the credit constrained and unconstrained groups, and $\varphi(\cdot)$ and $\Phi(\cdot)$ represent the probability density and cumulative density functions of standard normal

9. The criteria for choosing these two variables are high adoption rate and low possibility of violating the exclusion restriction. Compared to other assets such as motorcycles and electric cookers, sewing machines and small tractors are productive assets and are less likely to affect consumption dynamics through channels other than income. Also, the adoption rates of sewing machines and small tractors are 43.4% and 12.8%, respectively, while only 2.0% of households, for instance, own hand threshers.

distribution. In Equations (6) and (7), the time-dependent irrigation sensitivity parameters, $\gamma_s^{Z,C}$ and $\gamma_s^{Z,N}$ capture the impact of irrigation on expenditure through changing the patterns of income fluctuations. The time-invariant irrigation sensitivity parameters, $\gamma^{Z,C}$ and $\gamma^{Z,N}$ capture the impact through non-income channels presumably including the preference and access to markets.

According to the estimation results of the credit constraint equation reported in Table 5, the coefficients of irrigated land variables are jointly significant; for farmers holding 0.5 acre of irrigated land, an increase in the land holding decreases the probability of binding credit constraints by 1.8%. This result presumably reflects two channels. First, loan provisions are positively affected by access to irrigation facilities through enhanced solvency. Second, the irrigation accessibility might reduce the demand for credit by increasing farmers' asset holdings.

After controlling for the endogenous permanent income and credit constraints, the first and second columns in Table 6 report the reduced form estimation result for the household expenditure model. While the season-specific effects of irrigated land size through income on expenditure, $\gamma_s^{Z,C}$ and $\gamma_s^{Z,N}$, are not always significant, the joint *F* test for these effects shows that irrigation has an overall significant effect on household expenditure for the constrained group. By contrast, for the unconstrained group, the overall season-specific irrigation effects are not different from zero. These results are consistent with the theoretical implications of the intertemporal model of expenditure with and without binding credit constraints. Intriguingly, the time-invariant irrigation effects are positive and statistically significant only for the constrained group, i.e. $\gamma^{Z,C} > 0$, suggesting that irrigation accessibility could reduce poverty via paths other than improvement in income and credit accessibility.

Estimation result 3: Structural estimation

The reduced form model results cannot directly quantify the degree of credit constraint. Hence, we investigate the seasonal effect by estimating the structural model of Equation (3) with the endogenous credit constraint of Equation (5). By including the sample selection correction terms under joint normality of error terms, the estimation versions of Equations (3) and (5) become:

$$\ln E_s = \delta^{Y,C} \ln Y + X_S \delta^{X,C} + \delta^{Z,C} Z_S + \delta_s^{0,C} + \pi^C A_s + \delta^C \frac{\varphi(X_s\beta_1 + Z_s\beta_2 + S_s\beta_3)}{\Phi(X_s\beta_1 + Z_s\beta_2 + S_s\beta_3)} + v_s^C \quad \text{if } cc_j = 1 \tag{8}$$

$$\ln E_s = \delta^{Y,N} \ln Y + X_S \delta^{X,N} + \delta^{Z,N} Z_S + \delta_s^{0,N} + \pi^N A_s + \delta^N \frac{\varphi(X_s\beta_1 + Z_s\beta_2 + S_s\beta_3)}{1-\Phi(X_s\beta_1 + Z_s\beta_2 + S_s\beta_3)} + v_s^N \quad \text{if } cc_j = 0 \tag{9}$$

where δs are captured by monthly dummy variables. The income share variable, As, is treated as an endogenous variable which is instrumented by the interaction variable of season dummies and irrigated land size HkZS, as well as productive asset variables as before. The tests on the theoretical hypotheses 0 <πC <1 and πN = 0 will provide further direct evidence of the extent to which consumption is smoothed out against income fluctuation.

The third and fourth columns in Table 6 report the estimation results of the structural model. For consumption of the credit constrained groups, the coefficients of monthly income fluctuation π^C are positive and significant. Further, their 95% confidence intervals are [0.055, 0.224] and located within the range of [0,1]. On the other hand, the monthly income coefficient for the unconstrained households, π^N, is not statistically different from zero. Consumption by the constrained group tracks the fluctuated income path, suggesting that people under credit constraint cope with negative economic shocks by reducing consumption. By contrast, the unconstrained group is able to smooth over their consumption paths during income fluctuation. The results summarized here provide supportive evidence for our theoretical framework.

Estimation result 4: Test for conditional independency of irrigation placement

We use Equations (8) and (9) to further discuss the conditional independency. Specifically, we estimate the structural estimation model of (8) and (9) with the explanatory variables used in the previous estimations as well as the binary variable which takes unity for the samples of

Extension Area, and zero otherwise. Given that this test employs only the subsample of unirrigated farmers, the variables of irrigated plots are dropped. The testable implication in this specification is that if the estimation in the reduced form and structural form models satisfy the conditional independency, given the set of explanatory variables, the coefficient of the region dummy variable should be statistically insignificant.

The point estimates of the region dummy in the credit constrained and unconstrained subgroups are -0.178 and -0.02, respectively. The corresponding standard errors are 2.803 and 0.102, respectively. The region dummy variables are statistically insignificant at the 0.1 significance level in both equations. The result supports conditional independency.

Estimation result 5: Robustness tests

Here we perform three robustness tests on our results: relaxing the normality assumption of error terms, the inclusion of household fixed effects, and the estimation using the propensity score matching model. We only summarize the results here and more details are available upon request.

For the first robustness test, we relax the normality assumption by adopting the approach proposed by Lee (1982) and Newey, Powell, and Walker (1990). Thus far, the seasonal expenditure model with the endogenous credit constraint has been estimated under the assumption that the error terms in the reduced and structural form models follow trivariate joint normal distribution. However, if this assumption does not hold, it is likely that the second step estimators are seriously biased. The qualitative results are comparable under the relaxed assumption.

For the second robustness test, we incorporate unobserved heterogeneity by controlling for the household fixed effects. We reserve the endogeneity issue of the credit constraint and simply estimate the reduced form model of Equations (6) and (7) with the household fixed effects. The estimation results are the same qualitatively as without household fixed effects.

Finally, we relax the linearity assumption of the conditional expectation function by adopting the propensity score matching model. This is important particularly when the outcome variables are censored or binary variables (Wooldridge 2002). We estimate the treatment effects of irrigation separately for five periods – yearly average effect (full sample estimation), during the harvest season, the planting season, the rainy season, and the dry season – using three matching methods to construct the matched group: radius matching, kernel matching and the 1st nearest neighbor matching. Again, we find significant causal impact of irrigation infrastructure on the consumption, income, and the probability of binding credit constraints.

To check the validity of the conditional independence assumption of matching estimation, we employ the Mentel and Haenszel test proposed by Rosenbaum (2002) for the conditional independency of the irrigation placement. The null hypothesis for the test is that the treatment effect is zero, given a hidden bias caused by an unobserved variable which affects the irrigation placement. The amount of the hidden bias is specified as Γ, for which $\Gamma=k$ means the odd ratio of receiving the treatment can be k times larger in the worst case than that without the bias. The rejection of the null hypothesis with a large value of $\Gamma=k$ suggests the robustness of the existence of the treatment effect, even under unobserved elements. We apply this test, by following DiPrete and Gangl (2004), for the results of four specifications showing significant treatment effects in the nearest neighbor matching model: consumption (full sample), income (harvest season), consumption (harvest season), and consumption (planting season). We find supporting evidence of the existence of positive irrigation effects for the first and third specifications, while the other two show the potential for hidden bias causing the overestimation of the treatment effects.[10]

10. The Appendix tables for these robustness tests are available upon request from the corresponding author. The maximum values of Γ for which the test is not rejected at significance level 0.01 are 1.5 for the consumption for the whole periods, 2.2 for the consumption during the harvesting season, 1.10 for the consumption during the planting season and 1.15 for the income during the harvesting season. As mentioned in Aakvik(2001) , Γ=1.5 or more can be interpreted as a strong evidence of an existence of the non-zero treatment effect. On the other hand, as Becker and Caliendo (2007) mentioned, the failure of rejecting the null hypothesis at smaller values of Γ does not always indicate insignificant treatment effects, because this test evaluates the worst case scenario for the effects of unobserved elements.

5. Conclusion

In this paper, we identify a relationship between infrastructure development and poverty reduction with regard to seasonal fluctuations in consumption expenditure. We find that irrigation reduces chronic poverty by enhancing permanent income, and that it also eliminates the negative impact of transient poverty by reducing downside expenditure risk. Our results provide evidence in support of the role of infrastructure in reducing both chronic and transient poverty. Since very few micro-econometric studies have analyzed the role of infrastructure in mitigating chronic and transient poverty, we believe that this paper will close an important gap in the existing literature.

Intriguingly, we find that there is a positive and significant time-invariant irrigation effect on expenditure only for the credit constrained group. This finding suggests that irrigation access can reduce poverty via multiple paths, apart from improvement in credit accessibility. Usually, when irrigation infrastructure is constructed, other types of infrastructure, such as roads and electricity facilities, are developed alongside. The unexplained positive irrigation effects on the credit constrained group may be attributable to this aspect of infrastructure development. Further exploration of these broader external effects of irrigation infrastructure should be pursued in future studies.

References

Aakvik, A. 2001. Bounding a matching estimator: The case of a Norweigian training program. *Oxford Bulletin of Economics and Statistics* 63: 115-43.

Amemiya, T. 1985. *Advanced econometrics*. Harvard University Press.

Aoyagi, K., R. Kasahara, M. Shoji, and Y. Sawada. 2010. Does infrastructure facilitate social capital accumulation? Evidence from natural and field experiments in Sri Lanka. Mimeo. Japan International Cooperation Agency Research Institute.

Becker, S. O., and M. Caliendo. 2007. Sensitivity analysis for average treatment effects. *Stata Journal* 7 (1): 71-83.

Besley, T., and R. Burgess. 2003. Halving global poverty. *Journal of Economic Perspectives* 17 (3): 3-22.

Brockerhoff, M., and L. Derose. 1996. Child survival in East Africa: The impact of preventive health care. *World Development* 24 (12): 1841-57.

Canning, D., and E. Bennathan. 2000. The social rate of return to infrastructure investments. Policy Research Working Paper 2390. DECRG, World Bank.

Chen, S., and M. Ravallion. 2008. The developing world is poorer than we thought, but no less successful in the fight against poverty. World Bank Policy Research Paper 4703.

Datt, G., and M. Ravallion. 1998. Why have some Indian states done better than others at reducing rural poverty? *Economica* 65: 17-38.

Dercon, S., ed. 2005. *Insurance against poverty*. Oxford: Oxford University Press.

DiPrete, T. A., and M. Gangl. 2004. Assessing bias in the estimation of causal effects: Rosenbaum bounds on matching estimators and instrumental variable estimation with imperfect instruments. *Sociological Methodology* 34: 271-310.

Dollar, D., and A. Kraay. 2002. Growth is good for the poor. *Journal of Economic Growth* 7 (3): 195-225.

Duflo, E., R. Glennerster, and M. Kremer. 2008. Randomization in development economics: A toolkit. In *Handbook of development economics* 4, ed.T. Paul Shultz and John Strauss. Oxford: North-Holland/ Elsevier.

Duflo, E., and R. Pande. 2007. Dams. *Quarterly Journal of Economics* 122 (2): 601-46.

Esfahani, H., and M. Ramirez. 2003. Institutions, infrastructure, and economic growth. *Journal of Development Economics* 70 (2): 443-77.

Fafchamps, M. 2003. *Rural poverty, risk, and development*. Edward Elgar Publishing Limited.

Fafchamps, M., and J. Pender. 1997. Precautionary saving, credit constraints, and irreversible investment: Theory and evidence from semiarid India. *Journal of Business and Economic Statistics* 15 (2): 180-94.

Fan, S., and X. Zhang. 2004. Infrastructure and regional economic development in rural China. *China Economic Review* 15 (2): 203-14.

Flavin, M. A. 1981. The adjustment of consumption to changing expectations about future income. *Journal of Political Economy* 89: 974-1009.

Foster, A. D. 1995. Prices, credit constraints, and child growth in rural Bangladesh. *Economic Journal* 105 (430): 551-70.

Gibson, J., and S. Rozelle. 2003. Poverty and access to roads in Papua New Guinea. *Economic Development and Cultural Change* 52 (1): 159-85.

Heckman, J. J., H. Ichimura, and P. E. Todd. 1997. Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *Review of Economic Studies* 64 (4):605-54.
Hulten, C. R., E. Bennathan, and S. Srinivasan. 2006. Infrastructure, externalities, and economic development: A study of the Indian manufacturing industry. *World Bank Economic Review* 20 (2): 291-308.
Imbens, G. W., and J. M. Wooldridge. 2009. Recent developments in the econometrics of program evaluation. *Journal of Economic Literature* 47 (1): 5-86.
Jacoby, H. 2000. Access to markets and the benefits of rural roads. *Economic Journal* 110 (465): 713-37.
Jacoby, H., and B. Minten. 2008. On measuring the benefits of lower transport costs. Policy Research Working Paper 4484. World Bank.
Jalan, J., and M. Ravallion. 1998. Transient poverty in postreform rural China. *Journal of Comparative Economics* 26: 338-57.
———. 2003. Does piped water reduce diarrhea for children in rural India?" *Journal of Econometrics* 112 (1): 153-73.
Jappelli, T. 1990. Who is credit constrained in the US economy?" *Quarterly Journal of Economics* 105 (1): 219-34.
JBIC (Japan Bank for International Cooperation) and IWMI (International Water Management Institute). 2002. Impact assessment of irrigation infrastructure development on poverty alleviation: A case study from Sri Lanka. JBICI Research Paper 19. JBIC.
Jimenez, E. Y. 1995. Human and physical infrastructure. In *Handbook of development economics*, vol. 3B, ed. J. Behrman and T. N. Srinivasan, 2773-843. North-Holland/Elsevier.
Kurosaki, T. 2006. The measurement of transient poverty: Theory and application to Pakistan. *Journal of Economic Inequality* 4: 325–45.
Lee, L.-F. 1978. Unionism and wage rates: A simultaneous equation model with qualitative and limited dependent variables. *International Economic Review* 19: 415-33.
———. 1982. Some approaches to the correction of selectivity bias. *Review of Economic Studies* 49: 355-72.
Lee, M.-J. 2005. *Micro-econometrics for policy, program, and treatment effects*. Cambridge University Press.
Lipton, M., and M. Ravallion. 1995. Poverty and policy. In *Handbook of Development Economics*, vol. 3B, ed. J. Behrman and T. N. Srinivasan, 2551-657. North-Holland/Elsevier.
Lokshin, M., and R. Yemtsov. 2004. Combining longitudinal household and community surveys for evaluation of social transfers: Infrastructure rehabilitation projects in rural Georgia. *Journal of Human Development* 5 (2):265-77.
———. 2005. Has rural infrastructure rehabilitation in Georgia helped the poor? *World Bank Economic Review* 19 (2): 311-33.
Mahaweli Authority of Sri Lanka. 2002. Integrated Development Program Walawe Project. The Democratic Socialist Republic of Sri Lanka Ministry of Irrigation and Water Management.
Murphy, K., A. Shleifer, and R. W. Vishny. 1989. Industrialization and big push. *Journal of Political Economy* 97 (5): 1003-26.

Paxson, C. H. 1993. Consumption and income seasonality in Thailand. *Journal of Political Economy* 191 (1): 39-72.

Ravallion, M. 1988. Expected poverty under risk-induced welfare variability. *Economic Journal* 98: 1171-82.

———. 2001. Growth, inequality, and poverty: Looking beyond averages. *World Development* 29 (11): 1803-15.

Rosenbaum, P. R. 2002. *Observational studies*. 2nd ed. Springer.

Scott, K. 2000. Credit. In *Designing household survey questionnaires for developing countries: Lessons from ten years of LSMS experience, vol. 2*, ed. G. Margaret, and P. Glewwe. World Bank.

Townsend, R. M. 1994. Risk and insurance in village India. *Econometrica* 62: 539-91.

Van de Walle, D. 1996. Infrastructure and poverty in Vietnam. LSMS Working Paper 121. World Bank.

Zhang, X., and S. Fan. 2004. How productive is infrastructure? A new approach and evidence from rural India. *American Journal of Agricultural Economics* 86 (2): 492-501.

Figure 1. Study site

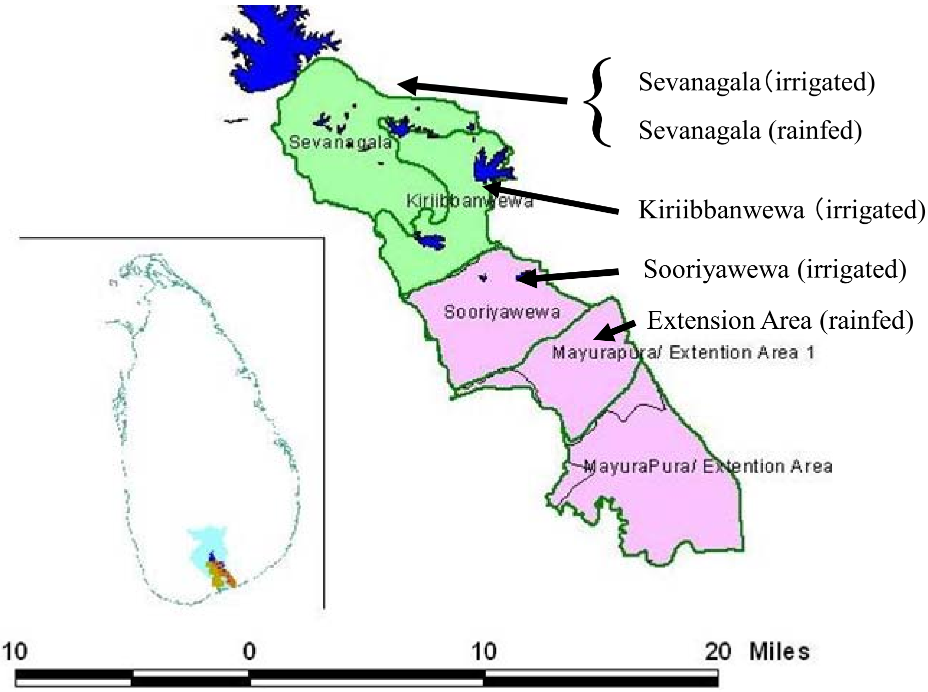

Figure 2. Monthly consumption (per adult male equivalent; in Rs.)

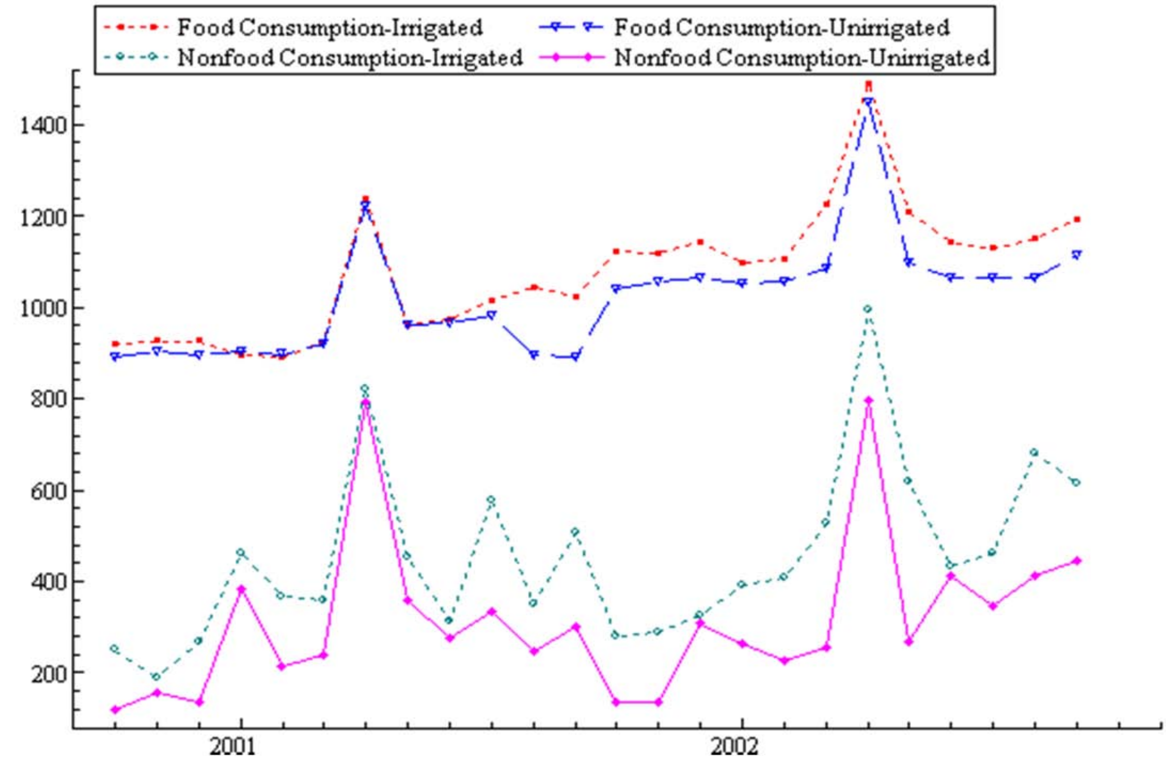

Figure 3. Monthly income (per adult male equivalent; in Rs.)

Table 1. Sample size

	Total households settled in the strata	Farm Households	Nonfarm Households	Total population
(1) Sevanagala	4,420	3,520	900	19,890
(2) Kiriibbanwewa	3,504	2,084	1,420	15,770
(3) Sooriyawewa	6,843	3,983	2,860	30,794
(4) Extension Area	1800	1,800	0	8,100
(5) Total	16,567	11,387	5,180	74,554
(6) Surveyed Households	712	548	164	
(7) = (6) / (5)	4.30%	4.80%	3.20%	

Source: JBIC and IWMI (2002)

Table 2. Poverty decompositions

	Whole Sample	Irrigated	Unirrigated
Total Poverty	0.030	0.028	0.033
Chronic Poverty	0.007	0.006	0.009
Transient Poverty	0.023	0.022	0.024

The decomposition is based on the poverty gap measure. The poverty line is set at 1.25 US dollars.

Table 3. Selected household characteristics by credit and irrigation accessibility

	Credit Constrained				Credit Unconstrained			
	Irrigated		Unirrigated		Irrigated		Unirrigated	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Irrigated land size (Acre) $	0.530	0.355			0.505	0.347		
Land with primitive water control (Acre) $	0.000	0.000	0.201	0.521	0.000	0.000	0.198	0.370
Rainfed land size (Acre) $	0.046	0.146	0.227	0.440	0.055	0.227	0.222	0.492
Log (age of head)	3.949	0.231	3.781	0.265	3.926	0.218	3.793	0.310
1 if female headed	0.123	0.329	0.149	0.357	0.119	0.324	0.104	0.306
Years of schooling	4.812	3.074	6.169	3.180	5.582	3.225	6.340	3.503
Males age 16 or over	1.851	0.957	1.780	1.141	2.116	1.198	1.718	0.997
Females age 16 or over	1.942	1.137	1.817	1.048	1.890	1.017	1.777	1.036
Children age 15 or under	1.261	1.468	1.699	1.397	1.433	1.476	1.412	1.229
Distance to daily market (km)	0.703	0.781	0.462	0.934	0.888	1.359	0.706	1.223
Distance to periodical market (km)	4.082	2.918	4.910	3.386	3.359	2.611	4.812	3.366
1 if paved road around the residence	0.119	0.324	0.335	0.473	0.247	0.431	0.406	0.491
1 if public transport motorized	0.473	0.500	0.654	0.477	0.561	0.496	0.697	0.460
Sewing machine (10^3 Rs) $	0.134	0.193	0.148	0.412	0.130	0.233	0.168	0.391
Tractor (10^6 Rs) $	0.000	0.001	0.000	0.001	0.001	0.016	0.002	0.027
1 if water shortage in planting season	0.020	0.080	0.015	0.074	0.024	0.082	0.016	0.078
1 if water shortage in harvest season	0.031	0.093	0.011	0.068	0.032	0.094	0.013	0.065
Observations	463		355		3745		2522	

$: Per adult equivalent scale. Unirrigated land includes rainfed land and land with primitive water control such as traditional tanks and reservoirs.

Table 4. Permanent income regression

	Coef.	Std. Err.
Irrigated land size	0.136***	0.050
Squared term	0.149***	0.020
Land with primitive water control	0.620***	0.084
Squared term	0.023	0.038
Rainfed land size	0.047	0.048
Squared term	0.030*	0.016
Log (age of head)	-0.526***	0.071
1 if female headed	-0.395	0.441
Years of schooling	-0.092**	0.041
Log (age of head) x female headed	0.151	0.113
Log (age of head) x years of schooling	0.026**	0.011
Males age 16 or over	0.114***	0.009
Females age 16 or over	-0.030***	0.010
Children age 15 or under	-0.145***	0.007
Distance to daily market (km)	-0.053***	0.015
Squared term	0.010***	0.002
Distance to periodical market (km)	-0.054***	0.009
Squared term	0.005***	0.001
1 if paved road around the residence	0.181***	0.024
1 if public transport motorized	-0.008	0.022
Sewing machine	0.170***	0.041
Tractor	0.595*	0.347
Constant	9.247***	0.277
Observations	7064	
R^2	0.190	

Robust standard errors are reported. *** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level.

Table 5. Estimated marginal effects of the credit constraint equation: Probit model

	Marginal effect	Std. Err.
Irrigated land size	-0.034	0.022
Squared term	0.016	0.010
Land with primitive water control	-0.170***	0.034
Squared term	0.104***	0.017
Rainfed land size	0.030	0.023
Squared term	-0.018	0.014
Log (age of head)	-0.047	0.029
1 if female headed	-0.440**	0.211
Years of schooling	-0.044***	0.016
Log (age of head) x female headed	0.115**	0.053
Log (age of head) x years of schooling	0.011**	0.004
Males age 16 or over	-0.010**	0.004
Females age 16 or over	0.008**	0.004
Children age 15 or under	0.002	0.003
Distance to daily market (km)	-0.022***	0.008
Squared term	0.0004	0.0012
Distance to periodical market (km)	0.010***	0.004
Squared term	-0.0005	0.0003
1 if paved road around the residence	-0.046***	0.010
1 if public transport motorized	-0.005	0.008
1 if water shortage in planting season	-0.073	0.049
1 if water shortage in harvest season	-0.025	0.046
Constant	-0.010	0.113
Observations	7064	
Pseudo R^2	0.033	

Standard errors are reported. *** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level. For dummy variables, discrete marginal effects when the variable shifts from zero to one are reported.

Table 6. Estimated results of the reduced and structural form expenditure equation

	Reduced form				Structural form			
	Credit constrained (1)		Unconstrained (2)		Credit constrained (3)		Unconstrained (4)	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Permanent income #	0.528***	0.155	1.026***	0.214	0.675***	0.246	0.930***	0.195
Income ratio #					0.140***	0.043	-0.035	0.061
Irrigated land size	0.942***	0.196	-0.106	0.099	0.267	0.206	-0.037	0.092
Squared term	-0.317***	0.110	-0.041	0.046	-0.102	0.119	-0.024	0.043
Land with primitive water control	0.679	0.515	-0.071	0.281	-1.384**	0.690	0.031	0.253
Squared term	-0.428	0.310	-0.169	0.150	0.591*	0.358	-0.173	0.142
Rainfed land size	-0.084	0.205	-0.104*	0.061	-0.248	0.305	-0.105*	0.058
Squared term	0.076	0.170	-0.004	0.025	0.112	0.237	0.001	0.023
Log (age of head)	-0.166	0.263	0.207	0.142	-0.512	0.323	0.180	0.134
1 if female headed	1.435	2.121	-2.046***	0.736	-2.108	2.500	-1.964***	0.690
Years of schooling	0.082	0.170	0.079	0.071	-0.336*	0.196	0.076	0.068
Log (age of head) x female headed	-0.406	0.543	0.442**	0.189	0.549	0.634	0.425**	0.178
Log (age of head) x years of schooling	-0.015	0.042	-0.020	0.018	0.087*	0.048	-0.019	0.017
Males age 16 or over	-0.013	0.041	-0.180***	0.028	-0.066	0.054	-0.170***	0.027
Females age 16 or over	-0.091***	0.032	-0.010	0.017	-0.085*	0.045	-0.014	0.017
Children age 15 or under	-0.017	0.029	0.065**	0.032	0.005	0.043	0.052*	0.030
Distance to daily market (km)	0.041	0.083	0.073**	0.035	-0.001	0.105	0.070**	0.033
Squared term	-0.001	0.010	-0.012***	0.003	-0.015	0.014	-0.011***	0.003
Distance to periodical market (km)	0.005	0.036	0.036*	0.019	0.109**	0.052	0.029*	0.018
Squared term	-0.0002	0.0024	-0.003**	0.001	-0.006*	0.004	-0.003*	0.001
1 if paved road around the residence	0.021	0.151	-0.140**	0.069	-0.222	0.185	-0.115*	0.063
1 if public transport motorized	-0.030	0.043	0.042	0.026	-0.041	0.056	0.053**	0.025
Seasonal effect of irrigation accessibility								
Harvest in rainy season	-0.095	0.112	0.002	0.091				
Planting in dry season	-0.298	0.189	0.133	0.088				
Harvest in dry season	-0.269	0.165	0.147*	0.077				
Seasonal effect of primitive water control								
Harvest in rainy season	-0.088	0.140	-0.071	0.127				
Planting in dry season	0.600***	0.158	0.106	0.132				
Harvest in dry season	0.642***	0.141	0.062	0.115				
Sample selection correction term	-0.233	0.679	-0.450	0.734	1.106	0.812	-0.346	0.691

Standard errors are in parentheses. *** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level. # denotes endogenous variables.

Table 6 Estimated results of the reduced and structural form expenditure equation (continued)

	Reduced form		Structural form	
	Credit constrained	Unconstrained	Credit constrained	Unconstrained
	(1)	(2)	(3)	(4)
Monthly fixed effects	Yes	Yes	Yes	Yes
F stat. for 1st stage IV (Permanent income)	11.18***	12.70***	4.42***	3.64***
F stat. for 1st stage IV (Income ratio)			4.64***	2.05**
F stat. for no seasonal irrigation or primitive water control effect	32.78***	5.65		
Sargan stat. for over-identification	0.57	0.14	8.67	6.18
Observations	818	6246	818	6246

Standard errors are in parentheses. *** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level. # denotes endogenous variables.

Appendix: Robustness Tests

Nonnormal sample selection

Thus far, the seasonal expenditure model with endogenous credit constraint has been estimated under the assumption that the error terms in the reduced and structural form models follow trivariate joint normal distribution. However, if this assumption does not hold, it is likely that the second step estimators are seriously biased. Hence, we relax the normality assumption by adopting the approach proposed by Lee (1982) and Newey, Powell, and Walker (1990). The structural form estimation results under this nonnormality assumption are presented in Table A1. The overall qualitative results are comparable even if we relax the normality assumption.

Nonrandom irrigation placements

As pointed out by Banerjee (2007) and Duflo and Kremer (2003), while randomization has become a *de facto* standard for program evaluation in development economics, there are some types of programs that cannot be evaluated through the methods of randomization. Irrigation infrastructure may be categorized into this type. Our careful examination exploiting the natural experimental situation shows that it satisfies a necessary condition for the conditional independence of irrigation accessibility, but it cannot directly test the sufficient condition of conditional independency. Therefore, we include household fixed effects to mitigate the correlation between unobserved heterogeneity and program placement.

In the fixed effect model, we reserve the endogeneity issues. In estimation for the model with both fixed effect and endogeneity, Kyriazidou (1997) proposes a semi-parametric, two-step estimation approach. In order to eliminate the household specific parameters, Kyriazidou (1997) uses the differenced values of the observed variables for the samples with the same values of the endogenous dummy variable. In our dataset, however, most of the explanatory variables, including the land holdings, have little time variation; thus, it is computationally difficult to adopt the methodology proposed by Kyriazidou (1997). Accordingly, we decide not to control endogeneity for our robustness check. Instead, we simply estimate the reduced form model of Equation (4) by incorporating the household fixed effects. Furthermore, the little variation causes the collinearity and therefore the squared terms of land holding variables are not used in this specification. According to the estimation results reported in Table A2, the results of both credit constrained and unconstrained groups show comparable results with the ones without household fixed effects.

Propensity score matching

The third robustness check uses the propensity score matching method of Rosenbaum and Rubin (1983). While the main text uses the linear regression approaches, the result could be sensitive to the econometric model, particularly when the dependent variables are binary or censored. The use of matching estimation addresses the issue. It estimates the average treatment effect to the treated (*ATT*), defined as $E\left(\ln E_s^1 - \ln E_s^0 \mid Z = 1\right)$, where Z takes the value of unity if a household receives irrigated land of WLB irrigation project, and zero otherwise, and the superscript also indicates the value of Z. In this article, the propensity score of irrigation accessibility as of the beginning of survey is estimated using a logit model. Yet, our data does not include information regarding the pretreatment period such as income and assets prior to irrigation placements. Hence, we use a set of covariates that are considered to be almost time-invariant, such as age, schooling years, and gender of household head, and the number of males and females aged sixteen or over. We do not use the data on land holdings and geographic characteristics because they are determined after the allocation of irrigated plots. The sample households of Extension Area are not used in this model, since they do not have access to the irrigation for the exogenous reason.

Table A3 presents the results of the logit estimation. It indicates that households with more members and/or with older heads are likely to have access to irrigation at the earlier stage.

These findings seem to reject the assumption of exogenous or random placement of irrigation facilities, while our previous estimations control for these variables.

The validity of the estimated propensity score is verified by using the balancing score test of Rosenbaum and Rubin (1983) and Dehejia and Wahba (1999, 2002); conditional on the propensity score, the covariates are independent of accessibility to irrigation. It is shown that the means of covariates are not significantly different between the irrigated and rainfed areas for any bundle of propensity scores, implying the validity of selection on observables assumption. We conduct the matching estimation with using the observations in the common support.

Table A4 presents the estimated *ATT* of access to irrigation. Three matching methods are used to construct the matching group: the radius matching, kernel matching and the 1st nearest neighbor matching. We calculate the *ATT* on the value of monthly income, monthly total consumption, and the indicator value of credit constraint. We estimate the *ATT* for five periods: yearly average effect (full sample estimation), during the harvest season, the plant season, the rainy season and the dry season.

The results presented at the table are consistent with the findings in the main text. The effects of irrigation on consumption are positive and statistically significant for 13 out of 15 specifications, while the impact on monthly income is significant only during the harvest season. The insignificant impact on income during the plant season is presumably because, while the availability of irrigation induces higher yield, it requires more valuable inputs during plant seasons. The irrigation accessibility also mitigates the probability of binding the credit constraint by around 4% during the dry seasons.

To check the robustness of the matching estimation, we also employ a Mentel and Haenszel test proposed by Rosenbaum (2002) for the conditional independency of the irrigation placement. The null hypothesis for the test is that the treatment effect is zero, given a hidden bias caused by unobserved variable which affects the irrigation placement. The amount of the hidden bias is specified as Γ, for which $\Gamma=k$ means the odd ratio of receiving the treatment can be k times larger in the worst case than that without the bias. The rejection of the null hypothesis with large value of Γ suggests the robustness of the existence of the treatment effect, even under unobserved elements.

We apply this test, by following DiPrete and Gangl (2004), for the results of four specifications showing significant treatment effects in the nearest neighbor matching model: consumption (full sample), income (harvest season), consumption (harvest season), and consumption (plant season). Table A5 shows the results. We find supporting evidence of the existence of positive irrigation effects for the first and third specifications, while the other two show the potential for the hidden bias causing the overestimation of the treatment effects. The maximum values of Γ for which the test is not rejected at significant level 0.01 are 1.5 for the consumption for the full sample, 1.15 for the income during the harvesting season, 2.2 for the consumption during the harvesting season, and 1.10 for the consumption during the planting season. As mentioned in Aakvik (2001), Γ=1.5 or more can be interpreted as a strong evidence of an existence of the non-zero treatment effect. Yet, as Becker and Caliendo (2007) mentioned, the failure of rejecting the null hypothesis at smaller values of Γ does not always indicate insignificant treatment effects, because this test evaluates the worst case scenario for the effects of unobserved elements.

Reference

Aakvik, A. 2001. Bounding a matching estimator: The case of a Norweigian training program. *Oxford Bulletin of Economics and Statistics* 63: 115-43.

Banerjee, A. V., ed. 2007. *Making aid work*. MIT Press.

Becker, S. O., and M. Caliendo. 2007. Sensitivity analysis for average treatment effects. *Stata Journal* 7 (1):71-83.

Dehejia, R. H., and S. Wahba. 1999. Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. *Journal of the American Statistical Association* 94 (448): 1053-62.

———. 2002. Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and Statistics* 84 (1): 151-61.

DiPrete, T. A., and M. Gangl. 2004. Assessing bias in the estimation of causal effects: Rosenbaum bounds on matching estimators and instrumenta variable estimation with imperfect instruments. *Sociological Methodology* 34: 271-310.

Duflo, E., and M. Kremer. 2003. Use of randomization in the evaluation of development effectiveness. Paper prepared for the World Bank Operations Evaluations Department (OED) Conference on Evaluation and Development Effectiveness.

Grosh, M., and P. Glewwe, eds. 2000. Designing household survey questionnaires for developing countries: Lessons from ten years of LSMS experience. World Bank.

JBIC (Japan Bank for International Cooperation) and IWMI (International Water Management Institute). 2002. Impact assessment of irrigation infrastructure development on poverty alleviation: A case study from Sri Lanka. JBICI Research Paper 19. JBIC.

Kyriazidou, E. 1997. Estimation of a panel data sample selection model. *Econometrica* 65: 1335-64.

Lee, L-F. 1982. Some approaches to the correction of selectivity bias. *Review of Economic Studies* 49: 355-72.

Newey, W. K., J. L. Powell, and J. R. Walker. 1990. Semiparametric estimation of selection models: Some empirical results. *American Economic Review* 80 (2): 324-28.

Rosenbaum, P. R. 2002. *Observational studies*. 2nd ed. Springer.

Rosenbaum, P. R., and D. B. Rubin. 1983. The central role of the propensity score in observational wtudies for causal effects. *Biometrica* 70: 41-55.

Table A1. Estimation under nonnormality assumption

	Reduced form				Structural form			
	Credit constrained (1)		Unconstrained (2)		Credit constrained (3)		Unconstrained (4)	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std. Err.	Coef.	Std. Err.
Permanent income #	0.547***	0.141	1.011***	0.244	0.483***	0.152	0.942***	0.238
Income ratio #					0.044**	0.022	-0.044	0.053
Irrigated land size	1.029***	0.188	-0.212*	0.117	0.692***	0.163	-0.149	0.117
Squared term	-0.359***	0.098	0.013	0.043	-0.227***	0.087	0.025	0.044
Land with primitive water control	1.009*	0.548	-0.638	0.478	0.791	0.553	-0.519	0.457
Squared term	-0.696**	0.327	0.183	0.220	-0.642**	0.317	0.155	0.212
Rainfed land size	-0.079	0.217	-0.009	0.077	-0.109	0.224	-0.017	0.074
Squared term	0.072	0.194	-0.067	0.044	0.058	0.199	-0.059	0.042
Log (age of head)	-0.044	0.217	0.064	0.131	-0.206	0.214	0.056	0.128
1 if female headed	2.731	2.042	-3.533***	1.122	1.248	1.879	-3.369***	1.077
Years of schooling	0.175	0.153	-0.056	0.096	0.038	0.143	-0.053	0.095
Log (age of head) x female headed	-0.740	0.527	0.828***	0.284	-0.348	0.481	0.787***	0.273
Log (age of head) x years of schooling	-0.038	0.038	0.013	0.023	-0.004	0.035	0.012	0.023
Males age 16 or over	-0.001	0.039	-0.211***	0.044	0.001	0.036	-0.203***	0.043
Females age 16 or over	-0.110***	0.033	0.014	0.029	-0.109***	0.034	0.010	0.028
Children age 15 or under	-0.023	0.029	0.069*	0.038	-0.040	0.028	0.059	0.037
Distance to daily market (km)	0.085	0.080	0.001	0.047	0.113	0.076	0.002	0.046
Squared term	-0.007	0.008	-0.012***	0.003	-0.014*	0.008	-0.011***	0.003
Distance to periodical market (km)	-0.016	0.042	0.066**	0.030	0.007	0.037	0.059**	0.029
Squared term	0.001	0.003	-0.004**	0.002	-0.0004	0.0025	-0.004**	0.002
1 if paved road around the residence	0.063	0.152	-0.290**	0.136	0.052	0.139	-0.263**	0.131
1 if public transport motorized	-0.006	0.044	0.026	0.027	0.008	0.044	0.039	0.026
Seasonal effect of irrigation accessibility								
Harvest in rainy season	-0.094	0.094	0.004	0.082				
Planting in dry season	-0.310	0.220	0.131	0.080				
Harvest in dry season	-0.295	0.201	0.140**	0.066				
Seasonal effect of primitive water control								
Harvest in rainy season	-0.088	0.062	-0.072	0.101				
Planting in dry season	0.541	0.267	0.125	0.121				
Harvest in dry season	0.564*	0.294	0.068	0.095				
Sample Selection Correction Term 1	-1.552	3.441	-3.377**	1.513	-7.743***	1.640	-2.955**	1.376
Sample Selection Correction Term 2	0.136	1.890	-0.981	1.410	-3.263***	0.775	-0.635	1.327
Sample Selection Correction Term 3	0.223	0.436	-2.664**	1.285	-0.499**	0.216	-2.317**	1.151
Monthly fixed effects	Yes		Yes		Yes		Yes	
F stat. for 1st stage IV (Permanent income)	11.74***		12.15***		4.27***		3.32***	
F stat. for 1st stage IV (Income ratio)					6.21***		2.07**	
F stat. for no seasonal irrigation or primitive water control effect	11.17*		7.32					
Sargan stat. for over-identification	0.928		0.215		9.486		7.175	
Observations	818		6246		818		6246	

Robust standard errors are reported. *** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level. # denotes endogenous variables. Sample Selection Correction Term 1 denotes the ordinary inverse Mills ratio; Term 2 is a product of the inverse Mills ratio times estimated conditional mean of expenditure given explanatory variables and credit constraint variable; and term 3 is a square of the product of the inverse Mill's ratio times the estimated conditional mean of expenditure.

Table A2. Reduced form estimation with household fixed effect

	Credit constrained (1)		Unconstrained (2)	
	Coef.	Std. Err.	Coef.	Std. Err.
Irrigated land size	-0.657	1.229	0.147	0.141
Land with primitive water control	Dropped		0.225*	0.129
Rainfed land size	-1.549***	0.134	-0.144	0.098
Seasonal effect of irrigation accessibility				
Harvest in rainy season	-0.080	0.062	0.014	0.033
Planting in dry season	-0.527***	0.191	0.104	0.073
Harvest in dry season	-0.493***	0.187	0.127*	0.074
Seasonal effect of primitive water control				
Harvest in rainy season	Dropped		-0.016	0.038
Planting in dry season	-2.338*	1.370	0.020	0.108
Harvest in dry season	-2.292*	1.370	-0.011	0.097
Constant	7.734***	0.445	7.202***	0.051
Monthly fixed effects	Yes		Yes	
F stat. for no seasonal irrigation or primitive water control effect	5.08***		0.68	
Observations	818		6267	

Robust standard errors are reported. *** denotes significance at the 1% level; ** at the 5% level; and * at the 10% level. In the first column, Land with primitive water control and its interaction with season dummy are dropped due to multicolinearity.

Table A3. Logit estimation of propensity score of irrigation accessibility

	Coeff.
Age of Head	0.085***
	(0.014)
1 if female headed	2.692
	(1.821)
Education of Head	0.009
	(0.039)
Age of Head x Female Head	-0.053
	(0.037)
Head Count of Adult Males	0.252*
	(0.133)
Head Count of Adult Females	0.260*
	(0.144)
Constant	-3.843***
	(0.629)
Observations	473
Pseudo R^2	0.194

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4. Propensity score matching estimation

Outcome Variables	Radius Matching (radius = 0.05)				Kernel Matching				Nearest Neighbor (1x1)			
	ATT	S.E.	# Treatment	# Control	ATT	S.E.	# Treatment	# Control	ATT	S.E.	# Treatment	# Control
Full Sample												
Monthly Income	105.3	97.1	3772	1352	117.6	84.1	3772	1352	389.1	322.8	3,675	1,364
Monthly Consumption	313.6***	44.3	4036	1439	323.6***	40.7	4036	1439	389.7***	88.1	3,934	1,451
Credit Constraint	-0.021	0.014	4036	1439	-0.022*	0.013	4036	1439	-0.015	0.049	3,934	1,451
Harvest Season (March, April, September, October)												
Monthly Income	565.1***	193.5	1275	449	563.0***	171.4	1275	449	678.2*	360.4	1,242	453
Monthly Consumption	486.8***	78.5	1338	476	498.9***	72.7	1338	476	653.5***	110.5	1,304	480
Credit Constraint	-0.026	0.023	1338	476	-0.026	0.024	1338	476	-0.015	0.049	1,304	480
Planting Season (Otherwise)												
Monthly Income	-106.7	103.0	2497	903	-115.1	111.8	2497	903	107.0	199.3	2,433	911
Monthly Consumption	226.0***	51.3	2698	963	236.5***	47.5	2698	963	237.9***	88.7	2,630	971
Credit Constraint	-0.021	0.016	2698	963	-0.020	0.016	2698	963	-0.014	0.049	2,630	971
Rainy Season (October to December & January to March)												
Monthly Income	164.3	112.6	1908	695	155.2*	87.2	1908	695	-197.3	480.5	1,859	701
Monthly Consumption	229.4***	44.8	2066	753	234.7***	42.2	2066	753	147.5	95.1	2,013	759
Credit Constraint	-0.007	0.019	2066	753	-0.004	0.016	2066	753	0.030	0.047	2,013	759
Dry Season (April to September)												
Monthly Income	80.1	152.0	1864	657	74.4	179.1	1864	657	401.5	307.1	1,816	663
Monthly Consumption	398.1***	74.9	1970	686	418.1***	71.9	1970	686	-93.2	167.6	1,921	692
Credit Constraint	-0.039**	0.019	1970	686	-0.040*	0.023	1970	686	-0.018	0.049	1,921	692

The matching estimation uses the monthly observations. The propensity score is considered not to change over a year. Bootstrap standard errors are reported in the Kernel Matching, *** p<0.01, ** p<0.05, * p<0.1

Table A5. Rosenbaum bounds

Sample	Full	Harvest		Plant
Variable	Consumption	Income	Consumption	Consumption
Gamma				
1	<0.0001	<0.0001	<0.0001	<0.0001
1.05	<0.0001	<0.0001	<0.0001	<0.0001
1.1	<0.0001	0.0004	<0.0001	0.0019
1.15	<0.0001	0.0038	<0.0001	0.0277
1.2	<0.0001	0.0215	<0.0001	0.1645
1.25	<0.0001	0.0798	<0.0001	0.4701
1.3	<0.0001	0.2076	<0.0001	0.7854
1.35	<0.0001	0.4029	<0.0001	0.9478
1.4	<0.0001	0.6188	<0.0001	0.9924
1.45	0.0003	0.7972	<0.0001	0.9993
1.5	0.0051	0.9103	<0.0001	1.0000
1.55	0.0438	0.9670	<0.0001	1.0000
1.6	0.1916	0.9898	<0.0001	1.0000
1.65	0.4753	0.9973	<0.0001	1.0000
1.7	0.7654	0.9994	<0.0001	1.0000
1.75	0.9315	0.9999	<0.0001	1.0000
1.8	0.9871	1.0000	<0.0001	1.0000
1.85	0.9984	1.0000	<0.0001	1.0000
1.9	0.9999	1.0000	<0.0001	1.0000
1.95	1.0000	1.0000	<0.0001	1.0000
2	1.0000	1.0000	<0.0001	1.0000
2.05	1.0000	1.0000	0.0002	1.0000
2.1	1.0000	1.0000	0.0008	1.0000
2.15	1.0000	1.0000	0.0024	1.0000
2.2	1.0000	1.0000	0.0063	1.0000
2.25	1.0000	1.0000	0.0147	1.0000
2.3	1.0000	1.0000	0.0308	1.0000
2.35	1.0000	1.0000	0.0585	1.0000
2.4	1.0000	1.0000	0.1015	1.0000
2.45	1.0000	1.0000	0.1623	1.0000
2.5	1.0000	1.0000	0.2412	1.0000

Abstract (in Japanese)

要約

物的なインフラへのアクセスが家計の厚生を高めることは広く理解されている。一方で、インフラの貧困削減効果をミクロデータを用いて実証的に分析した既存研究は非常に少なく、とくに貧困動態という観点からはほとんど分析されてこなかった。本稿は、こうした既存研究の穴を埋めるべく、スリランカで実施された大規模な灌漑事業をケースとして、独自に収集された世帯レベルの月次パネルデータを用い、計量経済学的な分析を行った。インフラの効果を識別する際には、政府による灌漑インフラの割り当てがくじびきによってなされたという自然実験的状況を利用した。計量経済モデルとしては、Paxson(1993)による消費平滑化モデルを拡張し、信用制約を内生化した。実証分析の結果、灌漑へのアクセスが、所得を増加させると同時に、流動性制約に陥る確率の減少を通じて一時的貧困を解消させることが示された。これらの結果は、灌漑というインフラが、慢性的貧困・一時的貧困の両方の削減に寄与し得ることを示している。さらに、構造モデルの推計によって、我々の理論枠組みが妥当であるという結果も得られた。

JICA Research Institute

Working Papers from the same research project

"Impact Assessment of Infrastructure Projects on Poverty Reduction"

JICA-RI Working Paper No. 3
Social Capital Formation in an Imperfect Credit Market:
Evidence from Sri Lanka
Masahiro Shoji, Keitaro Aoyagi, Ryuji Kasahara, Yasuyuki Sawada and Mika Ueyama

JICA-RI Working Paper No. 4
The Role of Infrastructure in Mitigating Poverty Dynamics:
A Case Study of an Irrigation Project in Sri Lanka
Yasuyuki Sawada, Masahiro Shoji, Shinya Sugawara and Naoko Shinkai

JICA-RI Working Paper No. 16
Motives behind Community Participation:
Evidence from Natural and Field Experiments in a Developing Country
Masahiro Shoji, Keitaro Aoyagi, Ryuji Kasahara and Yasuyuki Sawada

JICA-RI Working Paper No. 33
Social Capital as an Instrument for Common Pool Resource Management:
A Case Study of Irrigation Management in Sri Lanka
Takeshi Aida

JICA-RI Working Paper No. 47
Modes of Collective Action in Village Economies:
Evidence from Natural and Artefactual Field Experiments in a Developing Country
Yasuyuki Sawada, Ryuji Kasahara, Keitaro Aoyagi, Masahiro Shoji, and Mika Ueyama

JICA-RI Working Paper No. 59
How Access to Irrigation Influences Poverty and Livelihoods: A Case Study from Sri Lanka
Sonali Senaratna Sellamuttu, Takeshi Aida, Ryuji Kasahara, Yasuyuki Sawada,
and Deeptha Wijerathna