How Endowments, Accumulations, and Choice Determine the Geography of Agricultural Productivity in Ecuador

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Spatial disparity in incomes and productivity is apparent across and within countries. Most studies of the determinants of such differences focus on cross-country comparisons or location choice among firms. Less studied are the large differences in agricultural productivity within countries related to concentrations of rural poverty. For policy, understanding the determinants of this geography of agricultural productivity is important, because strategies to reduce poverty often feature components designed to boost regional agricultural incomes. Census and endowment data for Ecuador are used to estimate a model of endogenous technology choice to explain large regional differences in agricultural output and factor productivity. A composite-error estimation technique is used to separate systemic determinants from idiosyncratic differences. Simulations are employed to explore policy avenues. The findings suggest a differentiation between the types of policies that promote growth in agriculture generally and those that are more likely to assist the rural poor.

Regional differences in incomes within countries are often striking and are similar in many ways to differences in average incomes among countries. Why inequality takes on spatially identifiable forms is thought to be related to the characteristics of place that constrain and influence current economic choice and to the historical influences of geography on accumulations of assets by families and communities. To a large degree, spatial differences in economic opportunity are locally recognized and motivate the movement of labor among economic sectors and the migration of households that are a ubiquitous aspect of economic development. Most noticeably, such movements take the form of

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an out-migration from agriculture and a movement from rural to urban space (Larson and Mundlak 1997).

At the same time, not everyone is positioned to take advantage of opportunities in other sectors or locations. Moreover, barriers such as up-front costs, risks, and asymmetries in information further constrain migration. When this is so, circumstances related to household and location characteristics can work in persistent and reinforcing ways to impoverish communities and regions. Commonly, this gives rise to lagging regions with high concentrations of rural poor who depend substantially on agriculture for food and income.

For policymakers, a key question is whether the aspects of disadvantaged areas can be changed through policies in a way that creates greater economic opportunity for poor households. Related to this is the question of how quickly policy can affect the underlying determinants of regional inequality. In particular, the short-term efficacy of policy and the mutability of regional differences are expected to hinge on the degree to which geographic disparities in income depend on unchanging natural endowments, on quasi-fixed accumulations of public and private factors and institutions, and on policy-related incentives and constraints that shape how current resources are used.

To some extent, the study of what makes some regions within a country less prosperous than others is related to the question of what determines international differences in growth and productivity. In this area of research, evidence from cross-country macroeconomic data suggests that growth and productivity are driven by broad state variables that determine productivity directly and also influence choices that affect accumulations over time. A similar conclusion is reached in studies that look at what determines productivity differences among manufacturing firms.

This article takes another perspective and focuses on the determinants of spatial differences in agricultural productivity. It does so chiefly because lagging regions in poor developing countries usually have few linkages to sectors outside agriculture. Consequently, it is important to know whether policy instruments can be identified that bring about significant improvements in agriculture incomes. However, also of interest is the related question of whether results from cross-country and firm studies have counterparts in a study of what determines spatial income differences within a geographically pervasive sector of a single country.

There are several advantages to studying both issues in the context of agriculture in Ecuador. First, because disparities in agricultural productivity and incomes are large in Ecuador, the determinants of spatial inequality can be examined in the context of a sector that is important to Ecuador and in a framework that is different from that of other studies of regional inequality. Second, because census data are available, techniques can be employed that provide more focused measures of productivity and its determinants. Third, the role of endowments is more easily studied in the context of agriculture,

where soil and climate endowments are well measured and their potential contribution well identified.

I. Background

Most models of production, including related growth models, start with the assumption that observed income levels arise from a common technology.[1] The assumption is rooted in the firm-theory conditions required to derive a well-defined production function. However, the notion that all firms use the same method to produce creates logical tensions because very heterogeneous levels of productivity are often observed in practice.[2] For studies based on farm data, differences in productivity can arguably be assigned to idiosyncratic differences in farms and farmers. However, in studies based on aggregate country or sector data, differences in the capability to apply available technology are attributed instead to identifiable country or sector traits. Even so, a common underlying technology is expected to prevail in the long run, and this notion has consequences for modeling approaches.

One view, associated with the endogenous growth literature, suggests that output and productivity differences among nations and among firms are driven largely by differences in adopted technology.[3] Because, in this view, the cost of technology diffusion is low and the benefits are high, countries and firms will converge to a common technology in the long run. Trade and open investment channels are expected to facilitate technology diffusion. Consequently, this literature generally sees initial conditions and the speed with which new technologies can be adopted as keys to development. Empirically, studies of this type focus on short-run growth rates or rates of productivity convergence.

A related literature sees technology adoption as less automatic and focuses on barriers (see Parente and Prescott 1994 and references therein). In a similar way, the economic geography literature argues that the costs of adopting new production methods are often specific to location, potentially creating a range of barriers to adoption that vary geographically (see the survey by Henderson, Shalizi, and Venables 2001). In particular, local information about techniques and local-factor markets that support particular forms of production is seen as the basis for spillovers that contribute to productivity and become a force concentrating on economic activity. Transaction costs, the location of endowments, and history play a role as well, creating a shifting set of incentives for centers of economic activity.

1. Griliches (1996) provides a history of early efforts to measure productivity, including a review of early structural models. Mundlak (2001) reviews agricultural production modeling.

2. See related criticisms raised by Stigler (1976).

3. See early studies by Mankiw, Romer, and Weil (1992) and Barro and Sala-i-Martin (1992). Klenow and Rodriguez-Clare (1997) and Brock and Durlauf (2001) provide reviews.

The relationships among transaction costs, markets, and the capacity of governments to protect property rights and enforce contracts are the focus of another related set of studies that emphasize the role of institutions (North 1994; Hall and Jones 1997). Although expensive to build and maintain, institutions are expected to contribute to growth in several ways. Institutions are expected to reduce the risk of diversion or expropriation and to facilitate capital, insurance, hedging, and other related markets that allow risks to be shared. Reducing and sharing risks allow for anonymous exchange, increasing competition, and reducing marginal transaction costs. Dynamically, the workings of institutions allow for faster rates of accumulation of human and physical capital, which contribute directly to greater output.

Ideas related to institutions and economic geography are integrated with growth modeling in several studies designed to identify the deep-seated determinants of growth (Sachs and Warner 1997; Bhattacharyya 2004; Rodrik, Subramanian, and Trebbi 2004). In these studies, factor inputs are viewed as proximate endogenous variables because investment and other choices related to factor accumulation are influenced by the same conditioning variables that determine productivity. For this reason, these studies sometimes take an empirical approach that excludes factors as a determinant of production growth and instead rely on reduced-form applied models expressed in terms of the conditioning variables alone.

With this literature in mind, a model is developed in the following section in which production techniques are endogenous, although potentially constrained by available technology. The applied model includes many variables related to endowments, institutions, communities, and households that are expected to describe the decision environment that determines which of the available technologies is applied. Because some of these determinants are related to geographic features that cannot be affected by policy, the relative importance of these features in explaining regional income disparities is examined.

To some extent, the variables used to describe the decision environment are related to the types of variables viewed as the fundamental or deep determinants in the growth literature. This makes possible an exploration of whether the same basic notions about what determines income differences among countries hold in explaining regional differences in agricultural incomes. Because cross-sectional data are used, the study does not look at the dynamic relationship between factor accumulation and broad determinants of productivity. However, it does focus on the relative roles of factor use and technology choice to draw inferences about how quickly changes in these conditioning variables affect incomes.

This has relevance for policy because policies tend to work through the aspects of the conditioning environment. To the extent that current output is determined primarily by factors of production, the role of policy will be limited to its effect on the rates of accumulation. In this case, the benefits of improved policy will accrue slowly, and previous policies, embodied in current stocks of

accumulated factors, will determine outcomes largely in the short run. Alternatively, if policy directly affects the choice of technique, changes in policy can affect growth through productivity increases that are immediate and additional to long-run effects.

II. Theory and the Applied Model

The starting point for the applied model is Mundlak's (1988), 1993 model of endogenous implemented technology. The model accommodates heterogeneous production technologies, based on the assumption that the choices that producers make regarding which technology to apply, and therefore which inputs to use, are conditioned by earlier decisions, manifested in quasi-fixed factors, and by the decision environment in which the producers operate. Because the aspects of the decision environment vary among producers, a set of microeconomic production solutions results, each potentially characterized by a different technology.

Using the vectors y_n^* to denote production, s to denote state variables that characterize the decision environment, and $x^* = x(s)$ to denote inputs, the aggregation of output can be written as a function of s alone, where $\sum y_n^* \equiv F(x^*, s) \equiv \Phi(s)$. In general, the production function is not identified. It is however possible to find an approximating aggregate function, $F(x,s)$, based on the assumption that observed differences in input allocations are associated with different implemented technologies conditioned on s. Operationally, the result is an approximating empirical representative model of production, where elasticities are functions of the state variables and possibly of the inputs. This is written as $\ln y = \Gamma(s) + B(x, s)$, where y is output, $B(x,s)$ represents a production technology that depends jointly on production factors and state variables, and $\Gamma(s)$ represents a vector of additional productivity effects that depend on state variables alone. In this framework, productivity and the marginal contributions of inputs to output are endogenous and arise in response to the changing decision environment.

The applied model provides functional form to the conceptual model. Because the production technology function $B(x,s)$ potentially depends on the input and state variables, it is modeled as a flexible combination of the factors and exogenous state variables:

$$B(x, s) \equiv \sum_i b_i \ln x_i + \frac{1}{2}\sum_{i,j} b_{ij} \ln x_i \ln x_j + \frac{1}{2}\sum_{i,n} a_{in} \ln x_i \ln s_n. \tag{1}$$

The additional systemic state-specific productivity effects are modeled as a linear combination of the state variables, $\Gamma(s) \equiv \sum_n a_n \ln s_n$.[4] The model is

4. Although, in principle, the state variables are measured as log transformations, most state variables used to estimate the model are either discrete or expressed as a proportion.

completed by adding a farm-specific idiosyncratic productivity term, e. The applied model is therefore given by:

$$(2)\quad \ln y = \sum_n a_n \ln s_n + \sum_i b_i \ln x_i + \frac{1}{2}\sum_{i,j} b_{ij} \ln x_i \ln x_j + \frac{1}{2}\sum_{i,n} a_{in} \ln x_i \ln s_n + e.$$

In anticipation of the discussion of the data used to estimate the applied model, additional comments about the model are in order. Because cross-sectional data are used to estimate the model, farm-specific subscripts are implicit in equation (2). Some state variables relate to location or to ecological measures that are repeated over subsets of households, and thus it is possible to denote these using location-specific subscripts instead. Later this relationship is used to distinguish farm and household effects that are independent of effects related to geography.

The idiosyncratic term in equation (2) is given a specific form that is motivated by a potential constraint imposed by the set of available technologies from which the endogenous applied technologies are chosen. To see this, consider the stochastic productivity measure:

$$(3)\qquad P(x,s) \equiv \ln y - B(x,s) \equiv \Gamma(s) + e.$$

Implicit in the endogenous applied technology framework is the notion that some states will result, through technology choice, in higher levels of total factor productivity than others. This is reflected in the deterministic component, $\Gamma(s)$. However, productivity may be additionally affected by an idiosyncratic component related to unobservable characteristics of the farm or farmer. Without the loss of generality, it is possible to rank the deterministic component of productivity to say something about the idiosyncratic term.

The output outcome associated with the highest level of productivity can be labeled $P_0^* = \Gamma(s_0)$, and a conditioned measure of inefficiency with deterministic and idiosyncratic components $u_n^* = P_0^* - P_n^*$ can be calculated for each observation. If the conditional technology that produces P_0^* is binding in the sense that no greater output is feasible, the expected value of the inefficiency term will be non-negative. For a given set of state variables, producers might be expected to make the best of their available resources, so that the productivity outcomes cluster near the limiting technological frontier. However, relatively large inefficiencies are possible, in which case the distribution of the inefficiency term may be skewed as well as truncated.

The notion that stochastic productivity is constrained has motivated a series of applied stochastic frontier models. Generally, applied frontier models treat stochastic departures from the frontier as inefficiencies in the application of a single technology. This differs conceptually from the model developed here, where applied technologies are endogenous. Nevertheless, in a way that is similar to statistical frontier models, productivity in the applied model is stochastic and potentially constrained in a manner that would result in

idiosyncratic terms that have a skewed distribution. Consequently, the estimation techniques associated with frontier models can be used to potentially improve the estimation of the proposed model.

Specifically, the stochastic component of the model can be more fully specified as $e \equiv v - u$, so that the error is composed of a symmetric normally distributed error term, v, and a non-negative random term, u. By convention, the composite error is expressed as a difference between the two components. Consequently, all other things equal, lower values of u are associated with higher levels of output.

To estimate the composite-error model, it is necessary to assign a specific underlying distributional form to the unobserved distance term, u, to separate it from the also unobserved random component, v. For reasons that are developed later, a normal-truncated-normal composite error is specified, where $v \sim \text{iid}\, N\left(0, \sigma_v^2\right)$ and where $u \sim \text{iid}\, N^+\left[\mu(z), \sigma_u^2\right]$, where $\mu = \Sigma_k \delta_k z_k$. Using this specification, the distribution of the idiosyncratic productivity term can be modeled as conditional on additional variables. This feature is used later to include related endogenous variables that are expected to influence productivity.

Less complex error structures are nested within the normal-truncated-normal distribution given above. First, when $\mu = 0$, the two-parameter truncated-normal distribution collapses to the single-parameter half-normal, that is, $u \sim \text{iid}\, N^+\left[0, \sigma_u^2\right]$ (Stevenson 1980). Additionally, when $E(u) = 0$, the composite error can be represented by a single symmetric distribution, and simpler estimation techniques can be used. A variety of tests have been devised to test for the composite-error structure, as discussed after the following review of data used to estimate the model.

III. Data

Farm and household data used in the analysis are taken from the 2000 Third Agricultural Census of Ecuador. The data are generated by a complete census of large-scale farms and a large representative sample of smaller farms. The complete survey contains observations on more than 128,000 farms and is representative at the canton level. This study used data on the nearly 108,000 farms in Ecuador that produce field crops. The census contains information about physical output, land use, labor, and production methods, as well as key information related to marketing. Information about farming households is collected as well. Output prices are not part of the survey, although detailed spatial data on farm products are available from ongoing producer price surveys by the National Institute of Statistics and Census. How these data were matched with the physical output data is explained in a supplemental appendix (available at http://wber.oxfordjournals.org/). The census data were also supplemented with environmental and climate data from the *Sistema de Monitoreo Socioambiental Ecuatoriano* (Ecociencia 2002). These data were matched with the census data

at the canton level. After the data sets were matched, observations with inconsistencies were dropped. Large-scale plantations were also excluded, leaving a sample of 107,269 farms. The variables used to estimate the model are described briefly below.

Production is measured as valued crop output and is calculated for each farm by matching spatial price data with production quantities from the census. This measure does not include livestock production, although livestock production enters into the analysis as a conditioning variable. The factors of production—variables related to land, labor, and capital—are taken directly from the census and measured as quantities.

The census distinguishes between irrigated and rainfed croplands, and the share of cropland irrigated is included as an explanatory variable. The census data also reveal whether additional inputs, including fertilizers, pesticides, and improved seeds, were used in combination with irrigation or applied to rainfed land. The census does not indicate quantities of inputs applied but reports the surface area receiving inputs. In practice there is less variation in the data than the questionnaire might suggest, as the share of irrigated or rainfed land receiving additional inputs is frequently either zero or one, especially for small- and medium-scale farms. Moreover, when additional inputs are used, they are generally used in combination. Consequently, the share of rainfed land and the share of irrigated land receiving fertilizer are included as separate explanatory variables and taken as an indicator of additional input bundles. Specified in this way, the marginal effects of shifting into irrigation land that is already in production and the separate marginal effects of applying additional inputs to rainfed or irrigated lands can be identified.

Labor is given as the number of workers. The data distinguish between family members who work on the farm and hired workers. The census also notes the number of seasonal workers for farms that employ them. The census provides data on farm machinery used on each farm but does not provide sufficient information to calculate a standard representation of on-farm capital. Therefore, the number of vehicles—tractors, trucks, and related machinery (thrashers, plows)—used on each farm is a proxy for on-farm capital.

The state variables fall into three broad categories: farmer characteristics and social capital, markets and institutions, and nature and risk. The farmer characteristics and social networks include three household measures. One is a measure of the farmer's formal education, the second is of the level of agricultural education, both measured in years, and the third is a discrete variable indicating the gender of the primary farmer. Two variables capture social capital. One is a discrete variable that indicates whether the farmer has received assistance from a *gremio*, a type of voluntary producer association common in Ecuador. The other variable indicates whether an indigenous language other than Spanish is spoken at home and is meant to capture the effects of belonging to an indigenous ethnic group.

The second set of state variables captures the influences of markets and government services. Included are private markets for credit and technical assistance, intermediate buying arrangements, and participation in output markets. An additional variable signals whether the farm is isolated from markets and is set to one when the nearest market is 90 minutes or more away. Consequently, the variable captures both distance to market and the quality of the transportation system. Three variables capture differences in government services. Two are discrete variables indicating whether the farm has received technical assistance from the government and whether the government has provided credit. A third, a continuous variable, gives the share of farmland that is titled.

The third set of state variables captures nature and risk. The indicators of nature include climate and topology measures. The climate measure is the ratio of average precipitation to moisture lost from the soil due to evaporation and transpiration at the canton level. The measure is used to classify canton climates as arid/dry, moist, humid, or wet, following the classifications used by the United Nations Convention to Combat Desertification.[5] The topology measure is related to steeply sloped land in Ecuador and is reported as the percentage of canton area at risk of eroding. Two variables are related to production and income risk. One is the historic coefficient of variation in rainfall. The other is the share of farmland devoted to uses other than crops, a measure of diversification, a common risk mitigation strategy.

The census data reveal a wide range of scale for agriculture in Ecuador. Production technology choices likely vary in ways related to scale, as indicated by the descriptive statistics reported in table 1. The table contains sample averages and median values for three quantiles, which are based on farm area under field crops. First-quantile farms are very small; crops typically cover about two-thirds of a hectare and range up 1.5 hectares. Middle-quantile farms are typically 3 hectares in size, and the largest farms in the group are under 5 hectares. The third quantile contains a wide range of farms, including large-scale commercial farms of nearly 400 hectares.

Revenue per hectare from crops in Ecuador averaged $676 for the census year and increased with scale, from $472 for small-scale farms to $1,031 for the largest farms. The number of workers per farm increased with scale as well, but not proportionally. Small farms had more than five full-time workers for every hectare of land, whereas large farms had more than 3 hectares of land for every full-time worker. The decline in labor with scale was matched by an increase in capital.[6] Differences among the remaining variables in table 1 are small. The average share of cropland irrigated is slightly higher on small farms than on medium- and large-scale farms. The rates of fertilizer application on irrigated

5. Details of the climate classifications are available at www.unccd.entico.com/english/glossary.htm.

6. The movement of labor out of agriculture and capital into agriculture is a pervasive pattern associated with economic growth; see Mundlak, Larson, and Crego (1998).

TABLE 1. Descriptive Statistics, by Farm Size

	Small Scale	Medium Scale	Large Scale	All Farms
Number of farms	36,428	35,085	35,756	107,269
Median size of cropland	0.64	2.70	10.00	2.60
Farm averages				
Crop revenue per hectare (US$)	472	525	1,031	676
Cropland (hectares)	0.66	2.78	21.40	8.26
Family workers	3.34	3.50	3.19	3.34
Hired workers	0.11	0.29	2.79	1.06
Capital index	35	51	215	100
Average shares				
Share of full-time workers who are family members	0.96	0.94	0.79	0.90
Share of hired workers who are seasonal	0.10	0.21	0.67	0.33
Cropland irrigated	0.25	0.20	0.21	0.22
Irrigated cropland with fertilizer	0.17	0.15	0.20	0.17
Rainfed cropland with fertilizer	0.27	0.24	0.27	0.26
Landholdings titled	0.73	0.70	0.77	0.73

Source: Authors' analysis based on data described in text.

lands are relatively low, but similar across scale; fertilizer use rates were higher on rainfed land.

IV. ESTIMATION RESULTS

The model was estimated using the data described above. In some cases, input variables such as hired labor take on zero values. To handle this in a log-based functional form, we used a set of corresponding dummy variables, based on an approach suggested by Battese (1997). To address possible differences in the distribution of the composite error due to scale, we also added dummy variables to the set of variables determining u. With these modifications, the final model contains 118 parameters. Of these, 68 percent are individually statistically significant. To keep the discussion of the estimation results manageable, we calculated mean-value elasticities from the estimated parameters, and these are discussed below. The full set of estimated parameter results are given in tables S.1 and S.2 of the supplemental appendix.

Before the derived elasticities are discussed, results related to the composite-error specification should be mentioned. The composed form of the stochastic term may arise when the distribution of the farm-specific idiosyncratic components of productivity is skewed and truncated by a binding technology. The results from two tests are reported, and both are consistent with this characterization.

TABLE 2. Tests of the Composite-Error Structure

Test	Score
Parameter estimate, $\phi(\gamma)$	1.76 (0.019)*
Coelli's test statistic	−141.97*

Note: Numbers in parentheses are standard errors.
*Results are significant at the 1 percent level.
Source: Authors' analysis based on data described in text.

The first test is based on a statistic constructed from the variances of the two composite-error terms, $\gamma = \sigma_u^2/(\sigma_v^2 + \sigma_u^2)$. When $\gamma = 0$, the composite-error model is indistinguishable from a model with a symmetrically distributed error term, and thus a test of the statistical significance of γ constitutes a test of the composite-error specification. The test is easy to perform, because a related parameter, $\phi(\gamma)$, appears as a parameter in the model's likelihood function. The estimated value of the parameter is statistically different from zero, lending support for the assumed composite form (table 2).

Even so, because γ is tied to estimates of the composite-term variances, the test is conditional and potentially sensitive to how the composite error is specified. For this reason, a second test was applied, based on an approach developed by Schmidt and Lin (1984) and modified by Coelli (1995). The related test statistic is based on least squares residuals and consequently is independent of prior assumptions about the form of the composite error. The calculated statistic is also significant (table 2). Moreover, the test-statistic value is negative, which is consistent with a clustering of production technologies around a binding technological frontier (Coelli 1995, p. 253).

Elasticity Estimates

Elasticities and standard errors, calculated from estimated model coefficients and sample averages, are reported in table 3 for the four factors of production, for qualitative differences in the factors, and for state variables.

The factor elasticities relate to the slope function, $B(x,s)$. Because the elasticities are functions of both state and input variables, each farm is potentially associated with a different set of factor elasticities. In this sense, the elasticities reported in table 3 represent average effects across technologies.

The mean-valued factor elasticities in table 3 are all significantly different from zero. They sum to 1.159, suggesting increasing returns to scale for a typical farm in Ecuador.[7] The elasticity for family labor is positive, but quantitatively

7. It is also the case that the underlying parameters used to calculate the elasticities are collectively different from zero at standard confidence levels and that average returns to scale are different from 1. The elasticities for family and hired labor are statistically different from one another as well. See supplemental appendix table S.4.

TABLE 3. Elasticities Calculated at Mean Values

	Elasticity	Standard Error
Production factors		
Family labor	0.120	0.018**
Hired labor	0.264	0.025**
Cropland	0.656	0.008**
Capital	0.119	0.048*
Returns to scale	1.159	0.056**
Factor characteristics		
Irrigation	0.209	0.007**
Additional inputs on irrigated land	0.020	0.004**
Additional inputs on rainfed land	0.131	0.006**
Seasonal labor	0.069	0.003**
State variables		
Formal education	0.014	0.002**
Agricultural education	0.017	0.004**
Female head of house[a]	−0.125	0.015**
Indigenous ethnicity[a]	0.033	0.022
Participates in output markets[a]	0.562	0.044**
Sells to intermediate buyer[a]	0.019	0.020
Isolated from markets[a]	0.013	0.020
Assistance from the *gremio*[a]	0.055	0.026**
Precipitation variation	−0.047	0.010**
Land diversification	−0.039	0.009**
Moist climate[a]	0.161	0.028**
Humid climate[a]	−0.055	0.024*
Wet climate[a]	0.157	0.030**
Risk of erosion[a]	−0.027	0.004**

*Significant at the 5 percent level; **significant at the 1 percent level.

[a]Discrete variable.

Source: Authors' analysis based on data described in text.

less that half that of hired labor.[8] The land elasticity is about as large as the combined elasticities of the other production factors. The elasticity on capital is lower than might be expected, although the estimated value is consistent with cross-country studies that have relied on proxy measures of capital (Mundlak, Larson, and Butzer 1999).

Estimates related to qualitative differences in the factors suggest that bringing an additional 1 percent of existing cropland under irrigation increases output by 0.2 percent. Applying chemical inputs to irrigated land brings about a slight increase in output. The elasticity for chemical inputs on rainfed land is significantly higher and in line with fertilizer elasticities estimated from cross-country

8. As an anonymous referee pointed out, the marginal value product for family labor, given by the average product times the elasticity, is less than 15 percent that of hired labor at sample averages.

data. Supplementing full-time labor with seasonal workers has a small but statistically significant effect on output.

The elasticities reported in the bottom block of table 3 relate to the systemic state-specific productivity effects, $\Gamma(s)$. Because the state variables also affect the factor elasticities related to $B(x,s)$, the reported elasticities are partial and capture only the direct effect of the state variables on output and productivity. The role that the state variables play in determining factor elasticities is discussed later.

Although many of the state-variable elasticities are statistically significant, most are quantitatively small. Both general education and education related to agriculture have a small but positive effect on productivity. Productivity among households headed by a woman is lower, perhaps because this group includes a disproportionate number of single-parent households. Productivity does not differ significantly by ethnic group. The dummy variable that distinguishes between farmers who produce for market and those who do not is significant and quantitatively large, but because more than 90 percent of farmers in Ecuador already participate in output markets, the variable is less interesting for policy. Productivity is higher for farmers who participate in a marketing cooperative, but other variables related to marketing are not statistically significant or quantitatively large. Productivity is less for farms subject to greater rain variability and also for farms that diversify out of crops, a result consistent with the notion that some costs associated with risk take the form of forgone opportunities. The effects of climate and erosion risk are significant and similar in size.

As discussed, measured productivity includes both the systemic component, $\Gamma(s)$, and a stochastic term, ϵ, which includes the non-negative idiosyncratic term, u. To a degree, the idiosyncratic component of productivity relates to farm or farmer characteristics that cannot be observed. However, it is likely that some variables that ultimately affect technology choice and productivity are determined by a process that links these observed variables to the unobserved idiosyncratic characteristics of the farm or farmer. The most discussed example is access to credit, with the likelihood of receiving credit expected to be related to a borrower's unobserved entrepreneurial and cognitive abilities (McKernan 2002; Khandker and Faruqee 2003). However, related arguments have been made about the provision of government technical assistance (Godtland and others 2004) and land titling (Deininger and Chamorro 2004). For these reasons, some state-like variables are endogenous and therefore stochastic and are related to the idiosyncratic component of productivity. Consequently, a set of codetermined variables are included in the specification of e. These correspond to z in the model presented in Section III.[9]

9. This approach, believed to be novel, retains information about the stochastic component of the related endogenous variable. This information is stripped away in traditional approaches designed to construct nonstochastic proxies that can be treated as deterministic explanatory variables.

TABLE 4. *Z*-Variable Coefficients and Calculated Elasticities

	Elasticity	Coefficient	Standard Error
Technical assistance, private[a]	0.045	−0.501	0.069**
Credit, private[a]	0.075	−0.848	0.080**
Share of land titled	0.034	−0.363	0.034**
Technical assistance, public[a]	0.007	−0.077	0.086
Credit, public[a]	0.025	−0.270	0.105*
Medium scale[a]	0.048	−0.525	0.038**
Large scale[a]	0.106	−1.213	0.055**

*Significant at the 5 percent level; **significant at the 1 percent level.

Note: Elasticities are calculated as discrete changes.

[a]Discrete variable.

Source: Authors' analysis based on data described in text.

The five endogenous variables included as determinants relate to private market access for credit and technical assistance and access to public programs for credit, technical assistance, and land titling services. Additionally, two dummy variables are included, which correspond to the second (medium) and third (large) cropland quantiles, to account for possible differences in the distribution of the stochastic productivity measure related to scale.[10]

Related coefficients from the estimated model are summarized in table 4. As discussed, frontier production models conventionally represent the non-negative component of the composite error as a departure from the efficiency frontier. Consequently, the negative coefficients in table 4 indicate that these variables are associated with a reduction in the mode of the inefficiency distribution and, all other things equal, an increase in output. As table 4 summarizes, all coefficients are negative and all but the coefficient on public technical assistance are statistically significant.

Although indicative, the coefficients themselves are a very rough measure of how shifts in the distributional mode of u affect output. This is because the average effect of the stochastic productivity component is determined not only by the mode of the distribution but also by the overall shape of the distribution, especially the point of truncation. For this reason, discrete changes in the predicted value of u are used to calculate output elasticities, rather than relying on an evaluation of the elasticities at a single point along the distribution.

Because for each farm observation f the estimated model provides predictions of u_f conditional on v_f, the average effect of a discrete change in the z variables can be calculated. This is done by using the estimated model to simulate the

10. Larger farms and larger endowments of managerial skill are potentially related. However, heteroskedasticity related to variance of the strictly positive efficiency term will also affect its mean, so there are mechanical reasons for including the terms as well.

effect on each u_f of switching in sequence each z_k from zero to one, holding other values constant, so that $\Delta \ln y/\Delta z_k = -\Delta u|_{dz_k=0,1}$. Average effects, $\Delta \bar{u}_k$, can be calculated over all observations or any subgroup of farms. Given the specification in equation (2), the calculated difference is similar to the coefficient on a dummy variable in a semilogarithmic equation; consequently, mean elasticities are given by $\varepsilon_k = \exp(\Delta \bar{u}_k) - 1$ (Halvorsen and Palquist 1980).

Elasticity estimates based on the procedure outline above are also reported in table 4. Among these, elasticities associated with private market access to credit and technical assistance are large relative to public program elasticities and to some state-variable elasticities. This is noteworthy, because these effects are additional to past accumulations of physical or educational capital. Among the public programs, land titling has the largest effect on output. Although the elasticity on access to credit through public programs is smaller than the elasticity associated with private credit markets, the results suggest that credit programs have a measurable impact. In contrast, the measured effect of public technical assistance programs is quantitatively small and statistically insignificant.

Because the implicit small-farm dummy variable is suppressed in the estimated model, the elasticities associated with the remaining quantile dummy variables can be interpreted as differences from the efficiencies found on small-scale farms. The results indicate that as the amount of land brought under crops increases, inefficiencies decline in a way that is separate from the returns to scale or the related effects of increasing factor use. That is to say, for a given set of factors and conditioning state variables, larger farms tend to cluster more closely to a frontier that is presumably limited by technology. This has policy relevance because it suggests that innovations in technology will especially benefit larger farms that are currently constrained by available technology. The results also suggest a potential to improve agricultural incomes by identifying constraints that lead smaller farms to choose less efficient technologies.[11]

Choice and Factor Elasticities

In the conceptual model, technological choice is expected to affect both total factor productivity and the marginal productivity of factors. In the applied model, state variables are used to measure these influences. As discussed, one consequence is that measured values of total factor productivity take on geographic patterns because some determining state variables are location specific. To a degree, this is also true for measured factor elasticities. Nevertheless, factor elasticities depend on combined factor levels in addition to state variables, so that geography may play a relatively smaller role.

As a practical matter, it is possible to use parameters from the applied model to quantify the relative contributions of factors and state variables in

11. Key results are robust to alternative specifications. See tables S.4–S.6 in the supplemental appendix.

determining factor elasticities. To illustrate, consider the effect on output of a change in the first input:

$$\frac{\partial \ln y}{\partial \ln x_1} \equiv \frac{\partial B(x,s)}{\partial \ln x_1} = b_1 + \frac{1}{2}\sum_j b_{1j} \ln x_j + \frac{1}{2}\sum_n a_{1n} \ln s_n. \tag{4}$$

Of the three terms on the right side of equation (4), the first two are the portion of the factor elasticity that is due to input levels, whereas the last term captures changes due to state variables.

Using the approach illustrated in equation (4), factor elasticities were calculated based on variable averages from each of the three farm scale quantiles. The elasticities were further decomposed into factor and state-variable effects. Overall, the results suggest that factor elasticities are determined largely by input levels (table 5). This can be seen in the returns to scale elasticity, which summarizes the sometimes offsetting changes in the underlying composition of elasticities. The returns to scale elasticity falls slightly as scale increases, and both the absolute values of the elasticities and the direction of change are driven by factor effects. Moreover, for medium- and large-scale farms, the state variables largely account for differences from constant returns to scale.

For small farms, measured differences between the elasticities of family and hired labor are large, but the gap closes as more land is brought under production, operating mostly through factor effects. However, for hired labor, the complementary effects of state variables on the elasticity of labor increases

TABLE 5. Decomposition of Production Elasticities, by Farm Size

	Small Scale	Medium Scale	Large Scale
Elasticity			
Family labor	0.099	0.114	0.151
Due to factors	0.043	0.062	0.106
Due to state variables	0.056	0.052	0.045
Hired labor	0.343	0.239	0.192
Due to factors	0.273	0.127	0.022
Due to state variables	0.070	0.112	0.169
Cropland	0.693	0.680	0.642
Due to factors	0.724	0.717	0.685
Due to state variables	−0.031	−0.037	−0.043
Capital	0.102	0.153	0.122
Due to factors	0.066	0.118	0.119
Due to state variables	0.036	0.035	0.003
Returns to scale	1.238	1.186	1.107
Due to factors	1.106	1.024	0.932
Due to state variables	0.132	0.161	0.175
Technical efficiency	0.398	0.425	0.476

Source: Authors' analysis based on data described in text.

with scale, preventing the gap from closing further.[12] Differences in cropland elasticities are not large among the three quantiles and are driven by a slight decline due to factor effects. The elasticity of capital increases rapidly between the first and second quantiles, whereas the state-variable effect falls between the second and third quantiles.

As discussed, the estimated parameters suggest that the distribution of u shifts with scale. There are additional determinants of the distribution relating to markets and government programs, and related average participation rates vary among the three scale quantiles as well. The combined effect is reflected in the summary measure of technical efficiency, T_q, which is a quantile average of the farm-specific measures of technical efficiency, $E[\exp(-u_f|v_f)]$ (table 5). Generally, access to markets and government programs increases with scale, although the resulting elasticity differences are small. Consequently, the distributional determinants combine to produce rates of technical efficiency that increase with scale.[13]

V. Determinants of Regional Differences

This section turns to a key motivation of the article, explaining observed regional differences in output and productivity. The analysis relies on the estimated model, which is used to map observed differences in factor use and the conditioning state variables to observed differences in output. This allows a decomposition of differences in revenue among typical farms of each region into factor and productivity effects. In addition, spatial differences in factor productivity are further decomposed into effects that correspond to the following classes of the state variable: household characteristics and social capital, nature and risk, and markets and institutions. From a policy perspective, this approach complements the elasticity discussion, which focused on which factors are most important in determining agricultural output and productivity. This analysis explores how differences in the spatial array of factors and state variables combine to generate observed spatial differences in output and productivity.

Broadly, the simulation strategy is to construct regional and national representations of farm output and to use those representations to measure the relative importance of factor use and productivity in explaining average revenue differences among regions. Specifically, for each classification of farm scale (small, medium, and large), national averages are calculated for the vector of production factors ($\bar{x}_q$), state variables ($\bar{s}_q$), z-variables ($\bar{z}_q$), and also provincial averages ($\bar{x}_q^R$, $\bar{s}_q^R$, and $\bar{z}_q^R$). To take into account the indirect role of state variables

12. Calculated marginal value products follow the same pattern, but in a more dramatic fashion. Estimated marginal value product for family labor is roughly 1 percent that of hired labor for small farms and close to 70 percent for large farms.

13. Details about participation rates are summarized in table S.6 in the supplemental appendix.

in the factor marginal products, we calculated elasticities are calculated based on the regional averages and coefficients from the model.

Let $\varepsilon_{iq}^{R}(\beta)$ represent input factor elasticities evaluated at $\beta\left(\bar{x}_q^R, \bar{s}_q^R\right)$, and let $\varepsilon_{nq}^{R}(\Gamma)$ represent the systemic productivity elasticities evaluated at $\Gamma\left(\bar{s}_q^R\right)$. Following the approach noted earlier, regional idiosyncratic productivity elasticities, $\varepsilon_{kq}^{R}(u)$, are calculated based on regional quantile averages of $u_f(z)$. Consequently, the calculated productivity measure includes systemic differences due to differences in the level of state variables plus regional differences in the distribution of idiosyncratic efficiencies.

Expected differences in regional (R) output for each farm classification (q) can then be expressed as

$$\Delta y_q^R \equiv \Delta F_q^R + \Delta P_q^R, \tag{5}$$

where the change in factor use is given by

$$\Delta F_q^R \equiv \sum_i \varepsilon_{iq}^{R}(\beta)\left(\ln \bar{x}_{iq}^R - \ln \bar{x}_{iq}\right) \tag{6}$$

and the change in total factor productivity is given by[14]

$$\Delta P_q^R \equiv \sum_n \varepsilon_{nq}^{R}(\Gamma)\left(\ln \bar{s}_{nq}^R - \ln \bar{s}_{nq}\right) + \sum_k \varepsilon_q^{R}(u)\left(\bar{z}_{kq}^R - \bar{z}_{kq}\right). \tag{7}$$

For each class of farm, the exercise explains how differences in the distribution of factors and state variables result in differences in agricultural output. The simulation results are detailed and cover each of the 21 provincial areas of Ecuador. To conserve space, we reported only summary results here.[15]

The results illustrate the differences in regional output and productivity in Ecuador (table 6). Across all sizes of farms, regional differences average about 17 percent in absolute terms. In a mechanical way, output differences can be attributed primarily to factors generally and to land specifically. However, this is partly because the farm-size classes are based on area under crops. The first and third quantiles contain the tails of the underlying distribution of land among farms and therefore contain greater variation. After adjusting for land, output differences related to more intensive use of capital and labor inputs and those related to productivity are similar on average.

Still, the averages mask differences related to scale. With increases in scale, the role of productivity in explaining regional differences diminishes, whereas effects tied to factor intensification become more pronounced. This can be seen

14. The z variables and some state variables are expressed as shares (for example, share of farm land titled) and are therefore not converted into logs.

15. Detailed results are summarized in tables S.7–S.12 in the supplemental appendix.

TABLE 6. Average Absolute Differences in Regional Output and Related Determinants, by Farm Size

	Small Scale	Medium Scale	Large Scale	All Farms
Output	0.167	0.090	0.256	0.171
Factors	0.124	0.059	0.243	0.142
Land	0.117	0.035	0.180	0.111
Capital and labor	0.051	0.046	0.091	0.063
Productivity	0.073	0.053	0.034	0.053
Public programs	0.004	0.004	0.004	0.004
Households	0.021	0.017	0.009	0.016
Markets and networks	0.045	0.025	0.009	0.027
Risk	0.008	0.008	0.006	0.008
Nature	0.045	0.040	0.034	0.040

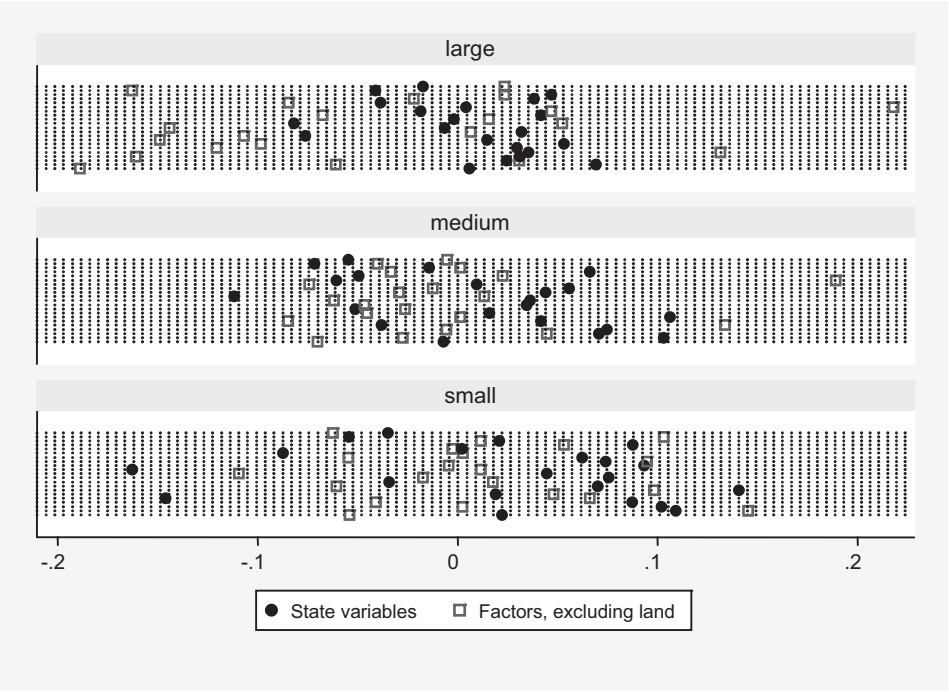
Note: Differences are expressed as shares of national average output value by scale.
Source: Authors' analysis based on data described in text.

graphically in figure 1, where the circles mark simulated differences due to capital and labor and the squares mark productivity effects for each of the 21 geographic areas in the data. For small-scale farms, the factor and productivity effects are commingled. In moving along the figure from the small- to medium- to large-scale farms, it can be seen that the state-variable effects begin to shift closer to zero, whereas the spread in capital-plus-labor effects increases.

The productivity effects can be further decomposed by the underlying determining state variables (table 6). The results suggest that the three public programs included in the model explain little of the observed regional differences in output, regardless of scale, even though the elasticities on the credit and titling programs were of moderate size. For credit, this is because program penetration is limited—only 2 percent of farms receive credit through this program. For titling, there is little regional variation, because most farmland in most provinces is titled. The effect of differences in household characteristics accounts for about 2 percent of regional output for small farms and less than 1 percent for large farms. Differences in the use of markets and networks accounts for about 4.5 percent of regional output among small farms, 2.5 percent among medium-scale farms, and less than 1 percent among large farms. The effects of risk, as given by the variation in rainfall and the effects of diversifying land use, have a limited role in explaining regional differences. In contrast, nature, as measured by differences in climate, soil conditions, and slope characteristics, is an important determinant of output differences.

To summarize, the simulation results suggest that differences in applied technologies, conditioned by the state variables and associated with productivity, diminish as farms become larger in scale and more intensive in other inputs. Of the differences attributable to productivity, nature is an important

FIGURE 1. Simulated Differences in Output Attributable to Factor Intensification and Productivity, by Farm Scale



Source: Authors' analysis based on data described in text.

determinant on all farms. For small farms, household characteristics and access to markets play important roles as well.

VI. SUMMARY AND CONCLUSIONS

Because farmers face different circumstances with different resources, they choose different approaches to farming. This means that economic data about agricultural production span a variety of applied technologies. This article applies a flexible-form model to measure the interrelated effects on production of inputs and the state variables that condition this endogenous choice of technology.

Working through the decision environment, state variables are expected to influence total factor productivity directly and to influence the elasticities of production inputs. Statistically significant evidence of both effects is found. Even so, the results suggest that some of the ways factors and state variable interact to determine different levels of output and productivity vary with scale, and this has implications for policy.

To a large degree, output differences among large- and medium-size farms are explained by differences in factor use. Factors are important for small-scale farmers as well; however, significant differences in productivity outcomes remain among small-scale farms even after factor differences are taken into account. These remaining differences are explained largely by differences in the conditioning state variables. This is consistent with the notion that technology choice is more constrained among smallholder farms and that productivity is therefore more sensitive to differences in the decision environment.

As farm scale increases, differences in productivity are reduced, and this comes about by way of two complementary effects. First, productivity contains a component related to the unobservable idiosyncratic characteristics of farms and farm managers. In the applied model, this gives rise to a composite-error stochastic term from which a measure of technical efficiency can be derived. Evidence is found in favor of the composite-error structure, and further evidence suggests that the derived measure of technical efficiency increases with farm size alone.

Second, there is also evidence that market and program participation outcomes, potentially related to these idiosyncratic farm characteristics, influence the technical efficiency measure. Access to such programs is more common among larger farms, which also boosts measured efficiency. Consequently, the two effects work in reinforcing ways to provide higher estimates of technical efficiency on larger farms. This is taken as evidence that larger farms are better able to, and frequently do, choose farming approaches that are closer to a binding technological frontier.

Taken together, the findings suggest a differentiation between the types of policy that promote growth in agriculture generally and those that are more likely to assist the rural poor. Because most agricultural output is produced on larger farms that operate close to the technological frontier, programs that promote relevant new technologies can be expected to spur sectorwide growth. For regions that depend primarily on agriculture, growth may have additional spillover effects on incomes through markets for related goods and services. At the same time, smallholder households in Ecuador that depend on agriculture are disproportionately poor and tend to use a ranging set of technologies. Consequently, policies most likely to benefit the poor are those that change the constraints and incentives that lead some households to choose less efficient technologies over more productive alternatives.

Still, the results suggest that building effective strategies for reducing rural poverty is no easy task. Many of the state variables that explain productivity differences among smallholders are related to the aspects of geography that are not easily changed. This limits the range of available policy instruments and the scope for policy-led increases in productivity. Among the remaining policy avenues, simulation results point to the importance of investments in infrastructure and institutions that support markets, especially credit markets. These

markets can lead to the adoption of more productive technologies in the short run and can facilitate the buildup of productive assets in the long run.

Accumulated assets can be lost, and the results suggest that farmers forgo more productive technologies to take ex ante precautions against such loss. This, together with evidence of the central role that productive assets play in determining incomes, suggests the importance of policies that promote formal and informal insurance markets and provide for safety nets when these markets prove inadequate.

Studies of cross-country growth experiences find important roles for geography and for market-enhancing institutions. In a similar way, the results of this study suggest that climate and institution-dependent markets influence regional differences in agricultural productivity. The study results also indicate the importance of accumulated factors to short-run output. With time, the same conditioning factors that influence short-run productivity will likely influence stocks of these variables as well. However, this process may take generations to complete. Consequently, care should be exercised in drawing policy conclusions about the pace of growth from studies that methodologically set aside the influence of accumulated factors. This is particularly the case for many developing countries, where agriculture remains an important component of national income.

References

Barro, Robert, and Xavier Sala-I-Martin. 1992. "Convergence." *Journal of Political Economy* 100(2):223–51.

Battese, George E. 1997. "A Note on the Estimation of Cobb-Douglas Production Functions When Some Explanatory Variables Have Zero Values." *Journal of Agricultural Economics* 48(2):250–52.

Bhattacharyya, Sambit. 2004. "Deep Determinants of Economic Growth." *Applied Economics Letters* 11(9):587–90.

Brock, William A., and Steven N. Durlauf. 2001. "What Have We Learned from a Decade of Empirical Research on Growth? Growth Empirics and Reality." *World Bank Economic Review* 15(2):229–72.

Coelli, Timothy J. 1995. "Estimators and Hypothesis Tests for a Stochastic Frontier Function: A Monte Carlo Analysis." *Journal of Productivity Analysis* 6(4):247–68.

Deininger, Klaus, and Juan Sebastian Chamorro. 2004. "Investment and Equity Effects of Land Regularisation: The Case of Nicaragua." *Agricultural Economics* 30(2):101–16.

Ecociencia 2002. *Sistema de Monitoreo Socioambiental Ecuatoriano*. Quito, Ecuador.

Godtland, Erin, Elisabeth Sadoulet, Alain de Janvry, Rinku Murgai, and Oscar Ortiz. 2004. "The Impact of Farmer-Field Schools on Knowledge and Productivity: A Study of Potato Farmers in the Peruvian Andes." *Economic Development and Cultural Change* 53(1):63–92.

Griliches, Zvi. 1996. "The Discovery of the Residual: A Historical Note." *Journal of Economic Literature* 34(3):1324–30.

Hall, Robert E., and Charles Jones. 1997. "Levels of Economic Activity Across Countries." *American Economic Review* 87(2):173–77.

Halvorsen, Robert, and Raymond Palquist. 1980. "The Interpretation of Dummy Variables in Semilogarithmic Equations." *American Economic Review* 70(3):474–5.

Henderson, Vernon, Zmarak Shalizi, and Anthony Venables. 2001. "Geography and Development." *Journal of Economic Geography* 1(1):81–105.

Khandker, Shahidur, and Rashid Faruqee. 2003. "The Impact of Farm Credit in Pakistan." *Agricultural Economics* 28(3):197–213.

Klenow, Peter J., and Andres Rodriguez-Clare. 1997. "Economic Growth: A Review Essay." *Journal of Monetary Economics* 40(3):597–617.

Larson, Donald F., and Yair Mundlak. 1997. "On the Intersectoral Migration of Agricultural Labor." *Economic Development and Cultural Change* 45(2):295–319.

Mankiw, N. Gregory, David Romer, and David Weil. 1992. "A Contribution to the Empirics of Economic Growth." *Quarterly Journal of Economics* 107(2):407–37.

McKernan, Signe-Mary. 2002. "The Impact of Microcredit Programs on Self-employment Profits: Do Noncredit Program Aspects Matter?" *Review of Economics and Statistics* 84(1):93–115.

Mundlak, Yair. 1988. "Endogenous Technology and the Measurement of Productivity." In S. M. Capalbo and J. M. Antle, eds., *Agricultural Productivity: Measurement and Explanation*. Washington: Resources for the Future.

———. 1993. "On the Empirical Aspects of Economic Growth Theory." *American Economic Review* 83(2):415–20.

———. 2001. "Production and Supply." In B. Gardner and G. Rausser, eds., *Handbook of Agricultural Economics. Volume 1A: Agricultural Production, Handbooks in Economics,* Vol.18. Amsterdam, London and New York: Elsevier Science, North-Holland.

Mundlak, Yair, Donald F. Larson, and Al Crego. 1998. "Agricultural Development: Issues, Evidence and Consequences." In Y. Mundlak, ed., *Contemporary Economic Issues: Proceedings of the Eleventh World Congress of the International Economic Association*, Volume 2, *Labour, Food, and Poverty, Conference*. New York: St. Martin's Press; London: Macmillan Press.

Mundlak, Yair, Donald F. Larson, and Rita Butzer. 1999. "Rethinking Within and Between Regressions: The Case of Agricultural Production Functions." *Annales d'Economie et de Statistique* 55–56: 475–501.

North, Douglas. 1994. "The Evolution of Efficient Markets." In John James and Mark Thomas, eds., *History in Capitalism in Context: Essays on Economic Development and Cultural Change in Honor of R. M Hartwell.* Chicago and London: University of Chicago Press.

Parente, Stephen, and Edward Prescott. 1994. "Barriers to Technology Adoption and Development." *Journal of Political Economy* 102(2):298–321.

Rodrik Dani, Arvind Subramanian, and Francesco Trebbi. 2004. "Institutions Rule: The Primacy of Institutions over Geography and Integration in Economic Development." *Journal of Economic Growth* 9(2):131–65.

Sachs, Jeffrey, and Andrew Warner. 1997. "Fundamental Sources of Long-Run Growth." *American Economic Review* 87(2):184–85.

Schmidt, Peter, and Tsai-Fen Lin. 1984. "Simple Tests of Alternative Specifications in Stochastic Frontier Models." *Journal of Econometrics* 24(March):349–61.

Stevenson, Rodney. 1980. "Likelihood Functions for Generalized Stochastic Frontier Estimation." *Journal of Econometrics* 13(May):57–66.

Stigler, George. 1976. "The Xistence of X-Efficiency." *American Economic Review* 66(1):213–16.