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Agricultural Productivity and Poverty Reduction in Nepal

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Abstract

This paper provides for the first time a clear quantitative link between agricultural productivity and poverty among rural households in Nepal. Using data from a nationwide Nepal Living Standard Survey 2004, we first estimate household-specific productivity per worker under both Cobb–Douglas and translog production functions. Second, the paper identifies the determinants of productivity. Third, we explore a theoretical link between productivity and poverty using Sen's poverty index and find empirically that productivity growth substantially helps poverty reduction. Finally, the integrated effects of changes in productivity determinants are found to be stronger than the outcomes of sectoral policies taken in isolation.

Introduction

The share of agriculture in Nepal's Gross Domestic Product has been falling over time. Yet agriculture still accounts for 33% of national production, 70% of all employment and a third of all exports (Ministry of Finance,). Unfortunately, the decline in agriculture has resulted from stagnant or falling productivity in the agriculture itself, and not because manufacturing or industry has rapidly overtaken agriculture in productivity changes. Thus, how to attain a continuous rise in agricultural productivity remains a concern of policy.

Productivity in agriculture remains constrained by a host of factors. High population density and limited cultivable area have led to severe land fragmentation. Almost 75% of households have holdings of less than one hectare, inadequate to meet their subsistence needs (Central Bureau of Statistics, 2004). Year round irrigation is available to only a third of arable land. Even where irrigation is no barrier to production, adoption of modern technology is constrained by limited access to extension services, or low risk taking ability of farmers. Agriculture in Nepal has grown much slower than elsewhere in South Asia.

A consequence of the poverty trap facing many rural farmers is that much of the young generation either migrates to India or, if the direct cost of migration is affordable, to East Asian or Persian Gulf countries, to supplement family incomes. Foreign employment cannot go far in tackling poverty when it can only absorb a tiny fraction of rural population growth. In contrast, industrialization and service sector development may have a large potential to make an impact on poverty. Yet that will require the emergence of a stable path of constitutional and political development that the current political stalemate in Nepal precludes. Agriculture still offers hope since even the current state of knowledge is enough to lift productivity significantly in this vital sector.[1]

In this paper we identify the determinants of agricultural productivity in Nepal and quantify their effects on poverty reduction. We use a comprehensive household survey to estimate the Cobb–Douglas (CD) and translog (TL) production functions so as to derive plausible measures of farm productivity. The paper then explores how much a rise in farm income reduces poverty. Finally, it decomposes such effect on poverty into factors that affect productivity. This approach allows us to identify the extent to which poverty reduction can be attributed to specific determinants of productivity and to derive important implications for policy on poverty.

Our paper is closely related to the strand of literature that examines productivity, income, and poverty in developing countries. Datt and Ravallion (1998) in an influential paper find that increases in agricultural productivity (mainly yield per acre) in India have cut poverty substantially. The impact accrued not only to the households at or near the poverty threshold but to those further down as well. Irz et al. (2001) assemble considerations from the literature to examine headcount poverty as a function of value added per unit of land and the land–labor ratio. Their estimates show a large impact of agricultural productivity on poverty reduction. The authors in this area claim that three channels—employment generation, strong linkages with the rest of the rural economy, and decreases in real cost of food—give agriculture its powerful poverty-reducing effects relative to alternative strategies for addressing poverty.

De Janvry and Sadoulet (2010) explore direct and linkage effects of agriculture on poverty. Their analysis of the Chinese data for 1980–2001 indicates that a 1% growth in agriculture during the period when agriculture comprised only 22% of the economy raised gross domestic product (GDP) by 0.45%. In comparison, non-agriculture raised GDP by twice as much (0.92%), but the size of this sector was over 3.5 times as large. Thus, the relative impact of agricultural growth on the overall economy was much greater. Thirtle et al. (2003) study the impact of research-led agricultural productivity growth on poverty reduction in Africa, Asia, and Latin America. They use a causal chain model to estimate the effect of agricultural R&D on agricultural productivity and, in turn, on poverty. They find substantial evidence that agricultural productivity growth makes a large dent in poverty, whereas productivity growth in industry and services does not.

Another approach to poverty analysis is the growth elasticity of poverty.[2] Christiaensen et al. (2010) start with a basic relation where poverty depends on its elasticity with respect to income multiplied by the change in income. They decompose a poverty change into a change in agricultural income, the linkage effect of agriculture on other sectors, the extent to which poor people participate in agriculture, and the overall size of this sector. Their cross-country evidence also confirms the claim made by others that agriculture helps poverty reduction better than does non-agriculture. Finally, Minten and Barrett (2008) analyze the Madagascar data to show that higher agricultural productivity lowers food prices benefitting consumers, raises farm output by more than price declines which benefits farmers, and lifts more people out of poverty.

Our paper takes a somewhat different approach. To provide depth to the productivity–poverty relationship, we use Sen's (1973) poverty concept. Defined this way, poverty adjusts headcount ratio for inequality changes among the poor. To extend Sen's poverty measure, we divide income into crop and noncrop incomes. However, our results also provide strong support that agricultural income facilitates poverty alleviation. In addition, our focus is on an extremely poor country, Nepal, for which only three rounds of household survey (Nepal Living Standard Survey (NLSS) I, II, and III) have been conducted in a consistent and scientific manner. We use data from NLSSII.

Agricultural Characteristics and Poverty Profile

Nepal has three major ecological zones: high mountains in the north covering 34% of the total area, hills in the middle with 44%, and plains (terai) in the south with 21%. The mountains are mainly rugged and barren whereas the hill region contains much agricultural and pasture land. The terai, with an altitude below 300 meters, is mostly flat and supplies most of the food grains to the country. From 2000 to 2009, total agricultural production increased at a rate of 2.9% per year, while population grew at 1.5% a year (Ministry of Finance, Nepal, 2010/11). Yields for the major crops have tended to stagnate or even decline, mainly in the hills where low productivity marginal land has been brought increasingly under cultivation.

We use data from NLSS 2003/04 (CBS). The samples were drawn from all three topographical regions going from east to west, and all five development zones going from north to south. Including all the households with positive numbers for crop production, we get a sample of 2,535 households with data on inputs and outputs in agriculture, and a range of household socio-economic characteristics which we use to identify factors that affect productivity. The northern mountains have low population density which makes the average cropped area per household look large there. but productivity per hectare in hills and terai is about twice as high. Combining productivities in cereal and vegetable crops, per person availability of food per year is 218 kg in the mountains, 264 kg in the hills and 257 kg in the terai. These averages indeed fall short of the minimum subsistence food needs turning Nepal from a food exporter until the 1980s to a net importer of food.

Nepal has remained one of the least developed countries in the world with a per capita GDP of 946 constant 2005 international purchasing power parity (PPP) dollars in 2010. In the survey year 2004, about 31% nationally and 35% in the rural areas lived below the national poverty line, a line set at a low US$104.5 per person. In contrast, the World Bank benchmark of US$1.25 per day per person shows a huge 55% of the population in poverty. The continuing uncertainty about the political situation in Nepal, following the difficult 1996–2006 communist insurgency, has also prevented poverty alleviation efforts. To address the problem of slow growth and acute poverty, we find a compelling need for scientific measurement of agricultural productivity at the household level which can provide a basis for determining the factors that influence productivity. A careful study that enhances knowledge of the level of productivity and its causal factors should yield clearer implications for policies to facilitate agricultural growth as well as poverty reduction in Nepal.

Methodology

Cobb–Douglas and Translog Production Functions

To estimate productivity in agriculture, we use the Cobb–Douglas and translogarithmic (TL) production functions. We compare the results for these functions so as to identify which of the two models represents our data better. Equation (1) shows our basic production function:

$$Y_i = f(X_i \cdot \beta)$$

where Y_i is the actual output of farmer i, $f(X_i \cdot \beta)$ is the production function where X_i is a vector of inputs used by farmer i and β is a set of parameters to be estimated. In logarithms:

$$\log Y_i = X_i \cdot \beta + \varepsilon_i$$

here $f(X_i \cdot \beta)$ is assumed to equal $\exp(X_i \cdot \beta)$ and ε_i is the residual term. The CD and TL production functions in equation (2) are assumed to satisfy all the basic properties of ordinary least squares (OLS).

Our labor input equals the sum of family labor, hired labor and exchange labor in man-days where family labor adjusts child labor for adult equivalence. Thus, per unit of labor, *crop* is the value of crops produced, *area* is land under crop production, *invest* is the amount of investments made, *fert* is the amount of fertilizers used, and *pest* is the amount of pesticides used.

The survey data do not give a direct measure of capital or investment. Thus, to construct a measure of investment, we compile information on different forms of agricultural machinery, apply depreciation to capital items, add recurring investments such as expenditures on improvements to land and buildings, and add payments for tractors and other rented equipment. Next, while 66% of farmers in the sample use fertilizers, only 16% use pesticides. Most pesticide users (98%) use chemical fertilizers as well but only 24% of fertilizer users also use pesticides. Further, the pesticides used amount to only Rs 453 among the users or barely Rs 74 (or about US$1.00) on average for all farmers in the sample. Thus, while the results for pesticides are noted, we focus more on crop area, investments, and fertilizers. We also use their square terms and interactions among them. The variables are measured in natural logarithms. The first three variables (land, investment and fertilizer) are used to estimate the CD function and the entire set in the TL function. Differences between these two functions give our first hypothesis:

Hypothesis 1. The translog function represents the data better as compared with the CD function. While the CD function for Nepal is restricted to the use of inputs directly, we expect to reject the null that, in the TL function, their squares and their interactive terms will be zero.

Effect of Productivity on Poverty

The estimates of production functions yield our productivity numbers, which are used in the second phase of our study. Here we are broadly interested in two things: how a change in productivity affects poverty and which factors affect productivity the most. Thus, our main goal in this study is to explore how changes in productivity enhancing factors can lead to poverty reduction. This and the next subsection describe our methodology to link these two parts.

Any policy geared toward poverty alleviation will be more appealing if it targets the poorest of the poor more. This idea is captured by Sen's (1973) index of poverty which incorporates distributional differences within the poor class.[3] The Sen index is given below:

$$P_s = P_0\left[1-(1-G^p)\mu^p/z\right]$$

where P_0 is the headcount poverty index and equals the proportion of poor in the population, N_0/N; G^p is the Gini coefficient of inequality within the poor class; μ^p is the mean income of the poor, or, in our extension of the Sen index, the sum of the mean incomes from crop and non-crop production for the poor: $\mu^p = \mu^c + \mu^o$; and z is the poverty line.

The term μ^p/z in (3) shows how far mean income of the poor is from the poverty line. Note that in the extreme case where $\mu^p = z$, every member of the poor class has the same income and hence $G^p = 0$. In that case the Sen index equals zero. In the more realistic cases, $\mu^p < z$, where the index helps compare two societies with the same headcount poverty and mean incomes for the poor but different levels of inequality among the poor.

As an example, suppose in both the countries the headcount poverty is 25% and the poor's mean income equals two-thirds of the poverty line. Now, one of the two countries, *A*, has Gini for the poor equal to 0.3 and the other country *B* has Gini for the poor equal to 0.45. Then, the Sen index in equation (3) yields 0.133 for *A* and 0.175 for *B*. Thus, *B* is about 32% poorer than *A* despite the fact that the headcount poverty is identical in both. This indicates a large difference in welfare resulting from differences of income distribution. In this paper, we accommodate such nuanced approach to poverty since it is central to Sen's poverty analysis.

Solving equation (3), we obtain

$$P_s = P_0 + (G^c - 1) P_0 \mu^c / z + (G^o - 1) P_0 \mu^o / z.$$

The second section of the Appendix shows the detailed derivation of this important equation, (4). Since the Gini indices for crop (G^c) and noncrop (G^o) incomes lie between zero and one, $(G^c - 1) \leq 0$, and $(G^o - 1) \leq 0$, the equation shows that poverty can be divided into three parts. The first is the headcount poverty (P_0), and the two other terms indicate two trends in poverty, namely, trends induced by average income from crops, and from other sources, weighted by respective distances of crop and non-crop based inequality from the perfect inequality of one. This background leads to a comparative static analysis that shows how a change in mean incomes will affect poverty.

Comparative statics

The effect of a change in average income from crops and non-crops on the level of poverty can be found from differentiating equation (4) with respect to mean incomes. For crops, we have:

$$\frac{dP_s}{d\mu^c} = (G^c - 1)\frac{P_0}{z} + \frac{P_0 \mu^c}{z}\frac{d(G^c - 1)}{d\mu^c} \Rightarrow \frac{dP_s}{d\mu^c} = (G^c - 1)\frac{P_0}{z} + \frac{P_0 \mu^c}{z}\frac{dG^c}{d\mu^c}.$$

Since proportionate increases in incomes do not change income inequality, i.e. $dG^c/d\mu^c = 0$, the last term on the right-hand side of this equation drops out. Then, defining $\delta = P_0/z$, we get

$$\frac{dP_s}{d\mu^c} = (G^c - 1) \times \delta$$

which leads to our second hypothesis as follows:

Hypothesis 2. An increase in average crop productivity significantly reduces poverty. More formally, we expect to reject the null hypothesis H_0: $(G^c - 1) = 0$.

A test of hypothesis (2) requires an evaluation of the statistical significance of $(G^c - 1)$. To that end, we use a bootstrapping procedure recommended by Efron

(1997) and Mills and Zandvakili (1997). From 1,000 iterations of our data, we obtain ($G^c - 1$), its 95% confidence interval, and the *t*- and *p*-values. If ($G^c - 1$) is statistically significant, i.e. if we reject the null under hypothesis (2), then one dollar increase in the average crop value reduces poverty by ($G^c - 1$) × δ where δ is the ratio of the headcount to the poverty line as defined in equation (5).

Effects of Factors Influencing Productivity on Poverty

Our analysis of the effect of productivity on poverty starts with the Gini index for the poor households (see equation (A3) in the Appendix) and substitutes the regression function for *y* to yield equation (6) which is obtained after some algebra as shown in the second section of the Appendix:

$$P_s = P_0 - \delta(\beta_0^k + \beta_0^l) + \delta\sum_{k=2}^{m}\beta_k \bar{x}_k (G_k - 1) + \delta\sum_{l=1}^{n}\beta_l \bar{x}_l (G_l - 1) + \delta(G_{\varepsilon k} - 1) + \delta(G_{\varepsilon l} - 1)$$

where the items in *x* are the explanatory variables in our productivity function. Table 3 in section 4 lists these variables. Equation (6) is our main equation because it can yield estimates of the elasticity of poverty reduction with respect to the determinants of productivity.

Comparative statics

Differentiating equation (6) with respect to $\bar{x}_k$ yields:

$$\frac{dP_s}{d\bar{x}_k} = \delta\beta_k (G_k - 1) + 0 \Rightarrow \frac{dP_s}{d\bar{x}_k} = \delta\beta_k (G_k - 1)$$

where G_k is the income related inequality in either the household assets or other determinants of productivity, and is called concentration index in the inequality literature. It is different from Gini because it shows inequality in the non-income measures of wealth but reflects income ordering of the households. Thus a concentration index (G_k) lies between minus one and one, not between zero and one. A positive G_k shows a pro-rich distribution x_k and a negative G_k a pro-poor distribution in x_k. The concentration index for fertilizer, for instance, would be negative if poor households were to use greater amounts of fertilizer than used by rich households. As G_k goes to zero starting from a positive value, the use of production inputs becomes more equitable while a value of zero indicates completely equal distribution. We calculate each G_k using the method proposed by Kakwani et al. (1997), which leads to our third hypothesis, as follows:

Hypothesis 3. A suitable change in the determinants of crop income significantly affects poverty. As $\delta \equiv P_0/z > 0$, (see equation (5)), we expect to reject the null that H_0: $\beta_k(G_k - 1) = 0$.

We test this hypothesis again through the bootstrapping procedure, noted earlier, that yields the value of $\beta_k(G_k - 1)$, its standard error and its confidence interval.

Finally, an analysis of equation (7) yields the following three propositions.

Proposition 1. An increase in x_k always reduces poverty (P_s) if it raises productivity.

Proof As G_k is the concentration index for a productivity covariate, it may be positive or negative. If $\beta_k > 0$ and $G_k > 0$, an increase in $\bar{x}_k$ raises productivity. In that case, the rise in productivity further increases G_k making the distribution pro-rich. However, $(G_k - 1)$ is then still negative. In that case, an increase in $\bar{x}_k$ by 1 unit will reduce P_s by $\delta\beta_k(G_k - 1)$. In contrast, if $\beta_k > 0$ and $G_k < 0$, i.e. inequality is pro-poor, an increase in $\bar{x}_k$ increases productivity. That could make G_k even more pro-poor. Thus $(G_k - 1) < 0$ and larger in absolute terms. In that case, an increase in $\bar{x}_k$ by 1 unit decreases P_s by $\delta\beta_k(G_k - 1)$.□

Proposition 2. Poverty reduction is faster if the distribution in x_k is pro-poor, i.e. $G_k < 0$.

Proof If the distribution is pro-poor, $-1 \leq G_k < 0$. Then $(G_k - 1) < 0$. If the distribution is pro-rich, $1 \geq G_k > 0$. In this case again, $(G_k - 1) < 0$. However, $|G_k - 1|$ is larger if distribution of x_k is pro-poor than if it is pro-rich. Hence, if $-1 \leq G_k < 0$, an increase in average x_k will reduce poverty faster than if $1 \geq G_k > 0$.□

Proposition 3. An integrated approach toward development reduces poverty faster than can an isolated sectoral development policy.

Proof For all $\beta_k > 0$, the combined effect of a higher $\overline{x}_k$ in absolute terms is $|\delta\Sigma_k(G_k - 1)|$, for all sectors k, which is always greater than the effect, $|\delta\beta_k(G_k - 1)|$, of sectoral policies taken in isolation

Results

We present our results in three main parts starting with productivity, i.e. output per worker, as a function of basic inputs, and of household-specific and other factors. We further explore whether the ways in which inputs affect output vary across crops. Finally, we bring these results together to examine how poverty is affected by crop income and its determinants.

Cobb–Douglas and Translog Production Functions

In the estimation of productivity, land area, investments in the form of farm tools and land improvements, and use of fertilizers provide direct contributions to output and are therefore used in the initial regressions. Table 1 provides the results for before and after we control for age, education level and the occupation of household head for both the CD and TL versions of the model. Other control variables used in the model are an irrigation dummy and an interactive term for fertilizer and pesticides in addition to the usual square and interaction terms in the TL model. In all the cases studied in this paper, we reject the null of zero coefficients for the square and cross product terms in the translog that are additional to the terms in the CD model. The hypothesis that the coefficients of square or interaction terms in the TL model are simultaneously zero is rejected at the one percent significance level. For instance, while investment affects output significantly, its interaction with other inputs fails the conventional significance test. Yet, the *F*-test shows that all the investment terms together remain highly significant. More importantly, the coefficient of log investment in the CD model equals 0.173 which suggests that any program to boost productivity per worker must include increases in farm investment.

Table 1. Productivity under Cobb–Douglas and Translog Production Functions

		Other controls				
Variables	**Inputs**	**agehd**	**eduhd**	**occhd**	**fertpes**	**Irridum**
Model I: Cobb–Douglas production function						
constant	5.503*	5.492*	5.609*	5.625*	5.679*	5.633*
area	0.717*	0.717*	0.714*	0.7109*	0.715*	0.712*
fert	0.098*	0.098*	0.096*	0.0949*	0.135*	0.131*
invest	0.274*	0.274*	0.272*	0.2703*	0.268*	0.264*
agehd		0.0002	0.0005	0.0024**	0.002**	0.002**
eduhd			−0.078*	−0.0277	−0.028	−0.029
occhd				−0.0839*	−0.084*	−0.084*
fertpest					0.006**	0.006***
irridum						0.083*
adj. R^2	0.555	0.556	0.559	0.559	0.560	0.560
Model II: Translog production function						
constant	5.899*	5.88*	5.929*	5.932*	5.8626*	5.850*
area	0.8511*	0.85*	0.8381*	0.8387*	0.8259*	0.8352*
fert	0.1835*	0.1834*	0.1812*	0.1751*	0.1675*	0.1666*
invest	0.2502*	0.2514*	0.2548*	0.2576*	0.2689*	0.2643*
areasq	0.0135	0.0135	0.0126	0.0131	0.0124	0.0133
fertsq	0.0267*	0.0267*	0.0260*	0.0257*	0.0278*	0.0277*
investsq	−0.0031	−0.0032	−0.0037	−0.0037	−0.0041	−0.0041
areafert	−0.0174**	−0.017**	−0.017**	−0.018**	−0.0136	−0.013
areainvest	−0.0127	−0.0126	−0.0119	−0.0121	−0.0107	−0.0112
fertinvest	0.0013	0.0013	0.001	0.0011	0.0004	0.0002
agehd		0.0003	0.0005	0.0022**	0.0023**	0.0023**
eduhd			−0.055**	−0.0083	−0.0062	−0.0072
occhd				−0.0778*	−0.0766*	−0.0765*
fertpest					−0.0073**	−0.0078**
irridum						0.0822*
adj. R^2	0.5677	0.5675	0.5682	0.5703	0.5708	0.5718

Notes: (1) Productivity is the natural logarithm of the following: crop value (in rupees) divided by days of adult equivalent labor used in a year. (2) Descriptive statistics for all variables are available upon request from authors. *, **, *** Represent statistical significance: at the 1%, 5%, and 10% levels, respectively.

Source: Calculated by authors.

In the CD estimates, the coefficient of land area does not vary much between the extended model that adds several control variables mentioned above and the basic model without those controls. However, the coefficient of fertilizer increases from 0.098 in the basic version to 0.131 in the extended one. Both are statistically significant at the 1% level. The estimates from the TL model are also more stable across specifications and show that this model has a higher explanatory power.

Thus, our investigation of the impact on poverty is based on the versions of the extended TL model that include all our control variables.

Table 2. Productivity Estimates by Crops

Regressors	Rice	Wheat	Maize	Cash Crops
Model I: Cobb–Douglas production function				
Constant	4.796*	4.556*	5.116*	4.604*
Area	0.518*	0.656*	0.593*	0.034
Fert	0.182*	0.114*	0.133*	0.024
Invest	0.173*	0.158*	−0.066*	0.167*
Agehd	0.007*	−0.006*	0.008*	−0.0025
Eduhd	−0.131*	−0.197*	−0.030	0.103***
Occhd	−0.056***	0.0152	−0.134*	0.0717***
Fertpest	−0.006	0.0007	0.013**	−0.0098
Irridum	−0.059	−0.157*	0.049	−0.0738
$\bar{R}^2$	0.388	0.321	0.193	0.0587
Model II: Translog production function				
Constant	6.9576*	6.207*	3.0928*	3.8176*
Area	1.046*	1.1956*	0.7395*	−0.5874*
Fert	0.3211*	−0.0955	0.2809*	−0.0233
Invest	−0.0886	−0.10945	0.6626*	−0.0149
Areasq	0.0362**	0.0648*	0.0499**	−0.0668*
Fertsq	0.0066	0.0199*	0.0084	0.0142**
Invests	0.0138	0.0183	−0.0449*	0.0225**
Areafert	0.0417*	−0.0288**	−0.0014	0.02552
Areainvest	−0.0167	−0.0109	0.0360	0.0161
Fertinvest	0.0015	0.021**	−0.0200***	0.0264**
Agehd	0.0074*	−0.0066*	0.0086*	−0.0027
Eduhd	−0.1113*	−0.1689*	−0.0243	0.1228**
Occhd	−0.0515	0.0183	−0.1378*	0.08503**
Fertpest	−0.0186*	−0.0064	0.0047	−0.0196*
Irridum	−0.053	−0.1579*	0.0575	−0.087
$\bar{R}^2$	0.3958	0.3319	0.2060	0.0761

Notes: *area fert*, and *invest*, either individually or interactively with other factors, are measured in per unit of labor terms. *, **, *** Represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Calculated by authors.

Even though the TL model better fits the Nepali data in comparison with the CD, the results from the two models look similar. The simple correlation between the two estimated productivity series is 0.989 and is highly significant. Further, most of the variable parameters are statistically significant at the 1% level except for the coefficient of education in some versions of the models, as shown in the last three columns of Table 1. We therefore compare our poverty results from both the

models, taking similar specifications in terms of controls provided by household characteristics including education, age, and occupation of the household head.

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Next, we recognize the fact that the aggregate labor productivity in farms consists of component productivities in different crops grown by farmers.[4] The question is: how do productivities differ across crops? The answer to such a question can be important for policymakers who seek to design incentive mechanisms to reorient production structure to raise output. Based on R in Table 2, our model provides a reasonably good explanation for the main staple crops such as rice and wheat, less so for maize, and not much for cash crops.

Because of high density of population on cultivable land, productivity of Nepali farmers is likely to benefit from an increase in the farming area. While a larger total land area is hard to bring into cultivation from a macro perspective, land utilization can still be increased through a greater cropping intensity, and through land consolidation measures with incentives given to less productive farmers to migrate to other occupations. From the translog model we find that the response of productivity to larger land sizes exceeds proportionate increases in land at least in the case of the main staples—rice (for which the coefficient of log area is 1.05) and wheat (1.20). Productivity in maize displays diminishing returns to land while it is negative for cash crops, suggesting a greater potential for productivity improvements if cash crops are concentrated more in smaller farms. Our results thus indicate that increasing the farm size can be one important way to raise productivity in Nepal's two of the three major staple crops: rice and wheat.

The cropwise estimates also reveal that the use of fertilizer raises yield per worker in rice but not in wheat while interaction between land and fertilizer makes a positive contribution to productivity in rice though not in others. Similarly, interaction between fertilizer and investment has a significantly positive effect on rice, wheat and cash crops, but not on maize.[5]

The overall finding about cropwise estimates of productivity indicates that greater effective landholding (multiple cropping), and fertilizer use are likely to boost yields and incomes relative to other factors for farmers in Nepal. This result is basically in line with our aggregate productivity results.

Table 3. Effects on Poverty

(a) **Effects of Average Increase in Crop Income on Poverty**						
	For both models: CD and TL					
	$(G^c - 1)$	***95% Cf. interval***		**Effect for $\delta = 0.0834$**		
Crop value	−0.8438*	−0.8439 to −0.8437		−0.0704		
(b) **Effect of Average Increase in Factors Affecting Crop Income on Poverty**						
	Model I: CD production function			**Model II: Translog production function**		
Regressors	**$\beta_k(G_k - 1)$**	***95% Cf. interval***	**Effect for $\delta = 0.0834$**	**$\beta_k(G_k - 1)$**	***95% Cf. interval***	**Effect for $\delta = 0.0834$**
Area	−0.6612*	−0.6623 to 0.660	−0.0551	−0.7757*	−0.7845 to −0.767	−0.0647
Fert	−0.1531*	−0.1551 to 0.151	−0.0127	−0.1927*	−0.1974 to −0.188	−0.0160
invest	−0.2557*	−0.2565 to −0.255	−0.0213	−0.2632*	−0.2706 to −0.256	−0.0219
areasq	—	—	—	−0.0154*	−0.016 to −0.0145	−0.0013
fertsq	—	—	—	−0.0332*	−0.0335 to −0.033	−0.0028
investsq	—	—	—	0.0043*	0.0039 to 0.0048	0.00036
areafert	—	—	—	0.0169*	0.0161 to 0.0177	0.0015
areainvest	—	—	—	0.0116*	0.0106 to 0.0125	0.00097
fertinvest	—	—	—	−0.0002	−0.0007 to 0.0003	−0.00001
agehd	−0.0023*	−0.0024 to −0.002	−0.0002	−0.0023*	−0.0024 to −0.002	−0.0002
eduhd	0.0310*	0.0293 to 0.0327	0.0025	0.0075*	0.0059 to 0.009	0.0006
occhd	0.0863*	0.0849 to 0.0876	0.0071	0.0805*	0.0791 to 0.0818	0.007
fertpest	−0.0070*	−0.0073 to −0.007	−0.0006	0.0095*	0.0091 to 0.0098	0.0008
irridum	−0.0812*	−0.0831 to −0.079	−0.0067	−0.0786*	−0.0805 to −0.077	−0.0066
Integr. effect	—	—	−0.087	—	—	−0.1023

Note: *, ** Represent statistical significance: at the 1% and 5%, respectively.

Source: Calculated by authors.

Effects of Productivity and Its Determinants on Poverty

Our discussion of agricultural productivity may be important on its own since agriculture provides employment to most people in Nepal. Yet, our central concern in this paper is how productivity can help poverty alleviation. The direct effect of productivity does need to be examined but, more importantly, we are interested in evaluating the effect on poverty that occurs through the determinants of productivity. The reason is that any change in policy would seek to influence these determinants as its instruments for bringing about productivity changes.

The national poverty line, converted into US dollars at the official rate, was set at US$104.50 per person per year for the survey year 2004. The poverty headcount for Nepal on that criterion (rather than US$1.25 a day) stood at 38.8% in that year. We also use US$104.50 (4.649 on the log scale) to evaluate the effects of productivity and its covariates on the level of poverty.

The parameter δ in our model (equation (5)) equals the ratio of headcount index to national poverty line and equals 0.0834. We arrive at the effect on poverty in the last column of Table 3, for each model specification, after multiplying $\beta_k(G_k - 1)$ by δ where, for each variable x_k, β_k is the elasticity of productivity with respect to variable k (if this variable is also in its logarithmic form), and G_k is the concentration index of variable k in the productivity equation. As explained in section 3, this "inequality" adjusted value of the elasticity, $\beta_k(G_k - 1)$, its statistical significance, and its 95% confidence interval are calculated through a bootstrapping procedure based on 1,000 iterations. The estimate of $(G^c - 1)$ for crop income per unit of labor and of $\beta_k(G_k - 1)$ for determinants of the crop income are statistically significant in both the CD and the translog models at 1% level. This helps us safely reject the null in hypothesis 2: $(G^c - 1 = 0)$ and hypothesis 3: $(\beta_k(G_k - 1) = 0)$ as stated in section 3 above.

Further Discussion

The results presented in Table 3 support our Propositions 1 and 3.
Proposition 1 stated that an increase in a factor, x_k, always reduces poverty (P_s) if it raises productivity. That is, for all regression coefficients ($\beta_k > 0$), a favorable change in the determinants of crop income, will lead to a fall in poverty. Second, an integrated effect of a change in all the covariates of productivity is always stronger than the combined effects of sectoral policies in isolation.

For example, an increase in farmland per unit of labor by 0.1 hectare decreases Sen's index of poverty by 0.00551 in CD and by 0.00647 (including square and interactions) in the TL model. We believe such an effect can be achieved in a reasonably short period of time by inducing a one-time change in the subsistence farming practice in most areas of the country. A two-pronged approach would seem desirable to address this problem. The first might be an effective training program for farmers in the use of technology and the second the strengthening of the rural–urban linkage through better transportation for agricultural surplus.

We find that increased use of fertilizers by 1 kg decreases poverty by 0.0160 according to the translog function. Among the control variables reflecting household characteristics, the age of the household head, while statistically significant, has only a small effect on poverty. Experienced farmers have an edge over younger farmers who may therefore benefit from some training to catch up on efficiency. Among other variables are education and occupation. Heads of households having one more year of schooling seem, surprisingly, to obtain slightly lower productivity. Thus, according to the cross-section analysis in this paper, training that is specifically geared towards better application of modern inputs, will likely be more valuable in raising productivity than greater general education of the kind that Nepal's schools provide.

In contrast, a more natural reduction in productivity is observed when heads of households shift their occupation from agriculture to industry or service. This is a more likely result when relatively educated people leave agriculture to pursue other interests. The direct implications of these agricultural changes for poverty may seem perverse. Lower productivity is associated with nonagricultural careers even though such careers can secure significant benefits for households relative to agricultural pursuits and help households move out of poverty. However, a reduction in productivity resulting from a change of occupation away from agriculture is a likely outcome of lower efforts made by the household heads towards farming. At the same time, lower productivity is also a great incentive for farmers to switch occupation. Since the scope for a productivity increase in Nepal is large, policy that aims at making farmers efficient through more training and extension services is thus likely to have a large payoff.

Finally, the combined effect of the factors considered in the determination of productivity is larger than when the factors are considered in isolation. The integrated effect reduces poverty by 0.1023 according to the translog model.[6] Sen's index of poverty calculated for the survey households is 0.1857 which implies that the combined effect would reflect a 55% decline in poverty. Comparing the results of the integrated effects on poverty with the Sen index we can conclude that public policy has the potential to reduce poverty by, among other factors, improving the technological knowhow of farmers through extension services and providing more irrigation. Applying the translog model to proposition two, if G_k is negative, which implies the distribution in the k-variable is pro-poor, the term $(G_k - 1)$ will be larger in absolute terms such that the overall effect on poverty is greater than if G_k is positive. This proposition is self-explanatory although our empirical model does indeed support this conclusion.

At this point it is useful to compare our results with those in related literature. Datt and Ravallion (1998), for instance, estimate the effect of several economic factors on poverty in India. These factors include real wage, the relative price of food, agricultural productivity (measured in terms of yield per acre), and a vector of other relevant variables such as inflationary shocks. Their results indicate that both higher agricultural wages and higher yields reduce rural poverty, with about the same elasticity. In addition, they also find an independent adverse effect of higher food prices. This last finding, however, deserves further analysis because the opposite changes can occur simultaneously in consumer and producer surpluses. A rise in the price of food increases producer surplus and reduces consumer surplus including the surplus for farmers as consumers. The net effects, not entirely captured by Datt and Ravallion (1998), could go either way.

Our approach in this paper is different from the approach taken by Datt and Ravallion (1998). Estimation of agricultural productivities using CD and translog functions leads to our decomposition of poverty to identify its relationship with different types of farm income (equations (4)and (5)) and shows that the increase in farm income from crops and its determinants reduces poverty among farmers. Our measure of poverty is sensitive to a change in inequality within the class of poor households and is, we believe, more useful in the context of a country where freedom from hunger remains a challenge for a significant chunk of the population. Despite differences in the two approaches, however, our results for Nepal are compatible with the main result of Datt and Ravallion (1998) for India that an increase in crop output leads indeed to a substantial reduction in poverty.[7]

Conclusion

This paper provides a first systematic analysis of the links through which an increase in agricultural productivity and factors affecting such productivity can reduce poverty in Nepal. The underlying calculations rest on our identification of the factors in the first stage of estimation that help explain agricultural productivity in the country.

At the second stage, we estimate the effects of an increase in productivity and its determinants on poverty. The average effects under CD and TL models, as reported in column (3) of Table 3, are calculated for the ratio of headcount index to the national poverty line (this ratio is δ, and equals 0.0834). We find the translog model to fit the data better. However, the estimated productivities for the two models are not very different from each other. Thus, we use both the CD and TL estimates to examine the effect on poverty of an increase in productivity per worker, and in the determinants of such income.

The results support our basic proposition that suitable changes in the factors affecting productivity lead to a decrease in poverty. More importantly, we find that a unit change in the productivity enhancing factors (our integrated effect) is always stronger than the effects of independently adopted sectoral policies such as an increased supply of irrigation and a greater use of fertilizers. Our estimated effects on poverty are not only statistically significant but also substantial in magnitude. The integrated effect of simultaneous changes in the covariates of productivity amounts to a 55% reduction in our preferred measure (the Sen index) of poverty. Finally, we expect our ongoing research comparing the results in this paper with an analysis based on the 2010/11 survey will provide a better understanding of the evolving poverty profile as well as its link to agricultural productivity in Nepal.

Appendix

Derivation of Equation (4)

Solving equation (3), we get

$$P_s = P_0[1-\mu^p/z]+(P_0\mu^p/z)\times G^p \quad \text{(A1)}$$

where the Gini coefficient for the poor is given by:

$$G^p = (2/n\mu^p)\sum_{i=1}^{n} y_i^p R_i - 1 \quad \text{(A2)}$$

where y_i^p is the income of *i*th household and *Ri* is its rank when households have been arranged in the non-descending order of income (Lerman and Yitzhaki, 1998).

For household *i*, $y_i^p = y_i^c + y_i^o$, the sum of income from crops and income from other sources. So, *Gp* is:

$$G^p = (2/n\mu^p)\left[\sum_{i=1}^{n}(y_i^c R_i + y_i^o R_i)\right] - 1 \quad \text{(A3)}$$

Using $G^c = (2/n\mu^c)\sum_{i=1}^{n} y_i^c R_i - 1 \Rightarrow \sum_{i=1}^{n} y_i^c R_i = [(G^c+1)/2]n\mu^c$, equation (A3) yields:

$$G^p = (\mu^c/\mu^p)G^c + (\mu^o/\mu^p)G^o \quad \text{(A4)}$$

which shows that inequality among the poor is simply a weighted average of inequality driven by income from crops (*Gc*) and inequality in income from other sources (*Go*).

Substituting the value of *Gp* from equation (A4) into equation (A1), we get

$$P_s = P_o + (G^c - 1)(P_0\mu^c/z) + (G^o - 1)(P_0\mu^o/z) \quad \text{(A5)}$$

which is equation (4) in the text.

Derivation of Equation (6)

Adding and subtracting 1 in equation (6), we get

$$G^p = \underbrace{(2/n\mu^p)\sum_{i=1}^{n} y_i^c R_i - 1}_{Term1} + \underbrace{(2/n\mu^p)\sum_{i=1}^{n} y_i^o R_i - 1}_{Term2} + 1. \quad \text{(A6)}$$

Then, substituting the regression function $y_i^c = \beta_0 + \sum_{k=1}^{m}\beta_k X_{ki} + \varepsilon_i$ into Term 1 and assuming $\eta_k = \beta_k \bar{x}_k/\mu^p$, equation (A6) becomes:

$$G^p = \sum_{k=1}^{m}\eta_k G_k + \sum_{l=1}^{n}\eta_l G_l + G_{\varepsilon k}/\mu^p + G_{\varepsilon l}/\mu^p \quad \text{(A7)}$$

where *Gk* is the income related Gini of variable *k* in the model.

Substituting this value of *Gp* into equation (4):

$$P_s = P_0[1-(\mu^p/z)] + (P_0\mu^p/z)\left[\sum_{k=2}^{m}\eta_k G_k + \sum_{l=1}^{n}\eta_l G_l + \frac{G_{\varepsilon k}}{\mu^p} + \frac{G_{\varepsilon l}}{\mu^p}\right].$$

Let $\delta = P_0/z$ as before. Then:

$$P_s = P_0 - \delta\mu^p + \sum_{k=2}^{m}(\beta_k\bar{x}_k)G_k + \delta\sum_{l=1}^{n}(\beta_l\bar{x}_l)G_l + \delta G_{\varepsilon k} + \delta G_{\varepsilon l}.$$

Finally, using $\mu^p = \mu^c + \mu^o = \beta_0^k + \sum_{k=1}^{m}\beta_k\bar{x}_k + \beta_0^l + \sum_{l=1}^{n}\beta_l\bar{x}_l$, we get:

$$P_s = P_0 - \delta(\beta_0^k + \beta_0^l) + \delta\sum_{k=2}^{m}\beta_k\bar{x}_k(G_k - 1) + \delta\sum_{l=1}^{n}\beta_l\bar{x}_l(G_l - 1) + \delta(G_{\varepsilon k} - 1) + \delta(G_{\varepsilon l} - 1)$$

(A8)

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Notes

1 Mosley and Suleiman (2007) find that aid funded government expenditures can reduce poverty if the expenditures support agricultural development directly and also indirectly through human capital expansion.

2 See, among others, Bourguignon (2003).

3 Thus, among the Foster–Greer–Thorbecke (FGT_{α}) class of generalized poverty measures, the Sen index incorporates poverty measures for $\alpha = 0$ and $\alpha = 1$, and also the Gini index (for the poor). See Foster et al. (1984).

4 The cropwise analysis has been made as per the referee's suggestion.

5 The survey data do not provide reliable information on intercropping pattern across households. When information is included on crops grown during a given season, such as beans (including soyabeans) together with maize in the same fields, we get a much higher value for average crop intensity of 3. This is, however, a rough approximation. Whether such intercropping leads to higher productivity through a change in soil nutrients, or greater ability to control insects or weeds needs more research. For an example of such a study in the context of Colombian hills, see Daellenbach et al. (2005).

6 For Cobb–Douglas, poverty is reduced by a slightly lower amount (0.087).

7 In a study of the Philippines, in contrast, Estudillo et al. (2008) find expansion in the *nonfarm* sector to have led to a significant reduction in rural poverty.