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Technical Change, Factor Bias and Input Adjustments: Panel Data Evidence from Irrigated Rice Production in Southern Palawan, Philippines*

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Introduction

Approximately 90 percent of the world's production and consumption of rice occurs in Asia, and regional demand is projected to increase by 70 percent over the next 30 years (Hossain 1997). Meeting this demand requires an expansion of the total area under irrigation in the coming decades, both to lift yields and to facilitate multiple cropping. How will irrigation expansion affect local labor markets? To what extent will irrigation expansion alleviate pressure on remaining resources? These questions are important to both agricultural policymakers and natural resource managers, especially when viewed against the backdrop of expanding rural populations in many parts of Asia. As an example, approximately 4.4 million jobs must be generated each year in the Philippines to absorb additions to the labor force, two-thirds of which comes from rural areas (Cruz et al. 1992). Rapid expansion of the labor force in frontier regions of the Philippines, such as

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Palawan, has exacerbated natural resource degradation and led to the expansion of low-input agriculture in many environmentally sensitive areas (Sandalo 1996; Western 1988).

The efficiency of rice production is a topic of longstanding interest for economists. Early investigations include Barker and Herdt's seminal 1985 work. Since then, additional empirical investigations have aimed at measuring the productive efficiency of rice farmers, and the agronomic and economic effects of irrigation (e.g., Bos and Wolters 1991; Keller et al. 1996; Kitamura 1990). In this paper we seek to contribute to this empirical literature by examining the evolving impact of irrigation development on patterns of input use on 150 low-income rice farms. We use panel data collected at two sites over six cropping seasons in Palawan. We estimate a stochastic frontier production function for rice, using an unbalanced panel of parcel level data. Our data set consists of 411 observations collected over the period 1995-1999. The data set covers a period in which farms underwent a transformation from rainfed to irrigated production. We estimate values for the parameters of a standard model of agricultural production, on the basis of which we derive the associated profit-maximizing input demands. We use this approach to measure two primary effects: (1) the impact of irrigation on observed and profit-maximizing factor proportions, especially per hectare and aggregate labor levels, and (2) the extent to which observed factor proportions converge to the estimated profit maximizing levels associated with the technical change.

Results support the hypothesis that irrigation exhibits factor bias vis-à-vis rainfed production. Observed data show that irrigation precipitates a release of labor and an increase in the use of fertilizers and pesticides. Prior to irrigation development and immediately following irrigation adoption, observed levels of labor use exceeded the implicit profit maximizing levels. Over time, actual levels of labor input declined toward profit maximizing levels. Fertilizer and pesticide application rates rose following irrigation. Analysis suggests that, on average, farmers in our sample underapplied fertilizer and overapplied pesticides based on profit-maximizing levels. From the perspective of overall labor demand following irrigation, the decrease in per-hectare labor use that followed irrigation was offset by an increase in the number of rice crops planted each year (i.e., back-to-back planting of rice). As a result, overall labor use rose by 52 percent on sample farms. From a policy perspective, our results demonstrate that despite the labor-saving bias associated with irrigation, short-run aggregate labor demand increased due to a rise in cropping intensity. We discuss how this increase in labor demand may be influencing economic and environmental conditions in the study area, especially at the forest margin.

Model

Our analysis begins with an extension of Seale's (1990) model of production, which is itself closely related to earlier and contemporaneous work by Kumbhakar (1987), Kumbhakar, Biswas, and Bailey (1989), and Kalirajan (1990). We assume expected profit-maximizing farmers who grow a single crop—rice—and who are price takers in both input and output markets. The farmer's problem lies in the choice of input levels to maximize expected profit. Following Fan (1991) we employ a parcel-level Cobb-Douglas production function with potentially time-varying coefficients:

$$y_{it} = A \prod_{j=1}^{k} x_{ijt}^{\beta_{jt}} e^{\varepsilon_{it}}, \qquad (1)$$

where $\varepsilon_{it} = v_{it} - u_{it}$, $i=1,\ldots,N$, $j=1,\ldots,k$, and $t=1,\ldots,T_i$. We denote expected yield for parcel *i* at time *t* as $E(y_{it})$. *A* is a constant, x_{ijt} is input *j* for farm *i* at time *t*, β_{jt} is the input elasticity for input *j* at time *t*, and ε_{it} is an error term for parcel *i* at time *t*.[1] This error term consists of two parts. The first is a symmetric idiosyncratic disturbance v_{it}, which represents random events such as weather. This is distributed i.i.d. N(0, σ_v^2). The second is an indicator of technical inefficiency u_{it}, which is distributed independently of v_{it}, such that $u_{it} \geq 0$. This two-part error specification forms a stochastic frontier such as the one proposed by Aigner, Lovell, and Schmidt (1977). The stochastic frontier accounts for random variability, as well as productivity differences between parcels. If production on a parcel is inefficient, yield will lie below the frontier. If it is efficient, yield will lie on the production frontier. Observations that lie above the frontier are ruled out, since this would imply a superior technology that does not exist (Aigner and Chu 1968). The stochastic frontier formulation is broadly consistent with economic theory (Kalirajan 1981; Schmidt 1986).

Note that our formulation differs from that of Aigner, Lovell, and Schmidt (1977) in that we use a panel of observations composed of both cross-section and time series components. The use of a panel allows us to isolate individual parcel-specific effects that may be unobservable with cross-section data alone and which may be correlated with other observed variables (Hausman and Taylor 1981). We also allow the production coefficients b_{jt} to vary over time.

[1]In diagnosis work, we tested for scale effects in equation (1), using farm size as a regressor in our production functions. We found no statistically significant basis for scale effects in our sample. We therefore assume parcel level optimization for this study.

With this setup for production in mind, we assume the farmer maximizes the following expected profit function with respect to parcel *i*, in each of T_i time periods:

$$E(\pi_{it}) = p_t E(y_{it}) - \sum_{j=1}^{k} w_{ijt} x_{ijt} \,, \qquad (2)$$

where E(π_{it}) is the expected profit for parcel *i* at time *t*, p_t is the output price for the good in question at time *t*, and w_{ijt} is the price of input *j* for parcel *i* at time *t.* Although it is customary to assume that the length of the panel, T_i, is the same for each unit *i*, this assumption is not required (Greene 1997).

Differentiating expected profit with respect to the choice variable x_{ijt}, we obtain a standard optimality condition for profit maximization:

$$p_t \frac{\partial E(y_{it})}{\partial x_{ijt}} = w_{ijt} \quad \forall ijt. \qquad (3)$$

In other words, the expected marginal revenue of input x_{ijt} must equal its marginal cost.

Some obvious drawbacks can be associated with an assumption of profit maximization and a Cobb-Douglas functional form for production. Different assumptions could lead to a different interpretation of the data. But this approach nevertheless affords a straightforward approach to studying changes associated with irrigation development. In the analysis that follows, we estimate a production function based on equation (1) and use the results in the context of an expected profit maximization problem with factor demands based on equation (3). We use these results both to assess the extent to which factor proportions might have changed over time and to determine profit-maximizing input levels for a representative farm making parcel-level decisions. We then compare profit maximizing factor-use decisions to observed levels of factor use.

Data and study site

Data used in the analysis consists of an unbalanced panel composed of 411 observations collected from a sample of 150 rice farms in Palawan. Two sites were sampled. These are Marangas (municipality of Bataraza) and Tamlang (municipality of Brooke's Point). The samples represent approximately 35 percent of each community's population. The study area has a distinct dry season from January to March, which makes it difficult for farmers to obtain multiple rice crops without irrigation. During the rest of the year rainfall is generally adequate; annual rainfall typically exceeds 1600mm. The region has slightly acidic clay loam soils with pH of 5 to 6. Data were collected over six cropping seasons in 1995, 1997, and 1999. During this time, farms underwent a transformation from rainfed to irrigated production. In 1995 all parcels in the sample were rainfed (non-irrigated); in 1997, 28 percent of dry season parcels were irrigated; and in 1999, 46 percent. Means and standard deviations of all variables used in the analysis are contained in Table 1. Labor is measured in man-days per hectare, fertilizer in kilograms per hectare, and pesticide in pesos per hectare. Binary variables identify season (rainy and dry), year (1995, 1997, and 1999), site, use of a hand tractor, and use of irrigation on the parcel during the dry season. Table 1 also contains annual farm-gate prices for rice and inputs (labor and fertilizer).

The data in Table 1 show that although yields initially rose between 1995 and 1997, yields in 1999 were lower than in previous years, despite the technical change associated with irrigation. Anecdotal evidence reported by farmers suggests this pattern may have resulted from unfavorable climatic conditions in 1999. Fertilizer and pesticide use both increased over time. Labor, after initially increasing, dropped to pre-1997 levels in 1999. Over time, the number of farms planting in the dry season rose, reflecting irrigation expansion. The use of mechanized production, as indicated by the use of a hand tractor, also increased.

Results

Although a trans-log functional form for the production function could not be rejected on purely statistical grounds, we failed to obtain-coefficient signs in the trans-log formulation that were consistent with economic theory. Furthermore, without restrictions, coefficients in the trans-log production function did not provide interior maxima during optimization. As a result, we rely on the more restrictive Cobb-Douglas functional form, using this function:

$$Y_{it} = L_{it}^{\beta_{Lt}} F_{it}^{\beta_{Ft}} P_{it}^{\beta_{Pt}} e^{\alpha_{it}} \, , \qquad (4)$$

where L, F, and P represent labor, fertilizer, and pesticide, and $\alpha_{it} = \gamma_0 + \gamma_1 D97 + \gamma_2 D99 + \gamma_3 site + \gamma_4 season + \gamma_5 irrigation + \gamma_6 tractor + \varepsilon_{it}$. As above, $\varepsilon_{it} = v_{it} - u_{it}$, where u_{it} serves as an indicator of technical inefficiency.

Table 1. Sample means for farm, data used in analysis

Variable	1995	1997	1999	All
Rice yield	2784	3429	2578	2979
(kg/ha)	(1413)	(1157)	(1321)	(1320)
Fertilizer	255	162	177	175
(kg/ha)	(108)	(69)	(130)	(107)
Labor	20.1	38.7	18.0	27.6
(man days/ha)	(10.1)	(16.3)	(13.9)	(18.0)
Pesticide	327	1480	1537	1435
(pesos/ha)	(445)	(890)	(1099)	(1018)
Site	1.00	0.33	0.48	0.45
(0/1)	(0.00)	(0.47)	(0.50)	(0.50)
Season	0.96	0.62	0.52	0.59
(0=dry, 1=rainy)	(0.19)	(0.49)	(0.50)	(0.49)
Dry season x	0.00	0.28	0.46	0.35
Irrigation (0/1)	(.00)	(0.45)	(0.50)	(0.48)
Tractor	0.00	0.29	0.29	0.27
(0=no, 1=yes)	(0.00)	(0.45)	(0.45)	(.44)
Rice price	7.5	8.0	7.5	—
(Pesos/kg)				
Fertilizer price	5.8	6.0	6.8	—
(Pesos/kg)				
Wage	88.9	96.3	104.7	—
(Pesos/man-day)				
N	26	187	198	411

Note: Standard deviations in parentheses.
Most 1995 plots planted corn and are excluded from the analysis; see text.

Given the limited time series, we use dummy variables to identify any potential time-varying technical efficiency. At this point, we maintain the restriction that Allen elasticities of substitution equal one and therefore that there is no temporal change in elasticities of substitution. Below, in the empirical estimations, we relax this assumption by including interaction terms between year, dummy variables and the logarithms of inputs.[2] Unlike the use of time-trend variables as in Cornwell, Schmidt, and Sickels (1990 and Kumbhakar (1991) we estimate a model in the spirit of Baltagi and Griffin (1988) and Lee and Schmidt (1993), and use dummy variables to represent time. Doing so places no restrictions on the temporal pattern of the u_{it} to be the same for all producers (Kumbhakar and Knox Lovell 2000).

We use maximum likelihood to estimate four versions of the production function in log-log form. Table 2 presents the results. Models 1 to 3 restrict the coefficients on labor, fertilizer, and pesticide to remain constant over the sample period. Model 4 relaxes this assumption. Model 1 is an ordinary least-squares (OLS) regression; Model 2 a stochastic frontier regression with no individual effects; and Models 3 and 4 are stochastic frontier regressions incorporating individual effects. In choosing whether to use fixed or random effects, we draw on Kumbhakar and Knox Lovell (2000), who argue that a random-effects model is preferred to a fixed-effects model whenever data sets contain a large number of cross-sectional observations and a short time series. A random effects model is also supported by the results of a Hausman test. We assume a half-normal distribution for u_{it} in the frontier specification.[3] In terms of firm or parcel-specific scores of technical efficiency, these can be recovered via the individual effects model.[4]

Most point estimates in Model 1 are significant at the 95 percent confidence level and all exhibit the expected signs. Only the dummy variable for tractor use exhibits a statistically weak explanatory power for yield. The year dummy variables indicate declining yields from 1995 to 1999, consistent with reports of growing conditions in the area. Rainy season yields are higher than dry season yields, although irrigation completely compensates for yield shortfalls in the dry season. Results for Model 2 indicate that when the model is estimated as a stochastic frontier (but without individual effects), the

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[2]We focus in this paper on the issue of technical efficiency. Direct measurement of allocative efficiency, i.e., the deviation of input choices from their cost-minimizing levels, is not generally possible using the production frontier approach. For a discussion, see Greene (1993).

[3]We also experimented with stochastic frontier models based on an exponential error distribution. Parameter results did not differ in sign or magnitude from those obtained from estimation using half-normal distribution. The half-normal assumption generally led to statistically stronger results.

[4]Our interest in this paper is not in farm-level scores of inefficiency per se. Given the large number of observation and space considerations, we do not report these scores. They are available to interested readers upon request.

Table 2. Production function regression results (dependent variable is log of rice yield, kg/ha)

Variable	Model 1	Model 2	Model 3	Model 4
Intercept	6.5024* (0.2749)	7.5914* (0.2316)	6.6086* (0.2500)	6.1960* (0.3885)
Site (0/1)	-0.3798* (0.0544)	-0.2800* (0.0479)	-0.3743* (0.0625)	-0.3259* (0.0740)
Rainy season (0/1)	0.3355* (0.1054)	0.1825* (0.0792)	0.3045* (0.0860)	0.2461* (0.0994)
Irrigation in dry season (0/1)	0.3355* (0.1054)	0.2304* (0.0822)	0.3131* (0.0842)	0.2666* (0.0957)
Year=1995 (0/1)	0.5055* (0.1224)	0.4441* (0.0979)	0.4601* (0.1197)	0.3854 (1.4875)
Year=1997 (0/1)	0.3015* (0.0607)	0.1824* (0.0546)	0.2795* (0.0551)	0.5163 (0.7511)
Tractor (0/1)	0.0581 (0.0539)	0.0278 (0.0485)	0.0685 (0.0624)	0.0564 (0.0630)
ln(Labor) (days/ha)	0.0619 (0.0393)	0.0624* (0.0275)	0.0833* (0.0364)	0.0636 (0.0447)
ln(Fertilizer) (kgs/ha)	0.0925* (0.0459)	0.0352 (0.0398)	0.1144* (0.0456)	0.0172 (0.0657)
ln(Pesticide) (Pesos/ha)	0.0580* (0.0171)	0.0437* (0.0115)	0.0527* (0.0147)	0.1948* (0.0411)
ln(Labor)*D95 (days/ha)	—	—	—	0.1718 (0.2172)
ln(Labor)*D97 (days/ha)	—	—	—	0.0190 (0.1024)
ln(Fertilizer)*D95 (kgs/ha)	—	—	—	0.1121 (0.2227)
ln(Fertilizer)*D97 (kgs/ha)	—	—	—	0.1899 (0.1232)
ln(Pesticide)*D95 (Pesos/ha)	—	—	—	-0.1451* (0.0485)

Table 2. Continued

Variable	Model 1	Model 2	Model 3	Model 4
ln(Pesticide)*D97 (Pesos/ha)	—	—	—	-0.1762* (0.0501)
λ	—	4.1151* (0.7873)	—	—
σ^2	—	0.7376* (0.0357)	—	—
λ^2	—	—	0.4394* (0.1281)	0.5458* (0.1576)
σ_v^2	—	—	0.1846* (0.0119)	0.1709* (.0108)
Log-likelihood	—	-242.65	-310.97	-299.93
R^2	0.30	—	—	—
N	411	411	411	411

Notes: Standard errors in parentheses; (*) denotes significance at the 5 percent level. Model 1 is an OLS regression; Model 2 is a stochastic frontier estimated with no individual effects; models 3 and 4 are stochastic frontiers estimated using parcel-level random effects.

Table 3. Observed average annual input use per farm per parcel

Year	Labor (man-days/ha)	Fertilizer (kg/ha)	Pesticide (Pesos/ha)	Average # of crops
1995	20.9	265	341	1.04
	(10.7)	(134)	(449)	(.20)
1997	62.5	262	2387	1.61
percent change	(29.3)	(122)	(1796)	(.54)
from 1995	+199 percent	-1 percent	+600 percent	+55 percent
1999	31.8	314	2718	1.77
percent change	(24.5)	(229)	(2048)	(.42)
from 1995	+52 percent	+19 percent	+697 percent	+70 percent

statistical significance of labor rises, while that of fertilizer falls. The dummy variable for tractor use remains statistically insignificant. Results provide statistical support for the existence of a stochastic frontier. Following Schmidt and Lin (1984), we use the square root of the variance ratio as the basis for testing the existence of a frontier in Model 2. In our case the estimated value (λ = 4.12, t = 5.27) is significantly different from zero at the 95 percent confidence level.

Model 3 is a frontier model estimated using parcel-level random effects. In Model 3 all point estimates are significantly different from zero at the 95 percent confidence level, with the exception of the dummy variables for years and tractor use. Coefficients on the year dummy variables suggest that yields were somewhat lower in 1999 than in 1995 or 1997. As in previous models, yields on parcels in site 2 (Tamlang) were lower on average than on those in site 1 (Marangas). Again, yields were much higher in the rainy season and approximately 52 percent higher in the dry season in the presence of irrigation. A Lagrange multiplier test provides statistical evidence that supports the parcel-level random effects specification. For this test, we compare panel and nonpanel regressions in the absence of a frontier. The Lagrange multiplier test statistic is distributed with one degree of freedom. The test statistic is 5.38, which exceeds the χ^2 critical value of 3.84. We therefore conclude that, in this case, an individual effects model is preferred to a model without individual effects at a 95 percent significance level. We note that the coefficients on labor, fertilizer, and pesticide are positive and significant in Model 3 and suggest diminishing returns to use of these inputs. Yields appear to be most sensitive to fertilizer application, followed by levels of labor and pesticides, respectively.

In Model 4 we relax the assumption of time-invariant production coefficients in order to assess the extent to which factor productivity changed over the sample period. For each input (labor, fertilizer, and pesticide), Model 4 introduces two additional regression coefficients in the form of input-dummy interaction terms for 1995 and 1997. For each input, the null hypothesis of no change in input elasticities can be examined via a Wald test. We test the assumption that the input-year interaction terms are jointly equal to zero, i.e., that the production coefficients are constant across time. With 411 observations and two restrictions, the critical χ^2 value is 3.00. In the case of labor, although the coefficient values point toward labor shedding on the part of sample farms over the period 1995-1999, the interaction terms are neither individually nor jointly significant at standard test levels (the test statistic W = 0.63, with a ρ-value of 0.73). Results suggest that production was more sensitive to fertilizer use in 1997 than in 1995, and less sensitive in 1999, although the interaction terms are neither individually nor jointly significant at standard test levels (W = 2.43, ρ = 0.30). In the case of pesticides, the year-specific coefficients are individually and jointly significant (W =

13.14, ρ = 0.001). In terms of overall magnitudes, the results of Model 4 suggest a decline in the coefficient on labor from 0.23 in 1995 to 0.08 in 1997 and 0.06 in 1999; a shift in the coefficient on fertilizer from 0.13 in 1995 to 0.21 in 1997 and 0.02 in 1999; and a shift in the coefficient on pesticide from 0.05 in 1995 to 0.02 in 1997 and 0.19 in 1999. Taken together, these patterns indicate a statistically significant reduction in returns to scale for the use of all variable inputs—from 0.41 in 1995 to 0.31 in 1997 and to 0.27 in 1999. With $n = 411$, $k = 6$, the Wald test statistic of 16.98 (ρ=0.01) indicates that we should not reject the hypothesis that returns to scale were falling over the sample period, i.e., a period concomitant with the shift from rainfed to irrigated production.

Although a structural break in the data that was not associated with irrigation cannot be strictly ruled out, our familiarity with the study site, based on repeated field visits, leads us to attribute observed changes in input use to the introduction of irrigation. In addition, despite the fact that the statistical evidence in support of time-varying technical coefficients is mixed, we nevertheless observe a strong empirical pattern of input reallocation between 1995 and 1999 that we attribute to irrigation. To examine this pattern from a different perspective, we use the results from Model 3 to derive profit maximizing input levels for the sample farms.

Substituting equation (4) into equation (2) and solving the expected profit maximization problem yields a set of three straightforward factor demand equations based on equation (3). These are:

$$L^* = \left[w_L \left(pe^{\alpha}\beta_L\right)^{-1} \left(\frac{\beta_P w_L}{\beta_L w_p}\right)^{-\beta_P} \left(\frac{\beta_F w_L}{\beta_L w_F}\right)^{-\beta_F} \right]^{\frac{1}{\beta_L+\beta_F+\beta_P-1}} \tag{5}$$

$$F^* = \frac{\beta_F w_L}{\beta_L w_F}\left[w_L \left(pe^{\alpha}\beta_L\right)^{-1} \left(\frac{\beta_P w_L}{\beta_L w_P}\right)^{-\beta_P} \left(\frac{\beta_F w_L}{\beta_L w_F}\right)^{-\beta_F} \right]^{\frac{1}{\beta_L+\beta_F+\beta_P-1}} \tag{6}$$

$$P^* = \frac{\beta_P w_L}{\beta_L w_P}\left[w_L \left(pe^{\alpha}\beta_L\right)^{-1} \left(\frac{\beta_P w_L}{\beta_L w_P}\right)^{-\beta_P} \left(\frac{\beta_F w_L}{\beta_L w_F}\right)^{-\beta_F} \right]^{\frac{1}{\beta_L+\beta_F+\beta_P-1}} \tag{7}$$

Using equations (5)-(7), in conjunction with the observed annual data on input and output prices in Table 1, we compute profit-maximizing input levels. We assume the dummy variable for tractor use is zero and allow all other dummy variables to vary. We compute a simple average input level across all site, year, season, and irrigation combinations. In conducting this exercise using results of Model 3, we implicitly assume that the *bs* in equations (5) to (7) are time-invariant. In other words, any computed adjustments in the optimal levels of inputs are driven by either changes in price ratios, or elements of *a*, which in this case includes change in season, year, and irrigation status.

The computed input demands suggest that, prior to irrigation, optimal rainy season input demands were much higher than dry season input demands. Post-irrigation input demands in the rainy and dry seasons were virtually identical. Observed and predicted yields follow similar patterns. We conclude that a dramatic rise in dry season productivity in the sample precipitated the observed increase in cropping intensity, which rose from 1.04 in 1995 to 1.77 in 1999.[5]

Previous researchers have argued that, even though irrigation may not have a “built-in” bias against labor, farmers who have access to irrigation also tend to adopt labor-saving methods such as mechanization or chemical-based weed control (Lingard 1994; Coxhead and Jayasuriya 1986). Our results are consistent with this view of a technology-induced bias. We find strong empirical evidence that per-hectare labor use decreased following irrigation. Observed levels of fertilizer and pesticide use rose slightly following irrigation. Irrigation precipitated the release of labor and an increase in the use of fertilizers and pesticides. However, our data show that in the aggregate, labor use increased on an annual basis due to the rise in the incidence of multiple crop. In this respect, irrigation increased overall annual farm employment while at the same time seasonal labor shedding took place.

Insights into the observed and optimal outcomes are provided by comparing input demands and yields under profit maximization with those actually observed. These comparisons are displayed graphically in figures 1 to 4. Figure 1 shows labor use across years and seasons. Although average and profit-maximizing labor levels were virtually identical on rainfed farms in 1995, following irrigation adoption, observed levels of labor use exceeded those that are profit maximizing. Data displayed in Figure 2 show that, regardless of irrigation status, fertilizer was consistently under applied compared with profit-maximizing levels. Figure 3 shows that pesticides were underapplied on rainfed farms; overapplied on 1997 irrigated farms; and then applied in nearly profit-maximizing levels on 1999 irrigated farms. While it is possible that changes in relative input-input and input-output prices

[5]In 1995, the most popular crop grown in the area was corn. By 1999 virtually all corn had all disappeared from the study site. Observations for corn production are not included in this analysis. Their omission results in a small sample size for 1995 (see Table 1), since the majority of parcels in that year - even those planted in the rainy season - were used for corn production. For more discussion on the topic, see Martinez and Shively (1998).

Figure 1. Observed and profit-maximizing labor levels (man-days/ha/season)

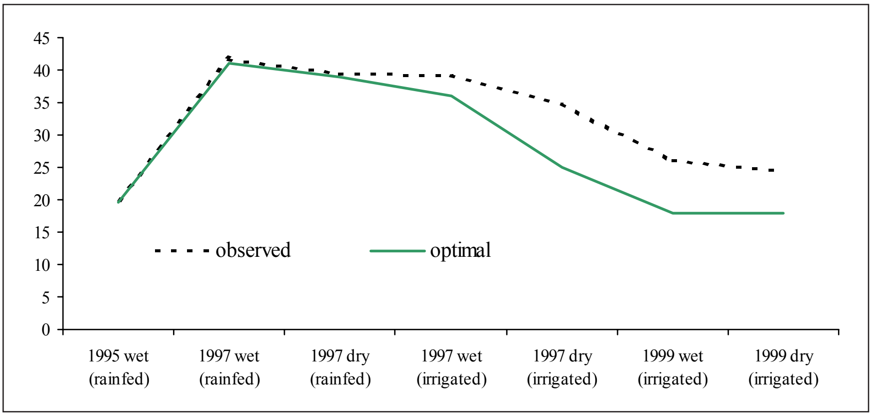


Figure 2. Observed and profit-maximizing fertilizer levels (kgs/ha/season)

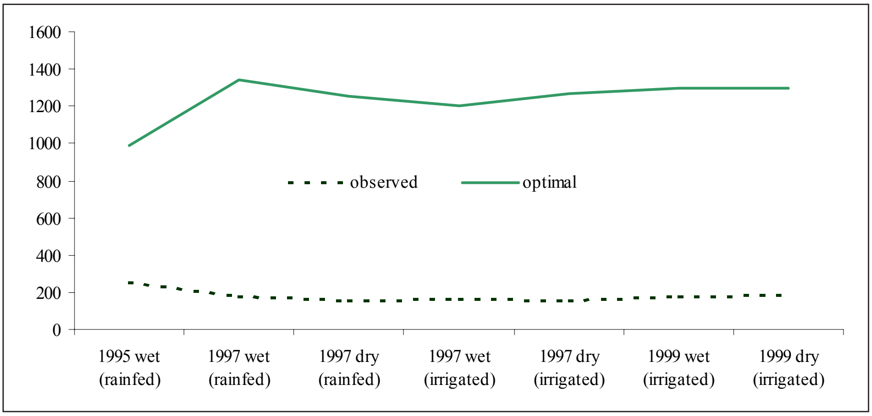
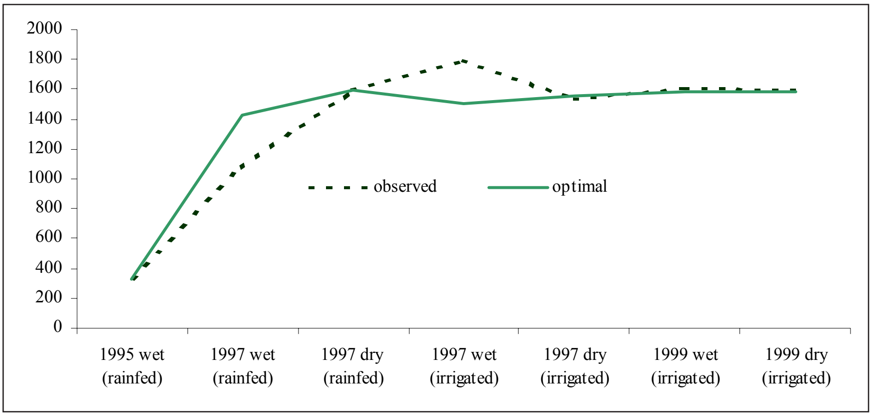


Figure 3. Observed and profit-maximizing pesticide levels (pesos/ha/season)

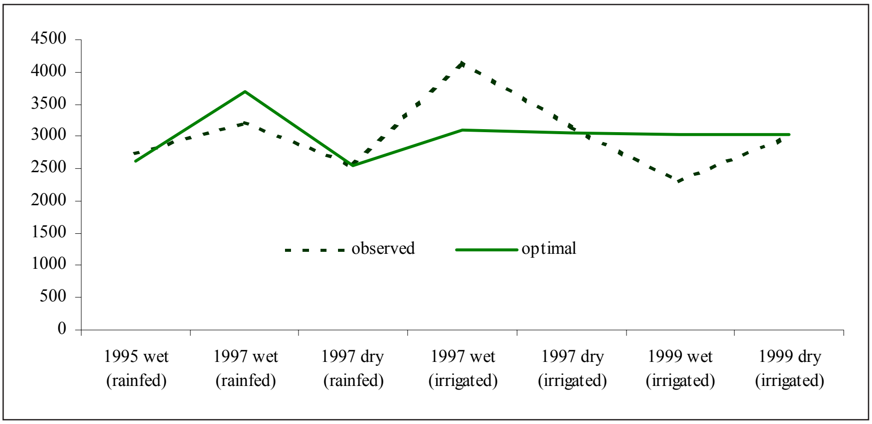


could explain such behavioral outcomes, such changes were not dramatic over the study period, leaving us to conclude that irrigation was the driving force behind the behavioral patterns we observe.

Regarding yields, Figure 4 suggests yields fell below profit-maximizing levels on rainfed farms in 1995 and on irrigated farms in 1999, but were above profit-maximizing levels on 1997 irrigated farms. In other words, high levels of labor and pesticide application in 1997 were correlated with high yields, did not translate into sufficiently high marginal value products to justify the cost of input application at these levels. In the case of pesticides, it may be that farmers assign risk-reducing properties to these inputs that we do not account for in this analysis. Nevertheless, observed pesticide application levels do approach those of profit-maximizing levels in 1999. Labor, on the other hand, remained "over-applied" in 1999 vis-à-vis profit-maximizing levels. In this analysis we value all labor, including household-supplied labor, at the average wage rate. Thus "over-application" may indicate that some households assigned a below-market shadow value to household labor. Separate (unreported) regressions, in which household and hired labor enter the production function separately, provide some weak statistical evidence that household labor was more productive than hired labor.

As a final step in the analysis, we use our data to calculate average annual input use on a parcel for a better understanding of the long-run implication of irrigation development on overall factor use. In Table 3 we account for the shift from a single crop of rice to multiple (back-to-back) crops of rice by computing average labor use over a calendar year. For parcels on which rice was only planted once, Table 3 entries are based on per-hectare input levels. For parcels in which rice was planted multiple times on the field during the year, entries represent per-hectare per-parcel averages (area-weighted, if the planted area differed between rainy and dry seasons). As the

Figure 4. Observed and profit-maximizing yields (kgs/ha/season)



final column of Table 3 indicates, virtually no dry-season cropping was observed in 1995. By 1999, 77 percent of parcels were planted in both rainy and dry seasons. In reading Table 3, it is important to note that data in the final column reflect the increase in cropping intensity.

In the case of labor, from 1995 to 1997 annual labor use increased by a factor of 3, from 21 days / hectare / year in 1995 to 63 days / hectare / year in 1997. This increase reflects both an increase in the incidence of multiple cropping in 1997 and a tendency to use much higher amounts of labor in 1997 (as documented in Figure 1). By 1999, significant labor shedding had occurred in both seasons, but multiple cropping had expanded further, and annual labor use remained 50 percent higher than in 1995. As a result, a hypothesis that irrigation increased overall employment is supported by the data.

From 1995 to 1997 annual fertilizer use remained stagnant, implying a reduction in per-season fertilizer use (see Figure 2). Fertilizer use recovered somewhat by 1999, but per-season levels of fertilizer use remained lower in 1999 than in 1995. No clear reason for this pattern is apparent—especially in light of evidence that these low levels of fertilizer use are sub-optimal—apart from the usual explanations that rely on cash and credit constraints. These explanations notwithstanding, the increase in pesticide use following the introduction of irrigation, from 341 pesos / hectare / year in 1995 to 2700 pesos / hectare / year in 1999 is dramatic. A shift toward the use of molluskacides in response to problems with snails is partly responsible for this increase in expenditure, as is a slight increase in pesticide prices over the sample period, but neither factor fully explains the rapid rise of outlays on pesticides among these farmers.

Conclusions and policy implications

Population growth in frontier regions of the Philippines, as elsewhere, creates a significant problem for policymakers, and leads to deforestation and agricultural expansion in environmentally sensitive upland areas (Western 1988). Annual crop production in upland areas is associated with biodiversity loss, high rates of soil erosion, and potential poverty traps (Barbier and Burgess 1996; Shively 2001a; Shively 2001b). Results from this study suggest that one way to increase labor absorption in existing agricultural areas is through intensification of farming in lowland areas. This study supports the hypothesis that aggregate annual labor demand increases with the implementation of irrigation on lowland farms. Although the observed per-hectare level of labor decreased, annual labor use actually increased due to an increase in the incidence of multiple cropping of rice. The question of where necessary labor has come from is an interesting one. One hypothesis would be that labor had been in surplus in lowland households and that, following irrigation, lowland households substituted work for leisure. However, among lowland families this pattern does not appear to hold, in particular because the amount of family labor in use has declined in the post-irrigation period. Instead, it seems that higher incomes have led lowland households to shift efforts elsewhere and to substitute hired labor for their own labor. Some of the hired labor comes from the lowlands, and some from the uplands. Among upland households the situation appears to be one in which labor is being re-directed from activities with low returns (such as charcoal production and cash crop production on hillside farms) to wage employment on adjacent lowland irrigated fields. That irrigation has acted as a magnet to pull labor away from forest margins is not mere conjecture, but is supported by a parallel set of data collected from upland households at the study site. Although a full exploration of the upland data is beyond the scope of the current paper, separate work reported by Shively (2001a) suggests the observed gain in employment that accrued to inhabitants of adjacent upland areas increased upland incomes and at the same time alleviated pressure on upland forest resources.

In the context of our production analysis, we find statistical support for both individual effects and a stochastic frontier. In the case of fertilizer and labor use, we also observe divergence between observed and profit-maximizing use. Farmers tended to overapply labor and to underapply fertilizer. This divergence, especially the observation of lower fertilizer use in 1999 compared with 1995, can only be explained by resorting to the idea that high rates of fertilizer use in 1995 reflected farmer beliefs that such application rates were necessary then, or, alternatively, that farmers in 1999 chose to use less fertilizer (or were in some way precluded from using more). Profit-maximizing behavior alone does not explain the patterns we observe. Instead the data may indicate a nonprofit maximizing objective on the part of sample farmers (such as risk aversion or safety-first considerations). The divergences may also reflect inefficiencies since the use of traditional inputs in conjunction with a new technology—in this case irrigation—could be more likely to produce technical inefficiency than allocative inefficiency problems. Implicitly, we have assumed for this analysis that this is the case: by computing optimal input demand functions from the estimated production function and observed prices, we have set the issue of allocative efficiency aside. Additional work is warranted to examine issues of allocative efficiency, which will require us to construct a set of demand equations that are properly integrated with a cost frontier.

Irrigation per se is not the driver of the results we observe. Instead, the driving force is irrigation infrastructure *plus* sufficient water to support two (or three) crops of rice. This finding points to the importance of sound water management as a key to economic gains. Of final note is that we have observed a significant increase in the use of pesticides following irrigation. Although pesticide expenditures appear to be roughly in line with amounts that are profit maximizing, they may nevertheless have negative environmental consequences that deserve monitoring and attention. Furthermore, to the extent labor absorption remains a policy goal in many frontier areas, policymakers must remain attentive to the unintended consequences arising from policies that promote capital use in low-income agriculture. Facilitating access to chemical inputs and hand tractors may be justified on private efficiency grounds, but will likely undermine attempts to alleviate agricultural pressure at forest margins.

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