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EFFICIENCY AND PRODUCTIVITY OF NEPALESE AGRICULTURE

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ABSTRACT

EFFICIENCY AND PRODUCTIVITY OF NEPALESE AGRICULTURE

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In the first chapter, a stochastic production frontier framework is used to examine the technical efficiency of rice production for a sample of irrigated farmers in the Rupandehi district of Nepal. Coefficient estimates from the production frontier indicate that: (a) source of irrigation and varietal choice are the two most important factors which enhance rice yields; (b) mid-season water stress and long term non-use of organic fertilizer, are the two primary factors which adversely effect rice yields. Farm level technical efficiency measures derived from the production frontier model, suggests that on average, rice yields could have potentially been increased by slightly over half a metric ton per hectare, corresponding to a 18% average increase in output, via a more efficient utilization of available resources at the current state of technology. I then explore for the relationship between technical efficiency and two sets of variables: (1) farmers's grasp of agronomic principles and knowledge; (2) socio-economic environment in which the farmer operates. I am particularly interested in examining how education and land ownership size is related to efficiency, two specific issues which have received considerable attention in the literature. I find a significant relationship between secondary education and efficiency. Average technical inefficiency in rice production is reduced by 16% in plots farmed by households in which the primary farm manager has completed more than five years of schooling. I also find a significant inverted U-shaped relation between technical inefficiency and land ownership size (i.e., a significant U-shaped

efficiency-size relationship). However, the significance of this efficiency-size relationship appears to be sensitive to model specification/endogeneity bias.

In the second chapter, a stochastic production frontier approach embedded in a meta-production function framework is used to : (a) estimate the district level rates of technical change in Nepalese agriculture based upon econometric estimation of the underlying production technology; (b) derive point estimates of district level technical efficiency from parametric estimation of the production technology; and (c) given that I am interested in comparing efficiency levels across districts, I also construct confidence intervals around the time varying technical efficiency estimates, using non-parametric bootstrap methods.

When literacy is included in the analysis, there appears to be no significant growth in TFP in the Terai region, while there appears to be a severe decline in TFP growth in the Hill region. Significant negative TFP growth rates in the Hill region might reflect a pernicious decline in the quantity/quality of the natural resource base, however, it is not possible to explicitly examine the interplay between natural resource degradation and agricultural productivity given the data available for this study. This study also highlights the fact that there exists substantial scope for increasing output via a better utilization of existing inputs and technologies in the Terai region. For example, agricultural output in 1991 could have been increased by 40 % in the Terai region via a more efficient utilization of existing inputs and technologies. There also exists tremendous potential for increasing output in the Hill region, however, this potential is perhaps being squandered due to natural resource degradation.

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Chapter 1

DETERMINANTS OF PRODUCTION EFFICIENCY IN A DYNAMIC AGRICULTURAL REGION OF NEPAL

I. Introduction

Nepal, which used to be a food-grain surplus country in the 1970's, has changed to a food grain-deficit country in the 1990's (Banskota 1992). Domestic cereal production and food availability per capita is on a decline in Nepal (Ali, Hobbs and Velasco 1993). Export earnings from both the agricultural and non-agricultural sectors are insufficient to allow Nepal to pursue a food security policy which primarily depends upon cereal imports (ADB 1992). Labor absorbing industrial development has yet to emerge as a significant factor in the Nepalese economy. Thus, Nepal cannot afford to spend its reserves of hard currency on procurement of cereals from the international market. Nepal must rather rely upon strategies which enhance domestic cereal production in an arable land-constrained environment.

Currently there is a dearth of empirical studies on the productivity of Nepalese agriculture at either the national, regional or the commodity specific level. The importance of having credible productivity measures of Nepalese agriculture is further highlighted by the troubling fact that there is growing concern and evidence that productivity growth in various intensive cropping systems of South Asia is either slowing down or even declining (Hobbs and Morris 1995; Cassman and Pingali 1995; Byerlee 1992). This intensification induced decline in productivity growth could be associated with various factors such as long term changes in soil physical characteristics/decline in soil fertility, ground water depletion and water quality degradation (Pinagli and Rosegrant 1993).

Most agricultural productivity studies in South Asia have been at the national level and have focused on macro-level determinants (e.g., investment in agricultural research and extension) of productivity change. It is difficult in national level studies to explicitly control for the effects of micro-level factors (e.g., specific farm level management practices) on agricultural productivity. Thus, regional and cropping system specific studies can provide a platform for more "fine-tuned" productivity measures and allow for exploration of micro-level determinants of productivity.

Economic efficiency in production is determined by the technique of applying inputs and levels of application of inputs. Technical efficiency (TE) reflects the firm's ability to obtain the maximum possible output from a given set of inputs. Allocative efficiency (AE) reflects the ability of the firm to maximize profits, by equating the marginal revenue product with the marginal costs of inputs. These efficiency measures depend upon the factors which determine the firm manager's technical knowledge, and the socio-economical environment in which the firm manager operates (Kalirajan 1990). While TE measures can be estimated from farm level input-output data, estimation of AE measures require cost/price information. It is not surprising then that TE is the most widely used measure of farm efficiency in the developing country literature (Bravo-Ureta and Evenson 1994), reflecting the fact that farm level cost of production data is relatively more scarce compared to mere physical input-output data. Analytically, estimation of farm level AE is further complicated by a host of market failures which plagues the agricultural sector of many developing countries (e.g., AE in production will fail to hold if the farm household faces either a credit/liquidity constraint or an input supply constraint). Thus, while farm level estimation of TE does not (explicitly) require assumptions of market efficiency, most farm level AE measures are obtained under the restrictive (and probably not realistic) assumption of a perfectly competitive market environment.

The focus of this study will be to estimate the technical efficiency of rice production for a sample of farmers in the rice-wheat cropping-system of the Terai region of Nepal. I will also explore for the relationship between farm level technical efficiency and farmer's technical knowledge and the socio-economic environment in which the farmer operates. This study is thus, both an effort to fill the gap in the productivity literature on Nepalese agriculture, and to add to the growing literature on farm level efficiency of South Asian agriculture[1].

Section II of this paper provides brief background information of agricultural issues pertinent to the Terai region of Nepal; Section III briefly discusses the nature of the project which generated the data set used in study; Section IV lays the analytic framework and empirical procedures used in this study, and presents the findings from the analysis ; and Section V highlights the main conclusions of this study and suggests relevant policy implications.

II. *Agricultural Issues in the Terai*

Nepal can be divided into three agro-ecological zones: The Terai (lowlands); The Hills (middle mountains); and The Mountains (the High Mountains, and the High Himalayas). The Terai comprises 54% of the cultivated land area and 45% of the population (Banskota 1992). The importance of the Terai stems from the fact that it remains as the only food grain-surplus region in Nepal and is the most favorable area for intensified agriculture.

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[1] Estimates of AE could not be conducted due to limited information in the data set.

Small-holders constitute the majority of farmers in the Terai. Agricultural land is the primary productive resource in rural Nepal, and accounts for more than 88% of the value of farm assets in the Terai (Banskota 1992). However the distribution of this primary means of production is highly skewed, with 16.1 % of the farmers owning 62.8% of the land (Banskota 1992). Land-holding is also the major determinant of access to production credit in the Terai (Yadav, Otsuka and David 1992). Existing government credit programs in Nepal do not appear to be benefitting small farmers, but rather large farmers have been the predominant beneficiaries (Banskota 1992). It is estimated that 77% of formal lending goes to large-scale farmers (Nelson 1987). In a comprehensive analysis of the government's agricultural credit policy in Nepal, Banskota (1992, pp.70) concludes that "small and marginal farmers have been left out, and access to modern inputs to enhance productivity is denied as they do not have the power to purchase the new technology which is embodied in inputs."

There is a tremendous potential for irrigation in most of the Terai which is endowed with a relatively high water table (combined with monsoon rains which provide a good source for recharge). Groundwater sources of irrigation water can be easily tapped into through small-scale, low-cost irrigation schemes. However the overall irrigation system in Nepal remains underdeveloped and underutilized. Upadhyaya and Thapa (1994) find that irrigation is the most significant determinant of MV seed adoption, intensity of fertilizer use and cropping intensity in Terai (and throughout all major agricultural regions in Nepal).

The introduction of wheat in the rice mono-culture has allowed farmers to fit in winter wheat within the traditional rice-based cropping pattern of the Terai. However, delays in rice harvest interfere with the optimal planting date of wheat. The short time available for turnaround for planting wheat often leads to sub-optimal land preparation and use of other inputs. Also, raising two major crops may affect soil quality and increase biotic stress (Hossain 1994).

Diagnostic surveys in the rice-wheat cropping system in the Terai have identified soil nutrient deficiencies (associated with nutrient mining) as one of the long term (sustainability) problems common to both rice and wheat, which if unaddressed will increasingly limit rice and wheat yields (Harrington et al. 1993). Plot-level data from long-term experimental stations in the Terai indicates decline in yields of both continuous rice and wheat (even in plots which were treated with recommended applications of inputs) rotations. The fact that both cereals, and different varieties of these cereals "experienced significant declines in yield despite constant levels of management suggests that soil fertility or other as yet unidentified factors were depressing yields" (Hobbs and Morris 1995, pp.31).

Ali (1996) examines the efficiency of wheat production drawing upon the same data source used in this study. The author finds that cropping practices such as continuous rice-wheat rotation and discontinuous organic fertilizer application on plots which exhibited both poor soil quality and drainage conditions, resulted in a negative impact on wheat yield. However, both the estimated yield function and associated efficiency measures presented in his study could be biased due to the exclusion of labor input in the analysis.

III. *Data Section*

A collaborative project has been formed by researchers from the International Maize and Wheat Improvement Center (CIMMYT), the International Rice Research Institute (IRRI), and the national agricultural research systems (NARSs) of Bangladesh, India, Nepal and Pakistan, to examine the issue of sustainablility of the irrigated rice-wheat systems of South Asia. The first country selected for micro-level monitoring was Nepal. The data set used in this study stems from CIMMYT's monitoring data of plot level practices and resource use in the major rice-wheat regions of Nepal. This study draws upon the survey data of 170 farmers in the Bhairahawa (a major rice-wheat region) study area located in the Rupandehi District of the Terai region of Nepal.

The primary objective of the project was to examine if there are signs of an inter-temporal decline in productivity in actual farmer fields. To this end, given budgetary considerations, emphasis was placed on fine-tuning data collection (perhaps too fine-tuned as we shall see) on plots which would most likely exhibit adverse consequences of intensification. Also, "interference" due to jumbling of issues were avoided (e.g., sample consists of farmers who are predominantly owner-operators, even at the plot level, therefore avoiding incorporation of incentive issues associated with various forms of contractual arrangements in land which would complicate the productivity analysis).

Farmers in the Rupandehi district are some of the most intensive farmers (in terms of irrigation water use, chemical fertilizer use, adoption of Modern Varieties, etc) in Nepal, benefitting from the marketing channels of the neighboring Indian state of Utter Pradesh. Farmers in the sample were pre-stratified according to whether they were participating in the Bhairahawa Lumbini Groundwater Project, a tubewell irrigation development project funded by the World Bank. The sample included 82 farmers from the groundwater project and 88 farmers from outside the project (referred to as non-project farmers)[2]. Sampling was designed so that all farmers within a stratum would have the same probability of being selected. In both strata, farmers were selected through a multiple-stage sampling.

Similar to patterns observed in this region, land holdings are extremely fragmented (while the average land holding size is 2 ha in this sample, the average number of plots is 10). After a particular farm household was selected, the principal farm manager was then asked to identify "an important" (in terms of being a productive plot from the view point of the farmer) rice-wheat plot owned by the household. Most of the plots (90%) were farmed on a continuous rice-wheat rotation - again, plots which most likely would exhibit productivity decline due to soil fatigue or other intensification factors.

Plot level data was then collected on farmer's practices and levels of input use, rice and wheat yields, resource quality, and other related variables. Data collection began in 1990/91 by scientists from the Bhairahawa Wheat Research Farm, CIMMYT, IRRI, and extension workers from the district Agricultural Development Office. The same plots have continued to be monitored since then. Figure 1 shows the long-run trend in both rice and wheat yield at the district level. Figure 2 compares the sample and district averages for both crops. We see that our sample farmers somewhat follow district patterns except for the fact that average yields for both crops are consistently higher in our sample (particularly for rice).

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[2] Project farmers and non-project farmers do not come from the same village.

Our sample is biased towards farmers who use irrigation, and continuously farm on Danda landtype. In this sample, two primary land types are identified, Khala (lower terraces characterized by heavier soils and poor drainage) vs. Danda (upper terraces characterized by lighter soil and few drainage problems, however drought prone). While constructing categories for land type (Danda or Khala) or land ownership holding was fairly straight forward (these categories were static during the sample period), categorizing farmers as "continuous" (plot under a continuous rice-wheat rotation is planted with rice followed by winter wheat during each crop year, and the same rotation is followed every subsequent crop year, and that plot is never allowed to remain fallow) v.s. "non-continuous" (which in our study area is primarily either rice-wheat-mustard or rice-wheat-pulse) ; and 'irrigated' v.s. 'non-irrigated", was a bit more complicated :

Continuous v.s. Non-Continuous : Under 'ideal' circumstances a continuous farmer should enter every year under both the rice and wheat sub-sections of the panel, while a 'non-continuous' farmer should enter every year in the rice sub-section and every other year in the wheat subsection. However, certain farmers had to keep their plot idle in particular years due to various non-agronomic factors (primarily pre-planting financial constraints). Thus, 'continuous' farmers are labeled as those who farm under a continuous rice-wheat regime, leaving the plot fallow *only* due to non-agronomic reasons;

Irrigated v.s. Non-Irrigated : In this study, we categorized a household as "non-irrigated" if the household did not use any source of irrigation water throughout the sample period (1991-1996). On the other hand, we classified a household as "irrigated" if the household irrigated its plot at least once during the sample period. Incidence of irrigation is more prevalent in wheat (which is grown during the dry winter season)

There were hardly any farmers in this panel who did not use chemical fertilizers and modern varieties. In the rice sub-section twenty nine percent of the farmers applied nitrogen fertilizer in a "discontinuous" manner (i.e, not every year they appeared in the panel), while 71% of farmers applied nitrogen fertilizer every year that they appeared in the panel (only one farmer never applied any nitrogen fertilizer) ; fifty three percent of the farmers applied non-organic phosphorus in a discontinuous manner, while 47% of farmers applied phosphorus fertilizer every round of the panel (only five farmers never applied any phosphorus fertilizer) ; Ninety percent of the farmers in the sample used modern rice varieties every year they appeared in the panel, while only 5% never used any modern varieties. In the wheat sub-section thirty one percent of the farmers applied nitrogen fertilizer in a discontinuous manner, while 69% of farmers applied nitrogen fertilizer every year that they appeared in the panel (only two farmers never applied any nitrogen fertilizer) ; thirty three percent of the farmers applied non-organic phosphorus in a discontinuous manner, while 67% of farmers applied phosphorus fertilizer every round of the panel (only one farmer never applied any phosphorus fertilizer) ; unlike the rice sub-section where farmers had intimate detail about every single rice variety that they used, the vast majority of the farmers claimed not to know what type of wheat variety they were using. We do not have sufficient information on other macro nutrient application (e.g., potassium) nor on any micro nutrient application (e.g., zinc). We do have information in certain years regarding use of farm yard manure at the plot level. However, organic fertilizer of such nature makes it difficult to quantify its "composition".

Farm households in this sample region hold two key natural resource assets in their portfolio which they draw upon for agricultural production: soil, and groundwater[3] (only irrigated farmers utilize this resource of course). There is negligible soil erosion in this particular region, and it seems unlikely that soil erosion will arise as a major problem in the near future, thus, leaving soil fertility as the key soil related issue. Soil samples were collected from each plot and analyzed during 1991 and 1995. In Table S1 we notice an alarming trend of both macro and especially, micro nutrient depletion (e.g., phosphorus has declined in 92% of the plots, while magnesium has declined in 84% of the plots). Macro nutrient decline in such a short time period comes as a surprise, given that most farmers use chemical fertilizers. While the implications of macro nutrients deficiency on plant growth has been throughly studied in various agro-ecological zones around the world, we yet do not have a clear understanding between micro nutrient and cereal yield interaction (particularly in this region).

In 1991, the average rice yields for irrigated farmers in the sample was 3.3 mt/ha. The average rice yields for the same irrigated farmers in 1996 was close to 4.5 mt/ha. Thus, in a period of five years, average rice yields for irrigated rice cultivated on the same plots, have increased by one mt/ha. In this sample, even non-irrigated farmers, farmers who never apply organic fertilizer (FYM), and farmers without formal education, enjoyed average increases in rice yields over the sample period (see Figure 3 - Figure 5). These yields have occurred without any significant increases of variable inputs (I do not however, have information on changes in labor input over time), without noticeable

[3] The data set does not contain information on actual quantity of water use. Irrigation information appears as number of irrigations given to the plot. Source of irrigations turns out to be a better measure of irrigation use.

changes in plant variety adoption, without new types of crop rotations, without adoption of new types of planting/land preparation techniques, nor without adoption of new farming technologies. Average rice yield increase in the same plot without any major changes in inputs/technology, does suggest that it is plausible that farmers in our sample have made efficiency gains in rice production (albeit, we cannot extrapolate from plot level performance to total farm level performance).

There are several limitations to this data set. First, it would have been better to have data on each plot owned by the household. This would have allowed us to explicitly examine *household level* productivity strategies over time, instead of merely examining plot level efficiency tied to certain household characteristics. To examine plot level technical efficiency in this study, I rely upon primal representations of the production technology (e.g, yield function). However, we are still left to deal with the problem of endogenity. Inputs used at the farm level are endogenous to the household decision framework, which for rural agricultural households involve simultaneously both consumption and production choices. Then, even if we were lucky enough to have "seperability" (Strauss, Singh and Squire 1986) between household consumption and production decisions, production inputs will still be governed by the matrix of relative prices, degree of risk aversion and other constraints faced by the farm household pursuing various production strategies, making the model nonseperable. I do not have sufficient information to construct robust instruments to address the problem of endogeneity in the primal estimation. On a final note, given that (limited) information on labor use in rice production is available only for the first round of the panel, I estimate TE measures of rice production using data from only the first round of the panel.

IV. Analytical Framework, Empirical Procedures, and Findings

Working with cross-sectional data limits the possible estimation strategies available to calculate plot level TE (for a thorough review of the issues involved with both cross-section and panel data based estimates of TE via econometric and non-parametric methods, see Fried, Lovell and Schmidt 1993). I will adopt an econometric approach towards estimating plot level TE, and within that framework, I will explore the "stochastic production frontier" approach (Aigner, Lovell and Schmidt 1977; Meeusen and Van de Broeck 1977; Jondrow et al. 1982). The general idea behind this framework is that each firm faces its own production frontier, and that frontier is randomly determined by a host of stochastic factors outside the control of the firm (Green 1993). However, once the firm-specific production frontier is randomly placed, any deviation from that frontier is due to firm-specific technical inefficiency. A "generic" characterization of our yield function within the stochastic frontier framework is as follows:

$$y_i = f(x_i, \beta) + e_i = f(x_i, \beta) + v_i - u_i \qquad \text{(E1)}$$

where, y: crop yield ; x: vector of inputs (including variable inputs and fixed factors) ; β: vector of unknown parameters; e: error structure; i: firm index.

The error term, e_i, can be decomposed into two parts: (1) v_i, the "familiar" independently and identically distributed (across plots) two sided $N(0,\sigma_v^2)$ random variable representing model mis-specification, measurement error and random shocks (taking on values which can either be, negative, zero, or positive); and (2) u_i, a random variable associated with firm-specific factors which influence whether firm/farmer i attains maximum efficiency of production (taking on values which can either be positive or zero) . This firm-specific time-invariant technical inefficiency parameter is known to the farmer, but not to the analyst. A value of 0 for u_i indicates that the farm is operating on its frontier. Any value greater than 0 indicates that the farm is below the frontier, implying that the farm's practices conditioned by its environment leads it to produce less than the maximum possible output. The random variables v_i and u_i are assumed to be independent.

The compound disturbance in this model ($e_i = v_i + u_i$), while asymmetrically distributed, can still be estimated from maximum likelihood (ML) estimation of Eq (1). However, before we can proceed with ML estimation, certain assumptions regarding the distributional properties of u_i have to be made. One of the most common characterization of u_i is to assign it a truncated (half) normal distribution $N(0, \sigma_u^2)$. While TE estimates have been found to be fairly consistent under various specifications of the functional form of the production technology, TE estimates are sensitive to the distributional specification of u (Bravo-Ureta and Evenson 1994). Unfortunately, currently there is no satisfactory method for choosing nor testing the 'validity' of any distribution (e.g., half normal or gamma distribution). This remains as the primary drawback of estimating TE measures in a stochastic frontier framework using cross-sectional data. Because we do not have plausible instruments in our data set, I also assume that firm-specific level of inefficiency is uncorrelated with the level of inputs (x). Recent developments in this field utilizes panel data to avoid some of the troublesome aspects related with estimating TE measures based upon cross-section data (e.g., Cornwell, Schmidt and Sickles 1990). Since I do not have labor data over time, I cannot estimate TE measures using panel data methods.

For the half-normally distributed inefficiency term, the log-likelihood function is (for details please see Aigner, Lovell and Schmidt 1977) :

$$l(\alpha,\beta,\lambda,\sigma) = -N * \ln\sigma - c + \sum_{i=1}^{N} [\ln\Phi(\frac{-\varepsilon_i * \lambda}{\sigma}) - \frac{1}{2} * (\frac{\varepsilon_i}{\sigma})^2] \qquad \text{(E2)}$$

where, N : number of observations ; $\sigma^2 = \sigma_v^2 + \sigma_u^2$; $\lambda = \sigma_u / \sigma_v$; and, (.) : Φ is the cdf of the standard normal distribution.

I obtain the estimates for σ_v and σ_u from the ML estimation of the yield function. To then obtain the farm specific measures of technical inefficiencies (TIE), I use the following formula (Jondrow, Lovell, Materov, and Schmidt 1982):

$$E[u_i|\varepsilon_i] = \frac{\sigma * \lambda}{(1+\lambda^2)} [\frac{\phi(\varepsilon_i * \lambda / \sigma)}{\Phi(-\varepsilon_i * \lambda / \sigma)} - \frac{\varepsilon_i * \lambda}{\sigma}] \qquad \text{(E3)}$$

where, the pdf and cdf, $\varphi(.)$ and $\Phi(.)$ respectively, is evaluated at $\varepsilon_i * \lambda / \sigma$.

After obtaining the farm/plot specific TIE measures, I then employ a multi-variate regression setting to explore for some of the possible 'determinants' of farm-specific efficiency.

Empirical Procedures and Findings

Data on labor input use is available for 101 plots during the 1991 rice season. Out of the 101 farmers, I segregate farmers into 87 "irrigated" and 14 "non-irrigated" farmers (i.e., farmers who do not have access to any type of irrigation source). Since it would be unwise to include these two categories in the same estimation model, I restrict the analysis to only irrigated farmers, and then try to control for other pertinent factors within the multi-variate regression setting. It is hypothesized that plot level rice yield (kg/ha) for irrigated farmers is a function of (x):

Variable inputs (besides irrigation) : (1) *labor* - pre-harvest family and hired labor (hrs/ha) (2) *nitrogen* - chemical nitrogen application (kg/ha) ; (3) *phosphorus* - chemical phosphorus application (kg/ha) ; (4) *animal-hrs* - hours of animal traction used during plowing and planking operations (hrs/ha) ; *tractor-hrs* - hours of tractor use during plowing and planking operation (hrs/ha) ;

Irrigation - we only have information on the number of times the plot was irrigated, however, we can control for the source of irrigation which is viewed to be a better measure of the impact of irrigation : (5) *number-irrg* - number of times the plot was irrigated; (6) *tubewell* - binary indicator variable taking on the value of 1 if the source of irrigation for the plot was tubewell ; (7) *canal* - binary indicator variable taking on the value of 1 if the source of the source of irrigation of the plot was canal ; otherirrg - binary indicator variable taking on the value of 1 if the source of irrigation was neither tubewell nor canal (e.g., pond), not included in the regression;

Varietal Choice of rice plant (all binary indicators) : (8) *Saryu 49*; (9) *Savitri* ; (10) *Masuli* ; (11) *Janaki* ; othervar - other types of modern varieties, not included in the regression (all 87 farmers in our data set planted traditional varieties) ;

Timing of Rice Transplant : (12) *transplant-date* - timing of crop establishment, binary indicator variable which takes on the value of 1 if transplant date was later than optimal date (all farmers in our data set transplanted rice from seed-bed, as opposed to employing direct seeding method);

Plot specific weather effects : (13) *drought* - binary indicator taking on the value of 1 if the plot suffered from severe drought (captures mid-season water-stress);

Management Practices with long-term carry-over effects on soil fertility : (14) *years-crw* - number of years the plot has been cultivated under the continuous rice-wheat rotation (a value of 0 indicates plots farmed under non-continuous rotations); (15) *never-manure* - binary indicator variable which takes on a value of 1 if field yard manure (FYM), or organic fertilizer, has never been applied to the plot.

Fixed Characteristics : (16) *plot-size* - size of plot (ha) ; (17) *land-type* - binary indicator which takes on the value of 1 if the plot is of land-type danda (upper terraces with generally good drainage) , 0 if the land-type is khala (lower terraces with generally poor drainage conditions) ; (18) *soil-medium* - binary indicator taking on the value of 1 if the soil-type of the plot is classified as medium ; (19) *soil-heavy* - binary indicator taking on the value of 1 if the soil-type of the plot is classified as heavy ; soillight - binary indicator variable taking on the value of 1 if the soil-type of the plot is classified as light, not included in the regression (see Table S2 for descriptive statistics of variables used in the estimation) .

I first introduced (right-hand side) variables linearly; then I added squared terms for labor, nitrogen, phosphorus, animal-hrs, tractor-hrs, and years-crw : squared terms which did not "add" to the estimation were removed from the final analysis (only the squared terms for years-crw added to the specification) ; finally, I interacted only certain variables to keep the model both plausible and parsimonious - variable inputs were interacted with each other, irrigation, variety, land-type and soil-type ; years-crw was interacted with variable inputs, irrigation, variety, land-type, soil-type, and never-manure. Since none of the variable interactions proved to be significant (cut-off point for significance was generous, set at the 30% level), they were subsequently not included in the final analysis.

Table 1 shows both the OLS and ML parameter estimates of the stochastic production frontier. As we can see in Table 1, both the magnitude and sign of the OLS and ML estimates are quite similar. However, the standard errors of the production function parameters obtained via OLS are incorrect. As long as the firm-specific level of inefficiency, u_i, is not equal to zero, the standard errors of the parameters under OLS will be incorrect even if: a) all the right-hand side variables are exogenous; b) u_i, is uncorrelated with the level of inputs. Given that the ML estimation indicates that $\sigma_u \neq 0$, the stand errors of the production function parameters obtained via ML are more appropriate. Thus, the ML estimates of σ_u and σ_v are used (along with the half-normality assumption) to obtain the firm-specific technical inefficiency measures - which shall be addressed in the next section.

While my primary objective in this paper is to discuss issues related to technical efficiency, I shall briefly highlight some results of the production function estimate in Table 1 and discuss them briefly:

1. Labor input has a positive and significant (at the 5% level) impact on rice yield. Exclusion of labor did not significantly alter the coefficient estimates of the other explanatory variables, suggesting that labor could be treated as orthogonal in this estimation (results not reported). However, this does not imply that I could have dropped labor from the analysis and used the full panel (recall that labor data is collected only in the first year of the panel), given that even if this orthogonal relationship held inter-

temporally, omitted labor would of course still be masked in the residuals, and thus, bias any attempt to derive efficiency measures which rely upon residuals from the estimation.

2. The two most important factors which increase rice yield are : (1) *tubewell irrigation* significantly (at the 1% level) boosts average rice yield by almost one ton/ha; (2) planting plots with *Savitri variety* significantly (at the 1% level) boosts average rice yields also by almost one ton/ha;

3. The two most significant factors which adversely effect rice yields are : (1) *severe mid-season water stress* drastically reduces average rice yields by 1.3 ton/ha (at the 1% significance level), even among this group of irrigated farmers; (2) *plots in which organic fertilizers have never been used*, on average have lower rice yields of 825 kg/ha (significant at the 1% level);

4.There is an inverted-U shape relationship between average rice yields and the number of years the plot has been under the continuous rice-wheat rotation. Holding everything else constant, on average, an additional year the plot is planted under the continuous regime increases rice yields by 86 kg/ha ; yields start to decline after the plot has been farmed under the continuous rice-wheat regime for more than 11 years. However, the quadratic term is not significant in the ML estimation. Also, while we do not have actual data on rice yields prior to 1991, most farmers report a general upward trend in rice yields over time. I will address this issue later on in the paper.

'Determinants' of Technical Inefficiency

Using parameter estimates presented in Table 1 and, using equation (E3), I derive the farm/plot level technical inefficiency measures (TIE). The average TIE for this group of irrigated rice farmers in 1991, was found to be 594 kg/ha (with a standard deviation of

105). Average TIE was (statistically) similar across various categories of farmers (e.g., project vs. non-project; continuous vs. non-continuous). This suggests, that on average, rice yields in 1991 could have potentially been increased by slightly over half a ton/ha, corresponding to a 18% average increase in output, via a more efficient utilization of current input levels and technology.

In this section of the paper I will explore for factors which might help to account for the variation in TIE across farms/plots. Before I do so, I should mention that this "two-step" procedure (i.e., first estimating efficiency measures, and then estimating a regression model exploring for factors which influence variation in efficiency) is one of the two general approaches in this literature (Bravo-Ureta and Rieger 1990; Kalirajan 1991). The other approach includes socio-economic variables which are thought to influence efficiency directly in the production frontier estimation (e.g., Battese, Coelli and Colby 1989; Battese and Coelli 1995). For example, Battese, Heshmati and Hjalmarsson (1998), employ maximum likelihood methods to simultaneously estimate: (1) the parameters of the production frontier model; (2) and the parameters of a second model which examines the determinants of the variation in individual level mean technical inefficiency. Whether to directly include socio-economic variables in the production frontier (or simultaneously estimate technical (in)efficiency and the determinants of technical (in)efficiency), or to examine the determinants of technical (in)efficiency in a separate analysis, tends to be left to the discretion of the researcher given that this debate has yet to be meaningfully resolved. In this section I am particularly interested in exploring the impact of two socio-economic factors on the variation of technical inefficiency, education and ownership of land, via a "two-step" approach.

The private and social returns to schooling have been a prominent research issues in the field of development economics. The impact of education has wide implications, ranging from it's effects on agricultural productivity (e.g., Chaudhury 1979; Lockheed, Jamison and Lau 1980, Jamison and Lau 1982; T.P. Schultz 1988; Singh 1990) to child health outcomes (e.g., Caldwell 1979; Strauss and Thomas 1995). The specific evidence on the relationship between education and farm level *technical* efficiency, however, suggests that education, particularly, only elementary education (4-5 years of schooling) might not have a significant effect on the technical efficiency of traditional farmers (Cotlear 1986; Azhar 1991; Bravo-Ureta and Evenson 1994). Farmers operating in more or less "static" low-technology, low-growth areas, might not have the opportunity to adequately utilize skills acquired through low levels of education to begin with. However, as Chaudhury (1979) and Singh (1990) pointed out, the impact of education (more specifically returns to secondary education) on agricultural productivity increases with the diffusion of new technologies and changes in the incentive structure. However, on the other hand, there is evidence that primary schooling plays a significant role in shaping *allocative* efficiency (e.g., Foster and Rosenzweig 1996). There is no a priori reason why empirical studies of technical efficiency should consistently establish that secondary schooling effects dominate primary schooling effects, while empirical studies of profit/allocative efficiency tend to find the contrary. Given that in this particular study I am only examining factors that influence technical efficiency, I refrain from any further discussion of this issue - I do surmise that secondary schooling should have a significant impact on technical efficiency in this district.

Ever since Sen (1962) sparked off the modern debate between farm size and productivity, primarily in the context of yield and other partial-productivity-ratios (PRRs), several studies in different countries have affirmed the inverse relationship between farm size and productivity (Berry and Cline 1979; Cornia 1985). Synthesis of the findings on the size-productivity relationship by Rudra and Sen (1980), show that the inverse size-productivity relationship attenuates or even turns positive with the introduction of irrigation. This debate has been further invigorated by evidence from various studies which show that this once strong negative relationship between farm size and yield is either being weakened or even reversed as a consequence of capital-led agricultural intensification (Griffin 1974; Rao 1975; Berry and Cline 1979; Ghose 1979; Roy 1981; Deolalikar 1981). A U-shaped relationship between farm size and productivity could arise if large farmers have a lower credit cost advantage while small farmers have a lower labor cost advantage, which is associated with their lower labor supervision cost advantage (Binswanger and Rosenzweig 1986). Two major criticisms levied against this general line of argument are that: (1) PPRs do not provide a comprehensive measure of productivity (TE, AE or TFP measures are more appropriate); (2) differences in quality of inputs, particularly land quality, was not factored in the analysis. The 'second wave' of empirical studies suggested that while the initial productivity of large farms might have been higher during the early stages of the Green Revolution, small farmers did manage to catch up (Barker and Herdt 1985; Hazell and Ramasamy 1991). The initially higher productivity of large farms "was soon mitigated by government credit programs and by induced institutional innovations, such as the interlinking of credit with product and input markets, which lowered the cost of credit to small-scale and tenant farmers" (David and Otsuka 1994, pp.

4). We certainly have yet to observe this phenomenon in Nepal. Reigniting the debate, Binswagner, Deiniger and Feder (1995) find the persistence of a negative size-productivity relationship in LDCs even after adjusting for quality of inputs, distinguishing between ownership and operational holding size, accounting for the number of family members able to act as supervisors, and using comprehensive measures of productivity. Van Zyle, Binswanger, and Thitle (1995) also find an inverse size-productivity relationship in South African agriculture (using both TE and TFP measures). Thus, in lieu of a resurgence of sound empirical validation for the size-productivity relationship and the particular setting of this study, I hypothesize that efficiency and farm-size should be negatively related (or a positive association between inefficiency and farm-size).

Technical inefficiency is assumed to be a function of two sets of variables: (A) farmers's grasp of agronomic principles and technical knowledge ; (B) broader socio-economic environment. The first set consists of : (1) *years-variety* - number of years the farmer has used the variety (recall variety was controlled for in the production frontier estimate), as a measure of variety specific knowledge; *(2) age* - age of the principle farm manager, as proxy for experience; (3) *elderly* - the number of elderly people in the household, as a proxy for stock of experience; - the number of elderly people in the household; (4) *primary* - binary dummy variable which takes on a value of 1 if the primary farm manager has completed between 1 to 5 years of schooling (31% of farmers in our sample); (5) *secondary*[4] - binary dummy variable which takes on a value of 1 if the primary farm manager has completed between 6 or more years of schooling (31% of farmers in our sample).

[4] There were only 3 farm managers who had completed two years of post-secondary schooling (i.e., beyond grade 10), however, they were also included in the *secondary* category.

The second set of variables consists of: (6) *land-holding* - amount of land (in hectares) owned[5] by the household (in this particular sample, none of the farmers rented in/out any land) ; (7) *buffalo* - number of buffalos owned by the household; (8) *cattle* - number of cattle owned by the household; (9) *tractor* - binary indicator variable which takes on the value of 1 if the household owns a tractor; (10) *farmworkers* - number of family members working on the farm and also acting to supervise hired labor; (11) *non-farmworkers* - number of family members engaged in non-farm employment. Kalirajan (1990) finds that technical efficiency was positively related to non-farm income among a sample of farmers from the Philippines, however, the effect could go either way, particularly if household time and effort fetches a higher return for non-farm activities compared to farming.

However, most of these asset and labor variables are potentially endogenous. Empirical studies by Rosenzweig and Wolpin (1989) and Binswanger and Rosenzweig (1993), have shown that Indian farmers choose their asset portfolio in response to their ability to cope with risk. In a credit/contingency constrained environment, buying and selling of assets provide a way to smooth consumption in the face of income fluctuations. Thus, buffalo, cattle, and tractor, are all potentially endogenous. However, land-holding can still be treated as exogenous, given that farm land transactions are still uncommon in this region (most land transactions in South Asia are in tenancy - selling of farm land occurs only in exceptional situations, such as during a severe famine). Similarly, household labor supply (on-farm and off-farm) decisions are potentially endogenous (e.g., Benjamin 1992), particularly in this environment where it is quite likely that farm

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[5] Unweighted gini coefficient of landholding in the sample was 0.74.

households fail to 'separate' consumption and production decisions. Given that I do not have robust instruments, I will present results both with and without including buffalo, cattle, tractor, farmworkers, and non-farmworkers.

The third set of variables consists of: (12) *project* - binary indicator variable which takes on a value of 1 if the plot is farmed by a project farmer. Since project farmers are formally involved in an externally financed group irrigation project, project participation could result in group 'synergies' which might increase efficiency. The remaining non-project farmers are covered by local extension services; (13) *migrant* -binary indicator variable which takes on a value of 1 for migrant households. Migrants from the Hill region of Nepal are perceived to be more productive than the local indigenous farmers on the region. While this might seem surprising, given that 'local' farmers would possess more specialized knowledge associated with farming in this region, agronomists with long-term experience in this study area stress that migrants in general are more willing to adopt new farming technologies and are more likely to use organic fertilizer (manure) compared to indigenous farmers; (14) *distance-road* : distance (in km) of village from nearest main (paved) road; (15) *electricity* - binary dummy variable which takes a value of 1 if the village has electricity. Besides these two sets of variables, I also control for : (16) *plot-accessability* - binary indicator variable taking on a value of 1 if the plot was near the homestead, it is assumed that if the household faces labor/supervision limitations, then plots far away from the homestead might suffer from inefficiencies in production; (17) *farm-parcels* - number of plots the total operational landholding size is divided into, similarly it is assumed that if the household faces labor limitations/limitations , then more fragmented holdings might reduce technical efficiency. Table S3 provides summary statistics of these variables.

Besides the variables mentioned above, I also include Village Development Committee (VDC) dummies in the estimation - VDC is an important level of administration in rural Nepal (villages are aggregated to wards, wards are aggregated to VDCs, and VDCs are aggregated to form the district).. Ignoring the issue regarding VDC dummies for now, the coefficient estimate of primary and secondary schooling might be biased negatively due to a host of factors. The rich wage-earnings literature has thoroughly examined the issue regarding the overestimation of the private returns to schooling due to unobserved ability (and other omitted variables such as school quality). Unobserved individual specific ability which is certainly masked in the error term of the regression, is certainly correlated with the dependent variable, plot specific technical inefficiency, and also correlated with explanatory variables such as schooling. Bias in any one coefficient (such as schooling) would bias all the other coefficients (such as landholding). I do not have sufficient data to construct instruments necessary to test the robustness of our cross-section analysis, nor can we draw upon familiar panel data techniques to address this heterogeneity factor (e.g., fixed effects regression should remove time-invariant heterogeneity influences). While I cannot control for individual fixed effects, I can at least control for VDC fixed effects. The 87 farmers in our working sample fall into 26 VDCs, and there is an average of 3.8 farmers per VDC (in our sample there are five households which uniquely fall into a VDC category, thus, for those cases VDC dummies are equivalent to individual fixed effects). Controlling for VDC fixed effects (via VDC dummies) would control for potential variations in school quality and other infrastructure/market characteristics which might have direct and indirect effects on production efficiency.

The impact of these factors on the TIE of farmers in the sample are explored via a multivariate OLS regression framework. Explanatory variables first enter linearly; then I added squared terms for years-variety, age, elderly, land-holding, buffalo, cattle, farmworkers and non-farmworkers. Besides the squared term for land-holding, none of the other squared terms added to the linear specification, and were not included in the final estimation. Results[6] presented in Column (1) of Table 2 show that the only significant factor influencing technical efficiency appears to be secondary schooling (significant at the 2% level). Average technical inefficiency is reduced by 16% in plots farmed by households in which the primary farm manager has completed more than five years of schooling. I do observe an inverted U-shaped relation between technical inefficiency and land ownership size (i.e., an U-shaped efficiency-size relationship), however, the relationship is statistically weak (land-holding and land-holding^2, are individually and jointly insignificant at the 10% level) [7].

It should be noted that the standard errors computed from this OLS regression are incorrect. However, given that our dependent variable is rather 'unorthodox', there exists no clear-cut correction procedures for this 'two step' approach. Another issue of concern which I addressed earlier is that several of the right-hand side variables presented in

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[8] Subset regressor test strongly suggests that the VDC fixed effects belong in the regression model (at the 1% level of significance) - coefficient estimates of the 25 VDC dummies are not reported.

[9] I also replaced the landholding variable with binary dummies for land quartile, however, none of the three quartile dummies included in the regression were significant. Results not reported.

Column (1) of Table 5 are potentially endogenous - I am particularly concerned with the asset and labor variables. Given that I do not have robust instruments, I re-run the OLS regression, dropping buffalo, cattle, tractor, farmworkers, and non-farmworkers. The new set of results are presented in Column (2) of Table 2. We now observe the emergence of a significant inverted U-shaped relation between technical inefficiency and land ownership size, or a significant U-shaped efficiency-size relationship: land-holding and (land-holding)^2 are individually and jointly significant at the 5% level. The coefficient on secondary-education becomes slightly more negative and significant. Thus, while the (statistical) significance of the relationship between landholding size and efficiency in this sample is quite sensitive to model specification/endogeneity bias, the effect of secondary education appears to be quite consistent.

V. Conclusion

Using a stochastic production frontier framework, I estimated plot level technical inefficiency for a sample of irrigated farmers in the Rupandehi district of Nepal. The results suggests that rice yields among this group of farmers could on average be increased by slightly over half a metric ton per hectare (mt/ha), through better utilization of available resources at the current level of technology. How realistic is it for farmers in our sample to achieve such efficiency gains ? I had previously mentioned, in a period of five years, average rice yields for irrigated rice cultivated on the same plots, have increased by one mt/ha. Thus, the efficiency estimates obtained from this study are plausible.

Despite the potential for greater efficiency of rice production, we should remind ourselves of the grim picture stemming from the soil sample analysis. At this moment, there is no evidence of declining productivity in rice production (coefficient estimates from the production frontier indicate that we are on an upward trend), however, macro and particularly, micro nutrient depletion might arise as serious limiting factors in the near future. It would rather be more prudent to begin a serious collaboration between agronomists, soil scientists, economists and farmers to explore ways to mitigate nutrient mining. Economists can help to design more efficient institutions which are capable of delivering macro and miro nutrients to farmers in a timely and adequate manner. To that end, we need further exploration of farm level demand characteristic, and marketing and infrastructure conditioners which shape supply characteristics. If we can apply any lessons learned from the high-end Green Revolution areas (e.g., Indian Punjab), economists must ensure that the incentive structure does not lead to an over-utilization of chemical inputs and associated environmental damage.

With the rapid shrinking of the last arable land frontier of Nepal, increases in efficiency will have to play a major role in increasing agricultural output. Policy makers have various instruments at their disposal to stimulate both greater levels of technical efficiency (e.g., facilitating a more efficient coordination between agricultural research, extension services and farmer feedback) and allocative efficiency (e.g., foster institutional innovations to deliver credit to collateral poor farmers). In Schultz's influential 1975 paper, "Value of the Ability to Deal with Disequilibria", he stressed the point that a farmer's ability to realign production activities in response to a rapidly changing environment is affected by his/her "allocative ability", which in turn is conditioned by his/her level of education and experience. Investment in education and extension services are critical instruments by which policy makers can increase agricultural efficiency, particularly appropriate in a dynamic environment. In this paper, I have highlighted the relationship between education and technical efficiency in rice production in our sample of farmers, albeit in a rather restrictive and incomplete manner. I only had information on the primary farm manager, while ideally one should do an analysis that incorporates information on educational attainment for all family farm workers (and education level of hired farm workers). Also, the analysis would be reinforced if one had information on quality of schooling and information on broader family background factors. Given the limited data available to me for this analysis, and the potential biases in the estimates, it still can be reasonably argued that results from my analysis suggest that secondary school education has payoffs in increasing technical efficiency in farm production. Further detailed exploration of the relationship between education and agricultural productivity in this dynamic region of Nepal would have immediate relevance to help guide policy makers in designing appropriate strategies to enhance agricultural efficiency, which will translate to higher farm incomes.

Table S1

Changes in Plot level Macro and Micro Nutrients

Element	*% of Plots undergoing decline in element between 1991 and 1995*	*Average % change in plot level element*
Nitrogen	41	5.5
Phosphorus	92	-42.5
Potassium	59	-34.1
Organic matter	43.8	1.82
Sulfur	93	-32
Magnesium	84	-17.74
Manganese	92	-43
Aluminum	77	-55
Copper	89	-38.3
Iron	92	-35.2

Table S2

Varible	*Mean*	*Standard Deviation*
rice yield	3281.01	1130.40
labor	51.73	31.91
nitrogen	40.72	24.96
phosphorus	16.15	10.91
animal-hrs	28.35	42.47
tractor-hrs	1.32	7.74
number-irrg	11.23	26.84
plot-size	0.58	0.77
years-crw	6.99	6.37
tubewell	0.31	0.47
canal	0.12	0.32
Saryu49	0.28	0.45
Savitri	0.24	0.43
Masuli	0.15	0.36
Janaki	0.07	0.25
transplant-date	0.54	0.50
drought	0.06	0.23
land-type	0.76	0.43
soil-medium	0.55	0.50
soil-heavy	0.36	0.48
never-manure	0.29	0.46

Table 1 : OLS and ML Estimation Results of Production Function

Dependent Variable (Y) : ***Rice Yield*** *(Yμ = 3281.01 kg/ha)*
(Number of Observations : 87)

	OLS (1)	**ML** (2)
R^2	0.62	.
Adjusted R^2	0.53	.
Variable (X)	β_{OLS}	β_{ML}
Labor	8.750 (2.030)*	8.744 (1.912)*
Nitrogen	11.836 (1.955)*	11.835 (1.430)
Phosphorus	-27.340 (-2.040)*	-27.940 (-1.463)
Animal-Hrs	6.640 (0.649)	6.710 (0.611)
Tractor-Hrs	16.579 (0.831)	16.601 (0.801)
Number-Irrg	11.027 (1.982)*	11.024 (1.330)
Tubewell	813.58 (2.820)**	814.67 (3.080)**
Canal	253.71 (0.460)	253.66 (0.353)
Saryu49	-367.69 (-1.254)	-367.51 (-1.690)
Savitri	865.23 (2.705)**	865.23 (2.957)**
Masuli	226.40 (0.631)	226.40 (0.747)
Janaki	371.42 (0.750)	371.42 (0.601)
Late-Transplant	-170.01 (-0.678)	-170.14 (-0.568)
Drought	-1312.0 (-2.720)**	-1312.0 (-2.845)**
Never-Manure	-825.17 (-3.281)**	-825.17 (-3.284)**

Table 1 Continued

Variable (X)	OLS (1) β_{OLS}	ML (2) β_{ML}
Years-CRW	85.874 (1.755)*	85.874 (1.701)*
$(\text{Years-CRW})^2$	-4.005 (-1.671)*	-4.012 (-1.506)
Plot-Size	131.06 (0.640)	131.014 (0.351)
Land-Type	215.55 (0.774)	216.81 (0.800)
Soil-Medium	-76.326 (-0.177)	-76.533 (-0.141)
Soil-Heavy	-34.801 (-0.077)	-34.811 (-0.061)
Intercept	4121.3 (4.298)**	4436.0 (2.611)**
λ	.	0.69 (0.391)
σ^2	.	772.82 (1.714)
Log likelihood	.	-694.108
Joint F test $\{H_0: \beta_{Years\text{-}CRW} = \beta_{(Years\text{-}CRW)^2} = 0\}$	3.21 [0.09]	2.86 [0.23]

- *Number in parenthesis represent t statistics (β / s.e.) ; Number in brackets represent p-values*
- ** represents significance at the 5% level ; ** represents significance at the 1% level*

Table S3

Variable	*Mean*	*Standard Deviation*
Technical Inefficiency	593.70	105.33
age	42.67	12.07
year-variety	3.25	2.47
elderly	0.36	0.61
farmworkers	3.84	2.07
offarmworkers	0.62	1.37
primary	0.20	0.41
secondary	0.42	0.50
landholing	2.07	2.24
buffalo	1.22	1.71
cattlem	1.92	1.40
distance-road	0.34	0.77
migrant	0.37	0.49
project	0.49	0.50
farmparcles	10.08	12.50
tractor	0.02	0.15
electricity	0.25	0.44
plot-accessability	0.59	0.50

Note: average number of years of schooling completed in the sample was 3.9 years

Table 2 : OLS Estimation Results of Determinants of Variation in TE

Dependent Variable : *TIE (TIEμ = 593.703 kg/ha)*
(Number of Observations : 87)

R^2	0.687	0.534
Adjusted R^2	0.488	0.491
Variable	β_{OLS}	β_{OLS}
	(1)	**(2)**
Years-Variety	-5.830 (-0.977)	-5.947 (-1.122)
Age	-1.923 (-1.350)	-2.10 (-1.465)
Elderly	-8.945 (-0.311)	-9.03 (-0.921)
Primary-Education	-15.670 (-0.397)	-16.311 (-0.794)
Secondary-Education	-96.784 (-2.60)*	-99.391 (-2.87)**
Land-Holding	49.446 (1.453)	57.397 (1.983)*
(Land-Holding)^2	-9.326 (-1.501)	-10.117 (-2.192)*
Buffalo	-11.977 (-0.813)	.
Cattle	-5.107 (-0.390)	.
Tractor	-352.473 (-0.980)	.
Farmworkers	-5.460 (-0.352)	.
Non-Farmworkers	14.860 (1.287)	.
Project	122.89 (1.361)	119.381 (1.173)
Migrant	-66.516 (-0.984)	-70.872 (-1.351)

Table 2 Continued

Variable	β_{OLS} (1)	β_{OLS} (2)
Distance-Road	-17.438 (–0.582)	-17.532 (-0.591)
Electricity	-10.771 (-0.471)	-11.421 (-0.716)
Plot-Accessability	-19.810 (-0.671)	-22.361 (-1.07)
Farm-Parcels	-19.213 (-0.953)	-19.927 (-1.105)
Intercept	587.82 (7.271)**	561.91 (6.829)**
Joint F test {H_0: $\beta_{Land\text{-}Holding} = \beta_{(Land\text{-}Holding)^2} = 0$}	1.54 [0.67]	3.31 [0.06]
Joint F test {H_0: All village dummies = 0}	3.75 [0.01]	3.83 [0.01]

- *Note* : The 25 VDC Dummy coefficient estimates are not reported ; Null Hypothesis that VDC dummies are not different from zero, was rejected at the 1% significance level for both specifications
- ***Number in parenthesis represent t statistics (β_{OLS} / s.e.) ; Number is brackets represent p-values***
- **** represents significance at the 5% level; ** represents significance at the 1% level***

Figure 1

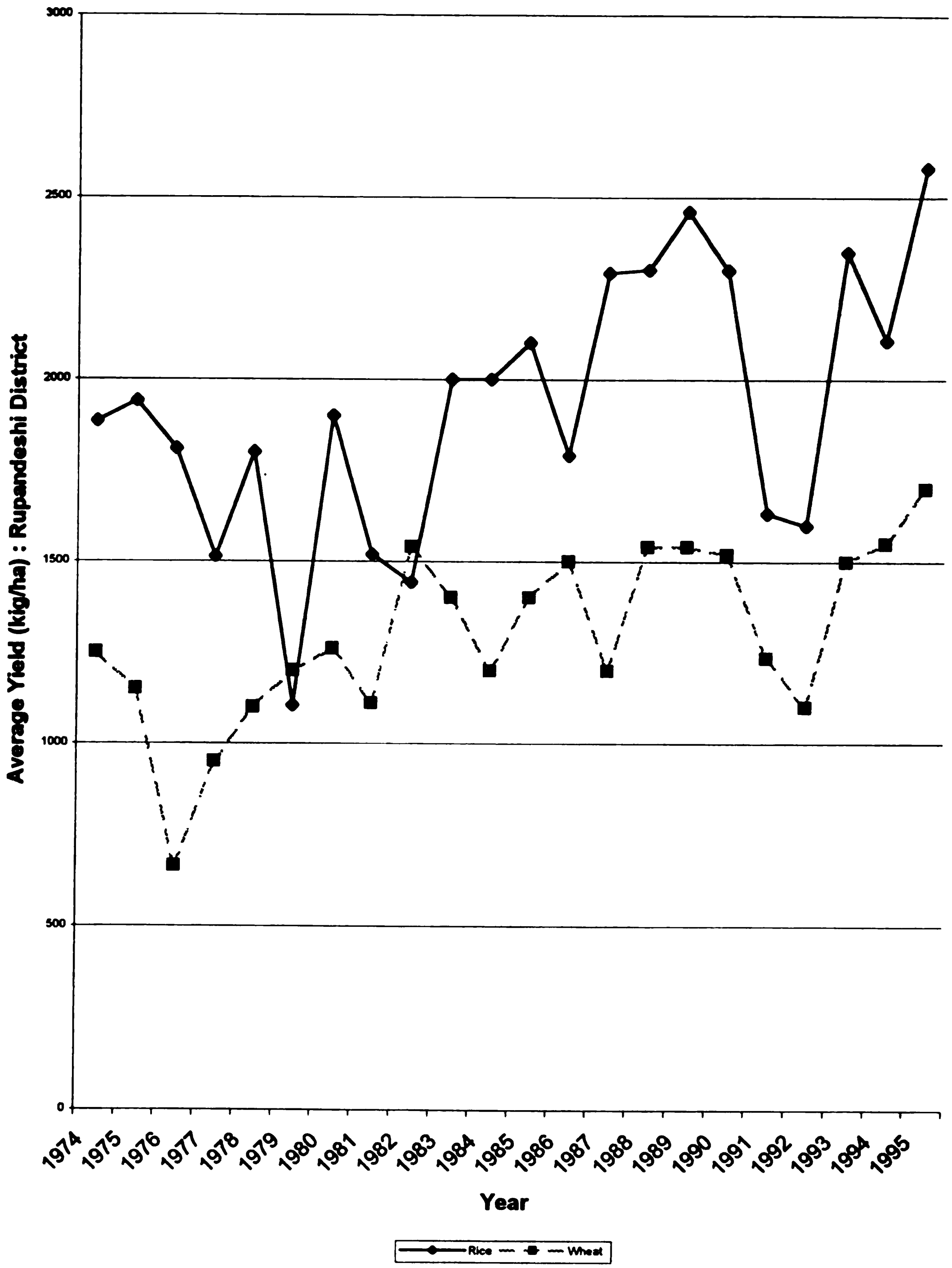

3000
2500
2000
1500
1000
500
0
Average Yield (kig/ha) : Rupandeshi District
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
Year
Rice
Wheat

Figure 2

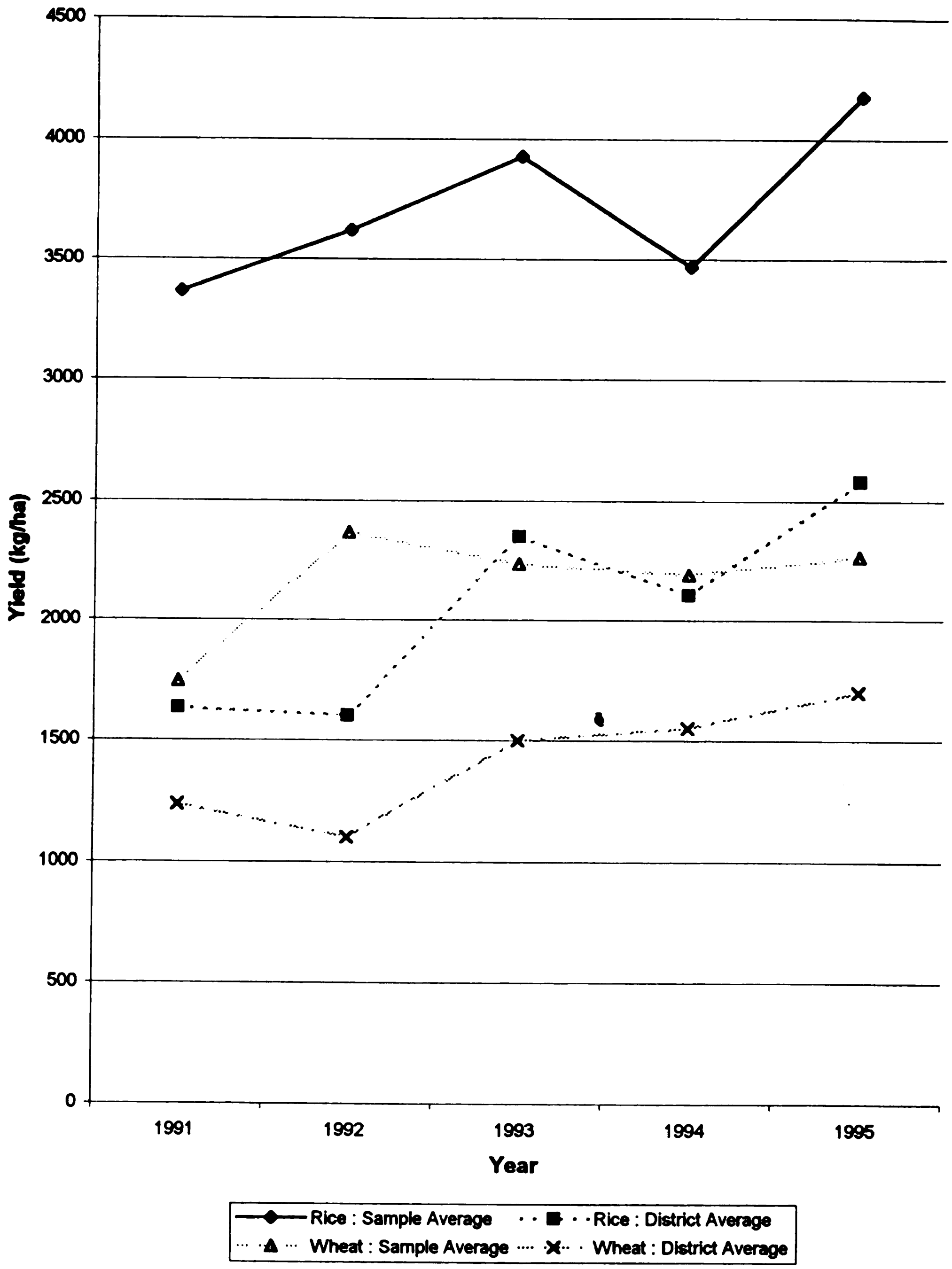

4500
4000
3500
3000
2500
2000
1500
1000
500
0
Yield (kg/ha)
1991
1992
1993
1994
1995
Year
Rice : Sample Average
Rice : District Average
Wheat : Sample Average
Wheat : District Average

Figure 3

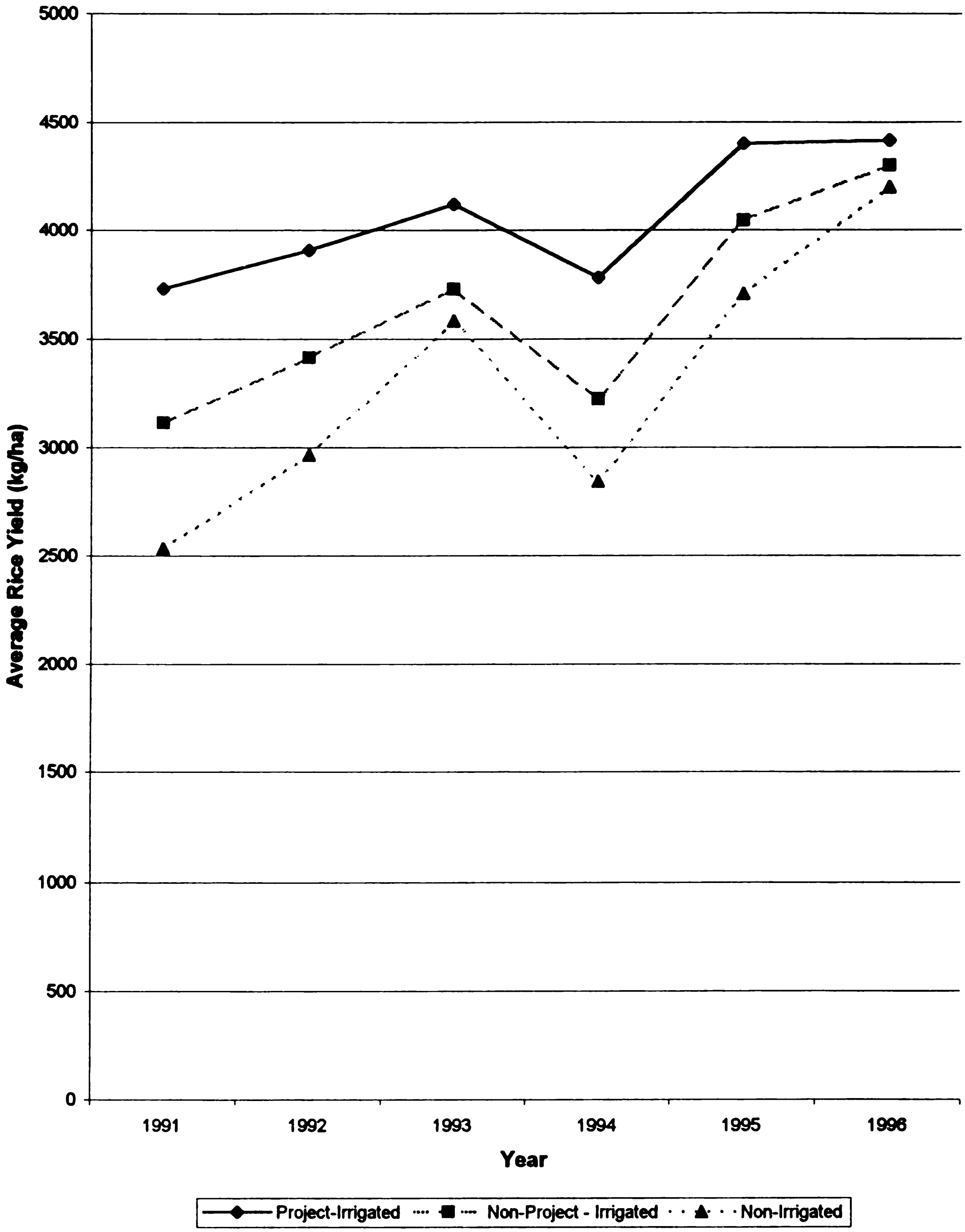
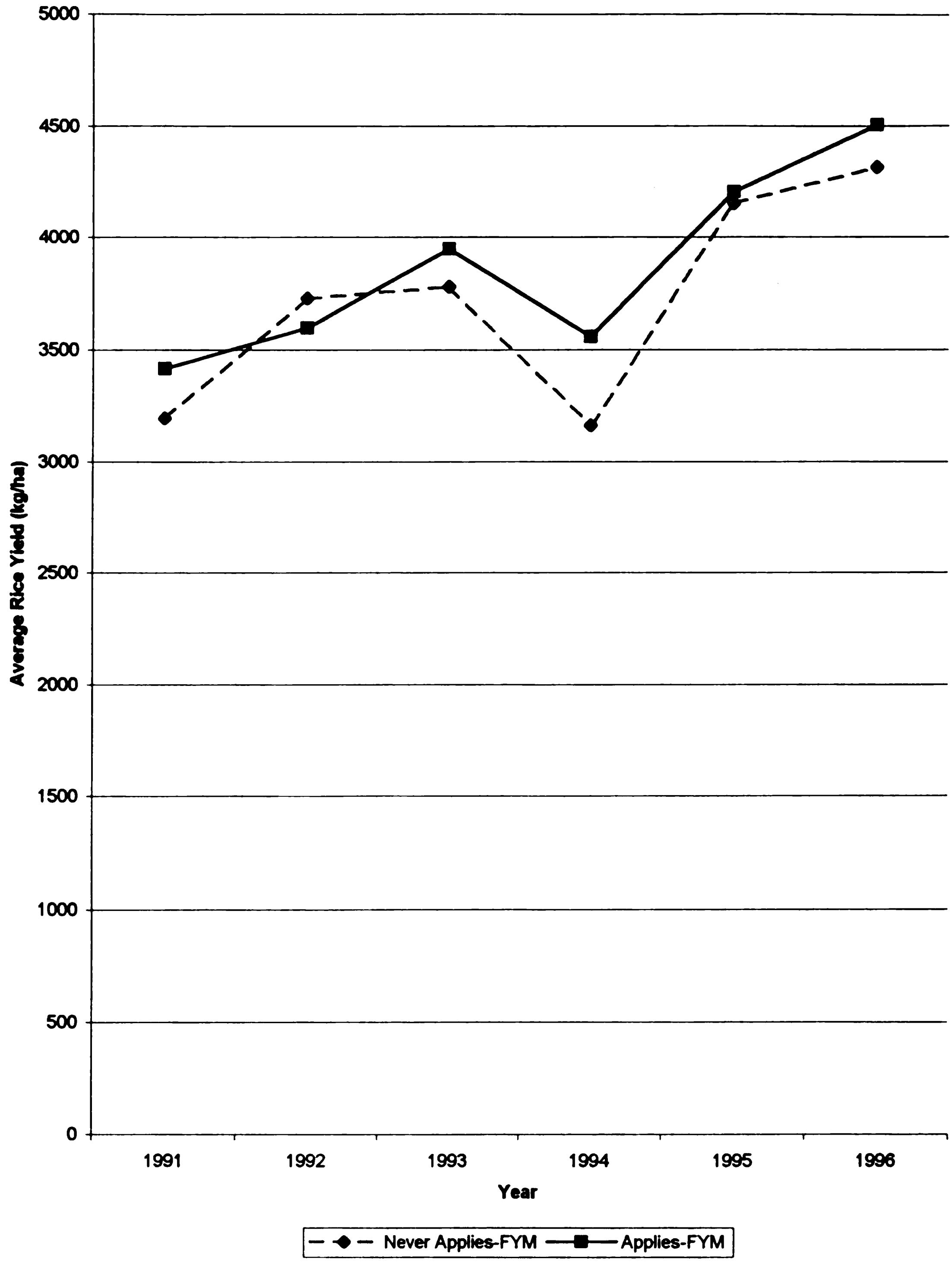
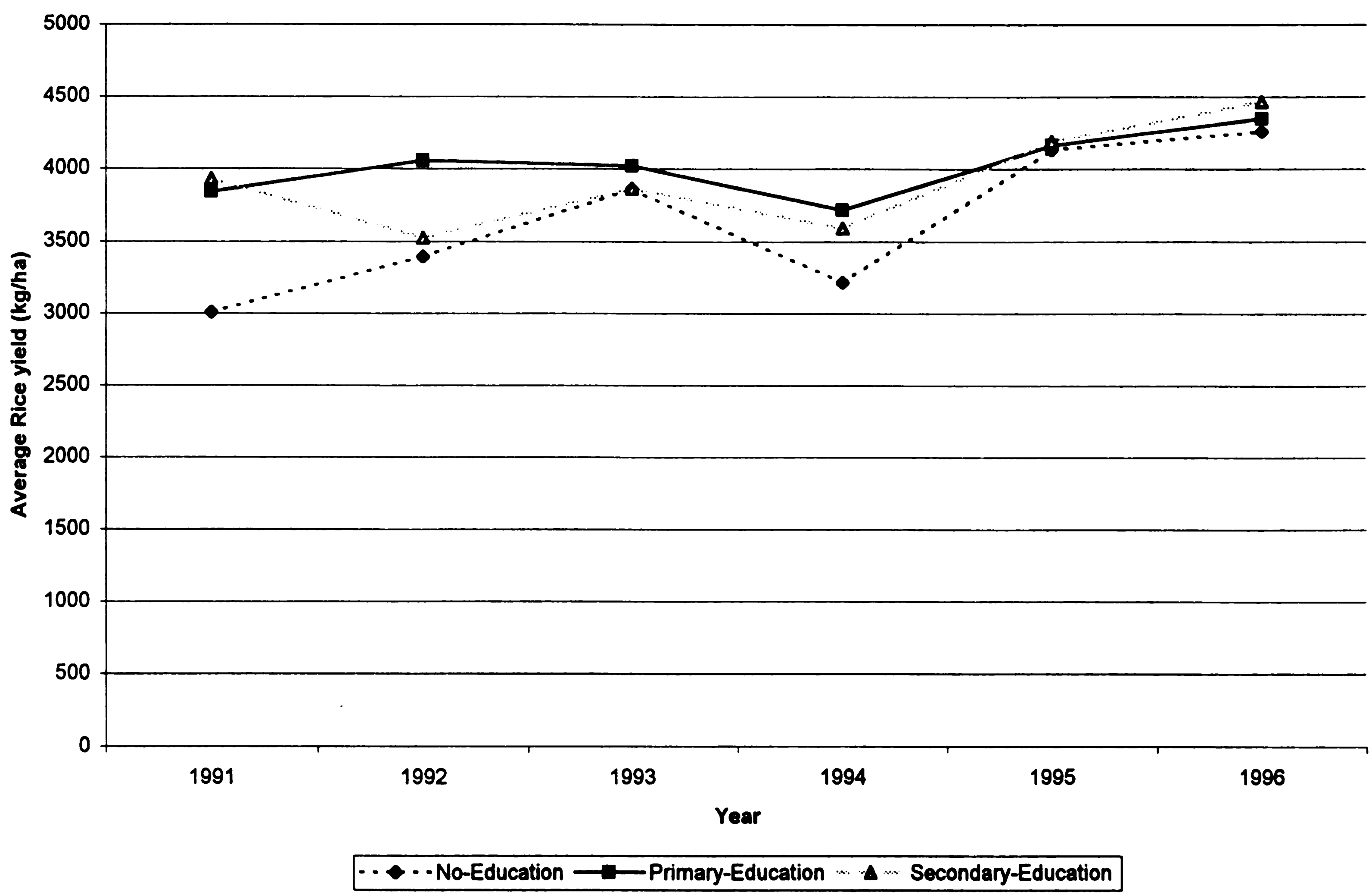

Average Rice Yield (kg/ha)
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
1991
1992
1993
1994
1995
1996
Year
Project-Irrigated
Non-Project - Irrigated
Non-Irrigated

Figure 4



5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
Average Rice Yield (kg/ha)
1991
1992
1993
1994
1995
1996
Year
Never Applies-FYM
Applies-FYM

Figure 5



5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
Average Rice yield (kg/ha)
1991
1992
1993
1994
1995
1996
Year
No-Education
Primary-Education
Secondary-Education

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Chapter 2

PRODUCTIVITY GROWTH OF NEPALESE AGRICULTURE

I. Introduction

The neoclassical growth models pioneered by Abramovitz (1956), Swan (1956), Solow (1957), Fabricant (1959), and Kendrick (1961), highlighted the role of (exogenous) technological change in driving macro economic growth. The "Solow residuals" - the residual growth in output not accounted for by the growth in factor inputs, were supposed to measure the contribution of technological progress (also often referred to as "Total Factor Productivity" growth). However, long before the emergence of "new growth theory" in macro economics which began to emphasize the role of investments in human capital and research-and-development (R&D) as endogenous drivers behind technological change (e.g., Romer 1986, 1987, 1990; Grossman and Helpman 1991; Aghion and Howitt 1992), Griliches' seminal empirical analysis on the measurement and explanation of productivity growth in United States agriculture, highlighted the role of education and public expenditures on agricultural research and extension (R&E), as the principle drivers of growth in the agricultural sector (e.g., Griliches 1963; 1964;1967). Building upon Griliches' work, various researchers have explored the determinants of productivity growth in the context of international agricultural development (e.g., Hayami and Ruttan 1971, 1985; Evenson and Kislev 1975, Boyce and Evenson 1975, Evenson and McKinsey 1991; Binswanger and Ruttan 1978; Mundlak and Hellinghausen 1982; Lau and Yotopoulos 1989).

Discourse on how to measure productivity and exploration of the determinants of productivity growth, continues to be an important agenda in international agricultural research. Particularly within a developing country context, productivity increasing technological change in agriculture has been recognized as one of the principal catalysts of growth. Ideally, the positive impacts of increasing productivity comes about through an interplay of boosting output, increasing demand for agricultural labor, lowering food prices, improving rural incomes, stimulating rural non-farm employment, and increasing purchasing power of poor consumers. Thus, the linkages between increasing agricultural productivity and its multipliers, helps to initiate the economic transformation from a predominantly agrarian to a primarily industrial and service-oriented economy (Timmer 1988; Mellor 1995).

The agenda of this study is to examine the productivity of Nepalese agriculture at the aggregate district (agro-ecological) level. Nation level analysis is useful in the sense that it provides a general picture of overall agricultural performance. However, given that in this study, I am relying upon estimates based upon primal representation of the underlying production technology, it is often difficult to estimate "individual country production functions from individual country data ... The first difficulty is insufficient variation of the quantities of inputs, due to multicollinearity ..., or due to restricted range of variations ..., or due to approximate constancy of factor ratios resulting from approximate constancy of relative factor prices ... Insufficient variation in the data due to any one of the above-mentioned reasons results in imprecision, unreliability, and possible under identification of the estimated parameters of the production function .. The second difficulty is the general inability of separate identification of the level of technological change of the production function of an individual country and its biases or the degree of returns of scale from time-series data on output and inputs of that country alone (Lau and

Yotopoulous 1989 , p.242). Thus, not only can district level analysis differentiated by agro-ecological zones provide a sharper picture of agricultural performance, it also avoids some of the pitfalls mentioned above.

Currently there is a dearth of empirical studies on the productivity of Nepalese agriculture at either the national, regional or commodity specific level. For example, an unpublished M.S. thesis in 1973 was the first and subsequently for 26 years, has been the only study in which someone attempted to estimate the Total Factor Productivity (TFP) growth of Nepalese agriculture (Shah 1973). The Nepalese economy is predominantly agrarian with more than 90% of the population living in rural areas (and about 80% of the active labor force employed in agriculture). Unfortunately the performance of the agricultural sector over the last few decades has been dismal, and "can generally be summarized as stagnant, with increasing population pressure leading towards fragmentation of land, lower labor productivity and further poverty" (Pokharel 1993, p.43). Nepal, which used to be a food-grain surplus country in the 1970's, has changed to a food grain-deficit country in the 1990's (Banskota 1992). Domestic cereal production and food availability per capita is on a decline in Nepal (Ali, Hobbs and Velasco 1993). Export earnings from both the agricultural and non-agricultural sectors are insufficient to allow Nepal to pursue a food security policy which primarily depends upon cereal imports (ADB 1992). Labor absorbing industrial development has yet to emerge as a significant factor in the Nepalese economy. However, currently only the agricultural sector has the size and the multipliers necessary to stimulate broad based economic growth. Thus, Nepal cannot afford to spend its reserves of hard currency on procurement of cereals from the international market. Nepal must rather rely upon strategies which enhance domestic cereal production in an arable land-constrained environment.

Thus, it is imperative that we analyze prospects for productivity growth in Nepalese agriculture. I am aware of the apprehensions Griliches expressed more than three decades ago regarding 'mere' estimation of technical change - "Identification of measured growth in total factor productivity .. provides methods for measuring technical change, but provides no genuine explanation of the underlying changes in real output and input. Simply relabeling these changes as Technical Progress or Advances of Knowledge leaves the problem of explaining growth in total output unsolved." (Griliches 1967, p.309). However, given the paucity of sound empirical diagnosis on the state of Nepalese agriculture, this study provides a necessary starting point from which to launch a systematic investigation of the productivity of Nepalese agriculture.

Changes in productivity growth reflect changes in scale, technology, human capital, quantity and quality of the natural resource base, and efficiency. Economic efficiency in production is determined by the technique of applying inputs and levels of application of inputs. Technical efficiency (TE) reflects the ability to obtain the maximum possible output from a given set of inputs. This is the most widely used measure of the efficiency of a production unit. Allocative efficiency (AE) reflects the ability to maximize profits, by equating the marginal revenue product with the marginal costs of inputs. While TE measures can be estimated from (primal) input-output data, estimation of AE measures requires (dual) cost/price information. It is not surprising then that TE is the most widely used measure of efficiency in the developing country literature (Bravo-Ureta and Evenson 1994), reflecting the fact that cost of production data is relatively more scarce compared to physical input-output data. Analytically, estimation of AE is further complicated by a host of market failures which plagues the agricultural sector of many developing countries (e.g., AE in production will fail to hold if farmers faces either a credit/liquidity constraint or an input supply constraint). Thus, while estimation of TE does not (explicitly) require assumptions of market efficiency, most AE measures are obtained under the restrictive (and probably unrealistic) assumption of a perfectly competitive market environment.

Most estimates of technical change or TFP are based upon non-parametric growth accounting methods embedded in the neoclassical framework, characterized by competitive equilibrium and constant return to scales (which imply that payments to factors should exhaust total product). The growth accounting approach is as follows: (a) detail accounts of all pertinent outputs and inputs of the production process are compiled; (b) these outputs and inputs are aggregated using various types of indexing procedures, and these indexes are used to calculate a TFP index. The various indexing procedures reflect economic assumptions of the underlying production technology and production environment. The basic idea is that if 'technological' change occurs, then payments to factors would not exhaust total product, and there would remain a residual output not accounted for by increases in total factor input (Capalbo and Antle 1988). This has been by far the most common representation of TFP. However, the principal drawback of the growth accounting method is that it is relatively data-intensive requiring extensive factor price information. As Block (1993) points out, the data-intensity of growth accounting methods makes it an impractical tool for examining the productivity in the agricultural sector of most African countries. Similarly most productivity studies of South Asian agriculture have been carried out using Indian and Pakistani data - countries like Nepal lack the institutional capacity to collect pertinent detailed data on a systematic basis in order to carry out most growth accounting exercises. Thus, in such data-constrained cases, parametric approaches which primarily draw upon physical input-output data, are more appropriate. While the growth accounting procedure makes strong assumptions about the underlying production technology (e.g., constant returns to scale) and production environment (e.g., perfect competition), the econometric approach makes an equally strong assumption - that the nature of technological change can be represented as a function of time[8].

Specifically, in this study, I will: (a) estimate the district level rates of technical change in Nepalese agriculture based upon parametric estimation of the underlying production technology within the "meta-production function" framework; (b) derive point estimates of district level technical efficiency from econometric estimation of the production technology within the 'stochastic production frontier framework'; and (c) given that I am interested in comparing efficiency levels across districts, I also construct confidence intervals around the time varying technical efficiency estimates, using non-parametric bootstrap methods. This study, is thus, both an effort to fill the gap in the productivity literature on Nepalese agriculture, and to add to the growing literature on the efficiency of South Asian agriculture.

Section II of this paper lays the analytical framework and empirical procedures used to estimate district level technical change and efficiency; Section III briefly discusses the district level data sources; Section IV presents the empirical findings from the analysis;

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[10] Technological change is synonymous to productivity change under the assumption that production is efficient or that the degree of inefficiency is constant.

and Section V highlights the main conclusions (and shortcomings) of this study, suggests direction of further research, and discusses relevant policy implications.

II. Analytical Framework

To estimate district level rates of technical change (RTC), I employ a "Meta-Production Function" approach as originally forwarded by Hayami (1969) and Hayami and Ruttan (1970, 1985), and extended by Lau and Yotopoulos (1989) and Lau et al. (1993). Under a meta-production function framework, it is assumed that all production units have access to the same underlying technology. As I will show, there is 'convergence' between the stochastic production frontier approach (Aigner, Lovell and Schmidt 1977; Meeusen and Van de Broeck 1977; Jondrow et al. 1982) and the resulting estimation framework of our production technology. District level time-varying TE estimates will be estimated following the approach of Schmidt and Sickles (1984) and Cornwell, Schmidt and Sickles (1990); bootstrap confidence intervals for the district level TE estimates will be constructed along the lines of Schmidt and Kim (1999).

Following Lau et al. (1993), I assume that all districts within a given agro-ecological region have access to the same technology, i.e., an underlying aggregate production function F(.), a meta-production function. However, different districts operate may operate on different parts of the meta-production function. These differences arise from possible differences in efficiencies of production, differences in quality of inputs (man-made and natural resources), or due to various measurement errors. Despite these differences, the measured outputs and inputs of the different states may be converted into standardized "efficiency-equivalent" units of outputs and inputs:

$$Y^*_{it} = F(X^*_{jit}, E_{it}) \quad \forall\ j = 1,\ldots,J\ ;\ i = 1,\ldots,N\ ;\ t = 1,..T \qquad (1)$$

where, Y is output; Xs are "conventional" inputs indexed by j (J inputs); E is education; district index i (N districts); and time index t (T time periods). The implicit assumption is that the meta-production function itself does not depend on i but may depend on t.

The "efficiency-equivalent" quantities of outputs and inputs are off course are not directly observable. They are however, assumed to be linked to the measured quantities of outputs and inputs, through possibly time-varying and district-and-commodity-specific augmentation factors:

$$Y^*_{it} = A_{oi}(t)Y_{it} \tag{2}$$

$$X^*_{jit} = A_{jit}(t)X_{jit} \qquad \forall j = 1,\ldots,J \tag{3}$$

$$E^*_{it} = E^*_{it} + A_{iE}(t) \tag{4}$$

There are many reasons why these commodity augmenting factors are not likely to be identical across districts. Examples include differences in climate, topography, natural resources and infrastructure; differences in definitions and measurements; and differences in the efficiencies of production. For empirical implementation, the commodity augmentation factors for output and all inputs besides education are assumed to have a constant exponential form with respect to time. The augmentation factor for education is assumed to have the linear form with respect to time. Thus,

$$Y^*_{it} = A_{oi}(t)Y_{it} = A_{oi} \exp^{(C_{oi} * t)} Y_{it} \tag{5}$$

$$X^*_{jit} = A_{jit}(t)X_{jit} = A_{ji} \exp^{(C_{ji} * t)} X_{jit} \; \forall j = 1,..,J \tag{6}$$

$$E^*_{it} = A_{iE}(t) + E_{it} = A_{iE} + C_{iE} * t + E_{it} \tag{7}$$

where, A's are the augmentation level parameters and C's are the augmentation rate parameters (assumed to be constants).

For this study, I assume that the meta-production function (1), takes on a Cobb-Douglas functional form[9]:

$$\ln Y^*_{it} = \ln Y_0 + \sum_{j=1}^{J} \alpha_j \ln X^*_{jit} + \alpha_E E^*_{it} \quad (8)$$

By substituting equations (5) through (7) into the Cobb-Douglas form, and rearranging terms, we get:

$$\ln Y_{it} = \ln Y_0 + \sum_{j=1}^{J} \alpha_j \ln X_{jit} + \alpha_E E_{it} + \{-\ln A_o + \sum_{j=1}^{J} \alpha_j \ln A_j\} + \{-C_{oi} + \sum_{j=1}^{J} C_{ji}\} * t \quad (9)$$

We can then rewrite (9) as:

$$\ln Y_{it} = \ln Y_0 + \sum_{j=1}^{J} \alpha_j \ln X_{jit} + \alpha_E E_{it} + A^*_i + C^*_i * t \quad (10)$$

In order to estimate equation (10) within a statistical framework, I add an independently and identically distributed (iid) two sided $N(0,\sigma_\varepsilon^2)$ stochastic disturbance term ε_{it}, having identical variance and assume that it is uncorrelated across districts:

$$\ln Y_{it} = \ln Y_o + \sum_{j=1}^{J} \alpha_j \ln X_{jit} + \alpha_E E_{it} + A^*_i + C^*_i * t + \varepsilon_{it} \quad (11)$$

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[11] Given the limits of the panel data and the number of inputs I include in the estimation, I cannot use a more flexible functional form such as a transcendental logarithmic function (Christensen et al. 1973). I also do not use a Cobb-Douglas plus (log) interactions of selected inputs due to computational limitations and generally weak results. I shall bring up this issue again in section V.

Thus, using the meta production function framework with a Cobb-Douglas specification, district level time-invariant heterogeneity, A_i ,and district level time-varying heterogeneity, C_i, enter the estimation in a linearly separable fashion. District level rate of technical progress/RTC, is captured by the district-specific heterogeneity term interacted with the time trend, C_i . The specification of equation (11) does not allow us to estimate separate commodity-specific rates of technical change (C_{ji} $\forall$ j = 1,..,J). However, given that in this study I am primarily interested in estimating overall rates of technical change at the district level, the specification of equation (11) will suffice.

The specification of equation (11) is similar to the Fixed-Effects Panel data framework regarding the estimation of technical (in)efficiency of production. A Cobb-Douglas specification within a stochastic frontier framework is as follows:

$$\ln Y_{it} = \ln Y_o + \sum_{j=1}^{J} \alpha_j \ln X_{jit} + \alpha_E E_{it} + \varepsilon_{it} - TIE_{it} \qquad (12)$$

where, TIE_{it} (≥ 0) represents time-varying inefficiency (i.e., firm-district technical inefficiency is allowed to change over time). We can rewrite equation (12) as:

$$\ln Y_{it} = \alpha_{it} + \sum_{j=1}^{J} \alpha_j \ln X_{jit} + \alpha_E E_{it} + \varepsilon_{it} \qquad (13)$$

where, α_{it} = ($\ln Y_0$ - TIE_{it}); We then represent the time-varying firm-district technical inefficiency effect as an explicit function of time: $\alpha_{it} = \theta_{1i} + \theta_{2i}{*}t$; we can then rewrite equation (13) as:

$$\ln Y_{it} = \sum_{j=1}^{J} \alpha_j \ln X_{jit} + \alpha_E E_{it} + \theta_{1i} + \theta_{2i} * t + \varepsilon_{it} \qquad (14)$$

The core idea behind the stochastic frontier framework is the same, regardless of cross-section or panel data applications. Let us look at the last three terms of equation (14). The last term, ε_{it}, is the "familiar" iid two sided $N(0,\sigma_\varepsilon^2)$ random variable representing model mis-specification, and random shocks (taking on values which can either be, negative, zero, or positive), while the TIE parameters, θ_{1i} and θ_{2i}, represent firm-district specific factors which influence whether firm-district i attains maximum efficiency of production (taking on values which can either be positive or zero). At any given time period, a value of 0 for TIE indicates that the firm-district is operating on its frontier, and any value greater than 0 indicates that the firm-district is below the frontier (under the assumption that all districts are bounded by the same frontier - if that assumption does not hold, then we cannot separate differences across districts from TIE within a district).

By construction of the model, the TIE parameters, θ_{1i} and θ_{2i}, are correlated with the Xs, thus, suggesting a Fixed-Effects (FE) specification as advanced by Schmidt and Sickles (1984), and extended by Cornwell, Schmidt and Sickles (1990), henceforth referred to as CSS 1990. Unlike the Random-Effects characterization of this problem which often requires strong distributional assumptions about the nature of the TIE parameters, the only further assumption I need to make is that of 'Strict Exogeneity'(Wooldridge 1996):

$$E(\varepsilon_{it} | \theta_{1i}, \theta 2_i, \ln X_{1i1},...,\ln X_{1iT},..., \ln X_{Ji1},...,\ln X_{JiT}, E_{i1},...,E_{iT}) = 0 \qquad (15)$$

When the strict exogeneity condition holds, X_{jit} $\forall$ t = 1,..,T (and $\forall$ j = 1,..,J) are strictly exogenous conditional upon the two unobserved (or latent) effects. This follows from the conditional mean specification:

$$E(\ln Y_{it} | \theta 1_i, \theta 2_i, \ln X_{1i1},...,\ln X_{1iT},..., \ln X_{Ji1},...,\ln X_{JiT}, E_{i1},...,E_{iT}) =$$

$$\sum \alpha_j \ln X_{jit} + \theta 1_i + \theta 2_i{*}t \tag{15.1}$$

Given the assumption of strict exogeneity[10], ignoring issues of efficiency for the moment, the parameter estimates of the production function (α_j $\forall$ j = 1,..,J) in equation (11)/(14) can be obtained through a number of econometric techniques (Green 1990; Wooldridge 1996). The specification of equation (11)/(14) is no more than that of the standard unobserved fixed-effects model augmented by a district-specific trend as an additional source of heterogeneity - a 'random growth model' (Heckman and Hotz 1988). Whenever the dependent variable is expressed in natural logs, the $\theta 2_i$ parameter can be viewed as the average growth rate over a period (holding the explanatory variables fixed). Possible estimation strategies include: simple least squares including district dummies and district dummies interacted with a time trend; Second-Differencing and then applying least squares; First-Differencing and then standard 'within' FE estimation (for the nuances pertaining to the consistency of the estimates and asymptotic properties implied by these different techniques, please see Wooldridge 1996).

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[12] If the strict exogeneity assumption fails to hold, then this problem can still be estimated using non-linear instrumental variable techniques, under the assumption of 'Weak Exogeneity'or 'Sequential Moment Restrictions':

$$E(\epsilon_{it} | \theta 1_i, \theta 2_i, \ln X_{1iT},\ln X_{1iT-1},...,\ln X_{1i1},..., \ln X_{JiT},\ln X_{JiT-1},...,\ln X_{Ji1}, E_{iT},E_{iT-1},...,E_{i1}) = 0, \ t = 1,..,T$$

For this study I will use the efficient instrumental variables approach advanced by CSS 1990 as a comprehensive approach towards estimating panel data models with heterogeneity in slopes as well as in intercepts. CSS 1990 specifies a systematic framework in which to obtain consistent estimates of both the production function parameters, and the time-varying district level productivity/(in)efficiency[11]. Following CCS 1990, I rewrite the data-intensive representation of equation (11) in matrix notation as follows:

$$Y = \ln Y_0 + X\beta + Qu + \varepsilon_{it} \qquad (16)$$

where: Y is the (NT x 1) output vector of stacked $\ln Y_{it}$ (stacked by each N which is observed T times); $\ln Y_0$ is (NT x 1) vector of 1s; X is the corresponding (NT x K) input matrix following the stacking order of Y - now including E_{it}; β is a (K x 1) vector of parameters to be estimated; Q is the (NT x NL) block-diagonal matrix (with ⌀ on the off-diagonals) representing district level time-invariant and time-varying heterogeneity[12]; and, u is the (N*L x 1) parameter vector of θs (L = 2 in our setting) - for example, the first 2 rows of u would be θ_{11} and θ_{21}, and the last two rows would be θ_{1N} and θ_{2N}, respectively.

Given that I will be dealing with the case in which L $\leq$T, Q will have full column rank, and thus, β will be identified. Let $P_Q = Q(Q'Q)^{-1}Q'$ be the projection onto the column space of Q (NT x NT). Let $M_Q = (I_{N\bullet T} - P_Q)$ be the projection onto the null space of Q (NT x NT). The consistent "within" estimator is given by:

$$\hat{\beta}_W = (X'M_QX)^{-1} X'M_QY \qquad (17)$$

[13] While instead of specifying the firm-district level effect as $\alpha_{it} = \theta 1_i + \theta 2_{2i}t + \theta 3_i t^2$ as in CSS 1990, in this study we end up with only a linear time effect.

[14] For example, the "first block" would be (there would be N such blocks): T rows of 1s in the first column; T rows of the time-trend (1 to T) in the second column.

The within estimator is an instrumental variable (IV) estimator, with instruments M_Q; note, that since $M_Q \ln Y_0 = 0$, the constant intercept term of the production function cannot be consistently estimated. Similar to the standard FE within model (i.e., when $\theta 2_i = 0$), equation (16) can be transformed by M_Q and the parameter estimates of the production function can be obtained via least square regression of $M_Q Y$ on $M_Q X$.

I can then estimate district level technical (in)efficiency measures using the within residuals ($\hat{e}_W = Y - X\beta_W$) following CSS 1990; Schmidt and Sickles (1984). For each district, we regress the T district residuals on a constant and a time-trend (i.e., a least square regression with T-L degrees of freedom), to get $\hat{\theta}1_i, \hat{\theta}2_i$ (which are consistent $\forall$ i and t, as $T \to \infty$). Once the $\hat{\theta}1_i, \hat{\theta}2_i$ estimates have been obtained (e.g., either through 'two-step' CSS 1990 method, or through 'one-step' OLS regression of output on inputs and district level dummies and district level dummies interacted with time), for each time period, we can evaluate $(\hat{\theta}1_{it} + \hat{\theta}2_{it} * t) \forall$ i = 1,..,N. Then we can define:

$$\hat{\theta}_{it} = \max_{i=1,\ldots,N}(\hat{\theta}1_{it} + \hat{\theta}2_{it} * t) \tag{18}$$

For each time period, we can obtain the technical inefficiency estimates for each district as follows:

$$\hat{T}I_{it} = \hat{\theta}_{it} - (\hat{\theta}1_{it} + \hat{\theta}2_{it} * t) \tag{19}$$

For any given time period, the district with the lowest value of $\hat{T}I_{it}$ can be thought of as the *best* district in the sample (with a value of 0 indicating that the production in the district is occurring on it's frontier). Thus, $\hat{T}I_{it}$ is an estimate of relative rather than absolute inefficiency. Given that the production technology follows a logarithmic specification, the technical efficiency estimate, TE_{it}, for each time period (and for each district) can be expressed as:

$$\hat{T}E_{it} = \exp^{(\hat{T}I_{it})} \tag{20}$$

Thus, technical efficiency estimates are also expressed "relative"to the most efficient (*best*) district (with a value of 1 indicating that the production in the district is occurring on it's frontier). With N fixed, as $T \to \infty$, $\hat{\theta}1, \hat{\theta}2$, are consistent estimates of θ1 and θ2 (∀ i and t), and similarly $\hat{T}I_{it}$ is a consistent estimate of α_{it} (∀ i and t). However, given that in this study I am using a sample with a relatively small T(=11), $\hat{T}I_{it}$ may be biased upwards - the "max" operator in equation (18) induces upward bias, since the largest $(\hat{\theta}1_{it} + \hat{\theta}2_{it} * t)$ is more likely to contain positive estimation error than negative error. This bias is large when N is large (relative to T), and when $(\hat{\theta}1_{it} + \hat{\theta}2_{it} * t)$ is measured imprecisely. Upward bias in $(\hat{\theta}1_{it} + \hat{\theta}2_{it} * t)$ induces an upward bias in $\hat{T}I_{it}$, and thus a downward bias in $\hat{T}E_{it}$ - thus, efficiency would be underestimated given that the level of the frontier has been overestimated. For a rigorous exposition of the asymptotic properties of these type of models, please see Park and Simar (1994).

Given that I have not made any distributional assumptions regarding the nature of the time-invariant and time-varying heterogeneity (or technical inefficiency), at this juncture I only have 'point estimates' of $\hat{TI}_{it}$ and $\hat{TE}_{it}$. I cannot rank (in)efficiency levels across firms-districts with statistical precision. The overwhelming majority of past empirical studies of efficiency have tended to overlook this issue. We can use (non-parametric) bootstrapping to construct confidence intervals both $\hat{TI}_{it}$ and $\hat{TE}_{it}$. (Simar 1992; Hall, Hardle and Simar 1993, 1995; Kim and Schmidt 1999). The bootstrap method was introduced in 1979 as a simulation-based method for estimating the standard error of any given estimator, $\hat{\theta}$, regardless of the mathematic complication of the estimator (the following section closely follows Efron and Tibshirani 1993). The core of this technique rests upon the notion of a bootstrap sample. For example, let $X = (x_1,\ldots,x_n)$ be an observed random sample from an unknown probability distribution F, with a corresponding estimator $\hat{\theta} = S(X)$, and unknown standard error $se_F(\hat{\theta})$. Let $\hat{F}$ be the empirical distribution, which places a probability of $1/n$ on each of the observed values . A bootstrap sample, X^*, is defined to be a random sample of size n drawn from $\hat{F}$. Thus, while X represents the actual data set, X^*, represents a resampled version of X - the bootstrap data points $(x^*_1,\ldots,x^*_n)$ are a random sample of size n drawn with replacement from the population of n objects $(x_1,\ldots,x_n)$. Therefore, the bootstrap data set $(x^*_1,\ldots,x^*_n)$ consists of the same members of the original data set $(x_1,\ldots,x_n)$, some appearing zero times, some appearing once, and some appearing more than once. The corresponding bootstrap replication of the estimator is, $\hat{\theta}^* = S(X^*)$. The bootstrap estimate of the standard error of the estimator/statistic $\hat{\theta}$, is a plug-in estimate that uses the empirical distribution function $\hat{F}$ instead of the unknown distribution F. The following is the algorithm for estimating non-parametric (since the estimate is based on the non-parametric estimate of the population) standard errors of any estimator from an observed random sample X:

(1) Select B independent bootstrap samples $X^{*1},\ldots,X^{*B}$, each of size n with values drawn with replacement from X.

(2) Evaluate the bootstrap replication corresponding to each bootstrap sample,

$$\hat{\theta}^*(b) = S(X^{*b}) \forall\, b = 1,\ldots,B$$

(3) Approximate $se_F(\hat{\theta})$ by the sample standard deviation of the B replications:

$$\hat{s}eB = \sqrt{\sum_{b=1}^{B} [\hat{\theta}^*(b) - \hat{\theta}(.)]^2 \Big/ (B-1)} \qquad ,$$

where, $\hat{\theta}(.) = \sum_{b=1}^{B} \hat{\theta}^*(b) \big/ B$; and asymptotically, $\lim_{B \to \infty} \hat{s}e_{\hat{F}} = se_{\hat{F}}$.

Now turning to the specifics of this study, I will outline the bootstrap procedure on how to simulate the standard errors and construct confidence intervals for the estimate[13] for which I am primarily interested in, $\hat{T}E_{it}$. Given that the within estimation described above is for all practical purposes analogous to doing least squares with district dummies and district dummies interacted with time - "the elaborate matrix results in their (CSS 1990) paper notwithstanding, for a moderately sized data set, the most expeditious way to handle this model is brute force, OLS" (Green 1990, p. 113), I will follow Green's advice when running the bootstrap simulation. Thus, $\hat{\theta}1_i, \hat{\theta}2_i$, is estimated in a 'one-step' procedure from the least square regression of output on inputs plus district dummies and district dummies interacted with time, i.e., OLS regression of equation (14). The bootstrap samples will then be drawn by resampling the OLS residuals. For the first iteration: (1) I resample the original OLS residuals; (2) generate a corresponding pseudo data set $Y^{(1)}$ (or a resampled Y) using the parameter estimates of the inputs and $\hat{\theta}1_i, \hat{\theta}2_i$, $Y^{(1)} = X\hat{\beta}OLS + \hat{\theta}1i + \hat{\theta}2i*t + \hat{e}^{(1)}OLS$; (3) redo the OLS estimation using original X and resampled $Y^{(1)}$, to get $\hat{\beta}^{(1)}{}_{OLS}, \hat{\theta}1_i{}^{(1)}, \theta2_i{}^{(1)}$;(4) use $\hat{\theta}1_i{}^{(1)}, \hat{\theta}2_i{}^{(1)}$ to estimate $\hat{T}I^{(1)}{}_{it}, \hat{T}E^{(1)}{}_{it}(\forall i, t)$. I repeat this procedure B(=2000 in this study) times to obtain

[15] Confidence intervals for θ1 and θ2 can of course be constructed via standard parametric techniques given that we already have the standard errors for these estimates, however, in this study I will also use bootstrapping methods to construct confidence intervals for these estimates.

bootstrap $\beta_{OLS}{}^{(b)}, \theta 1_i{}^{(b)}, \theta 2_i{}^{(b)}, TI_{it}{}^{(b)}, TE_{it}{}^{(b)}$. Proof of the validity of applying bootstrapping techniques for this problem is given by Hall, Hardle and Simar (1995).

The percentile bootstrap is the simplest bootstrap technique for constructing confidence intervals. Let $\hat{G}$ be the cumulative distribution function (cdf) of the B bootstrap replicates, $\hat{\theta}^{(*b)}$. The 1-2α percentile interval is defined by the α and 1-α percentiles of $\hat{G}$, with the lower and upper bound of the estimator given by: $[\hat{\theta}_{\%lo}, \hat{\theta}_{\%up}] = [\hat{G}^{-1}(\alpha), \hat{G}^{-1}(1-\alpha)]$. Since by definition:

$$\hat{G}^{-1}(\alpha) = \hat{\theta}^{*(\alpha)},$$

which represents the 100αth percentile of the bootstrap distribution, we can write the percentile interval as:

$$[\hat{\theta}_{\%lo}, \hat{\theta}_{\%up}] = [\hat{\theta}^{*(\alpha)}, \hat{\theta}^{*(1-\alpha)}]$$

For example, for a 90% confidence interval (CI), with B = 2000 and α = 0.05, the percentile interval is the interval ranging from the 100th to the 1900th ordered values of the 2000 bootstrap replicates. While the percentile technique is relatively simple, it might be an inaccurate method for relatively small time periods. The bias-corrected and accelerated (BCA) technique, is considered to be a substantial improvement over the percentile method in both theory and practice (for details please see Efron and Tibshirani 1993). The plug-in estimator tends to introduce downward bias in the bootstrap replicator. The BCA method automatically corrects for this bias. The BCA 1-2α CI is given by:

$[\hat{\theta}_{\%lo}, \hat{\theta}_{\%up}] = [\hat{\theta}^{*(\alpha 1)}, \hat{\theta}^{*(\alpha 2)}]$, where:

$$\alpha 1 = \Phi \{\hat{z}_o + \frac{\hat{z}_o + z^{(\alpha)}}{1 - \hat{a}(\hat{z}_o + z^{(1-\alpha)})}\} \; ; \; \alpha 2 = \Phi \{\hat{z}_o + \frac{\hat{z}_o + z^{(1-\alpha)}}{1 - \hat{a}(\hat{z}_o + z^{(1-\alpha)})}\}$$

where, Φ(.) Is the standard normal cdf and $z^{(\alpha)}$ is the 100αth percentile point of Φ(.). For example, $z^{(0.95)} = 1.645$, and $\Phi(1.645) = 0.95$. Note that if $\hat{a} = \hat{z}_o = 0$, then α1 = α, and α2 = (1-α), thus, I revert back to the percentile CI specification. The value of the *bias correction* $\hat{z}_o$ is obtained from evaluating inverse standard normal cdf at the proportion of bootstrap replications which are less than the original point estimate $\hat{\theta}$: $\hat{z}_o = \Phi^{-1}(\#\{\hat{\theta}^*(b) < \hat{\theta}\}/B)$; $\hat{z}_o$ measures the median bias of $\hat{\theta}^* and \hat{\theta}$, in normal units.

There are various methods that can be used to compute the acceleration factor, $\hat{a}$. A widely used method is to express it in terms of *jacknifed* values of a statistics. Jacknifing is similar to bootstrapping, and was used before the days of powerful PCs to save on computing time. Let X(i) be the original sample with the ith data point deleted; let the corresponding estimator be defined as $\hat{\theta}(i) = S(X(i))$, and define $\hat{\theta}(.) = \sum_{i=1}^{NT} \hat{\theta}(i) / NT$. An expression for the acceleration factor in terms of the jacknifed values is as follows:

$$\hat{a} = \frac{\sum_{i=1}^{NT} (\hat{\theta}(.) - \hat{\theta}(i))^3}{6 * \{\sum_{i=1}^{NT} ((\hat{\theta}(.) - \hat{\theta}(i))^2\}^{1.5}}$$

The acceleration factor refers to the rate of change of the standard error of $\hat{\theta}$ with respect to the true parameter value θ, measured on a normalized scale.

III. Data Section

I draw upon three data sources for this study: (1) *Revised Crop Area Statistics* ; National Planning Commission (NPC) 1994; (2) published and unpublished data from the Central Bureau of Statistics (CBS); (3) unpublished data from the Agricultural Input Corporation (AIC). Information on area planted to and production of major agricultural crops for the year 1974 - 1991 stems from the NPC 1994 data set. The NPC 1994 data is a revision/readjustment of area and production data collected by the Department of Food and Agricultural Marketing Services (DFAMS). This revision has brought about a drastic reappraisal of the performance of Nepalese agriculture (*Nepal: Agricultural Perspective Plan* 1995). Using unrevised DFAMS data, the growth rate of foodgrain production over the decade 1981-1991, was 5.03% per annum (compared to the population growth rate of 2.5% per annum). However, the area planted had been systematically under-measured in the DFAMS data set. The NPC 1994 data set corrects for this error (among other revisions). Using the NPC 1994 data, the growth rate of foodgrain production turns out to be 2.3% per annum, thus, less than the population growth rate during that decade.

Information of labor, livestock, literacy rates and rainfall, were obtained from the CBS. Fertilizer consumption data was obtained from the AIC.

Nepal can be divided into three agro-ecological zones (CBS 1997) : The Terai (lowlands); The Hills (middle mountains); and The Mountains (the High Mountains, and the High Himalayas). The Terai region is an extension of the Indo-Gangetic plains, comprises 23% of the land mass (and most of it arable) and 47% of the population; The Hill region comprises 42% of the land mass (however, only one tenth of its area is suitable for cultivation) and 46% of the population. The Mountain region comprises 35% of the land mass (less than 2% of the land in this region is suitable for cultivation) and 7% of the population. The importance of the Terai stems from the fact that it remains as the only food grain-surplus region in Nepal and is the most favorable area for intensified agriculture.

The three agro-ecological zones are divided into 75 districts: 20 districts fall in the Terai region; 39 districts fall into the Hill region; while, 16 districts fall into the Mountain region. In this study, I will exclude districts which fall in the Mountain region from my analysis. This is primarily due to the fact that data from the Mountain region tends to be erratic and in many instances may be unreliable. In terms of agricultural production, the Mountain region is a very minor player in Nepal, with most of the action taking place on the flood plains of the Terai or on the slopes and valleys of the Hill region. I also restrict the time frame of my analysis to cover the period 1981-1991, the period for which more complete data are available. The variables used in this study are as follows:

(1) *Output*: Aggregated value of Rice, Maize, Millet, Wheat, Barley, Oilseed, Potato, Tobacco and Sugarcane output, valued at 1991 prices (in Nepalese rupees). Time-series

data on area and production (dissaggregated to the district level) is only available for these major food and cash crops.

(2) *Land*: area planted to Rice, Maize, Millet, Wheat, Barley, Oilseed, Potato, Tobacco and Sugarcane. Unfortunately I do not have time-series district level information on area planted under modern varieties (MV), nor area under irrigation. This is problematic, since changes in the quality of conventional inputs will now be meshed into changes in TFP (Alston, J., G. Norton and P. G. Pardey 1995). This source of bias will be more acute in the Terai region where there has been more than a 50% increase in the ratio of irrigated land-to-cropped land between 1981 and 1991 (70% of the land under irrigation in Nepal is in the Terai)[14]. In this study, I do, however, control for major agro-climatic differences by conducting separate regional analyses.

(3) *Labor-Male*; (4) *Labor-Female*: Number of economically active males and females (age 10 and above) engaged in agriculture. Again, there is the issue of labor quality. We will address this issue later on in this section.

(5) *Fertilizer*: Quantity of chemical fertilizer (NPK) sold by the AIC. Nepal imports it's chemical fertilizers, and the AIC, until very recently had a monopoly on fertilizer imports and nation-wide wholesale distribution (at a very subsidized rate - the subsidy burden of fertilizer alone consumes 50% of the development budget under the Ministry of Agriculture). Thus, official estimates of fertilizer use are quite reliable (even after accounting for 'leakages' - smuggling of fertilizer from Nepal to India).

[16] District level information on irrigated land can be obtained only for two years, 1981 and 1991, from the National Sample Census of Agriculture 1981and National Sample Census of Agriculture 1991. However, there is no systematic district level irrigation for years between 1981-1991, thus, could not be included in this study.

(6) *Livestock*: number of draft animals. Animal traction for field operations is widespread while tractor use is still rare. Tractor use is catching on in some districts, particularly in the Terai, however, it is a reasonable assumption that exclusion of this input will not significantly affect results (I do not have information on tractor hours or number of tractors per district for all districts for the period 1981-1991).

(7) *Literacy-Male*; (8) *Literacy-Female*: ratio of literate males (age 10 and above) to all males (age 10 and above); ratio of literate females (age 10 and above) to all females (age 10 and above). Ideally I want a reasonable proxy for the average education level (not to even mention anything about the quality of education) of the labor force engaged in agriculture. Unfortunately, I only have access to district level literacy rates (a proxy for education which is widely used in these type of studies). Besides reflecting the literacy level of the labor force engaged in agriculture, this measure is confounded by the literacy level of the non-agricultural workforce, and more problematically, by non-working students. Districts with higher productivity levels, might be more wealthy, and thus, have higher demand for child schooling, resulting in higher district level literacy rates - thus, the causality could even run in the oppositive direction. Ideally, we should also differentiate the effect of education by primary and secondary levels, given that have may have differential effects on agricultural productivity. Therefore, given that literacy rates constitute a questionable proxy for labor quality, I will present results both with and without literacy rates.

Besides the eight explanatory variables, in the estimations I also explicitly control for, *Rainfall*: amount of annual rainfall as recorded in 21 weather stations. This is the only variable which is not expressed at the district level since usually more than one district falls under the coverage of a particular weather station. Classification of districts by weather stations (and relevant adjustments) was provided by the government of Nepal's Department of Hydrology and Meteorology. I present descriptive statistics of the variables used in the study in Table S1 and Table S2,for the Terai and Hill region, respectively. The growth rates of these variables in the Terai and Hill region are presented in Table S1.1 and Table S2.2.

IV. Empirical Findings

As was previously mentioned, since the available measure of education is an imperfect proxy, I present results both with and without male/female literacy rates. We can then see how our district level RTC and technical (in)efficiency estimates are altered due to inclusion of our imperfect measure of education, and to see if the resulting changes are plausible.

Results Without Literacy : Terai Region

Table 1 presents the within district estimates for the Terai region. The standard errors of the variable inputs are robust errors based on Huber-White "sandwich" estimation procedure. These standard errors should be robust to heteroskedasticity (since I do explicitly control for heterogeneity in this model) and more importantly, serial-correlation. I tested for serial-correlation using pooled cross-section time-series data within a simple OLS framework (Wooldridge 1996), i.e., without including the time-invariant and time-varying heterogeneity terms. Dropping the first three time periods, I regressed agricultural output on: (1) all inputs and rainfall ; (2) first, second and third lags of the pooled OLS residuals, $\hat{u}_{it-1}, \hat{u}_{it-2}, \hat{u}_{it-3}$. The coefficients on

$\hat{u}_{it-1}, \hat{u}_{it-2}, \hat{u}_{it-3}$, were 0.85, 0.61, and 0.05 respectively, with t-statistics of 57.63, 10.12, 1.08, respectively. Thus, serial-correlations appear to follow a AR(2) process and most importantly, the process appears to be stationary (if the process had been non-stationary, then the Huber-White procedure would have been insufficient/inappropriate to obtain the correct standard errors of the population parameters). Also using pooled data, I carried out a Lagrange Multiplier (LR) test for group-wise heteroschedasticity (Green 1993); as expected, the null hypothesis that the pooled OLS residuals were homoschedastic was soundly rejected at the 1% level of significance[15].

All of the variable inputs, except for land, are statistically insignificant (regardless of robust or non-robust standard errors). I had expected fertilizer to have a significant positive elasticity, given that there has been a 'take-off' in chemical fertilizer use in the Terai during this period (with an average per annum growth rate of 21.8% - see Table S1.2). The estimates of the production elasticities generally correspond to estimates obtained from cross-country studies involving developing country data (e.g., Lau and Yotopoulos 1989)[16], except for the production elasticity of male labor and land. The coefficient on agricultural male labor force participation is negative - which is a very rare finding, but, male labor is insignificant. As we can see in Table S1.2 and S2.2, males have been deserting the agricultural sector in both regions (female labor force participation rates in agriculture have also been dropping in the Terai, while they have been going up in the Hills). Despite negligible land expansion in the Terai during this period, we find that

[17] I conducted these test for both Terai and Hill regions, with and without literacy; tests indicate serial correlation in all models, thus, it is appropriate to include robust standard errors (test results not presents).

[18] For example, most production elasticities of labor tend to be around 0.40; livestock elasticities tend to vary considerably anywhere between the range of 0.30 - 0.09; so does fertilizer elasticities, 0.08 - 0.05.

land is highly significant (with a t-statistics of 7.8) and has the largest magnitude effect on agricultural output. A 1% increase in agricultural land during the 80's in the Terai, on average would have boosted output by more than 2% per annum. Unfortunately I do not have information on land quality, area under modern varieties (MV), nor do I have information on irrigation for this study. It is likely that the large elasticity of land reflects increases in productivity due to expansion of irrigation and area planted to MV (and possible changes in cropping intensities). The amount of rainfall also significantly effects agricultural output as expected (with a t-statistics of 4.6).

Point estimates of district level RTC (θ_{2i}) for the Terai region are presented in Table 2[17]. All of the θ_1's are highly significant, as well as most of the rates of technical change (θ_2's). Thus, district level time-varying and time-invariant heterogeneity significantly affects agricultural productivity. The average rate of technical change, or TFP growth for the 20 Terai districts during the 80's was 3%, with Saptari registering the highest growth rate at 7.4% (and Bardiya coming in last with a rate of 0.5%). A 3% per annum rate of technical change or TFP growth seems too high, particularly for Nepal (relative to the per annum output growth rate of 3.37% in the Terai). TFP growth rates for other South Asian countries usually have been found to hover around 1% per annum (e.g., Evenson and Rosegrant 1993a; Rosegrant and Evenson 1993; 1995). Looking at Table 2.2, we see that district level RTC estimates are generally large relative to actual district level growth rates in output. Thus, it seems as if upward bias in the RTC estimates is very strong. As seen in Table 3, the confidence interval for most of the RTC estimates

[19] The null hypothesis that the θ2's are jointly equal to zero, is soundly rejected at the 1% level of significance.

are too wide to rank the districts distinctly. For example, while Saptari, Mahotari and Jhapa have point estimates of RTC above 5%, there are 10 other districts with upper confidence band value above 5% (districts can however, be grouped based on ranges of rates of technical change.

Table 4 presents district level technical efficiencies for the first time period, 1981. The average technical efficiency of production is 60%, thus, implying that on average, agricultural production in the Terai region in 1981 could have been increased by 40% via a more efficient utilization of available resources. Based on point estimates, it appears as if Parsa was operating on its frontier in 1981, and was the most efficient district (with Jhapa coming in as the least efficient district, operating at only 36% of its potential). However, when we look beyond mere point estimates, we see that at least two other districts, Bardiya and Nawalparasi, have upper bound values of 1 (based on the BCA approach). It is again difficult to rank districts distinctly; however, I can again group districts based on ranges of efficiency levels. Table 5 shows district level technical efficiencies for the last time period, 1991. The average technical efficiency of production was 70%, thus, implying that on average, agricultural production in the Terai region in 1991 could have been increased by 30% via a more efficient utilization of available resources (average technical efficiency levels have risen by 10% over 1981-1991, or by 1% per annum). Both the 1981 and 1991 TE estimates seem rather high compared to results from the farm-plot sample analysis in Part I, where I found that farmers could have increased average output by 18%, via a more efficient utilization of available resources.. As we see in Table 5, district rankings based solely on point estimates have changed. While Parsa still remains as the most efficient district, 10 districts experienced increases in their efficiency of production, while there was a fall in efficiency levels in 9 districts. Factoring in information from the confidence bands, it appears as if there is some weak sign of 'convergence', while only 3 districts could have been operating on the frontier in 1981, 6 districts might well have been operating on the frontier in 1991.

Table ARC1 shows the year in which a local agricultural research center had been established in that district (9 out of the 20 districts in the Terai have a local agricultural research center). It is interesting to note that, Parsa which in 1981 was ranked the most efficient district in the Terai, has the oldest agricultural research center in the Terai (and is considered by many agronomists to be one of the best local agricultural research centers). However, if we simply plot district level technical efficiency against the number of years (up till 1981) there has been an agricultural research center based in that district, we realize that the relationship is rather week (see Figure 1). For example, Bardiya which has the second-highest point estimate for the Terai, has never had a local agricultural research center based in that district. Of course, districts without local agricultural research centers could still benefit from research/extension linkages with research centers of other districts. Also, we need a richer understanding of the quality of research of the local agricultural research centers, and the effectiveness of those centers in working with extension networks to disseminate agronomic information to farmers. I however, do not have access to such institutional information for this study.

Results Without Literacy : Hill Region

Table 6 shows the within estimates for the Hill Region. The elasticities are in line with previous studies, albeit on the low side for fertilizer elasticity. Unlike results from the Terai region, land does not appear to be a significant determinant of agricultural output.

Also, unlike results from the Terai region, male labor and fertilizer are significant (at the 5% level of significance). A 1% increase in the male labor force engaged in agriculture increases agricultural output by 0.36%; while a 1% increase in the use of chemical fertilizers results on average in a 0.02% increase in output. Rainfall is also an important factor in the Hill region, albeit not as significant as in the Terai.

Similar to results obtained from the Terai region, all of the $\theta 1$'s are highly significant, as well as most of the rates of technical change (please see Table 7)[18]. The average rate of technical change, or TFP growth for the 39 Hill districts during the 80's was 2.5% (the growth rate of output during this period in the Hill region was 2% per annum). Kavre registered the highest growth rate at 7.4%, while the capital, Kathmandu, come in last with a negative TFP growth rate of -1.85% (Bhaktapur was the only other district with a negative TFP growth rate). Negative TFP growth rates may reflect decline in the quantity and quality of the natural resource base (Lynam and Herdt 1989; Cassman and Pingali 1994; Ali and Byerlee 1998). However, since I do not have any pertinent measures such as soil nor water quality, I cannot surmise about the impact of resource degradation on productivity. Given widespread deforestation and associated loss of top-soil in the Hill region, I am surprised that more districts did not register a negative TFP growth rates. Again the RTC estimates appear to be too high relative to actual output growth rates (see Table 7.2). Even after factoring in confidence intervals (please see Table 8), I can still say that Kavre exhibited the highest rate of technical change in the Hill

[20] The null hypothesis that the $\theta 2$'s are jointly equal to zero, is soundly rejected at the 1% level of significance.

region during the 80's. However, the remaining Hill districts cannot be ranked in such a clear-cut fashion, but I can group districts based on ranges of rates of technical change.

Table 9 presents district level technical efficiencies for the first time period, 1981. The average technical efficiency of production was 45%, thus, implying that on average, agricultural production in the Hill region in 1981 could have been increased by 55% via a more efficient utilization of available resources. Thus, compared to results from the Terai region, agricultural production is less efficient in the Hill region. Based on point estimates, it appears as if Kathmandu was operating on its frontier in 1981, and was the most efficient district (Myagdi was the least efficient district, operating at only 16% of its potential). Factoring in confidence intervals, only one other district, Syangja, has an upper bound value of 1. It is again difficult to distinctly rank districts - what we can do is to use the confidence bands to group districts based on efficiency ranges. Table 10 presents district level technical efficiencies for the last time period, 1991. The average technical efficiency of production was 41%, thus, implying that on average, agricultural production in the Hill region in 1991 could have been increased by 59% via a more efficient utilization of available resources. It appears as if there was no efficiency growth during the 80's in the Hill region; rather efficiency fell by 4% during 1981-1991. Thus, average TFP growth in the Hill region must have taken place without increases in the level of technical efficiency. While Kavre emerges definitively as the most efficient district in 1991, there is no indication of 'convergence' in the Hill region (based on point estimates, 4 districts maintained their rankings, 17 districts experienced increases in their efficiency of production, while 18 districts experienced decreases in their level of efficiency).

Table ARC2 shows the year in which a local agricultural research center had been established in that district (11 out of the 39 districts in the Hill region have a local research center). We see that Kathmandu, the nation's capital, which in 1981 was ranked the most efficient district in the Hill region, has the oldest agricultural research center in the Hill region. However, similar to what we see in the Terai, there does not appear to be a coherent relationship between district level technical efficiency and how long a local agricultural research center has been based in that district (see Figure 2).

Results With Literacy : Terai Region

Unlike in Part I where I found that secondary education had a significant effect in lowering production inefficiencies among a sample of farmers in the Rupandehi district, I do not find a significant effect of education when drawing upon aggregate district data in the Terai region. While including male and female literacy rates does not significantly alter the production elasticities, RTC and efficiency estimates are however, altered in a significant manner. Table 11 presents within estimates for the Terai region, controlling for male and female literacy rates. As shown, this increases the elasticities of male and female labor, however, they still remain insignificant. Neither male nor female literacy rate is significant. Also, while the elasticity of literacy tends to vary between 0.10 - 0.20 in most developing country studies, the literacy elasticity in this study is very low (for both males and females). Table 12 shows that while most of the θ1 parameter estimates are still strongly significant, most of the θ2, or RTC parameter estimates are now insignificant[19]. Thus, I cannot make a strong case that there is significant variation in technical change across districts. Ignoring the issue of statistical significance for now, the average annual

[21] The null hypothesis that the θ2's are jointly equal to zero, cannot be rejected.

rate of technical change, or TFP growth for the 20 Terai districts during the 80's (after controlling for literacy rates), was -0.47%. Sixty five percent of the districts in the Terai region now appear to experienced negative TFP growth. The RTC estimates are more plausible in comparison to actual growth rates (please see Table 12.2), however, now they appear to be biased downwards. However, too much cannot be made of these estimates given their standard errors are too large (see Table 13 for the confidence intervals of the RTC point estimates).

Table 14 presents district level technical efficiencies for the first time period, 1981. The average technical efficiency of production was 47% (compared to 60% when I do not include literacy). Rankings based upon point estimates are quite different than the case in which we do not include literacy. Based on point estimates, it appears now appears as if it is Bardiya which was operating on its frontier in 1981 (with Jhapa again coming in as the least efficient district, operating at only 19% of its potential). However, when considering the CI intervals, we see that at least three other districts, Parsa, Nawalparasi, and Sunsari, have upper bound values of 1 (based on the BCA approach). It is again difficult to rank districts distinctly, however, I can group districts based on ranges of efficiency levels. Table 15 presents district level technical efficiencies for the last time period, 1991. The average technical efficiency of production was 57%(compared to 70% when I do not include literacy). Thus, average technical efficiency levels had also risen by 10% over 1981-1991, or by 1% per annum. Also, as reported in Table 15, district rankings based solely on point estimates have changed : 10 districts experienced increases in their efficiency of production, while there was a fall in efficiency levels in 6 districts. Again, there does not seem to be any signs of 'convergence'.

Results With Literacy : Hill Region

Similar to the Terai case, while including male and female literacy rates does not significantly alter the production elasticities, RTC and efficiency estimates are altered in a significant manner. However, unlike the Terai case (where neither male nor female literacy was significant), female literacy rate is mildly significant (t-statistics of 1.7), but, with a low elasticity (see Table 16). A 1% increase in female literacy rate in the Hill region appears to (on average) increase output by 0.04% (please see Table 16). From results presented in Table 17, opposite to the Terai case, the θ2/RTC parameter are mostly significant[20], while most of the θ1 parameter estimates are now statistically insignificant. Thus, I can make the case that significant variation in district level rates of technical change exists in the Hill region. Controlling for literacy in the estimation, results in negative rates of technical change, or decreasing TFP growth in all Hill regions. The average decline in TFP growth is -8.4% per annum. As shown in Table 18, the confidence intervals for the RTC estimates are quite wide. For example, the rate of technical change in Kavre could either be negative, zero, or positive. Even though the RTC estimates exaggerate the extent of decline in factor productivity (e.g., compare district level growth rates and RTC in Table 17.2), given the statistical significance of most of the RTC estimates, it is possible that these result might very well stem from the ravages of resource degradation in the Hill region of Nepal. Using comprehensive soil and water quality data, Ali and Byerlee (1998) find that widespread resource degradation in the wheat-rice system of Pakistan resulted in negative TFP growth. Similarly, Cassman

[22] The null hypothesis that the θ2's are jointly equal to zero, is soundly rejected at the 0% level of significance.

and Pingali (1994) associate the decline in TFP in the rice-wheat system of the Indian Punjab to intensification induced soil degradation. In the Hills, it is not unsustainable agricultural intensification which is the culprit; rather it is whole scale deforestation and associated loss of top soil which poses the greatest threat to agricultural productivity. Unfortunately, I do not have the data with which to examine this critical issue within the Nepalese context.

Table 19 presents district level technical efficiencies for the first time period, 1981. The average technical efficiency of production was 46% (these average results are almost identical to those obtained in the case when literacy was not include). Based on point estimates, it appears as if Dhading was operating on its frontier in 1981 (with Parbat coming in as the least efficient district, operating at only 16% of its potential). Factoring in confidence intervals, two other districts, Nuwakot and Salyan, have upper bound values of 1. Table 20 presents district level technical efficiencies for the last time period, 1991. The average technical efficiency of production was 40%. It appears that average efficiency levels fell slightly during the 80's in the Hill region. Again no indication of convergence is evident in the Hill region.

V. Conclusion

Using a stochastic frontier approach embedded within a meta-production function framework, I explore for district level technical change and efficiency of agricultural production for the Terai and Hill regions of Nepa during the period 1981-1991. I present a summary of the results obtained from the district level analysis in Table 21. As shown, the 'story' we wish to tell about technical change and efficiency in the Terai and Hill regions during this period, hinges upon whether we include literacy in the estimation.

Certainly, education belongs in the estimation of a meta-production function. Ignoring education would result in over estimating the rate of technical chanage. When literacy, an imperfect measure of the education level of the agricultural labor force, is included, there is indeed a drop in the district level rates of technical change. Alas, the reductions seems rather drastic, particularly for the Hill region. On the other hand, inclusion of literacy only bring about a -21% drop in average technical efficiency levels in the Terai region, while it does not appear to alter the average efficiency level in the Hill region. A drop in average efficiency levels in the Hill region (with and without inclusion of literacy) is notable between 1981 and 1991. Efficiency levels in general stay the same or increase over time as farmers within a district 'learn' to better use existing resources. Declining efficiency levels can however, be indicative of the changing production environment in the Hill region. Technical efficiency reflects the ability to maximize production, given a fixed set of inputs, which includes natural resources. If the quantity and the quality of the natural resource base is declining, and there exits limited substitutability between manmade and non-manmade inputs, then we could very well experience a decline in efficiency levels. The district level analysis was severely curtailed due to a lack of better proxies for education, from not having irrigation information for the Terai region, and from not having any measures of the quality and quantity of natural resources used in the production process, particularly in the Hill region. I however, able to control for irrigation when exploring for factors which might help to explain the variation in technical efficiency across districts for the first and last period of the panel.

Despite these deficiencies, the district level analysis provides an empirical 'starting-point' for examining the productivity of Nepalese agriculture at a aggregate (meso) level.

In spite of potential downward bias in the technical efficiency estimates, this study shows that there exits substantial scope for increasing output via a better utilization of existing inputs and technologies in the Terai region. There also exists tremendous potential for increasing output in the Hill region. However, this potential is perhaps being squandered due to natural resource degradation in the Hills. The significantly negative rates of technical change for the Hill districts (after inclusion of literacy) could very well be written off as nothing more than a statistical anomaly. However, if they do reflect an underlying decline in TFP growth due to degradation of the natural resource base, then we do have cause for concern, and therefore, this issue remains as an unanswered empirical question. To properly address that question requires a strong institutional commitment to help strengthen Nepal's capacity to collect such complex data in a systematic fashion.

Table S1

Growth Rates in the Terai Region for the period 1981-1991

District	Output	Land	Labor-M	Labor-F	Fertilizer	Livestock	Literacy-M	Literacy-F
Mahotari	0.058	0.005	-0.079	-0.168	0.775	0.031	0.045	0.050
Sarlahi	0.058	0.014	-0.056	-0.020	0.154	-0.042	0.045	0.072
Jhapa	0.057	0.002	-0.043	-0.046	0.169	0.064	0.035	0.056
Bara	0.054	0.010	-0.043	-0.004	0.689	-0.072	0.039	0.069
Saptari	0.047	-0.007	-0.044	-0.010	0.182	0.019	0.029	0.048
Dhanusa	0.042	0.001	-0.071	-0.040	0.085	0.001	0.041	0.077
Bardiya	0.042	0.021	-0.032	-0.049	0.127	0.119	0.076	0.074
Siraha	0.039	-0.002	-0.060	-0.063	0.156	-0.027	0.048	0.056
Kailali	0.038	0.010	-0.015	0.025	0.507	0.008	0.033	0.081
Morang	0.036	0.005	-0.064	-0.045	0.118	-0.007	0.043	0.058
Kanchanpur	0.031	0.009	-0.015	-0.213	0.272	0.013	0.056	0.064
Rautahat	0.030	-0.005	-0.058	-0.178	0.136	0.157	0.066	0.052
Nawalparasi	0.030	0.009	-0.016	0.028	0.140	0.038	0.044	0.078
Sunsari	0.026	0.010	-0.052	0.011	0.185	-0.047	0.032	0.121
Dang	0.026	0.013	-0.027	0.252	0.214	0.031	0.055	0.085
Chitawan	0.022	-0.002	-0.018	0.068	0.056	-0.003	0.035	0.069
Rupandehi	0.020	-0.004	-0.014	0.069	0.116	0.002	0.029	0.062
Banke	0.013	-0.009	-0.027	-0.040	0.130	0.008	0.056	0.080
Kapilbastu	0.005	-0.016	-0.023	-0.040	0.108	0.031	0.075	0.088
Parsa	0.001	-0.006	-0.049	-0.102	0.042	-0.096	0.043	0.036

Table S2

Growth Rates in the Hill Region for the period 1981-1991

District	Output	Land	Labor-	Labor-F	Fertilizer	Livestock	Literacy-M	Literacy-F
Kavre	0.056	0.015	-0.032	0.004	-0.031	0.090	0.045	0.065
Achham	0.038	0.017	-0.023	0.027	-0.012	0.030	0.063	-0.030
Rukum	0.033	0.017	-0.015	0.046	0.008	0.020	0.069	0.099
Lalitpur	0.032	0.004	-0.076	0.004	0.037	0.014	0.046	0.066
Jajarkot	0.031	0.012	-0.015	0.033	0.039	0.024	0.074	0.066
Lamjung	0.030	0.008	-0.039	0.054	-0.003	0.013	0.024	0.059
Khotang	0.030	0.011	-0.026	0.026	-0.045	0.025	0.049	0.082
Gorkha	0.028	0.003	-0.040	-0.014	0.191	0.011	0.072	0.117
Baitadi	0.027	0.012	-0.035	0.030	0.014	0.027	0.059	0.049
Makwanpur	0.025	0.008	-0.010	0.022	0.008	0.013	0.041	0.059
Myagdi	0.025	0.011	-0.046	0.034	0.024	0.041	0.054	0.084
Parbat	0.025	0.009	-0.034	0.008	0.033	0.010	0.030	0.098
Dadeldhura	0.025	0.002	-0.034	0.065	0.095	0.066	0.064	0.020
Dhading	0.024	0.007	-0.022	0.019	0.018	0.011	0.070	0.098
Baglung	0.023	0.017	-0.045	0.015	0.013	0.011	0.044	0.099
Palpa	0.023	-0.006	-0.041	0.027	-0.014	0.013	0.045	0.074
Tanahu	0.023	0.003	-0.043	0.005	0.030	0.014	0.057	0.099
Rolpa	0.023	0.013	-0.018	0.027	-0.012	0.086	0.069	0.028
Surkhet	0.022	0.006	-0.005	-0.001	0.020	0.024	0.056	0.094
Sindhuli	0.021	0.002	-0.017	0.029	-0.038	0.017	0.052	0.061
Dhankuta	0.021	-0.001	-0.018	0.037	0.036	0.013	0.033	0.083
Udayapur	0.020	0.000	-0.009	0.011	0.057	0.014	0.061	0.088
Ramechhap	0.019	0.012	0.024	0.098	0.026	0.096	0.049	0.063
Bhojpur	0.018	0.004	-0.033	0.013	-0.012	0.012	0.049	0.083
Terhathum	0.016	0.001	-0.031	-0.003	0.017	0.014	0.035	0.089
Kaski	0.016	0.003	-0.062	-0.006	0.018	0.012	0.037	0.074
Arghakhanchi	0.016	0.013	-0.055	0.062	0.011	0.130	0.050	0.088
Nuwakot	0.015	0.008	-0.016	0.013	0.101	-0.017	0.048	0.079
Gulmi	0.015	0.004	-0.051	0.015	-0.007	0.098	0.027	0.070
Salyan	0.014	0.010	-0.015	-0.004	0.013	0.019	0.076	0.090
Okhaldhunga	0.014	0.011	-0.029	0.001	0.006	0.020	0.063	0.119
Panchthar	0.011	0.005	-0.024	-0.014	0.009	0.017	0.045	0.106
Pyuthan	0.010	0.014	-0.030	0.003	0.023	0.018	0.062	0.097
Syangja	0.010	0.005	-0.043	0.013	-0.019	0.011	0.036	0.106
Dailekh	0.009	0.011	-0.017	0.012	0.008	0.016	0.048	0.046
Doti	0.008	0.006	-0.034	0.034	0.002	0.034	0.087	0.051
Ilam	0.007	0.007	-0.013	-0.002	0.032	0.013	0.035	0.071
Bhaktapur	-0.004	-0.009	-0.055	0.004	-0.060	0.014	0.048	0.086
Kathmandu	-0.021	-0.038	-0.123	-0.051	0.010	0.015	0.031	0.040

Table 1

Parameter Estimates of the Production Function (Without Literacy) - Terai

Dependent Vairable : Natural Log of Agricultural Output (Mean Value : 6.63)

Explanatory Variables (besides net school enrollment rates) are in Natural Logs

Independent Vairables	*Within-Estimates*
land	**2.234** **(0.285)***
labor-male	**-0.400** **(0.260)**
labor-female	**0.130** **(0.080)**
fertilizer	**0.030** **(0.023)**
livestock	**0.052** **(0.040)**
rainfall	**0.170** **(0.037)***
Observations	220
# of Districts	20
# of Time Periods	11

robust standard errors in parentheses ; * significant at 1% level

Note **: robust errors based on White's "Sandwich Method" are heteroskedasticity/serial-correlation consistent estimates**

Table 2

Parameter Estimates (Without Literacy) of time-invariant and time-varying heterogeneity : Terai

	Time-invariant heterogeneity			RTC^		
District	*Estimate*	*SE**	*t-stat*	*Estimate*	*SE**	*t-stat*
Saptari	-4.978	0.926	-5.377	0.074	0.010	7.067
Mahotari	-4.621	0.884	-5.230	0.053	0.012	4.433
Jhapa	-5.127	0.979	-5.236	0.051	0.010	5.010
Kapilbastu	-4.988	0.970	-5.141	0.044	0.011	4.179
Rautahat	-4.915	0.931	-5.281	0.044	0.010	4.366
Bara	-4.560	0.939	-4.855	0.042	0.012	3.542
Banke	-4.388	0.851	-5.157	0.042	0.010	4.049
Siraha	-4.781	0.930	-5.143	0.041	0.010	4.030
Dhanusa	-4.628	0.913	-5.067	0.038	0.010	3.770
Rupandehi	-4.837	0.957	-5.057	0.033	0.010	3.277
Sarlahi	-4.668	0.898	-5.199	0.029	0.011	2.724
Chitawan	-4.623	0.917	-5.043	0.028	0.010	2.820
Kailali	-4.862	0.930	-5.225	0.025	0.011	2.252
Morang	-4.846	0.968	-5.005	0.022	0.010	2.198
Kanchanpur	-4.459	0.883	-5.053	0.016	0.010	1.519
Parsa	-4.067	0.894	-4.550	0.016	0.010	1.535
Nawalparasi	-4.197	0.859	-4.888	0.014	0.010	1.369
Sunsari	-4.324	0.892	-4.850	0.009	0.010	0.894
Dang	-4.654	0.917	-5.077	0.007	0.011	0.626
Bardiya	-4.116	0.829	-4.967	0.005	0.011	0.425

* : Standard-Error

^ : *Rate of Technical Change (time-varying heterogeniety)*

Table 2.2

Terai - Without Literacy

District	GRY^	RTC
Mahotari	0.058	0.053
Sarlahi	0.058	0.029
Jhapa	0.057	0.051
Bara	0.054	0.042
Saptari	0.047	0.074
Dhanusa	0.042	0.038
Bardiya	0.042	0.005
Siraha	0.039	0.041
Kailali	0.038	0.025
Morang	0.036	0.022
Kanchanpur	0.031	0.016
Rautahat	0.030	0.044
Nawalparasi	0.030	0.014
Sunsari	0.026	0.009
Dang	0.026	0.007
Chitawan	0.022	0.028
Rupandehi	0.020	0.033
Banke	0.013	0.042
Kapilbastu	0.005	0.044
Parsa	0.001	0.016

^ GRY : growth rate of output

Table 3

Bootstrap Confidence Intervals for RTC Esimates (Without Literacy) :
90% Level - Terai

		Percentile		BCA	
District	*RTC Estimate*	*LB*	*UB*	*LB*	*UB*
Saptari	0.0735	0.0568	0.0892	0.0672	0.0985
Mahotari	0.0532	0.0358	0.0706	0.0470	0.0845
Jhapa	0.0506	0.0361	0.0648	0.0448	0.0735
Kapilbastu	0.0443	0.0286	0.0596	0.0381	0.0687
Rautahat	0.0441	0.0293	0.0587	0.0381	0.0662
Bara	0.0418	0.0243	0.0594	0.0361	0.0702
Banke	0.0417	0.0249	0.0573	0.0355	0.0647
Siraha	0.0407	0.0258	0.0553	0.0348	0.0635
Dhanusa	0.0377	0.0233	0.0532	0.0322	0.0648
Rupandehi	0.0331	0.0182	0.049	0.0276	0.0611
Sarlahi	0.0286	0.0138	0.0436	0.0226	0.0525
Chitawan	0.0282	0.0132	0.0429	0.0237	0.0544
Kailali	0.0250	0.0087	0.0416	0.0192	0.0519
Morang	0.0222	0.0079	0.0371	0.0163	0.0439
Kanchanpur	0.0158	0.0004	0.0313	0.0104	0.0413
Parsa	0.0155	0.0004	0.0303	0.0087	0.0345
Nawalparasi	0.0141	-0.0010	0.0293	0.0079	0.0379
Sunsari	0.0093	-0.0055	0.0242	0.0027	0.0308
Dang	0.0067	-0.0091	0.0219	0.0012	0.0313
Bardiya	0.0048	-0.0108	0.0212	-0.0013	0.0306

Table 4

Bootstrap Confidence Intervals for Technical Efficiency Esimates (Without Literacy) : 90% Level - Terai

Technical Efficiency Estimates for the First Period (1981)

		Percentile		BCA	
District	*Efficiency (T=1981)*	*LB*	*UB*	*LB*	*UB*
Parsa	1.000	0.915	1.000	0.962	1.000
Bardiya	0.943	0.816	1.000	0.891	1.000
Nawalparasi	0.877	0.765	0.967	0.839	1.000
Sunsari	0.768	0.673	0.846	0.733	0.931
Banke	0.745	0.637	0.831	0.711	0.890
Kanchanpur	0.676	0.589	0.755	0.642	0.826
Bara	0.627	0.529	0.724	0.593	0.818
Mahotari	0.597	0.513	0.674	0.565	0.751
Dhanusa	0.583	0.505	0.651	0.556	0.708
Chitawan	0.581	0.505	0.652	0.556	0.701
Sarlahi	0.555	0.487	0.621	0.531	0.703
Dang	0.551	0.474	0.620	0.526	0.682
Siraha	0.502	0.431	0.574	0.476	0.644
Rupandehi	0.471	0.393	0.549	0.443	0.626
Morang	0.462	0.381	0.545	0.432	0.649
Kailali	0.456	0.389	0.528	0.430	0.595
Rautahat	0.441	0.378	0.499	0.418	0.554
Saptari	0.426	0.368	0.481	0.405	0.530
Kapilbastu	0.410	0.341	0.486	0.386	0.548
Jhapa	0.359	0.292	0.428	0.333	0.523

Note: Efficiency estimates are expressed "relative" to the most efficient district in the sample (which has a value of 1)

Table 5

Bootstrap Confidence Intervals for Technical Efficiency Esimates (Without Literacy) :
90% Level - Terai

Technical Efficiency Estimates for the Last Period (1991)

		Percentile		BCA	
District	*Efficiency (T=1991)*	*LB*	*UB*	*LB*	*UB*
Parsa	1.000	0.891	1.000	0.946	1.000
Banke	0.968	0.841	1.000	0.908	1.000
Mahotari	0.871	0.756	0.954	0.822	1.000
Nawalparasi	0.865	0.757	0.951	0.821	1.000
Bardiya	0.847	0.733	0.933	0.806	1.000
Bara	0.816	0.664	0.957	0.753	1.000
Saptari	0.762	0.654	0.847	0.712	0.890
Dhanusa	0.728	0.617	0.813	0.681	0.875
Sunsari	0.722	0.618	0.801	0.681	0.863
Kanchanpur	0.678	0.587	0.755	0.643	0.813
Chitawan	0.659	0.564	0.730	0.621	0.786
Siraha	0.646	0.544	0.728	0.604	0.781
Sarlahi	0.633	0.534	0.714	0.594	0.764
Rautahat	0.587	0.501	0.661	0.552	0.694
Rupandehi	0.562	0.461	0.648	0.523	0.705
Kapilbastu	0.547	0.457	0.620	0.509	0.668
Jhapa	0.510	0.402	0.610	0.464	0.662
Dang	0.505	0.412	0.579	0.467	0.624
Kailali	0.502	0.411	0.584	0.463	0.646
Morang	0.494	0.395	0.590	0.448	0.630

Note: Efficiency estimates are expressed "relative" to the most efficient district in the sample (which has a value of 1)

Table 6

Parameter Estimates of the Production Function (Without Literacy) - Hill

Dependent Vairable : Natural Log of Agricultural Output (Mean Value : 5.507)

Explanatory Variables are in Natural Logs

Independent Vairables	*Within-Estimates*
land	**0.116** **(0.23)**
labor-male	**0.36** **(0.18)****
labor-female	**0.017** **(0.087)**
fertilizer	**0.022** **(0.010)****
livestock	**0.056** **(0.047)**
rainfall	**0.066** **(0.030)****
Observations	429
# of Districts	39
# of Time Periods	11

robust standard errors in parentheses ; ** significant at the 5% level

Note : robust errors based on White's "Sandwich Method" are heteroskedasticity/serial-correlation consistent estimates

Table 7

Parameter Estimates (Without Literacy) of time-invariant and time-varying heterogeneity :Hill

	Time-invarient heterogeneity			RTC^		
District	*Estimate*	*SE**	*t-stat*	*Estimate*	*SE**	*t-stat*
Kavre	5.267	0.651	8.093	0.088	0.011	7.813
Achham	4.191	0.512	8.183	0.050	0.010	5.295
Rukum	4.814	0.599	8.036	0.040	0.009	4.333
Jajarkot	4.095	0.526	7.791	0.039	0.009	4.286
Myagdi	4.050	0.497	8.142	0.038	0.009	4.074
Khotang	5.003	0.633	7.905	0.037	0.009	4.033
Baitadi	4.302	0.527	8.168	0.037	0.009	3.967
Lamjung	4.897	0.596	8.217	0.034	0.009	3.775
Lalitpur	4.867	0.497	9.798	0.032	0.009	3.636
Gorkha	5.329	0.676	7.887	0.032	0.009	3.625
Surkhet	5.137	0.647	7.934	0.030	0.009	3.322
Makwanpur	5.535	0.649	8.531	0.029	0.009	3.225
Palpa	5.040	0.634	7.949	0.028	0.009	3.169
Dhading	5.262	0.625	8.426	0.028	0.009	3.124
Dadeldhura	4.412	0.545	8.092	0.028	0.009	3.148
Tanahu	5.261	0.657	8.008	0.028	0.009	3.090
Parbat	4.798	0.599	8.007	0.028	0.009	3.090
Sindhuli	5.239	0.638	8.206	0.027	0.009	3.045
Baglung	4.795	0.581	8.249	0.026	0.009	2.783
Rolpa	4.700	0.557	8.432	0.025	0.009	2.767
Dhankuta	5.183	0.627	8.262	0.024	0.009	2.742
Udayapur	4.969	0.593	8.385	0.024	0.009	2.761
Bhojpur	5.201	0.621	8.382	0.022	0.009	2.443
Ramechhap	4.826	0.578	8.343	0.021	0.009	2.356
Salyan	5.103	0.648	7.874	0.021	0.009	2.289
Doti	4.588	0.550	8.341	0.020	0.009	2.207
Terhathum	4.919	0.567	8.681	0.020	0.009	2.247
Kaski	5.427	0.672	8.080	0.020	0.009	2.239
Okhaldhunga	4.673	0.522	8.955	0.020	0.009	2.154
Arghakhanchi	4.694	0.552	8.508	0.019	0.009	2.144
Gulmi	5.077	0.626	8.111	0.018	0.009	2.000
Panchthar	5.295	0.626	8.454	0.016	0.009	1.753
Pyuthan	4.714	0.565	8.340	0.015	0.009	1.681
Dailekh	4.565	0.548	8.331	0.014	0.009	1.589
Nuwakot	5.621	0.646	8.699	0.014	0.009	1.551
Syangja	5.770	0.734	7.866	0.010	0.009	1.120
Ilam	5.465	0.617	8.863	0.010	0.009	1.101
Bhaktapur	5.270	0.475	11.103	-0.002	0.009	-0.202
Kathmandu	5.915	0.610	9.692	-0.018	0.010	-1.854

* : Standard-Error

^ : *Rate of Technical Change (time-varying heterogeniety)*

Table 7.2

Hill - Without Literacy

District	GRY^	RTC
Kavre	0.056	0.088
Achham	0.038	0.050
Rukum	0.033	0.040
Lalitpur	0.032	0.032
Jajarkot	0.031	0.039
Lamjung	0.030	0.034
Khotang	0.030	0.037
Gorkha	0.028	0.032
Baitadi	0.027	0.037
Makwanpur	0.025	0.029
Myagdi	0.025	0.038
Dadeldhura	0.025	0.028
Parbat	0.025	0.028
Dhading	0.024	0.028
Baglung	0.023	0.026
Palpa	0.023	0.028
Tanahu	0.023	0.028
Rolpa	0.023	0.025
Surkhet	0.022	0.030
Sindhuli	0.021	0.027
Dhankuta	0.021	0.024
Udayapur	0.020	0.024
Ramechhap	0.019	0.021
Bhojpur	0.018	0.022
Terhathum	0.016	0.020
Arghakhanchi	0.016	0.019
Kaski	0.016	0.020
Nuwakot	0.015	0.014
Gulmi	0.015	0.018
Salyan	0.014	0.021
Okhaldhunga	0.014	0.020
Panchthar	0.011	0.016
Pyuthan	0.010	0.015
Syangja	0.010	0.010
Dailekh	0.009	0.014
Doti	0.008	0.020
Ilam	0.007	0.010
Bhaktapur	-0.004	-0.002
Kathmandu	-0.021	-0.018

^ GRY : growth rate of ouptut

Table 8

Bootstrap Confidence Intervals for RTC Esimates (Without Literacy) : 90% Level - Hill

District	RTC Estimate	Percentile LB	Percentile UB	BCA LB	BCA UB
Kavre	0.088	0.070	0.105	0.081	0.115
Achham	0.050	0.035	0.065	0.044	0.073
Rukum	0.040	0.027	0.054	0.035	0.062
Jajarkot	0.039	0.025	0.052	0.034	0.064
Myagdi	0.038	0.025	0.052	0.033	0.058
Khotang	0.037	0.022	0.050	0.031	0.058
Baitadi	0.037	0.023	0.049	0.031	0.057
Lamjung	0.034	0.020	0.047	0.029	0.055
Lalitpur	0.032	0.018	0.045	0.027	0.062
Gorkha	0.032	0.019	0.045	0.028	0.055
Surkhet	0.030	0.016	0.042	0.026	0.052
Makwanpur	0.029	0.015	0.042	0.024	0.053
Palpa	0.028	0.016	0.041	0.023	0.047
Dhading	0.028	0.014	0.041	0.023	0.051
Dadeldhura	0.028	0.014	0.041	0.023	0.049
Tanahu	0.028	0.013	0.040	0.023	0.048
Parbat	0.028	0.013	0.040	0.023	0.052
Sindhuli	0.027	0.014	0.041	0.022	0.046
Baglung	0.026	0.011	0.039	0.021	0.051
Rolpa	0.025	0.012	0.038	0.021	0.047
Dhankuta	0.024	0.012	0.038	0.020	0.045
Udayapur	0.024	0.012	0.039	0.020	0.048
Bhojpur	0.022	0.008	0.035	0.017	0.043
Ramechhap	0.021	0.008	0.034	0.016	0.044
Salyan	0.021	0.007	0.035	0.016	0.046
Doti	0.020	0.006	0.034	0.015	0.040
Terhathum	0.020	0.007	0.034	0.015	0.042
Kaski	0.020	0.006	0.032	0.015	0.041
Okhaldhunga	0.020	0.006	0.033	0.015	0.043
Arghakhanchi	0.019	0.006	0.032	0.015	0.040
Gulmi	0.018	0.004	0.031	0.012	0.039
Panchthar	0.016	0.002	0.028	0.010	0.034
Pyuthan	0.015	0.001	0.029	0.011	0.040
Dailekh	0.014	0.001	0.028	0.009	0.036
Nuwakot	0.014	0.001	0.026	0.009	0.036
Syangja	0.010	-0.004	0.024	0.005	0.032
Ilam	0.010	-0.004	0.022	0.005	0.035
Bhaktapur	-0.002	-0.015	0.011	-0.006	0.021
Kathmandu	-0.018	-0.032	-0.004	-0.023	0.005

Note : Theta2 represents time-varying district level heterogeneity

Table 9

Bootstrap Confidence Intervals for Technical Efficiency Esimates (Without Literacy) : 90% Level - Hill

Technical Efficiency Estimates for the First Period (1981)

District	*Efficiency (T=1981)*	Percentile *LB*	Percentile *UB*	BCA *LB*	BCA *UB*
Kathmandu	1.000	0.864	1.000	0.931	1.000
Syangja	0.889	0.704	1.000	0.800	1.000
Nuwakot	0.769	0.669	0.845	0.729	0.912
Makwanpur	0.716	0.619	0.789	0.677	0.855
Ilam	0.655	0.566	0.730	0.622	0.773
Kaski	0.637	0.541	0.712	0.602	0.763
Gorkha	0.584	0.495	0.651	0.551	0.705
Kavre	0.581	0.494	0.661	0.548	0.730
Panchthar	0.556	0.482	0.624	0.525	0.670
Dhading	0.545	0.473	0.606	0.520	0.651
Tanahu	0.544	0.469	0.606	0.515	0.663
Bhaktapur	0.533	0.371	0.681	0.477	0.760
Sindhuli	0.532	0.461	0.592	0.504	0.651
Bhojpur	0.509	0.438	0.564	0.486	0.615
Dhankuta	0.502	0.431	0.556	0.475	0.607
Surkhet	0.481	0.414	0.535	0.457	0.575
Salyan	0.461	0.393	0.511	0.438	0.549
Gulmi	0.448	0.387	0.496	0.425	0.534
Palpa	0.436	0.378	0.484	0.413	0.518
Khotang	0.424	0.367	0.476	0.401	0.511
Udayapur	0.405	0.341	0.458	0.383	0.495
Terhathum	0.384	0.316	0.437	0.359	0.471
Lamjung	0.380	0.320	0.431	0.357	0.468
Lalitpur	0.368	0.269	0.457	0.334	0.498
Rukum	0.352	0.302	0.393	0.333	0.430
Ramechhap	0.350	0.293	0.396	0.331	0.429
Parbat	0.342	0.290	0.385	0.322	0.413
Baglung	0.341	0.281	0.389	0.320	0.431
Pyuthan	0.311	0.255	0.360	0.292	0.392
Rolpa	0.310	0.249	0.360	0.291	0.384
Arghakhanchi	0.306	0.245	0.352	0.283	0.385
Okhaldhunga	0.300	0.228	0.357	0.276	0.394
Doti	0.276	0.222	0.321	0.257	0.349
Dailekh	0.268	0.211	0.314	0.247	0.346
Dadeldhura	0.233	0.184	0.273	0.217	0.297
Baitadi	0.210	0.164	0.251	0.193	0.273
Achham	0.191	0.146	0.233	0.174	0.258
Jajarkot	0.171	0.130	0.208	0.157	0.227
Myagdi	0.164	0.118	0.208	0.145	0.228

Note: Efficiency estimates are expressed "relative" to the most efficient district in the sample (which has a value of 1)

Table 10

Bootstrap Confidence Intervals for Technical Efficiency Esimates (Without Literacy)
90% Level - Hill
Technical Efficiency Estimates for the Last Period (1991)

District	*Efficiency (T=1991)*	**Percentile** *LB*	*UB*	**BCA** *LB*	*UB*
Kavre	1.000	1.000	1.000	1.000	1.000
Syangja	0.708	0.602	0.844	0.661	0.892
Makwanpur	0.685	0.611	0.767	0.653	0.816
Nuwakot	0.633	0.565	0.717	0.608	0.748
Kathmandu	0.601	0.500	0.730	0.554	0.813
Gorkha	0.577	0.508	0.650	0.549	0.685
Kaski	0.557	0.494	0.628	0.532	0.669
Ilam	0.519	0.447	0.594	0.487	0.633
Dhading	0.516	0.456	0.589	0.489	0.629
Tanahu	0.514	0.452	0.583	0.488	0.626
Sindhuli	0.500	0.442	0.575	0.473	0.614
Panchthar	0.466	0.405	0.533	0.440	0.566
Surkhet	0.466	0.411	0.529	0.442	0.555
Dhankuta	0.460	0.401	0.527	0.435	0.572
Bhojpur	0.453	0.400	0.520	0.431	0.567
Khotang	0.439	0.384	0.499	0.414	0.538
Palpa	0.415	0.362	0.479	0.393	0.520
Salyan	0.407	0.358	0.462	0.386	0.489
Gulmi	0.383	0.334	0.443	0.364	0.469
Lamjung	0.382	0.321	0.453	0.356	0.486
Rukum	0.378	0.327	0.437	0.357	0.472
Bhaktapur	0.375	0.261	0.534	0.330	0.639
Udayapur	0.371	0.312	0.439	0.345	0.485
Lalitpur	0.364	0.271	0.487	0.323	0.555
Terhathum	0.336	0.280	0.408	0.310	0.455
Parbat	0.323	0.274	0.382	0.299	0.407
Baglung	0.316	0.266	0.376	0.297	0.431
Ramechhap	0.310	0.262	0.369	0.291	0.415
Rolpa	0.285	0.235	0.350	0.262	0.385
Arghakhanchi	0.266	0.221	0.324	0.245	0.352
Okhaldhunga	0.262	0.204	0.335	0.238	0.376
Pyuthan	0.260	0.219	0.310	0.241	0.350
Doti	0.242	0.195	0.303	0.221	0.334
Achham	0.227	0.179	0.288	0.205	0.321
Dailekh	0.222	0.180	0.274	0.204	0.302
Dadeldhura	0.220	0.175	0.280	0.202	0.319
Baitadi	0.218	0.173	0.276	0.197	0.311
Jajarkot	0.182	0.141	0.231	0.165	0.268
Myagdi	0.172	0.128	0.230	0.151	0.264

Note: Efficiency estimates are expressed "relative" to the most efficient district in the sample (which has a value of 1)

Table 11

Parameter Estimates of the Production Function (With Literacy) - Terai

Dependent Vairable : Natural Log of Agricultural Output (Mean Value : 6.63)

Explanatory Variables (besides net school enrollment rates) are in Natural Logs

Independent Vairables	*Within-Estimates*
land	**2.300**
	(0.295)*
labor-male	**-0.523**
	(0.45)
labor-female	**0.420**
	(0.31)
fertilizer	**0.0130**
	(0.015)
livestock	**0.042**
	(0.040)
rainfall	**0.190**
	(0.034)*
literacy-male	**0.011**
	(0.017)
literacy-female	**0.024**
	(0.016)
Observations	220
# of Districts	20
# of Time Periods	11

robust standard errors in parentheses ; * significant at the 1% level

Note : robust errors based on White's "Sandwich Method" are heteroskedasticity/serial-correlation consistent estimates

Table 12

Parameter Estimates (With Literacy) of time-invariant and time-varying heterogeneity
Terai

	Time-invarient heterogeneity			RTC^		
District	*Estimate*	*SE**	*t-stat*	*Estimate*	*SE**	*t-stat*
Saptari	-6.084	1.179	-5.160	0.047	0.021	2.206
Mahotari	-5.466	1.002	-5.457	0.025	0.025	1.012
Rautahat	-5.699	1.0080	-5.654	0.016	0.028	0.579
Bara	-5.454	1.0930	-4.990	0.011	0.024	0.469
Siraha	-5.665	1.070	-5.295	0.010	0.028	0.371
Kapilbastu	-5.761	1.050	-5.489	0.004	0.034	0.122
Dhanusa	-5.518	1.0740	-5.137	0.004	0.024	0.165
Sarlahi	-5.503	1.0250	-5.368	-0.002	0.024	-0.072
Banke	-5.2590	0.989	-5.318	-0.003	0.031	-0.085
Rupandehi	-6.004	1.215	-4.940	-0.005	0.022	-0.242
Kailali	-5.792	1.127	-5.140	-0.007	0.022	-0.309
Jhapa	-6.574	1.2900	-5.096	-0.010	0.032	-0.330
Parsa	-5.0900	1.065	-4.781	-0.0130	0.027	-0.487
Chitawan	-5.943	1.234	-4.818	-0.033	0.030	-1.093
Morang	-6.106	1.211	-5.044	-0.033	0.034	-0.997
Kanchanpur	-5.4650	1.069	-5.113	-0.034	0.039	-0.872
Nawalparasi	-5.194	1.069	-4.861	-0.034	0.030	-1.155
Bardiya	-4.870	0.913	-5.334	-0.038	0.035	-1.065
Dang	-5.616	1.095	-5.130	-0.047	0.036	-1.301
Sunsari	-5.453	1.192	-4.573	-0.089	0.041	-2.177

* : Standard-Error

^ : *Rate of Technical Change (time-varying heterogeniety)*

Table 12.2

Terai - With Literacy

District	GRY^	RTC
Mahotari	0.058	0.025
Sarlahi	0.058	-0.002
Jhapa	0.057	-0.010
Bara	0.054	0.011
Saptari	0.047	0.047
Dhanusa	0.042	0.004
Bardiya	0.042	-0.038
Siraha	0.039	0.010
Kailali	0.038	-0.007
Morang	0.036	-0.033
Kanchanpur	0.031	-0.034
Rautahat	0.030	0.016
Nawalparasi	0.030	-0.034
Sunsari	0.026	-0.089
Dang	0.026	-0.047
Chitawan	0.022	-0.0330
Rupandehi	0.020	-0.005
Banke	0.013	-0.003
Kapilbastu	0.005	0.004
Parsa	0.001	-0.0130

^ GRY : growth rate of output

Table 13

Bootstrap Confidence Intervals for RTC Esimates (With Literacy) : 90% Level - Terai

		Percentile		BCA	
District	*RTC Estimate*	*LB*	*UB*	*LB*	*UB*
Saptari	0.0472	0.0166	0.0791	0.0349	0.0950
Mahotari	0.0251	-0.0119	0.0578	0.0115	0.0779
Rautahat	0.0161	-0.0250	0.0550	0.0006	0.0779
Bara	0.0114	-0.0244	0.0454	-0.0024	0.0699
Siraha	0.0102	-0.0284	0.0498	-0.0053	0.0687
Kapilbastu	0.0041	-0.0457	0.0502	-0.0163	0.0824
Dhanusa	0.0039	-0.0303	0.0362	-0.0091	0.0563
Sarlahi	-0.0017	-0.0354	0.0296	-0.0144	0.0513
Banke	-0.0026	-0.0480	0.0389	-0.0205	0.0649
Rupandehi	-0.0053	-0.0382	0.0247	-0.0181	0.0436
Kailali	-0.0069	-0.0417	0.0227	-0.0200	0.0445
Jhapa	-0.0104	-0.0576	0.0327	-0.0287	0.0585
Parsa	-0.0130	-0.0525	0.0246	-0.0291	0.0507
Chitawan	-0.0330	-0.0787	0.0084	-0.0505	0.0328
Morang	-0.0334	-0.0833	0.0133	-0.0527	0.0401
Kanchanpur	-0.0342	-0.0918	0.0195	-0.0565	0.0601
Nawalparasi	-0.0343	-0.0796	0.0060	-0.0517	0.0335
Bardiya	-0.0375	-0.0889	0.0105	-0.0578	0.0393
Dang	-0.0471	-0.1023	0.0008	-0.0687	0.0344
Sunsari	-0.0886	-0.1462	-0.0330	-0.1087	0.0188

Table 14

Bootstrap Confidence Intervals for Technical Efficiency Esimates (With Literacy) : 90% Level - Terai

Technical Efficiency Estimates for the First Period (1981)

District	Efficiency (T=1981)	Percentile LB	Percentile UB	BCA LB	BCA UB
Bardiya	1	0.8890	1	0.9330	1
Parsa	0.8220	0.6022	1	0.7212	1
Nawalparasi	0.7249	0.4934	0.9769	0.6259	1
Banke	0.7015	0.5602	0.8192	0.6457	0.8764
Mahotari	0.5866	0.4786	0.6776	0.5493	0.7878
Bara	0.5853	0.4135	0.7458	0.5207	0.8813
Kanchanpur	0.5531	0.3799	0.7167	0.4775	0.7945
Sarlahi	0.5503	0.4368	0.6523	0.5077	0.7192
Dhanusa	0.5453	0.3924	0.6957	0.4844	0.8305
Sunsari	0.5304	0.2917	0.8543	0.4334	1
Siraha	0.4736	0.3516	0.5920	0.4283	0.7188
Dang	0.4693	0.3210	0.6132	0.4034	0.6772
Rautahat	0.4601	0.3734	0.5435	0.4264	0.6194
Kapilbastu	0.4274	0.3336	0.5332	0.3898	0.6316
Kailali	0.4099	0.2663	0.5735	0.3526	0.7115
Chitawan	0.3434	0.1753	0.5949	0.2756	0.7826
Rupandehi	0.3321	0.1860	0.5219	0.2708	0.6179
Saptari	0.3231	0.1912	0.4830	0.2694	0.5914
Morang	0.2915	0.1641	0.4426	0.2397	0.5568
Jhapa	0.1869	0.0899	0.3272	0.1455	0.4333

Note: Efficiency estimates are expressed "relative" to the most efficient district in the sample (which has a value of 1)

Table 15

Bootstrap Confidence Intervals for Technical Efficiency Esimates (With Literacy)
: 90% Level - Terai

Technical Efficiency Estimates for the Last Period (1991)

		Percentile		BCA	
District	*Efficiency (T=1991)*	*LB*	*UB*	*LB*	*UB*
Mahotari	1	0.8174	1	0.8958	1
Parsa	0.9568	0.754	1	0.8809	1
Bardiya	0.9114	0.7584	0.9842	0.8606	1
Banke	0.9066	0.7217	1	0.8347	1
Bara	0.8701	0.6999	0.9907	0.8039	1
Dhanusa	0.7522	0.6172	0.8223	0.7043	0.8779
Sarlahi	0.7178	0.5891	0.7935	0.6758	0.8749
Rautahat	0.7165	0.5523	0.8134	0.6628	0.8894
Siraha	0.6957	0.5614	0.7753	0.6503	0.8882
Saptari	0.6866	0.4808	0.8617	0.6054	0.9803
Nawalparasi	0.6820	0.4825	0.8361	0.6053	0.9486
Kapilbastu	0.5906	0.4886	0.6483	0.5545	0.6876
Kanchanpur	0.5209	0.3254	0.7144	0.4460	0.8876
Kailali	0.5073	0.3939	0.5851	0.4620	0.6503
Rupandehi	0.4176	0.2822	0.5354	0.3633	0.6520
Dang	0.3885	0.2595	0.5137	0.3345	0.6183
Chitawan	0.3274	0.1726	0.5257	0.2681	0.7193
Sunsari	0.2900	0.1519	0.4895	0.2426	0.8768
Morang	0.2769	0.1554	0.4200	0.2268	0.5681
Jhapa	0.2233	0.1097	0.3925	0.1761	0.5859

Note: Efficiency estimates are expressed "relative" to the most efficient district in the sample (which has a value of 1)

Table 16

Parameter Estimates of the Production Function (With Literacy) - Hill

Dependent Vairable : Natural Log of Agricultural Output (Mean Value : 5.507)

Explanatory Variables (besides literacy rates) are in Natural Logs

Independent Vairables	*Within-Estimates*
land	**0.180**
	(0.16)
labor-male	**0.46**
	(0.210)**
labor-female	**0.335**
	(0.234)
fertilizer	**0.024**
	(0.011)**
livestock	**0.069**
	(0.063)
rainfall	**0.063**
	(0.029)**
literacy-male	**0.049**
	(0.032)
literacy-female	**0.039**
	(0.023)**
Observations	429
# of Districts	39
# of Time Periods	11

robust standard errors in parentheses ; ** significant at the 10% level

Note : robust errors based on White's "Sandwich Method" are heteroskedasticity/serial-correlation consistent estimates

Table 17

Parameter Estimates (With Literacy) of time-invariant and time-varying heterogeneity
Terai

District	Time-invarient heterogeneity Estimate	SE*	t-stat	RTC^ Estimate	SE*	t-stat
Kavre	1.4665	0.9414	1.558	-0.0352	0.0189	-1.862
Lamjung	0.5016	0.9143	0.549	-0.0424	0.0126	-3.365
Achham	1.4593	0.7083	2.060	-0.0642	0.0235	-2.732
Makwanpur	1.7015	0.9325	1.825	-0.0664	0.0144	-4.611
Gulmi	0.5797	0.9664	0.600	-0.0674	0.0133	-5.068
Jajarkot	1.6405	0.7069	2.321	-0.0675	0.0185	-3.649
Parbat	0.3390	0.9370	0.362	-0.0730	0.0160	-4.563
Sindhuli	1.7857	0.8983	1.988	-0.0755	0.0164	-4.604
Dhankuta	0.8099	0.9658	0.839	-0.0769	0.0148	-5.196
Nuwakot	2.1278	0.9140	2.328	-0.0778	0.0143	-5.441
Ramechhap	1.4965	0.8235	1.817	-0.0811	0.0171	-4.743
Dailekh	1.3717	0.7801	1.758	-0.0839	0.0173	-4.850
Rukum	1.8425	0.8274	2.227	-0.0863	0.0206	-4.189
Khotang	1.2824	0.9169	1.399	-0.0888	0.0180	-4.933
Baglung	1.1304	0.8482	1.333	-0.090	0.0164	-5.488
Myagdi	0.9868	0.7051	1.400	-0.0901	0.0182	-4.951
Palpa	1.0057	0.9338	1.077	-0.0906	0.0165	-5.491
Dhading	2.1769	0.8608	2.529	-0.0931	0.0181	-5.144
Rolpa	1.8440	0.7660	2.407	-0.0952	0.0219	-4.347
Bhojpur	1.4651	0.9033	1.622	-0.0985	0.0170	-5.794
Terhathum	0.5114	0.9098	0.562	-0.0998	0.0167	-5.976
Ilam	1.1814	0.9336	1.265	-0.1001	0.0157	-6.376
Kaski	0.8343	1.0091	0.827	-0.1009	0.0169	-5.970
Baitadi	1.1048	0.7591	1.455	-0.1042	0.0239	-4.360
Panchthar	1.3999	0.9269	1.510	-0.1052	0.0167	-6.299
Udayapur	1.6884	0.8410	2.008	-0.1052	0.0190	-5.537
Syangja	1.1205	1.1024	1.016	-0.1057	0.0173	-6.110
Surkhet	1.4472	0.9301	1.556	-0.1066	0.0192	-5.552
Arghakhanchi	1.1987	0.8057	1.488	-0.1087	0.0176	-6.176
Salyan	2.0394	0.8906	2.290	-0.1108	0.0213	-5.202
Pyuthan	1.6426	0.7929	2.072	-0.1131	0.0195	-5.800
Kathmandu	0.8265	0.9776	0.845	-0.1137	0.0164	-6.933
Lalitpur	0.8795	0.7728	1.138	-0.1149	0.0194	-5.923
Dadeldhura	1.1854	0.7787	1.522	-0.1169	0.0267	-4.378
Gorkha	1.8974	0.9444	2.009	-0.1205	0.0203	-5.936
Okhaldhunga	1.6453	0.7436	2.213	-0.1220	0.0197	-6.193
Doti	1.9936	0.7463	2.671	-0.1240	0.0254	-4.882
Tanahu	1.3845	0.9453	1.465	-0.1252	0.0201	-6.229
Bhaktapur	1.4960	0.7426	2.015	-0.1452	0.0191	-7.602

* : Standard-Error
^ : *Rate of Technical Change (time-varying heterogeniety)*

Table 17.2

Hill - With Literacy

District	GRY^	RTC
Kavre	0.056	-0.035
Achham	0.038	-0.064
Rukum	0.033	-0.086
Lalitpur	0.032	-0.115
Jajarkot	0.031	-0.068
Lamjung	0.030	-0.042
Khotang	0.030	-0.089
Gorkha	0.028	-0.121
Baitadi	0.027	-0.104
Makwanpur	0.025	-0.066
Myagdi	0.025	-0.090
Dadeldhura	0.025	-0.117
Parbat	0.025	-0.0730
Dhading	0.024	-0.093.
Baglung	0.023	-0.0900
Palpa	0.023	-0.091
Tanahu	0.023	-0.125
Rolpa	0.023	-0.095
Surkhet	0.022	-0.107
Sindhuli	0.021	-0.076
Dhankuta	0.021	-0.077
Udayapur	0.020	-0.105
Ramechhap	0.019	-0.081
Bhojpur	0.018	-0.099
Terhathum	0.016	-0.100
Arghakhanchi	0.016	-0.109
Kaski	0.016	-0.101
Nuwakot	0.015	-0.078
Gulmi	0.015	-0.067
Salyan	0.014	-0.111
Okhaldhunga	0.014	-0.1220
Panchthar	0.011	-0.105
Pyuthan	0.010	-0.113
Syangja	0.010	-0.106
Dailekh	0.009	-0.084
Doti	0.008	-0.1240
Ilam	0.007	-0.100
Bhaktapur	-0.004	-0.145
Kathmandu	-0.021	-0.114

GRY^ : growth rate of output

Table 18

Bootstrap Confidence Intervals for RTC Esimates (With Literacy) : 90% Level - Hill

District	RTC Estimate	Percentile LB	Percentile UB	BCA LB	BCA UB
Kavre	-0.0352	-0.0638	-0.0061	-0.0470	0.0137
Lamjung	-0.0424	-0.0618	-0.0244	-0.0496	-0.0132
Achham	-0.0642	-0.0991	-0.0282	-0.0797	-0.0124
Makwanpur	-0.0664	-0.0869	-0.0439	-0.0755	-0.0323
Gulmi	-0.0674	-0.0886	-0.0476	-0.0752	-0.0351
Jajarkot	-0.0675	-0.0946	-0.0388	-0.0784	-0.0211
Parbat	-0.0730	-0.0977	-0.0505	-0.0822	-0.0350
Sindhuli	-0.0755	-0.0997	-0.0506	-0.0858	-0.0361
Dhankuta	-0.0769	-0.0993	-0.0553	-0.0855	-0.0364
Nuwakot	-0.0778	-0.0995	-0.0580	-0.0869	-0.0445
Ramechhap	-0.0811	-0.1055	-0.0552	-0.0921	-0.0396
Dailekh	-0.0839	-0.1101	-0.0577	-0.0955	-0.0411
Rukum	-0.0863	-0.1161	-0.0559	-0.1002	-0.0358
Khotang	-0.0888	-0.1151	-0.0625	-0.1003	-0.0437
Baglung	-0.0900	-0.1151	-0.0672	-0.0997	-0.0515
Myagdi	-0.0901	-0.1169	-0.0629	-0.1015	-0.0473
Palpa	-0.0906	-0.1156	-0.0669	-0.1008	-0.0488
Dhading	-0.0931	-0.1199	-0.0666	-0.1053	-0.0484
Rolpa	-0.0952	-0.1288	-0.0620	-0.1098	-0.0449
Bhojpur	-0.0985	-0.1233	-0.0726	-0.1083	-0.0557
Terhathum	-0.0998	-0.1246	-0.0746	-0.1102	-0.0613
Ilam	-0.1001	-0.1225	-0.0758	-0.1099	-0.0657
Kaski	-0.1009	-0.1260	-0.0755	-0.1114	-0.0593
Baitadi	-0.1042	-0.1394	-0.0683	-0.1207	-0.0491
Panchthar	-0.1052	-0.1299	-0.0806	-0.1156	-0.0631
Udayapur	-0.1052	-0.1331	-0.0758	-0.1177	-0.0603
Syangja	-0.1057	-0.1325	-0.0806	-0.1158	-0.0635
Surkhet	-0.1066	-0.1338	-0.0770	-0.1178	-0.0597
Arghakhanchi	-0.1087	-0.1345	-0.0818	-0.1199	-0.0674
Salyan	-0.1108	-0.1414	-0.0784	-0.1236	-0.0655
Pyuthan	-0.1131	-0.1418	-0.0837	-0.1262	-0.0658
Kathmandu	-0.1137	-0.1381	-0.0890	-0.1228	-0.0732
Lalitpur	-0.1149	-0.1431	-0.0855	-0.1261	-0.0664
Dadeldhura	-0.1169	-0.1555	-0.0780	-0.1336	-0.0556
Gorkha	-0.1205	-0.1507	-0.0889	-0.1327	-0.0684
Okhaldhunga	-0.1220	-0.1505	-0.0915	-0.1337	-0.0735
Doti	-0.1240	-0.1606	-0.0858	-0.1385	-0.0616
Tanahu	-0.1252	-0.1547	-0.0955	-0.1366	-0.0755
Bhaktapur	-0.1452	-0.1736	-0.1170	-0.1572	-0.0959

Note : Theta2 represents time-varying district level heterogeneity

Table 19

Bootstrap Confidence Intervals for Technical Efficiency Esimates (With Literacy) : 90% Level - Hill

Technical Efficiency Estimates for the First Period (1981)

District	*Efficiency (T=1981)*	Percentile *LB*	Percentile *UB*	BCA *LB*	BCA *UB*
Dhading	1	0.8857	1	0.9501	1
Nuwakot	0.9667	0.8295	1	0.9107	1
Salyan	0.8563	0.7463	0.9307	0.8110	0.9842
Doti	0.8072	0.6226	0.9915	0.7322	1
Gorkha	0.7357	0.6115	0.8220	0.6922	0.8809
Rukum	0.7206	0.6212	0.7993	0.6821	0.8415
Rolpa	0.7154	0.5643	0.8409	0.6577	0.9247
Sindhuli	0.6883	0.5997	0.7454	0.6569	0.7898
Makwanpur	0.6385	0.5294	0.7156	0.6001	0.7753
Udayapur	0.6062	0.5239	0.6703	0.5716	0.7186
Jajarkot	0.6001	0.4413	0.7696	0.5355	0.8738
Pyuthan	0.5745	0.4728	0.6678	0.5379	0.7209
Okhaldhunga	0.5709	0.4395	0.7102	0.5169	0.8205
Kavre	0.5208	0.4215	0.6015	0.4861	0.6629
Ramechhap	0.5126	0.4262	0.5801	0.4802	0.6577
Achham	0.5022	0.3722	0.6409	0.4472	0.7273
Bhojpur	0.4881	0.4067	0.5534	0.4559	0.5893
Bhaktapur	0.4805	0.3190	0.6836	0.4155	0.8588
Surkhet	0.4756	0.3903	0.5346	0.4437	0.5808
Panchthar	0.4543	0.3564	0.5450	0.4142	0.5970
Dailekh	0.4511	0.3598	0.5406	0.4147	0.5940
Tanahu	0.4385	0.3504	0.5082	0.4062	0.5568
Khotang	0.4106	0.3385	0.4662	0.3832	0.5009
Arghakhanchi	0.3702	0.2963	0.4385	0.3407	0.4855
Ilam	0.3670	0.2833	0.4453	0.3306	0.5262
Dadeldhura	0.3623	0.2899	0.4305	0.3328	0.4880
Baglung	0.3523	0.2806	0.4167	0.3253	0.4816
Syangja	0.3434	0.2167	0.4853	0.2941	0.5964
Baitadi	0.3385	0.2596	0.4198	0.3035	0.4597
Palpa	0.3108	0.2492	0.3613	0.2850	0.4039
Myagdi	0.3051	0.2173	0.4143	0.2656	0.4756
Lalitpur	0.2674	0.1869	0.3636	0.2309	0.4518
Dhankuta	0.2591	0.1901	0.3323	0.2296	0.3934
Kaski	0.2591	0.1873	0.3315	0.2272	0.3922
Kathmandu	0.2539	0.1739	0.3448	0.2189	0.4339
Gulmi	0.2078	0.1506	0.2706	0.1841	0.3210
Lamjung	0.1970	0.1466	0.2499	0.1769	0.3020
Terhathum	0.1878	0.1320	0.2533	0.1619	0.3181
Parbat	0.1624	0.1137	0.2169	0.1430	0.2835

Note: Efficiency estimates are expressed "relative" to the most efficient district in the sample (which has a value of 1)

Table 20

Bootstrap Confidence Intervals for Technical Efficiency Esimates (With Literacy) : 90% Level - Hill

	Technical Efficiency Estimates for the Last Period (1991)	**Percentile**		**BCA**	
District	*Efficiency (T=1991)*	*LB*	*UB*	*LB*	*UB*
Nuwakot	1	0.9678	1	0.9669	1
Dhading	0.8876	0.7897	0.9928	0.8428	1
Kavre	0.8252	0.6911	0.9655	0.7676	1
Makwanpur	0.7406	0.6501	0.8321	0.7018	0.8809
Sindhuli	0.7287	0.6450	0.8150	0.6907	0.8559
Jajarkot	0.6887	0.5069	0.9565	0.6057	1
Rukum	0.6846	0.5809	0.7910	0.6449	0.8410
Salyan	0.6372	0.5618	0.7176	0.6067	0.7653
Rolpa	0.6219	0.4945	0.7783	0.5625	0.8450
Achham	0.5953	0.4306	0.8256	0.5062	0.9356
Doti	0.5263	0.4006	0.6849	0.4654	0.7479
Ramechhap	0.5132	0.4210	0.6240	0.4772	0.6739
Gorkha	0.4967	0.4225	0.5743	0.4624	0.6064
Udayapur	0.4769	0.3999	0.5648	0.4402	0.6068
Dailekh	0.4390	0.3358	0.5638	0.3904	0.6119
Pyuthan	0.4177	0.3424	0.5050	0.3819	0.5461
Bhojpur	0.4107	0.3509	0.4775	0.3852	0.5160
Khotang	0.3805	0.3260	0.4423	0.3546	0.4723
Okhaldhunga	0.3796	0.2867	0.4986	0.3348	0.5522
Surkhet	0.369	0.3109	0.4308	0.3428	0.4581
Panchthar	0.3575	0.2961	0.4261	0.3275	0.4563
Baglung	0.3226	0.2664	0.3833	0.2970	0.4193
Ilam	0.3038	0.2459	0.3748	0.2764	0.4152
Lamjung	0.2904	0.2350	0.3541	0.2662	0.3977
Palpa	0.2830	0.2340	0.3403	0.2606	0.3731
Tanahu	0.2824	0.2253	0.3473	0.2583	0.3719
Arghakhanchi	0.2811	0.2218	0.3473	0.2514	0.3809
Myagdi	0.2793	0.1927	0.3968	0.2379	0.4565
Dhankuta	0.2705	0.2182	0.3327	0.2476	0.3694
Baitadi	0.2691	0.1915	0.3711	0.2324	0.4280
Syangja	0.2688	0.1885	0.3700	0.2337	0.4183
Dadeldhura	0.2536	0.1786	0.3543	0.2210	0.4249
Bhaktapur	0.2535	0.1573	0.3978	0.2062	0.4917
Gulmi	0.2387	0.1953	0.2881	0.2206	0.3153
Kaski	0.2128	0.1578	0.2765	0.1869	0.3125
Lalitpur	0.1908	0.1285	0.2775	0.1592	0.3314
Kathmandu	0.1835	0.1226	0.2680	0.1556	0.3284
Parbat	0.1763	0.1369	0.2217	0.1598	0.2484
Terhathum	0.1560	0.1157	0.2066	0.1372	0.2395

Note: Efficiency estimates are expressed "relative" to the most efficient district in the sample (which has a value of 1)

Table ARC1

Districts with local agricultural research center and year of establishment (Terai)

District	Year Agricultural Research Center was established	*Efficiency (T=1981)* (without literacy)
Parsa	1959	1.000
Bardiya	*	0.943
Nawalparasi	*	0.877
Sunsari	1960	0.768
Banke	1960	0.745
Kanchanpur	*	0.676
Bara	1972	0.627
Mahotari	1965	0.597
Dhanusa	1961	0.583
Chitawan	1972	0.581
Sarlahi	1976	0.555
Dang	*	0.551
Siraha	*	0.502
Rupandehi	1972	0.471
Morang	*	0.462
Kailali	*	0.456
Rautahat	*	0.441
Saptari	*	0.426
Kapilbastu	*	0.410
Jhapa	*	0.359

Note: * Indicates that district does not have a local agricultural research center

Table ARC2

Districts with local agricultural research center and year of establishment (Hill)

District	Year Agricultural Research Center was established	*Efficiency (T=1981)* (without literacy)
Kathmandu	1955	1.000
Syangja	*	0.889
Nuwakot	1971	0.769
Makwanpur	*	0.716
Ilam	*	0.655
Kaski	1960	0.637
Gorkha	*	0.584
Kavre	1961	0.581
Panchthar	*	0.556
Dhading	*	0.545
Tanahu	1977	0.544
Bhaktapur	*	0.533
Sindhuli	*	0.532
Bhojpur	*	0.509
Dhankuta	1961	0.502
Surkhet	*	0.481
Salyan	1991	0.461
Gulmi	*	0.448
Palpa	*	0.436
Khotang	*	0.424
Udayapur	*	0.405
Terhathum	*	0.384
Lamjung	*	0.380
Lalitpur	1965	0.368
Rukum	*	0.352
Ramechhap	*	0.350
Parbat	*	0.342
Baglung	*	0.341
Pyuthan	*	0.311
Rolpa	*	0.310
Arghakhanchi	*	0.306
Okhaldhunga	*	0.300
Doti	1962	0.276
Dailekh	1968	0.268
Dadeldhura	*	0.233
Baitadi	*	0.210
Achham	*	0.191
Jajarkot	*	0.171
Myagdi	*	0.164

Note: * Indicates that district does not have a local agricultural research center

Table 21

		Without Literacy			*With Literacy*		
	GRY	ARTC	ATE81	ATE91	ARTC	ATE81	ATE91
TERAI	3.37%	3%	60%	70%	-0.47%	47%	57%
HILL	2%	2.50%	45%	41%	-8.40%	46%	40%

where,

GRY : growth rate of output

ARTC : average rate of district level technical change

ATE81 : average level of distirct level technical efficiency in 1981

ATE81 : average level of distirct level technical efficiency in 1991

Figure 1

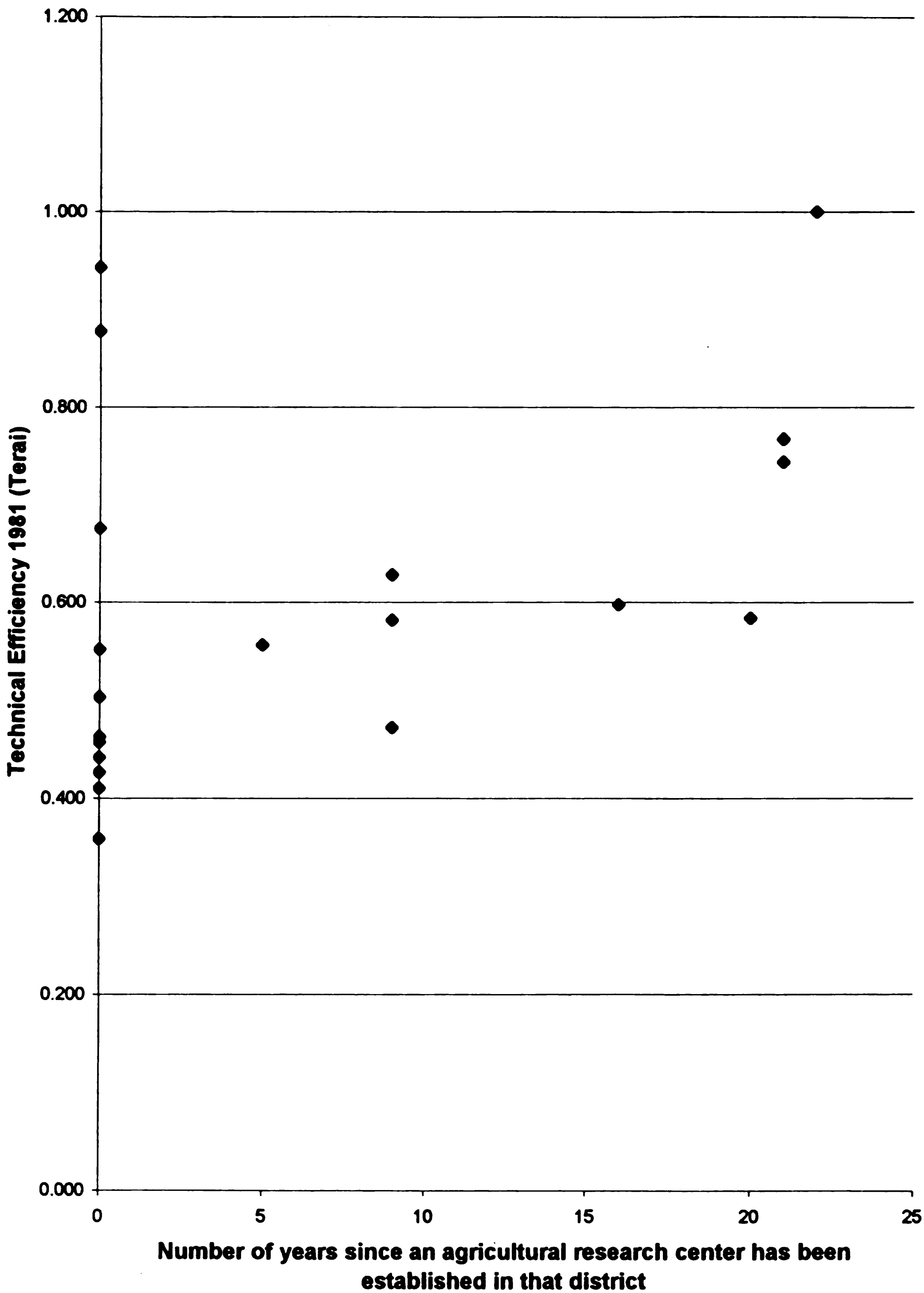
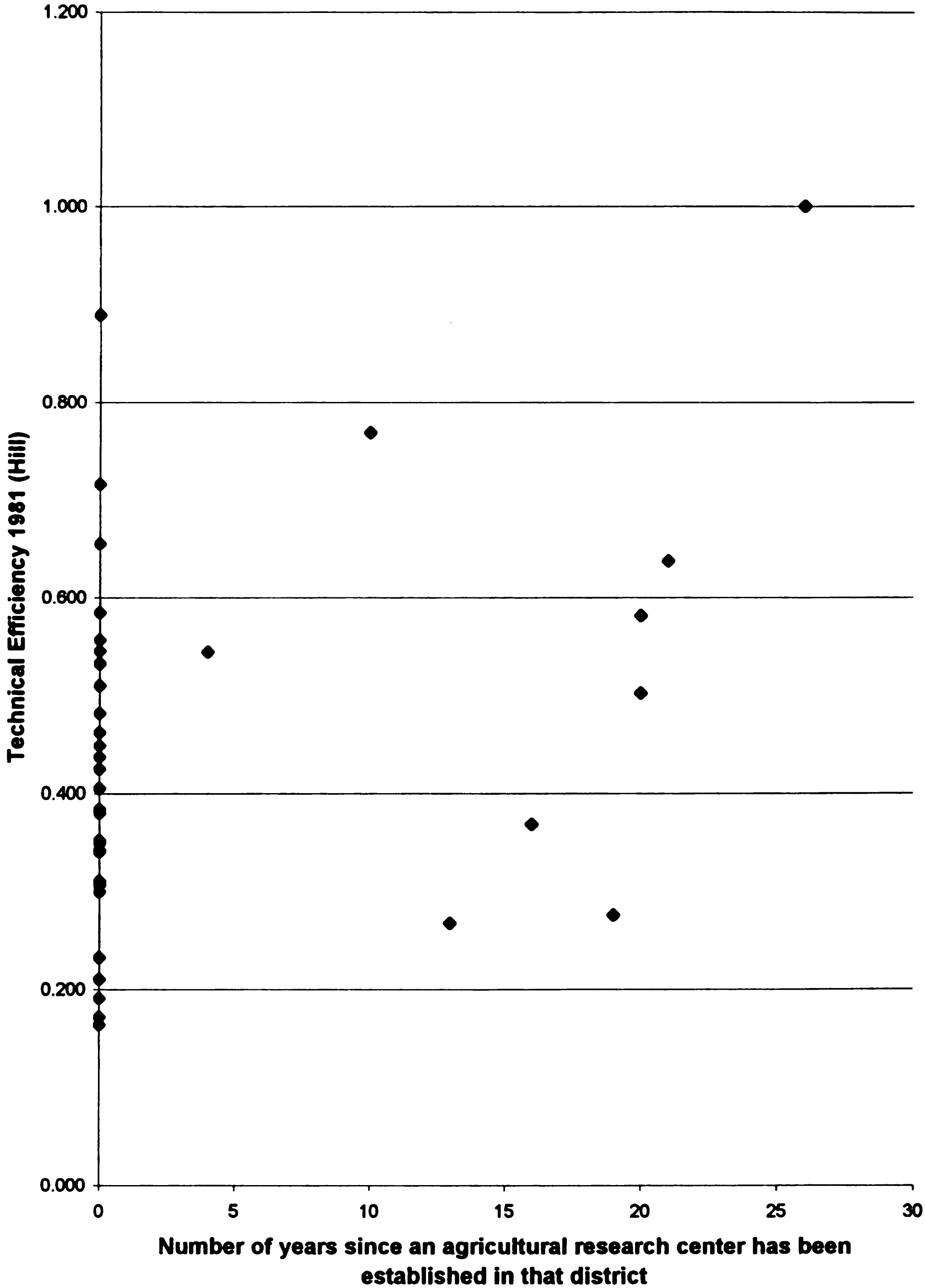

1.200
1.000
0.800
0.600
0.400
0.200
0.000
Technical Efficiency 1981 (Terai)
0
5
10
15
20
25
Number of years since an agricultural research center has been established in that district

Figure 2


1.200
1.000
0.800
0.600
0.400
0.200
0.000
Technical Efficiency 1981 (Hill)
0
5
10
15
20
25
30
Number of years since an agricultural research center has been established in that district

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