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

by

Yasuyuki Sawada**
Faculty of Economics, University of Tokyo, Japan

Masahiro Shoji
Faculty of Economics, University of Tokyo, Japan

Shinya Sugawara
Department of Economics, University of Wisconsin-Madison, USA

Naoko Shinkai
Graduate School of International Development, Nagoya University, Japan

Revised: August 8, 2008

Abstract

Although it is known that access to physical infrastructure enhances household welfare, there are hardly any micro-econometric studies that analyze the role of infrastructure 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 project implemented in Sri Lanka. We extend the seasonal consumption smoothing model of Paxson (1993) by introducing endogenous credit constraints. We collected unique household-level monthly panel data over a period of two years. According to the point estimates, with irrigation accessibility, per capita food and non-food consumption expenditures increase by around 20% and 45%, respectively, on average, and the probability of binding credit constraint is reduced by 5.6% during the dry season. The latter result implies that irrigation enhances households' access to the credit market which, in turn, contributes to further reduction in transient poverty. These empirical results suggest that irrigation infrastructure has a positive impact on reducing both chronic and transient poverty. The structural estimation results support the validity of our theoretical framework.

Keywords: Poverty Reduction, Role of Infrastructure, Monthly Panel Data

* This paper forms part of the research project titled "Impact Assessment of Infrastructure Projects on Poverty Reduction," conducted by the Japan Bank for International Cooperation (JBIC) 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 by Ousmane Badiane, Marcel Fafchamps, Yoshihisa Godo, Ernesto Garilao, Yujiro Hayami, Hidehiko Ichimura, Masahiro Kawai, Carol A. Litwin, Megumi Muto, Ryuji Kasahara, Takashi Kurosaki, Keijiro Otsuka, Motoki Takahashi, Ryuhei Wakasugi, and the participants of a wide variety of seminars and conferences, including the Annual Bank Conference on Development Economics (ABCDE) 2006 Tokyo, the FASID Hakone Conference 2006, Asian Development Bank Institute (ADBI) conference on Infrastructure and Poverty in 2002, the Global Development Network Rio de Janeiro Conference 2001, and Japanese Economic Association. Needless to say, we are responsible for any remaining errors.

** Corresponding Author: Yasuyuki Sawada, Faculty of Economics, the University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033, Japan. E-mail: sawada@e.u-tokyo.ac.jp

1. Introduction

In this paper, we aim to evaluate the role of irrigation infrastructure in mitigating the negative impact of poverty dynamics using unique household panel data from Sri Lanka. Such research is largely missing although development economists have considered physical infrastructure to be an indispensable precondition of industrialization and economic development (Murphy, Shleifer, and Vishny, 1989).[1] Many empirical studies demonstrate that physical infrastructure development improves the long-term production and income levels of an economy (Canning and Bennathan 2000; Esfahani and Ramirez 2003; Lipton and Ravallion 1995; Jimenez 1995). For instance, Hulten, Bennathan, and Srinivasan (2006) found that in India, from 1972 to 1992, highways and electricity accounted for almost half of the growth of the Solow residuals of the 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; and Zhang and Fan, 2004). Based on 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 been repeatedly found in existing 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 the water supply system, Lokshin and Yemtsov (2004, 2005) on the poverty reduction effect of community-level infrastructure improvement projects on water supply systems in Georgia, Brockerhoff and Derose (1996) and Jalan and Ravallion (2003) investigated the role of water supply and public health systems, and Jacoby

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

While these existing micro-econometric studies are insightful in uncovering the role of infrastructure in reducing poverty, two issues remain to be addressed. The first important issue is the proper identification of the effectiveness of irrigation infrastructure in reducing poverty (Duflo and Pande 2007). This may be an inevitable consequence because randomized evaluation, which has been developing rapidly in recent times (Duflo, Glennerster, and Kremer 2008), is difficult to implement by nature in the context of large-scale infrastructure. The second issue is that, to the best of our knowledge, all the preceding micro studies on the nexus between infrastructure and poverty reduction employ the static concept of poverty, although recent studies on poverty focus exclusively on the dynamic and stochastic nature of poverty (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 bridge this gap 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. To achieve this end, we employ a unique monthly household panel data set on households' accessibility to irrigation infrastructure, which was collected exclusively for our study through extensive field surveys in Sri Lanka. 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 conduct a wide variety of robustness tests such as propensity score matching methods and nonnormal error terms. The rest of the paper is organized as follows: In Section 2, we present our theoretical framework, and in Section

3, we describe our data collection procedure, field environment, sampling method, sample structure, and summary statistics. Section 4 presents the estimation strategy and results; the final section concludes the paper.

2. Modeling the role of infrastructure in reducing poverty dynamics

With respect to the theoretical framework, we extend Paxson's (1993) seasonal consumption model by introducing endogenous credit constraints in order to evaluate the role of irrigation infrastructure in mitigating chronic and transient poverty. Each household determines seasonal consumption by maximizing its lifetime utility subject to its intertemporal budget constraint. At this point, we assume that all the households have perfect credit market accessibility. Suppose that a household's decision maker 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 the purpose of exposition, we exclude the year subscript in the following presentation. It should be noted that α_s represents a taste parameter, and a is the coefficient of relative risk aversion. Then, 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 exogenous seasonal interest rate, $r \equiv R-1$. Assuming no consumption tilting, i.e., $\beta R = 1$, we have the following optimal expenditure for season s, as derived by Paxson (1993):

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

where $E_s^* = P_s C_s$ with P_j represents the price of consumption in season s; ω and Π are utility weights assigned to consumption in season s and the household's total asset, 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 constraints. If $\pi = 0$, then the credit constraint is not binding, and if $\pi = 1$, it is 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. 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 reduces the dependency of agricultural production on rainfall, thereby reducing the output fluctuation. In order to capture this, we postulate that the income seasonality A is a linear function of a discrete variable of irrigation accessibility Z: $Z = 1$ if irrigation accessibility exists, $Z = 0$ otherwise. Then, we can derive the following reduced form estimation equation of seasonal expenditures:

(4) $$\ln E_s = \ln Y + \gamma_s^0 + \gamma_s^Z Z + u_s,$$

where, following Paxson (1993), γ_s^0 denotes common season-specific intercepts, reflecting the season-specific preferences and prices. The irrigation-specific seasonal coefficients γ_s^Z capture the extra effect of seasonality with irrigation accessibility ($Z = 1$). If the credit constraint is not binding, i.e., if $\pi = 0$, then the parameters γ_s^1 for households with $Z = 1$ should jointly be zero. This is a joint test for determining credit accessibility and ineffectiveness of irrigation accessibility.

Program Placements

Note that equation (4) can be viewed as a linear program evaluation equation (Lee 2005). The parameters γ_s^1 capture the extra amount of expenditure that farmers can achieve; these expenditures would be enabled by the irrigation infrastructure, or simply, the season-specific treatment effect of irrigation infrastructure. However, an endogeneity issue would remain to be addressed. Since our data are taken from a newly developed farming area, irrigation accessibility is determined according to the government's land allocation rule.

The government set the land eligibility criteria as follows: First, land recipients should be married, Sri Lankan citizens aged eighteen years and above, landless or small land holders with land holdings less than 0.8 ha, and citizens with an annual income of less than Rs. 9,000.[3] Government officials were not eligible for land allocation. The government choosed the beneficiaries based on these criteria. There were also additional considerations such as how long citizens resided in the project area, the household size, and records of current or past participation in any poverty reduction program organized by the government. Admittedly, irrigation infrastructure may still be correlated with unobserved determinants of seasonal expenditure. Yet, the correlation is likely to be negative because the government provided irrigated lands mainly to the poors, e.g., landless or small farmers. Hence, from the viewpoint of this study, our irrigation accessibility variable may underestimate rather than overestimate the impact of irrigation. In order to mitigate this endogeneity problem, however, we conduct a wide variety of robustness tests using, among others, the fixed effects model and the propensity score matching method.

Endogenous Credit Constraints

In the development literature, it is commonly accepted that poor households in developing countries, which typically comprise landless farmers, have only limited access to credit markets. A conventional empirical approach to incorporate credit constraints into estimation models ignores the endogeneity of the constraints and the exogenous splitting of the sample into those 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 constraints. 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 true if the credit constraint is binding. Defining the gap between E^* and E in that $H \equiv E^* - E$, we follow Jappelli (1990) to postulate a reduced form equation of the gap H., i.e., $H_s = X_s\gamma + \varepsilon_s$. Then, a discrete model of credit constraint is obtained as follows:

(5) $$cc_s = 1[X_s\gamma + \varepsilon_s > 0],$$

where $1[\cdot]$ denotes an indicator function for a discrete variable of credit constraints, cc; X includes income, assets, demographic variables, and squared variables; and ε denotes an error term that captures unobserved elements and a measurement error.

3. The Field Survey

The Survey Area

As the sample for our evaluation study, we selected the Walawe Left Bank (hereafter, WLB) irrigation system in the underdeveloped area of southern Sri Lanka. According to this system, the WLB Irrigation Upgrading and Extension Project was initiated in 1997 with the help of concessional loans from the Japan Bank for International Cooperation (JBIC), formerly Overseas Economic

Cooperation Fund (OECF).[4] In the WLB area, the *Yala* (dry) season begins in February and ends in September, while the *Maha* (rainy) season begins in October and extends up to January. According to the rainfall pattern in this area over the past six years, the average monthly rainfall is less than 60 mm in May, June, and July.

The WLB system can be divided into two areas: the first is that with adequate access to irrigation water and the second is the area that is presently rainfed but where there are provisions for irrigation in the near future. The entire irrigation infrastructure in the first area has already been rehabilitated, and the second area is an adjacent rainfed area; in this sense, the former and the latter areas can be considered as the treatment and control groups, respectively, of this irrigation project. The type of farming in the study area varies from irrigated to rainfed and *chena*, that is, slash and burn cultivation. This categorization is suitable for evaluating the role of infrastructure in reducing poverty. The project area exhibits considerable variability in cropping patterns. The main crops grown in the area include paddy, sugarcane, banana, and other upland crops.

Field Surveys

Approximately 75,000 residents are covered under the WLB, including government allottees, encroachers, and nonfarm household members. In order to select the representative sample households, the entire area was divided into six strata, depending on irrigation accessibility—Sevanagala irrigated, Sevanagala rainfed, Kiriibbanwewa, Sooriyawewa, Extension, and Ridiyagama areas. We adopted a multistage stratified random sampling strategy using a complete list of all households within each cluster. The actual samples consist of 858 households, including 660 farm households and 198 nonfarm or landless households.

Household surveys have been conducted five times in 2001 and 2002. The first, second, and third surveys were implemented in June, August, and October 2001, respectively. The first survey was conducted specifically to obtain monthly data for the previous *Maha* season. The second and third surveys 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 *Maha* and *Yala* seasons in 2002.

Descriptive Statistics

As in Hussain, Marikar, and Thrikawala (2002) and Table 1, several basic characteristics of households are summarized as follows: Approximately 75% of the household heads perform agricultural work as their primary occupation. Irrigation coverage is measured by the percentage of population that uses water from the irrigation canal. There is an important variation in the irrigation rate, ranging from the broadest coverage of 88% in the Sooriyawewa area to merely 13% and 2% in the extension and rainfed Sevanagala areas, respectively.

With regard to the households' livelihood information, consumption is divided into two large categories, namely, food consumption and nonfood consumption. Nonfood consumption includes broadly defined, nondurable expenditures comprising items such as medical care and education. On the other hand, income is calculated by aggregating the income from the sale of crops, the imputed value of self-production, income from noncrop agriculture such as livestock income, and agricultural and nonagricultural wages. Our data include information on monthly income only for the latter twelve months, i.e., from October 2001 to September 2002, while we have information on monthly consumption for twenty-four months, from October 2000 to September 2002. Thus, for the purpose of our econometric analysis, we employ the data pertaining to the overlapping twelve months. We also utilize a set of income and expenditure variables expressed as those per adult male equivalent. We employ the age-sex weights used by Townsend (1994) in the context of Southern India. While irrigation accessibility appears to be positively correlated with income and assets systematically, it is necessary to conduct further, meticulous investigations to identify the causal effect of infrastructure on chronic and transient poverty.

In this study, it is important for us to estimate the endogenous credit constraint model of equation (5). Yet, regular household surveys do not include credit information that directly enables an identification of the credit conditions persisting (Scott 2000). To deal with this issue, we carefully designed the special credit module in our questionnaire so as to directly identify credit-constrained households. In particular, we asked two questions simultaneously. First, we queried about the amount of credit a household obtained in a particular period. Second, among those who did not obtain credit, we asked about their reasons for not borrowing. If a household responded that they did not need to borrow money, then we labeled that household as a noncredit constrained household. On the other hand, if a household listed reasons such as fear of default or impossibility of borrowing, we identified the household as a "discouraged borrower," i.e., credit constrained.

Figure 1 show the average monthly consumption by irrigation accessibility. First, it is obvious that households in rainfed areas have systematically lower expenditures than those in the irrigated areas throughout the year. This suggests that the incidence of chronic poverty could be more serious in the rainfed areas than in the irrigated areas.[5] Second, while expenditure levels vary significantly depending on the accessibility to irrigation infrastructure, the pattern of monthly expenditure fluctuations appears to be fairly similar across areas. Expenditure levels are stable from October through February, increasing in April immediately after the *Maha* harvesting months, decreasing during May and June, and slightly increasing in September after the *Yala* harvesting months. A similar pattern of the transient nature of poverty is illustrated in Figure 2, which represents the monthly patterns of income fluctuations. It shows that there is a conspicuous increase in income in April and September during harvest.

4. Econometric Analysis

Our econometric analysis comprises four models. First, we conduct a benchmark estimation using the entire sample. Second, after splitting the sample into two groups depending on credit constraint status, we estimate a reduced form model of seasonal expenditure by the maximum likelihood method with normality assumption. Third, we test the validity of our model framework by estimating a structural version of the model. Fourth, we conduct a wide variety of robustness tests by relaxing the normality assumption and employing the fixed effect and propensity score matching models to mitigate the possible biases arising from endogenous program placements.

Estimation Results 1: Benchmark Estimation with Entire Sample

We first attempt to estimate equation (4) using the entire sample as a benchmark analysis. Table 2 presents a series of results pertaining to the monthly consumption effect. It is evident that households with irrigation access have higher consumption levels than those with no irrigation access, even after controlling for the difference in permanent incomes. Per adult male equivalent food and non-food consumption expenditures are larger in the irrigated areas than those in the rainfed areas by 15.3%-22.5% and 34.5%-56.4%, respectively (Table 2). Provided that the measure of chronic poverty can be simply poverty at time mean consumption for all dates as Jalan and Ravallion (2000), , This indicates that chronic poverty is more serious in the rainfed areas than it is in the irrigated areas.

It is possible that these remaining monthly effects reflect the impact of credit constraints as well as other factors such as additional seasonal income effects created by irrigation infrastructure. Since a binding credit constraint can, theoretically, reduce the consumption level under negative income shock, it may be a significant source of transient poverty. If the rainfed group faces a higher probability of binding credit constraints than the irrigated group, the former group can achieve only lower and more volatile consumption profiles. Moreover, an increased probability of facing credit constraints will increase the incentive of accumulating precautionary savings, leading to lower consumption levels. Through these channels, a better credit market accessibility will also increase the monthly consumption level.

Estimation Results 2: Maximum Likelihood Estimation

The results presented in table 2 may involve a sample selection bias arising from endogenous credit constraints because the entire sample is used, regardless of the credit constraint status. In order to cope with the sample selecting bias arising from endogenous credit constraints, we follow Jappelli (1990) and employ a qualitative response model of endogenous credit constraint, using credit constraint in equation (5).[6] Accordingly, we can combine this endogenous credit constraint approach with the seasonal expenditure model of Paxson (1993) in equation (4). In particular, we have the following econometric model of expenditures under the endogenous credit constraints, which can be estimated by the type 5 Tobit model of Amemiya (1985, pp.399–408).

(6) $$\ln E_s = \gamma_0^C \ln Y + \gamma_s^C + \gamma_s^{Z,C} Z + u_s^C \qquad \text{if } cc_s = 1,$$

(7) $$\ln E_s = \gamma_0^N \ln Y + \gamma_s^N + \gamma_s^{Z,N} Z + u_s^N \qquad \text{if } cc_s = 0,$$

together with equation (5), where superscripts C and N denote the credit constrained and unconstrained groups, respectively. By estimating the irrigation sensitivity parameter, $\gamma_s^{Z,C}$ and $\gamma_s^{Z,N}$ for different seasons in equations (6) and (7), we investigate the role of irrigation infrastructure in alleviating both chronic and transient poverty.

We jointly estimate equations (5), (6), and (7) by using a full-information maximum likelihood method under a joint normality assumption of three error terms, namely, ε_s, u_s^C, and u_s^N.

Tables 3 reports the estimation results of a system of reduced form of equations (6) and (7) for food and nonfood expenditures, after controlling the endogenous credit constraints of equation (5). These results in Table 3 illustrate that the monthly effects of food consumption for the irrigated group appear consistently larger than those for the rainfed group. As seen in the columns of nonfood consumption for the credit constrained group, the difference in the nonfood consumption between irrigated and rainfed groups is significant for seven months and the significant gap between irrigated and rainfed groups for nonfood consumption partially disappears. This implies that credit access can explain, at least partially, the higher monthly effect for households with irrigated lands. In fact, according to the estimation results of the credit constraint equation, the probability of binding credit constraints is a negative function of irrigation accessibility. This result implies that loan provisions are positively affected by the access to irrigation facilities possibly through enhanced land value.

However, credit constraints cannot fully explain the remaining differences in the monthly effects between the irrigated and rainfed groups. When focusing on the unconstrained group, we note that the significant difference in the monthly effects persists. This implies that irrigation accessibility could reduce poverty via paths other than improvement in credit accessibility.

Estimation Results 3: Instrumental Variable Estimation for Credit Constraints with Subsamples

The above reduced form model cannot directly quantify the degree of credit constraints. Hence, we investigate the monthly 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 version of equations (3) and (5) becomes

$$(8) \qquad \ln E_s = \delta_0^C \ln Y + \delta_s^C + \pi^C A_s + \delta^C \frac{\phi(X_s\gamma)}{\Phi(X_s\gamma)} + \nu_s^C \qquad \text{if } cc_j = 1,$$

(9) $$\ln E_s = \delta_0^N \ln Y + \delta_s^N + \pi^N A_s + \delta^N \frac{\phi(X_s\gamma)}{1-\Phi(X_s\gamma)} + v_s^N \quad if\, cc_j = 0,$$

where δ_s are captured by monthly dummy variables, and φ (·) and Φ(·) represent the probability density and cumulative density functions of normal distribution and their ratio is the inverse Mill's ratio. Since the share variable A_s is endogenously determined, we have estimated the model by treating A_s as an endogenous variable. We employed the interaction terms between month dummies and an irrigation dummy and other exogenous variables as instruments. The tests on the theoretical hypotheses $0 < \pi^C < 1$ and $\pi^N = 0$ will provide further direct evidence on the extent to which consumption is smoothed against income fluctuations.

Due to the endogeneity of the income fraction variable A_s, it is difficult to construct an accurate testing procedure for the hypothesis via the maximum likelihood method. Alternatively, we employ the following two-stage least squares (2SLS) approach. Let G denote a set of explanatory variables in equation (8) or (9), i.e., ln$Y$, seasonal dummy, A_s, and inverse Mill's ratio; let Q denote a set of instrumental variables for A_s. The consistent estimator of the coefficients for G can be obtained by the usual 2SLS estimator as follows:

(10) $$\beta = [G'Q(Q'Q)^{-1}Q'G]^{-1}G'Q(Q'Q)^{-1}Q'\ln E.$$

In order to obtain the asymptotic variance of the coefficients in the Tobit models via the two-step approach, we adopt a simple bootstrapping method.[7] The bootstrap sample of (G, Q, lnE_s) is obtained by sampling with replacement from the entire sample. Then, the bootstrap estimator of the coefficients can be constructed with the bootstrap sample, as was the case in (10). We repeat this process B times and obtain estimators for each of the iterations: $\hat{\beta}_b$, b = 1,2, ..., B. Letting $\hat{\beta}$ denote the consistent estimator for the coefficient with whole samples, the bootstrap variance estimator is given by

(11) $$\frac{1}{B}\sum_{b}(\hat{\beta}-\hat{\beta}_b)(\hat{\beta}-\hat{\beta}_b)'.$$

This is consistent in terms of the size of whole samples (Hahn 1996). The t-statistics and confidence intervals can be calculated from the bootstrap variance estimator. Tables 4 presents the structural estimation results with B = 5,000. We also conduct F-tests for validity of instruments for the endogenous income share, A_s. The Wald statistics reported in Table 4 shows the validity of the instrument. For the probit estimation on the endogenous credit constraint which is not reported in this paper, the Wald statistics for the null hypothesis that all the coefficients are zero is 49.80 and its p-value is 0.00. We also include the inverse Mill's ratio for explanatory variables in Table 4. Then, we adopt Ryu (1996)'s asymptotic variance estimator in order to adjust the variance-covariance matrix of the two-step estimator.

For food and nonfood consumption of the credit constrained groups, the coefficients of monthly income fluctuation π^C are positive and significant. Further, their 95% confidence intervals are [0.029, 0.098] and [0.204, 0.492] for food and nonfood expenditure, respectively, and both are located within the range of [0,1]. On the other hand, the monthly income coefficients for the unconstrained households π^N are not statistically different from zero. Consumption of the constrained group tracks the fluctuated income path, suggesting that people under credit constraint cope with negative economic shocks by reducing consumption. In contrast, the unconstrained group can smooth their consumption paths under income fluctuation. The results summarized here provide supportive evidence with our reduced form results, which are presented in table 3.

Estimation Results 4: Nonnormal Sample Selection and nonrandom irrigation placements[8]

Here we perform several robustness tests of our results. 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. Hence, we relax the normality assumption by adopting the approach proposed by Lee (1982) and Newey, Powell, and Walker (1990). Qualitative results are comparable even if we relax the normality assumption (Sawada et al., 2008).

As pointed out by Banerjee (2005) and Duflo and Kremer (2003), while randomization becomes a de facto standard for program evaluation in development economics, there are some types of programs that cannot be evaluated with the methods of randomization. Typically, irrigation infrastructure would be categorized into this type. In the area covered by our survey, the central government distributed irrigated land to the poor based on a set of criteria, and therefore, the nonrandomized distribution of irrigated land might cause a biased estimation in the program effect. In order to correct this bias, we adopt two strategies. First, we include household fixed effects to mitigate the correlation between unobserved heterogeneity and program placement. Second, we employ the propensity score matching estimator proposed by Rosenbaum and Rubin (1983).

With regard to the first approach of including 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) by incorporating the household fixed effects. The estimation results of both reduced form and structural form models are the same qualitatively to the one without household fixed effects (Sawada et al., 2008).

In the second approach, we use the propensity score matching method of Rosenbaum and Rubin (1983), setting aside the endogenous credit constraints. We aim to estimate 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 owns irrigated land, and zero otherwise, and the superscript also indicates the value of Z.[9] The results are reported in Sawada et al. (2008) indicate that the effects of irrigation on consumption are positive and statistically significant for all months; this implies that accessibility to irrigated land significantly increases consumption levels. In the rainy and dry seasons, the estimated effects on credit constraint are –0.042 and –0.056, respectively, and the effect is statistically significant in the dry season at the 10% significance level, suggesting that accessibility to irrigation decreases the probability of binding credit constraint by 5.6% during the dry season.

5. Concluding Remarks

In this paper, we have identified the relation between infrastructure development and poverty reduction with regard to seasonal fluctuations in consumption expenditure. We found that irrigation reduces chronic poverty by enhancing permanent income and it also eliminates the negative impact of transient poverty by reducing the downside expenditure risk. The point estimate shows that, with irrigation accessibility, per capita food and non-food consumption expenditures increase by around 20% and 45%, respectively, on average, and the probability of binding credit constraint is reduced by 5.6% during the dry season. Our results provide evidence in support of the role of infrastructure in reducing both chronic and transient poverty. We also found that irrigation systems enhance households' accessibility to the credit market, which, in turn, contributes to a further reduction in poverty. Moreover, the structural estimation results support the validity of our theoretical framework. These results are fairly robust against a variety of econometric specifications, including nonnormal distribution of error terms, household fixed effects, and propensity score matching methods. Since there are very few micro-econometric studies that analyze the role of infrastructure in mitigating chronic and transient poverty, we believe that this paper will bridge an important gap in the existing literature.

Interestingly, the significant difference in monthly effects persists even when we focus our empirical analysis on the unconstrained group. This finding indicates that irrigation access could reduce poverty via multiple paths apart from improvements in credit accessibility. Usually, when irrigation infrastructure is constructed, other types of infrastructure such as road and electricity facilities are developed alongside. The unexplained positive irrigation effects of the unconstrained group may be attributed to such a wide variety of infrastructure developments. Further exploration of these wider external effects of irrigation infrastructure development should be pursued in future studies.

Footnotes

[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, sewage systems, hospitals, and school facilities.

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

[3] This threshold is significantly lower than the poverty lines set by government agencies (Hussain, Marikar, and Thrikawala 2002) and the PPP-converted one-dollar-per-day poverty line.

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

[5] We also calculated 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%, where the highest head count ratio is observed in the Extension area with 14% and the lowest poverty rate is found in Kiriibbanwewa with 8%. These figures indicate that the accessibility to irrigation infrastructure is systematically related to the incidence of poverty.

[6] In the context of a developing country, a similar framework has been employed by Barham et al. (1996).

[7] Ryu (1996) showed that the ordinary two-step approach yields a bias because the contribution of the correlation of the approximation errors for the inverse Mill's ratio to the variance estimator is not asymptotically negligible. Ryu's (1996) consistent estimator cannot be applied to our study because of the endogeneity of A_s.

[8] The results of these robustness tests are not presented in this paper but available in the electronic Appendix.

[9] Since $\left(\ln E_s^0 \mid Z = 1\right)$ is unobservable counter-factual situation, we postulate the conditional independency assumption. This assumption implies that the log expenditure of rainfed observation $\ln E_s^0$ is independent of access to irrigation Z, though conditional on the set of observed determinants of access to irrigation.

References

Alderman, H., and C. H. Paxson. 1992. "Do the Poor Insure? A Synthesis of the Literature on Risk and Consumption in Developing Countries." Policy Research Working Paper No. 1008, World Bank.

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

Banerjee, A. V. ed. 2007. *Making Aid Work*. MIT Press.

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

Besley, T., and S. Coate. 1992. "Workfare versus Welfare: Incentive Arguments for Work Requirements in Poverty Alleviation Programs." *American Economic Review* 82(1):249-261.

Brockerhoff M., and Derose L. 1996. "Child Survival in East Africa: The Impact of Preventive Health Care." *World Development* 24(12):1841-1857.

Canning, D., and E. Bennathan. 2000. "The Social Rate of Return to Infrastructure Investments." Policy Research Working Paper No. 2390, DECRG, World Bank.

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.

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

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.

Duflo, E., R. Glennerster, and M. Kremer. 2008.), "Randomization in Development Economics: A Toolkit." In T. Paul Shultz and John Strauss, eds. *Handbook of Development Economics*, 4.

Duflo, E., and R. Pande. 2007. "Dams." *Quarterly Journal of Economics* 122(2):601-646.

Esfahani, H., and M. Ramirez. 2003. "Institutions, Infrastructure, and Economic Growth." *Journal of Development Economics* 70(2):443-477.

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):180-194.

Fan, S., and Z. Xiaobo. 2004. "Infrastructure and Regional Economic Development in Rural China." *China Economic Review* 15(2):203-214.

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):551-570.

Garcia, Rene, Annamaria Lusardi, and Serena Ng(1997), "Excess Sensitivity and Asymmetries in Consumption: An Empirical Investigation," Journal of Money, Credit, and Banking 29(2), 154-76

Gibson, J., and S. Rozelle. 2003. "Poverty and Access to Roads in Papua New Guinea." *Economic Development and Cultural Change* 52(1):159-185.

Grosh, M., and P. Glewwe, eds. 2000. *Designing Household Survey Questionnaires for Developing Countries: Lessons from Ten Years of LSMS Experience.* The World Bank.

Hahn, J. 1996. "A Note on Bootstrapping Generalized Method of Moments Estimators." *Econometric Theory* 12(1):187-197.

Hayashi, F. 1985. "The Effect of Liquidity Constraints on Consumption: A Cross-Section Analysis." *Quarterly Journal of Economics* 100:183-206.

Hulten, C. R., E. Bennathan, and S. Srinivasan. 2006. "Infrastructure, Externalities, and Economic Development: A Study of the Indian Manufacturing Industry." *The World Bank Economic Review* 20(2):291-308.

Hussain, I., F. Marikar, and S. Thrikawala. 2002. *Impact Assessment of Infrastructure Development on Poverty Alleviation-Case Studies on Irrigation Projects: Final Report*, International Water Management Institute, Colombo, Sri Lanka.

Isham, J., D. Narayan, and L. Pritchett. 1995. "Does Participation Improve Performance? Establishing Causality with Subjective Data." *World Bank Economic Review* 9(2):175-200.

Jacoby, H. 2000. "Access to Markets and the Benefits of Rural Roads." *Economic Journal* 110(465):713-737.

Jacoby, H., and B. Minten. 2008. "On Measuring the Benefits of Lower Transport Costs." Policy

Research Working Paper No. WPS 4484. The World Bank.

Jalan, J., and M. Ravallion. 2000. "Is Transient Poverty Different? Evidence for Rural China." *Journal of Development Studies* 36(6):82-99.

Jalan, J., and M. Ravallion. 1998. "Transient Poverty in Postreform Rural China." *Journal of Comparative Economics* 26:338-357.

Jalan J., and Ravallion M. 2003. "Does Piped Water Reduce Diarrhea for Children in Rural India?" *Journal of Econometrics* 112(1):153-173.

Jappelli, T. 1990. "Who Is Credit Constrained in the U.S. Economy?" *Quarterly Journal of Economics* 105(1):219-234.

Jimenez, E. Y. 1995. "Human and Physical Infrastructure." In Behrman, J., and T. N. Srinivasan, eds. *Handbook of Development Economics*, Volume 3B, Elsevier Science, North Holland, pp. 2773-2843.

Kyriazidou. 1997. "Estimation of a Panel Data Sample Selection Model." Econometrica 65:1335-1364.

Lancaster, T. 2000. "The Incidental Parameter Problem since 1948." *Journal of Econometrics* 95:391-413.

Lee, L-F. 1978. "Unionism and Wage Rates: A Simultaneous Equation Model with Qualitative and Limited Dependent Variables." *International Economic Review* 19:415-433.

Lee, L-F. 1982. "Some Approaches to the Correction of Selectivity Bias." *Review of Economic Studies* 49:355-372.

Lee, M-J. 2005. *Micro-Econometrics for Policy, Program, and Treatment Effects*. Cambridge University Press.

Lipton, Michael, and Martin Ravallion(2005), "Poverty and Policy," Handbook of Development Economics, Volume 3B, Elsevier Science, North Holland, 2551-2657

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):265-277.

Lokshin, M., and R. Yemtsov. 2005. "Has Rural Infrastructure Rehabilitation in Georgia Helped the Poor?" *The World Bank Economic Review* 19(2):311-333.

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):1003-1026.

Newey, W. K., J. L. Powell, and J. R. Walker. 1990. "Semiparametric Estimation of Selection Models: Some Empirical Results." *American Economic Review* 80(2):324-328.

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

Ravallion, M. 2001. "Growth, Inequality, and Poverty: Looking Beyond Averages." *World Development* 29(11):1803-1815.

Rosembaum, P. R., and D. B. Rubin. 1983. The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrica* 70:41-55.

Ryu, K. 1996. "Consistent, Positive-definite Covariance Matrix Estimation of Heckman's Two-step Estimator." *Journal of Economic Theory and Econometrics* 2(2):65-76.

Sawada, Y., M. Shoji, S. Sugawara, and N. Shinkai (2008), "The Role of Infrastructure in Mitigating Poverty Dynamics: The Case of an Irrigation Project in Sri Lanka," *JBICI Discussion Paper* No. 16, JBIC Institute, Japan Bank for International Cooperation.

Scott, K. 2000. "Credit." In Margaret G. and P. Glewwe, eds. *Designing Household Survey Questionnaires for Developing Countries*: *Lessons from Ten Years of LSMS Experience*, Volume 2, The World Bank.

Townsend, R. M. (1994), "Risk and Insurance in Village India," *Econometrica* 62, 539-591.

Van de Walle, D. 1996, "Infrastructure and Poverty in Vietnam." *LSMS Working Paper* No. 121. The World Bank. Washington, D.C.

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.

Zeldes, S. P. 1989. "Consumption and Liquidity Constraints: An Empirical Investigation." *Journal of Political Economy* 97:305-346.

Figure 1

Monthly consumption

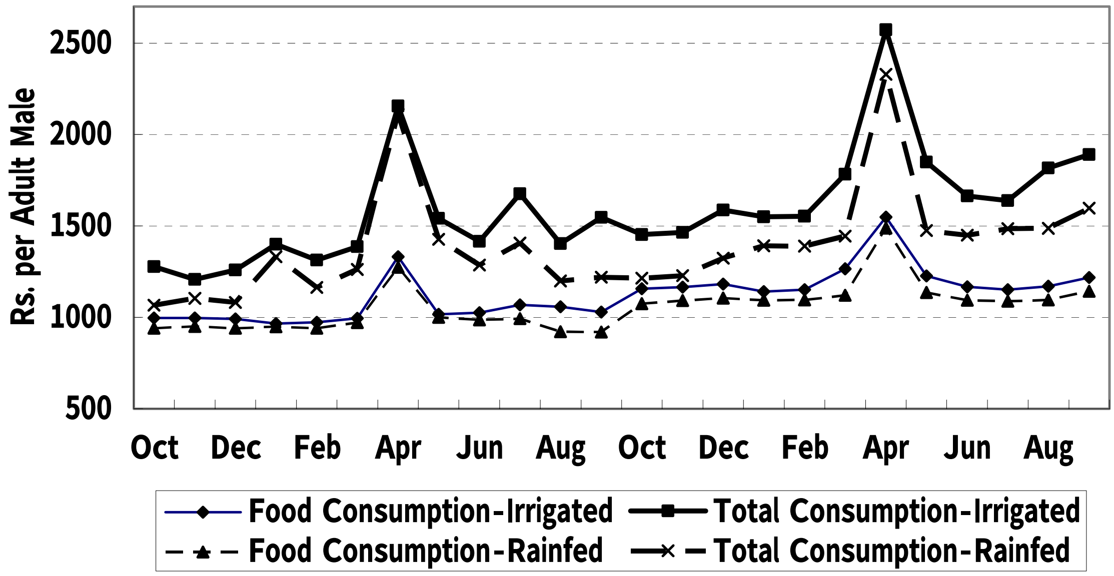

Figure 2

Monthly income

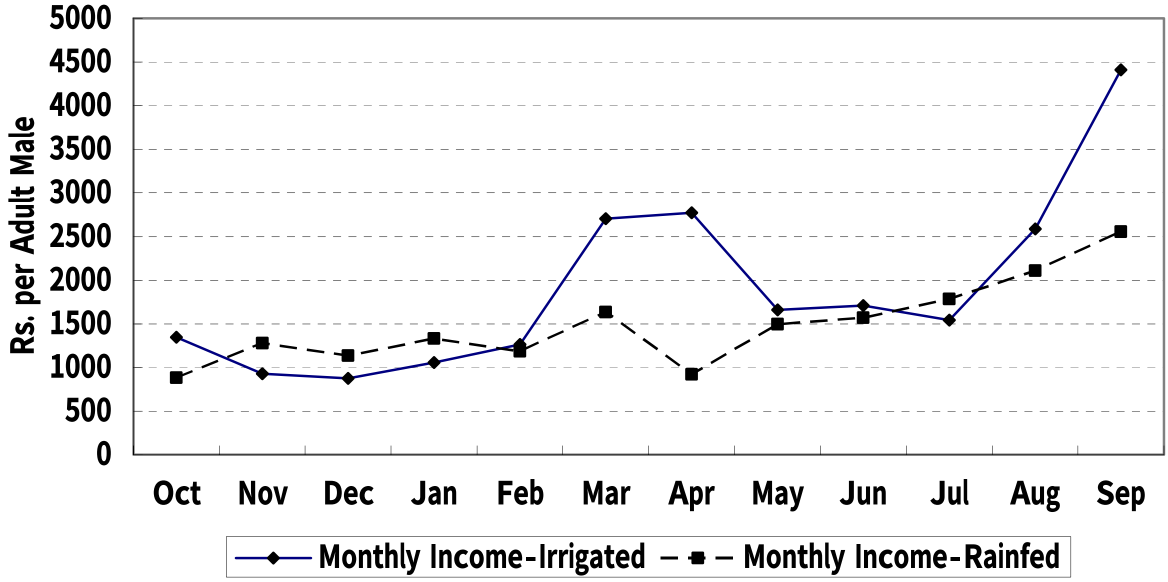

Table 1
Selected Household Characteristics by Credit and Irrigation Accessibility

Variable	Unit	Credit Constrained		Credit Unconstrained	
		Irrigated	Rainfed	Irrigated	Rainfed
		Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)
Head's Years of Schooling	Year	5.30	5.56	5.75	5.82
		(3.36)	(3.32)	(3.30)	(3.38)
Head Count of Adult Males	#	2.03	1.54	2.05	1.48
		(1.18)	(0.95)	(1.11)	(0.89)
Head Count of Adult Females	#	1.92	1.51	1.90	1.50
		(0.99)	(0.85)	(1.03)	(0.89)
Head Count of Children	#	1.41	1.86	1.34	1.74
		(1.44)	(1.34)	(1.40)	(1.32)
Monthly Food Consumption per Adult Male	Rs.	1033.06	963.42	1134.97	1080.16
		(581.70)	(508.90)	(616.99)	(535.60)
Monthly Nonfood Consumption per Adult Male	Rs.	384.42	280.59	487.88	349.11
		(1015.88)	(827.24)	(1277.76)	(995.48)
Monthly Income per Adult Male	Rs.	1990.75	1587.39	1930.64	1493.91
		(4977.67)	(2010.39)	(4618.61)	(5043.45)
Age of Head	Year	52.37	41.96	52.41	41.53
		(11.25)	(11.34)	(11.65)	(12.04)
Female Head	Dummy	0.13	0.10	0.12	0.09
		(0.34)	(0.30)	(0.32)	(0.28)
Land Holding per Adult Male	Acre	0.71	0.53	0.74	0.57
		(0.48)	(0.49)	(0.55)	(0.58)
Years since Settlement	Year	28.38	20.51	28.77	20.37
		(11.94)	(12.59)	(11.86)	(13.61)
Experience of Agriculture	Year	27.98	18.17	27.43	18.35
		(10.14)	(10.44)	(11.15)	(10.37)

Table 2
Reduced Form Estimation with the Entire Sample [Equation (4)]

	Log (Food Consumption)		Log (Nonfood Consumption)	
	Coef.	Std. Err.	Coef.	Std. Err.
Log of Average Monthly Income	0.139***	(0.007)	0.235***	(0.020)
Age of Head	-0.0048***	(0.0004)	-0.010***	(0.001)
Female Head Dummy	-0.075***	(0.014)	-0.219***	(0.048)
Head Count of Adult Male	-0.104***	(0.004)	-0.095***	(0.014)
Head Count of Adult Female	-0.099***	(0.004)	0.043***	(0.015)
Head Count of Children	-0.080***	(0.003)	-0.117***	(0.011)
Monthly Effect				
November	0.012	(0.034)	-0.083	(0.108)
December	0.027	(0.035)	0.123	(0.109)
January	0.017	(0.034)	0.591***	(0.104)
February	0.016	(0.035)	0.150	(0.109)
March	0.043	(0.034)	0.386***	(0.108)
April	0.323***	(0.036)	1.900***	(0.100)
May	0.072**	(0.033)	0.409***	(0.113)
June	0.039	(0.032)	0.301***	(0.108)
July	0.032	(0.032)	0.476***	(0.109)
August	0.036	(0.032)	0.594***	(0.112)
September	0.073**	(0.033)	0.781***	(0.112)
Monthly Irrigation Effect				
October	0.198***	(0.030)	0.383***	(0.098)
November	0.194***	(0.029)	0.487***	(0.102)
December	0.193***	(0.030)	0.470***	(0.103)
January	0.169***	(0.030)	0.404***	(0.094)
February	0.175***	(0.030)	0.458***	(0.106)
March	0.225***	(0.030)	0.424***	(0.104)
April	0.150***	(0.032)	0.345***	(0.084)
May	0.172***	(0.028)	0.442***	(0.110)
June	0.153***	(0.027)	0.564***	(0.101)
July	0.154***	(0.027)	0.495***	(0.103)
August	0.167***	(0.027)	0.480***	(0.107)
September	0.168***	(0.028)	0.496***	(0.106)
Constant	6.519***	(0.059)	3.337***	(0.179)
N	9016		8813	

*** denotes significance at the 1% level, and ** at the 5% level.
Robust standard errors are indicated in parentheses.

Table 3 Switching Regression Model

	Log (Food Consumption)				Log (Nonfood Consumption)			
	Unconstrained		Constrained		Unconstrained		Constrained	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Log of Average Monthly Income	0.134***	(0.007)	0.155***	(0.020)	0.222***	(0.021)	0.198***	(0.059)
Age of Head (γ_0^C , γ_0^N)	-0.0044***	(0.0005)	-0.005***	(0.001)	-0.008***	(0.002)	-0.028***	(0.005)
Female Head Dummy	-0.080***	(0.016)	-0.007	(0.045)	-0.249***	(0.057)	-0.462***	(0.136)
Head Count of Adult Male	-0.114***	(0.005)	-0.052***	(0.014)	-0.096***	(0.016)	0.001	(0.046)
Head Count of Adult Female	-0.092***	(0.005)	-0.134***	(0.011)	0.033*	(0.017)	0.081*	(0.042)
Head Count of Children	-0.081***	(0.004)	-0.071***	(0.011)	-0.115***	(0.013)	-0.245***	(0.033)
Monthly Effect (γ_s^C , γ_s^N)								
November	0.011	(0.039)	0.025	(0.095)	-0.119	(0.129)	-0.035	(0.263)
December	0.031	(0.039)	0.023	(0.096)	0.054	(0.125)	0.235	(0.270)
January	0.016	(0.039)	0.054	(0.104)	0.587***	(0.121)	0.502*	(0.296)
February	0.019	(0.040)	0.010	(0.095)	0.183	(0.127)	-0.248	(0.284)
March	0.043	(0.039)	0.048	(0.093)	0.416***	(0.125)	0.104	(0.288)
April	0.312***	(0.040)	0.337***	(0.104)	1.952***	(0.122)	1.842***	(0.277)
May	0.050	(0.037)	0.104	(0.091)	0.457***	(0.127)	-0.111	(0.299)
June	0.013	(0.036)	0.072	(0.091)	0.354***	(0.125)	-0.277	(0.269)
July	0.005	(0.036)	0.075	(0.091)	0.533***	(0.122)	-0.058	(0.303)
August	0.005	(0.037)	0.088	(0.091)	0.610***	(0.127)	0.327	(0.317)
September	0.048	(0.038)	0.091	(0.087)	0.789***	(0.129)	0.362	(0.308)
Monthly Irrigation Effect($\gamma_s^{Z,C}$, $\gamma_s^{Z,N}$)								
October	0.163***	(0.034)	0.221***	(0.083)	0.445***	(0.111)	0.211	(0.281)
November	0.158***	(0.033)	0.219***	(0.082)	0.632***	(0.121)	-0.054	(0.245)
December	0.158***	(0.034)	0.224***	(0.081)	0.604***	(0.116)	0.126	(0.264)
January	0.139***	(0.033)	0.152	(0.093)	0.516***	(0.107)	0.111	(0.288)
February	0.141***	(0.035)	0.180**	(0.082)	0.494***	(0.119)	0.633**	(0.320)
March	0.198***	(0.034)	0.191**	(0.080)	0.495***	(0.116)	0.372	(0.303)
April	0.131***	(0.037)	0.104	(0.096)	0.379***	(0.104)	0.423*	(0.243)
May	0.160***	(0.031)	0.175*	(0.089)	0.410***	(0.121)	1.073***	(0.279)
June	0.143***	(0.030)	0.165*	(0.085)	0.562***	(0.114)	1.189***	(0.253)
July	0.145***	(0.030)	0.139	(0.086)	0.481***	(0.110)	0.989***	(0.288)
August	0.163***	(0.031)	0.143*	(0.085)	0.457***	(0.118)	0.962***	(0.319)
September	0.154***	(0.032)	0.196**	(0.081)	0.469***	(0.119)	1.275***	(0.303)
Constant	6.613***	(0.067)	5.857***	(0.176)	3.111***	(0.197)	5.451***	(0.626)

*** denotes significance at the 1% level, and ** at the 5% level; Robust standard errors are indicated in parentheses.

Table 3
Switching Regression Model (Continued)

	Dummy=1 if Constrained			
	Food Consumption		Nonfood Consumption	
	Coef.	Std. Err.	Coef.	Std. Err.
Access to Irrigation Dummy	-0.181***	(0.045)	-0.149***	(0.044)
Log(Land Holding)	-0.072	(0.068)	0.107***	(0.040)
(Log(Land Holding))2	-0.022	(0.024)	0.043***	(0.014)
Monthly Income	-8.89E-06*	(4.78E-06)	-2.63E-06	(5.16E-06)
Age of Head	0.004**	(0.002)	0.002	(0.002)
Female Head	0.077	(0.059)	0.028	(0.060)
Head Count of Adult Male	-0.070***	(0.019)	-0.036*	(0.019)
Head Count of Adult Female	0.009	(0.022)	0.039**	(0.019)
Head Count of Children	-0.005	(0.014)	0.035**	(0.014)
Constant	-1.152***	(0.095)	-1.258***	(0.087)
N	8356		8166	
Sigma Unconstrained	0.379***	(0.009)	1.431***	(0.019)
Sigma Constrained	0.417***	(0.036)	1.374***	(0.075)
Cov Unconstrained	0 .137**	(0.066)	-0.995***	(0.055)
Cov Constrained	0.224***	(0.078)	-0.672***	(0.170)

*** denotes significance at the 1% level; **, at the 5% level; and *, at the 10% level.
Robust standard errors are indicated in parentheses.

Table 4 Structural Estimation

	Food Consumption		Nonfood Consumption	
	Unconstrained	Constrained	Unconstrained	Constrained
Ratio of Income Earned in Month to	0.003	0.059**	-0.001	0.363**
Average Monthly Income# (π^C, π^N)	(0.014)	(0.030)	(0.031)	(0.146)
Log of Average Monthly	0.138***	0.241***	0.232**	0.701***
Income(δ_0^C, δ_0^N)	(0.044)	(0.046)	(0.091)	(0.244)
Age of Head	-0.002***	-0.001	0.002	-0.019***
	(0.001)	(0.001)	(0.002)	(0.005)
Female Head Dummy	0.0005	0.066	0.002	-0.198
	(0.019)	(0.048)	(0.060)	(0.151)
Head Count of Adult Male	-0.140***	-0.078***	-0.197***	-0.090
	(0.007)	(0.014)	(0.020)	(0.060)
Head Count of Adult Female	-0.075***	-0.137***	0.091***	0.042
	(0.006)	(0.014)	(0.017)	(0.066)
Head Count of Children	-0.079***	-0.058***	-0.111***	-0.146***
	(0.011)	(0.012)	(0.025)	(0.052)
Monthly Effect(δ_s^C, δ_s^N)				
October	6.956***	3.994***	4.366***	-3.036*
	(0.367)	(0.403)	(0.767)	(1.742)
November	6.968***	4.006***	4.378***	-3.295*
	(0.382)	(0.408)	(0.791)	(1.768)
December	6.987***	4.015***	4.530***	-2.849
	(0.381)	(0.405)	(0.793)	(1.746)
January	6.958***	4.011***	4.987***	-2.556
	(0.374)	(0.404)	(0.782)	(1.745)
February	6.962***	4.008***	4.589***	-2.788
	(0.369)	(0.403)	(0.773)	(1.802)
March	7.025***	4.003***	4.819***	-2.924*
	(0.389)	(0.410)	(0.804)	(1.772)
April	7.238***	4.206***	6.256***	-1.413
	(0.372)	(0.424)	(0.782)	(1.841)
May	7.007***	4.028***	4.811***	-2.911
	(0.375)	(0.416)	(0.780)	(1.836)
June	6.958***	3.988***	4.797***	-3.013*
	(0.370)	(0.417)	(0.771)	(1.816)
July	6.951***	3.934***	4.923***	-3.183*
	(0.370)	(0.429)	(0.768)	(1.891)
August	6.958***	3.955***	4.993***	-2.772
	(0.358)	(0.429)	(0.753)	(1.886)
September	6.995***	3.961***	5.181***	-2.743
	(0.348)	(0.434)	(0.733)	(1.936)
Sample Selection Correction	-1.974***	0.919***	-5.645***	1.909***
Term(δ^C, δ^N)	(0.216)	(0.168)	(0.628)	(0.689)
N	7382	974	7228	938
Wald Statistics for Valid Instruments	18596***	148.244***	17459***	151.420***

*** denotes significance at the 1% level; **, at the 5% level; and *, at the 10% level. Bootstrap standard errors are indicated in parentheses. # denotes an endogenous variable