JOURNAL OF ECONOMIC DEVELOPMENT
Volume 35, Number 4, December 2010

HEALTH, TECHNICAL EFFICIENCY, AND AGRICULTURAL PRODUCTION IN INDIAN DISTRICTS

Atheendar S. Venkataramani, K.R. Shanmugam and Jennifer Prah Ruger*

Washington University School of Medicine, Madras School of Economics and Yale University Schools of Medicine and Public Health

We investigate whether better population health may impact economic performance through improvements in technical efficiency in agricultural production. Using district-level data from India, we employ a random-coefficients approach to estimate a Cobb-Douglas production function, computing overall and input-specific technical efficiencies for each district. We then model health (district infant mortality rate) as a determinant of (in)efficiency in a second stage, controlling for a range of other socioeconomic variables. In the preferred specifications, we find that decreases in the infant mortality rate are associated with substantively and statistically significant increases in overall technical efficiency, and that a good portion of this association is likely due to improvements in the efficiency of labor use.

Keywords: Agricultural Production, Economic Development, Health, India, Labor, Random Coefficients, Technical Efficiency
JEL classification: I10, O13, Q01

1. INTRODUCTION

The process of economic development in poor countries is multi-faceted and involves a number of independent and interrelated factors ranging from investment, technological change, public policy and institutional change, human capital (health and

* We would like to thank discussion group participants at the International Health Economics Association 5th World Congress and the Madras School of Economics, and the editor and several anonymous reviewers for helpful comments. We would also like to thank the Washington University School of Medicine and the Whitney and Betty MacMillan Center for International and Area Studies for financial support, and the Madras School of Economics, Madras Institute of Development Studies (both in Chennai, India) and Yale University School of Public Health for facilities and computing support. We thank Nora Ng and Takudzwa Shumba for research assistance. All errors are the responsibility of the authors.

education), natural resource endowments, and geography, to name a few. Recent research has highlighted the potential role of health as a component of human capital in spearheading the processes of development and augmenting wealth accumulation. For example, various micro studies provide evidence of a strong relationship between health and wage returns, although the effects of health indicators are larger in some countries than in others (see, for example, Deolalikar, 1988; Schultz and Tansel, 1997; Schultz, 2002 and 2003; and Strauss and Thomas, 2008). Consistent with these findings, macroeconomic evidence points to strong associations between measures of population health and wealth (see, for example, Bhargava *et al*., 2001; Gallup and Sachs, 2001; Bloom *et al*., 2004; Barro and Sala-i-Martin, 2004), though whether these correlations can be interpreted as causal has been debated in recent work (Acemoglu and Johnson, 2007; Ashraf, Lester and Weil, 2008; Bleakley, 2010). Weil (2007), for example, in employing estimates from well-identified microeconomic studies to construct macroeconomic estimates of the effect of health on Gross Domestic Product (GDP) per capita, finds economically significant effects, but notes that his estimates are "substantially smaller than estimates of the effect of health on economic growth that are derived from cross-country regressions" (Weil, 2007, p. 1265).

Bloom and Canning (2000) and Ruger *et al*. (2001, 2006) suggest several possible avenues through which health can exert a positive influence on overall economic performance. As implied by the results of studies looking at wage returns, better health as a component of human capital can improve labor productivity. Additionally, healthier individuals are more likely to increase investment in and derive greater returns from schooling and education (Alderman *et al*., 2001; Glewwe *et al*., 2001; Behrman and Rosenzweig, 2004; and Miguel and Kremer, 2004; which all look at the impact of child health status on schooling and other indicators of present and future economic performance). Increased savings and the resulting investment in physical capital, increased foreign direct investment, and demographic benefits from decreased fertility and lower dependency ratios may all follow improvements in health capital, as well (Bloom and Canning, 2000; Bloom *et al*., 2003; and Alsan *et al*., 2006).

In the present study, we approach the question of the economic returns to health from a different perspective. In particular, we explore whether health may influence economic development through its impacts on technical efficiency in production. Technical efficiency is a measure of how well the decision-making units use their inputs in generating outputs, and represents an interesting way to think about the role of health and human capital more generally in the production process. Our approach conceptualizes health (and components of human capital) as factors that allow firms to use their physical and financial inputs (such as labor or physical and financial capital) in a more efficient manner.

Using cross-sectional agricultural production data for over 260 Indian districts in the early 1990s, we employ the random coefficients technique to compute district-level input-specific and overall technical efficiency values. We then model overall technical efficiency and input-specific efficiencies as functions of district population health status (using infant mortality rate (IMR) as proxy) and of a set of socioeconomic and ecological controls. We find that (i) Indian districts vary widely in efficiency in agricultural production, (ii) better health is strongly associated with increased technical efficiency, and (iii) much of this association may be due to the strong relationship between health and efficiency in labor use.

Our study makes several contributions to the existing literature. In particular, it differs from those that denote health as an input in the production function process more generally. While these approaches allow for a direct assessment of production returns to health, they say little about how health yields these returns. Also, specifying health as an input to production by the same method as one would specify labor or physical and financial capital may not necessarily be desirable since health, and perhaps other forms of human capital in general, are perhaps better viewed as factors that affect the production process indirectly.[1] To our knowledge, this is one of the few studies that consider the relationship between health and technical efficiency, and one of the first to model this relationship explicitly for both overall and input-specific efficiencies.[2] While we are limited in our ability to account for the endogeneity of health, which warrants caution in interpreting our estimates as causal, our findings will be useful in motivating future research and policy discussions on the role of health in agricultural production and in development more generally.

The structure of the remainder of the article is as follows. In section 2, we develop the econometric framework and modeling strategy. In section 3, we describe the data and variables. In section 4, we present empirical results of the frontier production function. In section 5, we discuss the technical efficiency estimates and the determinants of overall and input-specific technical efficiency. In section 6, we offer some

[1] The cross-country study by Bloom *et al*. (2004) models health, experience, and education as labor-augmenting inputs in an aggregate Mincer production model.

[2] Croppenstedt and Muller (2000) consider the production effects of weight-for-height and morbidity in a firm-level study on Ethiopian agriculture. While they employ the stochastic frontier method to calculate technical efficiency, they still model health as an input in the production function. In another part of the study, the effect of height and weight-for-height on wages, assuming wages fully reflect the productivity of labor, is estimated. Croppenstedt and Demeke (1997) use the mixed fixed-random coefficients approach to estimate input-specific and overall technical efficiencies for Ethiopian farms. While they do allude to the possibility that health and nutrition can drive differential labor productivity, they do not model these explicitly in their technical efficiency equations. Mitra *et al*. (2002) study the effect of various infrastructure components on total factor productivity (TFP) in Indian industry at the state-level. After calculating TFP for different industrial categories, they study its determinants by considering the effect of an aggregate infrastructure index (which includes the infant mortality rate (IMR) as one of its components). Separating out the effect of each infrastructure variable on industry-specific TFP, they find IMR to be an important determinant of TFP in several industries. However, because of multicollinearity they are unable to estimate the returns to this variable explicitly.

conclusions, prospects for future work, and policy implications.

2. MODELING

In this section, we outline the methodology used to quantify the effect of improved population health on technical efficiency in agricultural production. We employ a two-step procedure: we first estimate overall and input-specific technical efficiency values for each district and subsequently use these estimates as dependent variables, specifying health and other factors as independent variables.

2.1. Determining Efficiency Using the Random Coefficients Model

There are several econometric methodologies that can be used to compute firm-specific technical efficiency, defined as the ratio of actual output to that obtained through optimal use of all existing inputs and technology. Consider the classic Cobb-Douglas production function:

$$\ln Q_i = \beta_0 + \sum_j \beta_j \ln X_{ij} + u_i \; ; \quad i = 1,2,...,n \text{, and } \quad j = 1,2,...,k \, , \tag{1}$$

where Q_i represents the output of the i^{th} firm, X_{ij} represent firm-specific stocks of inputs j; β_0 is the intercept term, β_j are input elasticities for the j_{th} input, and u_i is the residual term. The most widely used approach to computing technical efficiency, the stochastic frontier approach, models the error term u_i as partly Gaussian noise and partly a one-sided, typically half-normal distribution. In this model, estimated by maximum likelihood methods, the latter part of the error term is the relative deviation from the output of the most productive firm.[3]

The stochastic frontier approach assumes that all firms derive the same returns from the marginal input X_{ij}. However, this assumption may be too strong and unjustified by theory. The random coefficients approach, first suggested by Nerlove (1965), further developed and popularized by Swamy (1970, 1971) as well as Kalirajan and Obwona (1994a, b), relaxes this assumption and allows for firm-specific returns to different inputs. Following the discussion in Kalirajan and Obwona (1994a), as well as Croppenstedt and Demeke (1997), we illustrate the random coefficients model by rewriting the production function above as:

[3] Aigner *et al*. (1977) and Meeusen and Van Den Broeck (1977) independently developed the stochastic frontier approach. See Bauer (1990), Battese (1992), Greene (1993), Kalirajan and Shand (1994), Kumbhakar (1998) and Ray (2004) for reviews and further extensions.

$$\ln Q_i = (\overline{\beta}_0 + v_i) + \sum_j (\overline{\beta}_j + w_{ij}) \ln X_{ij} + u_i \,; \quad i = 1,2,...,n \text{, and } \quad j = 1,2,...,k \,, \qquad (2)$$

where the input elasticities are now allowed to vary from firm to firm by random disturbances v_i and w_{ij} from the means $\overline{\beta}_0$ and $\overline{\beta}_j$ respectively. More formally, the model assumes that- $E(w_{ij}) = 0$, $E(w_{ij}^2) = \sigma_j$, and $E(w_{ij}, w_{lm}) = 0$ for $i \neq l$ and $j \neq m$, implying that β_{ij} -are i.i.d with fixed mean $\overline{\beta}_j$. These assumptions hold for v_i, as well.

Using the iterative procedure suggested in Swamy (1970), one can obtain feasible GLS estimates of $\overline{\beta}_j$ and, using the procedure suggested in Griffiths (1972), one can obtain the individual firm-specific response coefficients. The highest magnitude of each of the estimated input response coefficients, that is, $\hat{\beta}_j^* = Max(\hat{\beta}_{ij})$, and the intercept $\beta_0^* = Max(\beta_{0i})$ form the production coefficients of the potential frontier production function. Using the frontier coefficients $\hat{\beta}^*$s, one can compute the potential output, Q_i^* of each firm as:

$$\ln Q_i^* = \hat{\beta}_0^* + \sum \hat{\beta}_j^* \ln X_{ij} \,. \qquad (3)$$

The technical efficiency (TE) of the i^{th} firm, which is the ratio of actual to potential output, can then be calculated as:

$$TE_i = \frac{Q_i}{\exp(\ln Q_i^*)} \,. \qquad (4)$$

And the input-specific efficiency of the i^{th} unit, which is given by the ratio of actual to potential response coefficient, can be computed as:

$$\pi_{ij} = \frac{\hat{\beta}_{ij}}{\hat{\beta}_j^*} * 100 \,. \qquad (5)$$

In this study we consider Indian districts to be the firms or decision-making units for which we would like to compute input-specific and overall technical efficiencies. We begin by specifying the following Cobb-Douglas production function:

$$\ln(Q_i) = \beta_0 + \beta_{1i} \ln(A_i) + \beta_{2i} \ln(L_i) + \beta_{3i} \ln(F_i) + \beta_{4i} \ln(T_i) + u_i \,, \qquad (6)$$

where Q is the value of agricultural output in district i in India, A is the gross cropped area, L is the total labor force devoted to agriculture, F is fertilizer input, T is the number of tractors (a proxy for machinery), and the β's are input-specific response coefficients for each i^{th} district. We also tried to use the more flexible trans-log specification, but found that the Cobb-Douglas approach fit the data best. We then employ the procedure outlined above, calculating the overall and input-specific technical efficiencies from the estimated β's.

We should note that we do not endogenize production inputs since we are constrained by the lack of credible sources of identification, especially in the context of a single cross-section (for example, input prices, which depend on aggregate supply and demand, are likely endogenous as well). However, while the assumption of input exogeneity is likely strong, it is consistent with the bulk of the literature on technical efficiency at the aggregate level.

2.2. Modeling Health as a Determinant of Technical Efficiency

To consider the determinants of technical efficiency, we then estimate the following efficiency equation:

$$TE_i = \zeta + \alpha IMR_i + \sum_k \gamma_k Z_{ik} + \sum_m \delta_m REGION_{im} + e_i \, , \tag{7}$$

where *TE* represents overall or input-specific technical efficiency for the i^{th} district, *IMR* is the district's rural infant mortality rate, *Z* is a vector of variables including rural literacy rate, electrification, blacktop or asphalt roads (a proxy for both infrastructure as well as access to rural markets), agro-climatic zones, level of irrigation and cropping intensity, and *REGION* is a vector of fixed effects representing the region in which the district is situated (see below); ζ, α, γ_k, and δ_m are parameters to be estimated. We use *IMR* as a proxy for health since measures of adult health (adult death rates, life expectancy at the age of 15, and disease morbidity), which are more appropriate for an analysis of technical efficiency, are not available at the district level.

We use the region fixed effects to control for unmeasured socioeconomic, agro-climatic and institutional characteristics that may jointly influence health and technical efficiency. We estimate separate models using fixed effects for states and National Sample Survey (NSS) regions. The NSS regions are constructed by grouping districts with broadly similar socio-demographic and agro-climatic profiles. These regions respect state boundaries: that is, adjacent districts with similar socioeconomic profiles that lie in different states are not grouped together.

As we discuss later, an important limitation with this approach is that it does not adequately deal with the endogeneity of health. One potential solution would be to use time series data on agricultural production to estimate fixed effects models, which would eliminate time-invariant sources of unobserved heterogeneity. However, because the methods to calculate district-level mortality rates vary across different census years, comparability over time becomes difficult. More fundamentally, fixed effects models would still present difficulties as far as inference in that we would not be able to address unobserved time invariant heterogeneity. A potential solution here would be an instrumental variables approach. As we discuss later, we do experiment with this approach but find it wanting due to the paucity of plausibly exogenous variation.

Given these issues, our main strategy is to explore the sensitivity of our estimates to the inclusion of the elements in Z_i and region fixed effects as a means of assessing the role of omitted variables in driving our results. This approach is similar in spirit to that developed by Altonji *et al*. (2005). However, given that this is an imperfect strategy, one should be careful in interpreting these results as causal effects.

3. DATA AND MEASURES

Most of the production inputs and agricultural output data have been taken from Bhalla and Singh (2001), who provide average figures for 288 districts spanning 17 Indian states for the following three-year periods 1962-5, 1970-3, 1980-3, 1990-3. We use the data for 1990-3, currently the most recent period for which both detailed district-level agricultural production and rural infant mortality rate data are available. Our output measure, the value of agricultural output, represents the price-weighted sum of output for 35 crops, which account for over 97% of the total value of agricultural production in India. Similarly, gross cropped area (in 1000 hectares), our measure of land input, was calculated for the same 35 crops. Our measure for fertilizer use is the tonnage of fertilizer (NPK) consumed, and our measure for machinery and physical capital is the number of tractors per district. For labor, we used data from the 1991 Census (Government of India, 1991). The total work force in agriculture was computed by adding the number of agricultural workers and cultivators. We weighted males, females and children by 1, 2/3, and 1/3, respectively. Mean values by state for each of the input and output indicators can be found in Table 1. There is a great deal of heterogeneity across states and districts with respect to agricultural production.

For the technical efficiency equations, district-level rural infant mortality rates were taken from Irudaya Rajan and Mohanachandran (1998). Rural literacy rates and the percentage of villages with blacktop and paved roads and electricity for agricultural use were from the Government of India (1997). The percentage of gross cropped area irrigated and cropping intensity (gross cropped area divided by net sown area) were calculated from Bhalla and Singh (2001). State-level means for each of the second stage variables are in Table 2.

Table 1. Sample Means by State for Input and Output Variables

State	Gross Cropped Area (‘000 hectares)	Fertilizer (tonnes)	Labor (male equivalents)	Tractors (total number)	Value of Agricultural Output (‘000 Rs)
Andhra Pradesh	835816	91078	1007394	1871	6496513
Assam	464199	4713	541289	92	3747417
Bihar	687741	39953	1267752	2809	3276013
Gujarat	623079	42420	413818	2671	3061675
Haryana	801182	84901	354971	13472	6972447
Karnataka	635578	44730	491274	1664	3663874
Kerala	407621	30641	409908	262	5104529
Madhya Pradesh	541619	19167	374807	920	2203879
Maharashtra	905098	54385	633583	1515	3340865
Orissa	872153	17929	628416	173	4337459
Punjab	682658	110234	297713	21076	7788069
Rajasthan	706352	14996	329802	3253	2166225
Tamil Nadu	632107	73827	1058039	1985	6549084
Uttar Pradesh	521150	46231	566272	4616	4117483
West Bengal	529565	62047	732473	702	5570756

Source: Data for gross cropped area, fertilizer, tractors and value of agricultural output, the price weighted sum of 35 crops, from Bhalla and Singh (2001).

Notes: 1) State level means for data from 261 districts. 2) Male equivalents for labor calculated using data from 1991 Census of India. Total workforce in agriculture is the sum of the “agricultural workforce” and “cultivators”. Males, females and children were weighted by factors of 1, 2/3 and 1/3, respectively.

To control for agro-climatic conditions, we used rainfall data for the year 1991 and the Sehgal *et al*. (1992) grouping of districts into 20 agro-ecologic zones based on climate, topography, water resources, and soil type.[4]

[4] We also attempted to control for crop mix by designating districts as rice, wheat, or “other districts,” based on concentrations of particular crops. We constructed these indicators from Center for Monitoring the Indian Economy (2000). We also tried to control for institutional climate using per capita credit to agricultural enterprises as a proxy variable. This measure was taken from CMIE (2000) as well. However, because of issues related to data completeness, we chose not to include these variables in our final model. The substantive results of our analysis remained consistent regardless of how we treated these variables.

Table 2. Sample Means by State for Socioeconomic Indicators and Overall, Land and Labor Efficiencies

State	Infant Mortality Rate (per 1000 births)	% Villages with Paved Roads	% of Villages Electrified	% Literate	Cropping Intensity	% Irrigated Area	Overall Technical Efficiency	Land Technical Efficiency	Labor Technical Efficiency
Andhra Pradesh	51.73	55.32	73.97	34.46	120.16	40.28	35.55	69.32	69.40
Assam	84.88	26.92	1.86	49.88	126.92	6.40	91.18	58.71	90.93
Bihar	71.28	25.62	25.32	33.90	132.93	36.53	26.39	72.02	63.74
Gujarat	69.48	61.37	85.19	52.90	106.54	26.54	36.74	70.20	67.72
Haryana	61.18	97.97	96.01	48.73	158.74	69.53	56.73	65.28	77.20
Karnataka	65.53	68.52	96.46	49.29	114.65	22.14	45.59	68.36	71.38
Kerala	35.54	98.63	96.34	89.57	137.58	14.40	79.69	62.23	83.78
Madhya Pradesh	65.54	42.89	69.74	55.13	117.10	12.84	28.13	72.14	63.99
Maharashtra	116.65	23.34	57.34	36.26	121.25	19.50	42.70	69.39	69.29
Orissa	113.47	22.89	21.12	42.53	148.23	28.83	64.22	63.64	80.56
Punjab	60.76	95.96	96.79	54.60	176.35	90.29	62.17	64.52	78.64
Rajasthan	90.69	31.11	48.19	28.89	122.92	26.06	43.80	69.91	68.36
Tamil Nadu	56.12	78.30	84.50	56.74	121.19	43.94	44.55	67.34	73.44
Uttar Pradesh	94.90	45.04	56.69	36.98	148.44	59.82	44.68	68.02	71.97
West Bengal	62.17	33.23	19.87	54.89	154.37	46.69	46.96	67.26	73.50

Source: IMR, paved roads, electrification, literacy data from Government of India (1997); Cropping intensity ([Gross Cropped Area/Net Sown Area]*100) from Bhalla and Singh (2001).

Notes: 1) State level means for data from 261 districts. 2) Overall, land and labor technical efficiencies derived from random coefficients estimation of Model 6 (see Table 3).

4. RESULTS: FRONTIER PRODUCTION FUNCTION ESTIMATES

In Table 3 we provide Ordinary Least Squares (OLS) (for comparative purposes) and Maximum Likelihood Estimation (MLE) estimates of the Cobb-Douglas production function, as well as the minimum and maximum value for the input response coefficients. The OLS results show that fertilizer, land area, and labor, in descending order of magnitude, are statistically significant determinants of agricultural production. Surprisingly, the number of tractors carries a negative elasticity, though this is not significantly different from zero at any level of confidence.

Table 3. OLS and Random Coefficients Model Estimates of Cobb-Douglas Agricultural Production with Ranges for Actual District-Input Level Response Coefficients

	(1) OLS Estimates	(2) Mean Response Coefficients	(3) Maximum Response Coefficients	(4) Minimum Response Coefficients
ln(Gross Cropped Area)	0.27	0.22	0.32	0.17
	(4.22)	(2.22)		
ln(Fertilizer)	0.36	0.42	0.43	0.42
	(11.07)	(7.59)		
ln(Labor)	0.25	0.25	0.35	0.04
	(4.44)	(2.24)		
ln(Tractors)	0.00	0.01	-	-
	(0.02)	(0.21)		
Constant	2.49	2.59	2.59	2.59
	(2.98)	(1.59)		
R-squared	0.67	-	-	-
Observations	261	261	-	-

Notes: 1) Absolute t-statistic, correcting for clustering at the NSS region level, in parentheses. 2) Column 2 provides estimates of mean response coefficients from random coefficients estimation of Model 6. 3) Column 3 and 4 provide the maximum and minimum district mean response coefficients computed from random coefficients estimation of Model 6.

The MLE results of the random-coefficients specification are presented in the second column of Table 3. We first note that we find the model to be valid (statistically significant at the 5% level or better), as ascertained by the Breusch-Pagan Lagrange multiplier test. The estimated mean response coefficients are generally in line with the OLS estimates. In the third and fourth columns of Table 3 we find that districts vary greatly in terms of production returns to inputs use and, consequently, the production process as a whole. In particular, there is a great deal of variation in returns to labor, with an order of magnitude difference between the district with the lowest response coefficient and the district with the highest.[5] Land elasticity also varies, though the range is smaller than that for labor.[6] For fertilizer use, while we do find statistically significant heterogeneity between districts, the distribution of response coefficients is quite tight.

5. RESULTS: TECHNICAL EFFICIENCY AND ITS DETERMINANTS

5.1. Patterns in Technical Efficiency

Using the procedures outlined in Section 2, we computed the input-specific and overall technical efficiency values for each district in the sample. In the last three columns of Table 2, we present state-level mean values for overall technical efficiency, land efficiency, and labor efficiency, along with data for various socioeconomic indicators that we use to explain the variation in efficiency. What should be immediately clear is that the overall and input-specific efficiencies vary quite widely across Indian districts and states. Overall mean efficiency ranges from a low of 26.39, on average, in Bihar, to a high of 91.18 in Assam.

Of the 261 districts in our sample, 181 (about 70%) have overall efficiency scores below 50%. Of these 181, 99 districts belong to four states: Bihar, Madhya Pradesh, Rajasthan and Uttar Pradesh. These states are collectively well known for their relatively low per capita incomes and human development performance.

However, it is clear that inefficiency is not simply a problem for poorer states. Numerous districts in Maharashtra, Gujarat, and Tamil Nadu, all states with relatively high per capita incomes, lag in using inputs effectively in agriculture. To present this point differently, we plot overall technical efficiency by the percentage of the rural population living below the poverty line for the year 1993-4 in Figure 1. It is clear from the scatter plot that there is no discernable relationship, one way or the other, between poverty and inefficiency.[7]

[5] A wide variation in labor elasticity was also computed in a firm-level study of Ethiopian farms conducted by Croppenstedt and Demeke (1997). The lowest and highest computed values in their study were 0.04 and 0.37, quite similar to our results. They postulate that the wide variation in labor elasticity is due to differential labor quality (such as health status). However, as mentioned earlier, they do not explicitly control for health and nutritional status as a determinant of labor or overall technical efficiency.

[6] The distribution of mean response coefficients for land falls below those typically found in the literature (0.4-0.6, see Kalirajan and Shand, 1994). This could perhaps suggest that farmers are not necessarily constrained by the availability of land.

[7] The correlation between the two variables is -0.054, and is not statistically significant.

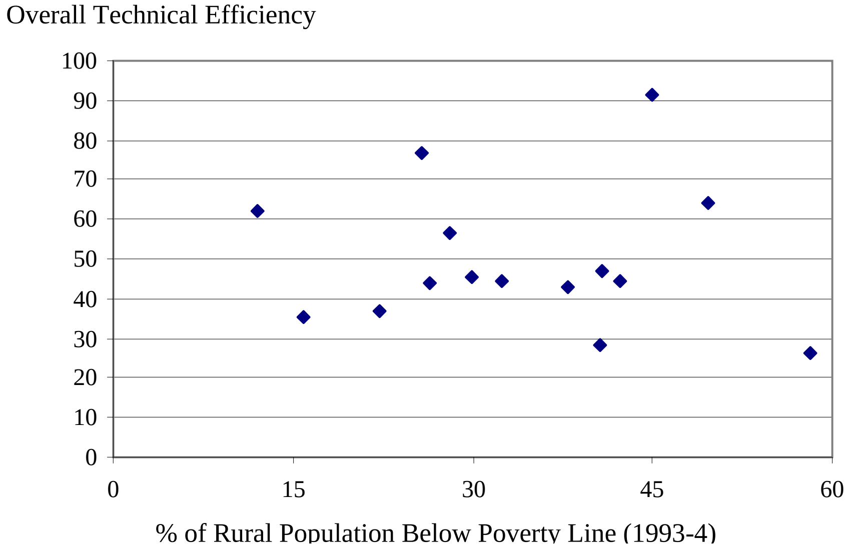

Figure 1. Rural Technical Efficiency and Rural Poverty

Another point to note from Table 2 is that overall efficiency seems to be determined more by labor efficiency than land or fertilizer efficiency. This can be seen from the MLE results in Table 3 as well, where we pointed out that labor use coefficients vary much more greatly than those for land and fertilizer. Indeed, we find that labor efficiency and overall technical efficiency are positively correlated, while land efficiency is negatively correlated to both of these measures. The results suggest that the two inputs are substitutes in terms of efficiency of use.[8]

5.2. Determinants of Technical Efficiency

In Table 4, we present the OLS estimates of the technical efficiency model presented in Section 2.[9] In column 1, we estimate Equation (7) without region-level fixed effects.

[8] Neither production theory nor the random coefficients estimation method imposes any restrictions on the input coefficients, such that a low elasticity for one variable means a higher elasticity for another. Hence, it is quite interesting that we are seeing a negative correlation between input efficiencies in our results.

[9] Many of the state-level control variables (not shown here) are statistically significant, indicating that the dummy variables are capturing a number of determinants for which we cannot adequately control more explicitly. Some of the state-level effects are especially large: Assam and Orissa — two of the poorest performing states in our sample with respect to poverty and human development coefficients — differ significantly from other states. It is likely that available data does not quite capture differential state-level

In this specification, lower IMR is associated with *lower* technical efficiency, and the estimate is statistically significant at the 0.10 level. With the exception of village electrification and cropping intensity, the signs on the other coefficients are in line with our *a priori* expectations.

Table 4. Determinants of Overall Technical Efficiency

	(1)	(2)	(3)	(4)
IMR	0.13	-0.13	-0.19	-0.18
	(1.73)	(2.29)	(2.39)	(2.39)
% Literate	0.479	0.253	0.245	0.258
	(3.81)	(2.18)	(1.82)	(1.88)
% Irrigated Area (coeff x 10)	0.00	0.02	0.01	0.01
	(0.11)	(2.26)	(1.09)	(1.45)
% Village with Paved Roads	0.20	0.10	-0.03	-0.05
	(2.26)	(0.98)	(0.76)	(0.41)
% Village Electrified	-0.26	-0.17	-0.11	-0.17
	(2.67)	(2.71)	(1.56)	(1.53)
Cropping Intensity	0.08	-0.13	-0.07	-0.08
	(0.98)	(2.45)	(2.39)	(1.34)
Controls				
State FE	No	Yes	No	No
NSS Region FE	No	No	Yes	Yes
Agroclimate Zone FE	No	No	No	Yes
Rainfall (mm)	No	No	No	Yes
R-squared	0.20	0.63	0.75	0.79
Observations	261	261	261	253

Notes: 1) Absolute t-statistic, correcting for clustering at the NSS region level, in parentheses. 2) OLS estimates for Model 7 with Overall Technical Efficiency as dependent variable. 3) State FE and NSS region FE refer to fixed effects for states and National Sample Survey Region, respectively (see Section 3). Agroclimatic Zone FE refers to the National Bureau of Soil Survey and Land Use Planning's (1992) grouping of districts into 20 zones on the basis of climate, topography, water resources and soil type.

The inclusion of state-level fixed effects (column 2) leads to significant changes. The coefficient for IMR is now *negative* and significant, implying that a decrease of 10 deaths (per 1,000) is associated with a 1.29 percentage point increase in technical efficiency. This association is statistically significant at the 0.05 level. Note that, in this

environmental and institutional factors. As a result, we are limited in our attempts to disaggregate the large unexplained effects that state particulars confer on technical efficiency.

specification, the point estimate on the coefficients for literacy rates, roads, and electrification move closer to zero when compared to column 1. The coefficient for the percentage of land area irrigated is now statistically significant. Finally, the model R^2 increases markedly, further underscoring the importance of the state fixed effects.

Using NSS region-level fixed effects (column 3) leads to a larger and more negative estimate of the IMR coefficient (-0.193, absolute t-statistic: 2.39). The coefficients on literacy rates, roads, and electrification move further towards zero in this specification. As mentioned earlier, the idea behind the NSS region is to group districts that are similar in agro-climatic and socio-demographic composition. Thus, NSS-region fixed effects can be viewed as better controls for district-level unobserved heterogeneity than state fixed effects.

Given this, the movement in the point estimates on IMR across columns 1 to 3 is interesting. Controlling for state fixed effects changes the sign on the estimated IMR effect/association. Potentially controlling for a greater portion of district-level heterogeneity using NSS regions fixed effects magnifies this association. These results imply that state/region-level institutional, agro-climatic and socioeconomic factors that are positively (negatively) correlated with technical efficiency are negatively (positively) correlated with health. It is difficult to speculate on what these factors might be. For example, agro-climatic conditions (humidity, temperature and soil content) that are favorable to production efficiency may also be favorable to disease-causing pathogens. Or, it may be that, government spending priorities towards one goal may crowd out investments in the other.

More mechanically, much of the change in coefficients between columns 1 and 2 appears to come from accounting for district membership in Assam and Orissa, two states with relatively high levels of both IMR and production efficiency. While fully explaining the nature of the factors subsumed in the state/NSS region fixed effects is beyond the focus of this study, we expect that a credible explanation would address the findings with respect to Assam and Orissa.

The coefficients for literacy rates and road infrastructure become smaller in magnitude and insignificant in the fixed effects models. This finding suggests we are picking up a salient portion of the unobserved heterogeneity with the inclusion of fixed effects. That the negative association between IMR and technical efficiency *increases* in strength with the inclusion of these state/region controls speaks towards the robustness of this result. Finally, in column 4, we include controls for agro-climatic zone and rainfall. The coefficient on IMR drops slightly, but still remains quite stable.[10]

[10] We also estimate the model with controls for a large set of public goods (tap water sources, medical facilities, primary schools, waterways, post offices and banks) and find that the coefficient on IMR is virtually unaffected.

Table 5. Determinants of Labor Efficiency

	(1)	(2)	(3)	(4)
IMR	0.03	-0.06	-0.09	-0.08
	(1.09)	(2.16)	(2.09)	(2.24)
% Literate	0.18	0.06	0.02	0.05
	(3.24)	(1.22)	(0.44)	(0.86)
% Irrigated Area (coeff x 10)	0.00	0.01	0.01	0.01
	(0.27)	(2.42)	(1.39)	(2.12)
% Village with Paved Roads	0.07	0.02	-0.04	-0.01
	(1.33)	(0.40)	(0.62)	(0.18)
% Village Electrified	-0.09	-0.05	0.01	-0.09
	(1.53)	(0.73)	(0.12)	(1.92)
Cropping Intensity	0.06	-0.02	-0.02	-0.02
	(1.80)	(-0.81)	(0.03)	(0.57)
Controls				
State FE	No	Yes	No	No
NSS Region FE	No	No	Yes	Yes
Agro-climate Zone FE	No	No	No	Yes
Rainfall (mm)	No	No	No	Yes
R-squared	0.15	0.47	0.59	0.70
Observations	261	262	263	253

Notes: 1) Absolute t-statistic, correcting for clustering at the NSS region level, in parentheses. 2) OLS estimates for Model 7 with Labor Technical Efficiency as dependent variable. 3) See notes for Table 4 and main text for details on control variables.

Finally, we present OLS results of the equations for labor efficiency in Table 5. The first thing to note here is how, in general, the coefficients of the independent variables are qualitatively similar to those in the overall efficiency equation. Specifically, the point estimates on IMR follow the same pattern as in Table 4: the coefficients become increasingly negative and significant as state and region fixed effects are added. We do not show models for land and fertilizer efficiency as the results were quite unrevealing: few of the explanatory variables were statistically significant. This result comports with the extensive microeconomic literature on wage returns to investments in health and nutrition, and suggests that much of the association between IMR and overall technical efficiency in production can be explained by the correlation between IMR and labor efficiency.

5.3. Robustness Checks and Endogeneity

We first investigate whether our substantive results are robust to using alternate methods to calculate technical efficiency. To do this, we used the stochastic frontier method (see Section 2.1) to calculate overall technical efficiencies and used these estimates as dependent variables for a second-stage OLS analysis. We present these results in Table 6. The results are qualitatively similar to those presented in Table 4 and further support our modeling approach.[11]

Table 6. Determinants of Overall Technical Efficiency Calculated Using Stochastic Frontier Method

	(1)	(2)	(3)	(4)
IMR	0.07	-0.29	-0.36	-0.33
	(0.64)	(3.12)	(2.47)	(2.43)
% Literate	0.76	0.20	0.19	0.22
	(2.99)	(1.06)	(1.01)	(1.08)
% Irrigated Area (coeff x 10)	0.00	0.04	0.04	0.05
	(0.29)	(3.03)	(1.85)	(2.32)
% Village with Paved Roads	0.40	0.33	0.10	0.03
	(2.48)	(1.89)	(0.20)	(0.15)
% Village Electrified	-0.51	-0.43	-0.29	-0.36
	(2.56)	(3.62)	(1.95)	(1.59)
Cropping Intensity	0.19	-0.12	-0.12	-0.12
	(1.50)	(0.80)	(1.01)	(1.04)
Controls				
State FE	No	Yes	No	No
NSS Region FE	No	No	Yes	Yes
Agroclimate Zone FE	No	No	No	Yes
Rainfall (mm)	No	No	No	Yes
R-squared	0.23	0.64	0.76	0.78
Observations	261	261	261	253

Notes: 1) Absolute t-statistic, correcting for clustering at the NSS region level, in parentheses. 2) OLS estimates for Model 7 using Overall Technical Efficiency computed with the stochastic frontier method. 3) See notes for Table 4 and main text for details on control variables.

The more pressing issue is, as discussed above, the potential endogeneity of the health variable. Despite the strengthening negative association between IMR and TE as more controls are added, it is still possible that our estimates reflect: (i) the presence of

[11] The difference in the magnitude of the coefficients between the random coefficients and stochastic frontier specifications is to be expected given that the mean district efficiency value differs across the two models. Thus the most sensible comparisons of slopes across these models are with respect to sign and significance.

unobserved factors that are correlated with both IMR and TE, or (ii) simultaneous determination of IMR and technical efficiency. In either case, econometric estimation using OLS would lead to biased and inconsistent estimates of the coefficient for IMR. To get at this potential problem, we looked for a source of exogenous variation that is correlated with health but plausibly uncorrelated with unobservables in the production efficiency equation. Finding such an instrumental variable (IV) is difficult: there is no guarantee that the typical instruments for health employed at the micro-level (commodity prices, access to health care institutions) are exogenous at a more aggregate level. Furthermore, we were unable to find large-scale health care policies or interventions that occurred during the time period of our study as potential sources of exogenous variation. Even when we attempted to use variables that were likely not defensible *a priori* from the standpoint of the exclusion restriction — in particular the percentage of villages with tap water and medical facilities — we found that these variables did not meet another criterion of a good IV: both variables were only weakly correlated with health status and insignificant in the reduced form equation for IMR. As such, our findings should be interpreted with caution. Unfortunately, given data constraints and the paucity of clearly acceptable instruments, we are unable to achieve greater certainty in this study.

Table 7. Efficiency Gains from Improvements in IMR for 15 Least Efficient Districts

District	State	Overall Efficiency	Gains from IMR
Jaisalmer	Rajasthan	4.91	9.30
Bikaner	Rajasthan	15.21	6.44
Bhagalpur	Bihar	17.40	6.44
Muzaffarpur	Bihar	18.76	7.09
East Nimar	Madhya Pradesh	19.49	13.01
Monghyr	Bihar	20.51	6.96
Bangalore	Karnataka	20.80	4.58
Ahmednagar	Maharashtra	21.80	3.29
Nanded	Maharashtra	21.44	5.86
Gaya	Bihar	22.35	6.75
Nashik	Maharashtra	22.47	5.86
Jalgaon	Maharashtra	22.70	6.86
Sholapur	Maharashtra	23.10	4.29
Satna	Madhya Pradesh	23.19	17.02
Pune	Maharashtra	23.31	2.86

Notes: 1) Overall technical efficiency derived from random coefficients estimation of Model 6 (see Table 3). 2) Gains from IMR calculated using coefficients in column 4 of Table 4 multiplied by the difference between the district's IMR and the lowest IMR value in the sample.

5.4. Magnitude of Health-Mediated Gains in Efficiency

In practical terms, what do our findings mean for Indian districts? That is, just how potent is health in promoting efficiency in input use? In Table 7, we compute the overall efficiency gains associated with improvements in IMR for the 15 least efficient districts in the sample using the coefficient on IMR estimated in column 4 of Table 4. The efficiency gains were computed by multiplying the regression coefficient by the difference between the district's IMR and the lowest IMR in the sample.

In general, we see that potential gains in technical efficiency from improvements in IMR can be substantial in both absolute and relative terms. Again, we urge caution in interpreting our estimates of the IMR-technical efficiency relationship as causal. However, these large magnitude associations warrant further research and policy attention to the potential role of population health as an engine for agricultural and economic development.

6. DISCUSSION AND CONCLUSIONS

Almost 60% of India's population relies on agriculture to make a living (National Portal of India, 2010). In recent years, low productivity and lack of efficiency in this sector have concerned many policymakers, especially in the context of increasing global competition. Given the large labor force concentrated in agriculture and the many forward and backward linkages between agriculture and other sectors, ensuring the prosperity of this sector is of paramount importance. The numerous empirical studies at the micro and macro levels suggesting potentially large economic benefits from improvements in individual and population health thus command attention. In particular, many of the micro studies have focused on the effect of various health indicators on agricultural wages or farm-level production.

In this study, we consider the impact of health on agricultural production at a more aggregate level. In doing so, we diverge from the typical approach of including health status variables as inputs in the production function. Rather, we model health (IMR) as a factor which influences the efficiency of the production process, a strategy we feel better captures the role of health as a component of human capital.

We find that on the whole, Indian districts are quite inefficient in producing agricultural goods, and that the range of (in)efficiency across states and districts is quite wide. We also find that the level of rural poverty in a given state has no bearing on the average efficiency of districts within that state, and that inefficiency in agriculture is therefore not just a problem of the poor.

Going back to the main objectives of this study, we find that population health is associated with technical efficiency in agricultural production and that, notably, the efficiency of labor use persists even after controlling for a set of confounding factors. These results are not only consistent with the growing body of cross-country and micro-level studies on the economic benefits of good health, but are also in line with other literature in India demonstrating the role of health in reducing poverty and promoting economic growth (Mitra *et al*., 2002; and Gupta and Mitra, 2004). In the context of this literature, our study adds to the argument that population health investments are an important component of policy packages seeking to promote better economic performance — both in growth and efficiency terms — and to reduce poverty.

We do not, however, know with certainty the way in which health makes for more efficiency in input use. We can speculate that improved population health is useful in the causal chain because labor is not marginalized or otherwise lost to sickness or caring for the sick, such that more productive labor is utilized in the production process. Another possible explanation rests on the notion that better population health means that each individual unit of labor is more fully productive than it otherwise would have been, suggesting that the mechanism is not more labor or laborers who are unfettered by their or a family member's sickness, but that each individual worker is exposed to less morbidity and thus is more productive than he or she would have been in a climate of greater population infirmity. The exact causal mechanisms are ripe for further study, particularly through examination that can more closely assess the cause and effect of this relationship.

Along these lines, there are several limitations in our study. First, and perhaps most important, we cannot be sure that we have addressed the potential endogeneity of health, thus limiting our ability to make causal claims on our estimates. Second, it would be better to use standardized adult death rates or life expectancies as our measure of health rather than infant mortality rates. To the extent that the latter fails to proxy adult health, some form of measurement error will appear in our estimates. In addition, if the production of child health vis-à-vis technical efficiency is different from the production of adult health, the nature of the omitted variable bias might differ in the two situations as well. For example, to the extent that biological hardiness is determined during youth, child health might be more prone to reverse causality from better efficiency in production than adult health. As a result, the use of region fixed effects to reduce unobserved heterogeneity would be less likely to parse out the reverse causal pathway. Such differences might hinder our ability to make statements about the effects of health on technical efficiency. Unfortunately, adult death rates, life expectancy, and morbidity data are unavailable at the district level.

Third, to the extent that the efficiency of production of different crops varies (both across crops and within districts), our estimates of technical efficiency may be imprecise. Unfortunately, we are unable to disaggregate the production function for specific crops due to limitations in the available data. Fourth, in estimating our production function, we specify the production inputs as exogenous. This is likely to be a strong assumption, though one that will be difficult to relax for estimation purposes given the lack of credible identifying variation.

Despite these limitations, our study proposes an interesting mechanism to demonstrate health's positive influence on economic performance. These results stimulate future work to carefully characterize the links between health and technical efficiency, and economic development more broadly.

REFERENCES

Acemoglu, D., and S. Johnson (2007), "Disease and Development: The Effect of Life Expectancy on Economic Growth," *Journal of Political Economy*, 115(6), 925-985.

Aigner, D., C.A.K. Lovell, and P. Schmidt (1977), "Formulation and Estimation of Stochastic Frontier Production Function Models," *Journal of Econometrics*, 6(1), 21-37.

Alsan, M., D.E. Bloom, and D. Canning (2006), "The Effect of Population Health on Foreign Direct Investment Inflows to Low-and Middle-Income Countries," *World Development*, 34(4), 613-630.

Altonji, J., T.E. Elder, and C.R. Taber (2005), "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools," *Journal of Political Economy*, 113(1), 151-184.

Ashraf Q., A. Lester, and D. Weil (2008), "When Does Improving Health Raise GDP?" in Acemoglu, D., K. Rogoff, and M. Woodford, eds., *NBER Macroeconomics Annual 2008*, 23, Chicago: University of Chicago Press.

Barro, R., and X. Sala-i-Martin (2004), *Economic Growth*, 2nd ed., Cambridge, MA: MIT Press.

Battese, G.E. (1992), "Frontier Production Functions and Technical Efficiency: A Survey of Empirical Applications in Agricultural Economics," *Agricultural Economics*, 7(3-4), 185-208.

Bauer, P.W. (1990), "Recent Developments in the Econometric Estimation of Frontiers," *Journal of Econometrics*, 46(1-2), 39-56.

Behrman, J.R., and M.R. Rosenzweig (2004), "Returns to Birthweight," *Review of Economics and Statistics*, 86(2), 586-601.

Bhalla, G.S., and G. Singh (2001), *Indian Agriculture: Four Decades of Development*, Thousand Oaks, CA: Sage Publications.

Bhargava, A., D.T. Jamison, L.J. Lau, and C.J.L. Murray (2001), "Modeling the Effects of Health on Economic Growth," *Journal of Health Economics*, 20(3), 423-440.

Bleakley, H. (2010), "Health, Human Capital and Development," *Annual Reviews of Economics*, 2, 283-310.

Bloom, D.E., and D. Canning (2000), "The Health and Wealth of Nations," *Science*, 287(5456), 1207-1209.

Bloom, D.E., D. Canning, and B. Graham (2003), "Longevity and Life-Cycle Savings," *Scandinavian Journal of Economics*, 105(3), 319-338.

Bloom, D.E., D. Canning, and J. Sevilla (2004), "The Effect of Health on Economic Growth: A Production Function Approach," *World Development*, 32(1), 1-13.

Center for Monitoring the Indian Economy (CMIE) (2000), *Profiles of Districts*, Mumbai, India: CMIE.

Croppenstedt, A., and M. Demeke (1997), "An Empirical Study of Cereal Crop Production and Technical Efficiency of Private Farmers in Ethiopia: A Mixed Fixed-Random Coefficients Approach," *Applied Economics*, 29(9), 1217-1226.

Croppenstedt, A., and C. Muller (2000), "The Impact of Farmers' Health and Nutritional Status on Their Productivity and Efficiency: Evidence from Ethiopia," *Economic Development and Cultural Change*, 48(3), 475-502.

Deolalikar, A. (1988), "Nutrition and Labor Productivity in Agriculture: Estimates for Rural South India," *Review of Economics and Statistics*, 70(3), 406-413.

Gallup, J.L., and J.D. Sachs (2001), "The Economic Burden of Malaria," *American Journal of Tropical Medicine and Hygiene*, 64(1, 2 suppl.), 85-96.

Glewwe, P., H.G. Jacoby, and E.M. King (2001), "Early Childhood Nutrition and Academic Achievement: A Longitudinal Analysis," *Journal of Public Economics*, 81(3), 345-368.

Government of India (1991), *Census of India, Section 3B (Economic Tables)*, CD-ROM, New Delhi.

_____ (1997), *Availability of Infrastructural Facilities in Rural Areas of India: An Analysis of Village Directory Data* (Volume 40 of Census of India 1991), New Delhi: Office of the Registrar General.

Greene, W.H. (1993), "The Econometric Approach to Efficiency Analysis," in Fried, H.O., C.A.K. Lovell, and S.S. Schmidt, eds., *The Measurement of Productive Efficiency: Techniques and Applications*, New York: Oxford University Press, 68-119.

Griffiths, W.E. (1972), "Estimation of Actual Response Coefficients in the Hildreth-Houck Random Coefficient Model," *Journal of the American Statistical Association*, 67(339), 633-635.

Gupta, I., and A. Mitra (2004), "Economic Growth, Health and Poverty: An Exploratory Study for India," *Development Policy Review*, 22(2), 193-206.

Irudaya, R.S., and P. Mohanachandran (1998), "Infant and Child Mortality Estimates: Part 1," *Economic and Political Weekly*, 33(19), 1120-1140.

Kalirajan, K.P., and M.B. Obwona (1994a), "A Measurement of Firm- and Input-Specific Technical and Allocative Efficiencies," *Applied Economics*, 26(4), 393-398.

_____ (1994b), "Frontier Production Function: The Stochastic Coefficients Approach," *Oxford Bulletin of Economics and Statistics*, 56(1), 87-96.

Kalirajan, K.P., and R.T. Shand (1994), *Economics in Disequilibrium: An Approach from the Frontier*, New Delhi: Macmillan India Ltd.

Kumbhakar, S.C. (1998). "Estimation of Input-Specific Technical and Allocative Inefficiency in Stochastic Frontier Models," *Oxford Economic Papers*, 40(3), 535-549.

Meeusen, W., and J. van Den Broeck (1977), "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error," *International Economic Review*, 18(2), 435-444.

Miguel, E., and M. Kremer (2004), "Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities," *Econometrica*, 72(1), 159-217.

Mitra, A., A. Varoudakis, and M. Veganzones-Varoudakis (2002), "Productivity and Technical Efficiency in Indian States' Manufacturing: The Role of Infrastructure," *Economic Development and Cultural Change*, 50(2), 395-426.

National Portal of India (2010), "Agriculture," http://india.gov.in/sectors/agriculture/index.php (accessed March 31, 2010).

Nerlove, M. (1965), *Estimation and Identification of Cobb-Douglas Production Functions*, Chicago: Rand McNally & Co.

Ray, S.C. (2004), *Data Envelopment Analysis: Theory and Techniques for Economics and Operations Research*, Cambridge, UK: Cambridge University Press.

Ruger, J.P, D.T. Jamison, and D.E. Bloom (2001), "Health and the Economy," in Merson, M.H., R.E. Black, and A.J. Mills, eds., *International Public Health: Diseases, Programs, Systems, and Policies*, Gaithersburg, MD: Aspen, 617-666.

Ruger, J.P., D.T. Jamison, D.E. Bloom, and D. Canning (2006), "Health and the Economy," in Merson, M.H., R.E. Black, and A.J. Mills, eds., *International Public Health: Diseases, Programs, Systems, and Policies*, 2nd Edition, Sudbury, MA: Jones and Bartlett Publishers, 601-648.

Schultz, T.P. (2002), "Wage Gains Associated with Height as a Form of Health Human Capital," *American Economic Review*, 92(2), 349-353.

_____ (2003), "Wage Rentals for Reproducible Human Capital: Evidence from Ghana and the Ivory Coast," *Economics and Human Biology*, 1(3), 331-366.

Schultz, T.P., and A. Tansel (1997), "Wage and Labor Supply Effects of Illness in Cote D'Ivoire and Ghana: Instrumental Variable Estimates for Days Disabled," *Journal of Development Economics*, 53(2), 251-286.

Sehgal, J.L., and National Bureau of Soil Survey and Land Use Planning (NBSS and LUP) (1992), *Agro-Ecological Regions of India*, 2nd ed., New Delhi: NBSS and LUP.

Strauss, J., and D. Thomas (2008), "Health Over the Life Course," in Schultz, T.P., and J. Strauss, eds., *Handbook of Development Economics*, vol. IV, Amsterdam: North-Holland, 3375-3474.

Swamy, P.A.V.B. (1970), "Efficient Inference in a Random Coefficient Regression Model," *Econometrica*, 38(2), 311-323.

_____ (1971), *Statistical Inference in Random Coefficient Regression Models*, New York: Springer-Verlag.

Weil, D. (2007), "Accounting for the Effect of Health on Economic Growth," *Quarterly Journal of Economics*, 122(3), 1265-1306.

Mailing Address: Atheendar S. Venkataramani, Washington University School of Medicine, 660 S. Euclid Ave, St Louis, MO 63110, USA. Tel: (001)518-859-0995. E-mail: venkataat@wusm.wustl.edu.

Received June 2, 2009, Revised November 30, 2009, Accepted July 16, 2010.