AN ABSTRACT OF THE DISSERTATION OF

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Title: International Comparison and Evaluation of Agricultural Productivity Growth

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Steven T. Buccola

Long-run food price changes respond to long-run changes in food demand, quasi-fixed and variable production factors, and agricultural productivity. Recent global food-price volatility puts a renewed spotlight on the trends and sources of any agricultural productivity growth. Because food prices' most critical effects are on human hunger, it is especially important to examine productivity conditions in newly emerging economies. Two such economies evaluated in this dissertation are Indonesia and Brazil.

As agriculture's share of the Indonesian economy declines in the post-Green Revolution era, government attention increasingly has shifted to the industrial sector and away from agriculture. In light of these trends, we use province-level data and a multi-output frontier distance function approach to estimate product-specific productivity change on Indonesian farms, decomposing it into its technical-change and efficiency-change components. We find, at a 1.4% annual growth rate, that technical change has been modest and that little of this growth can be ascribed to government research efforts.

Furthermore, average farm efficiency relative to the best-practice frontier has declined 0.4% per annum, so that mean productivity has risen by only 1% per year. Over-centralization of the agricultural research system may partly account for this poor performance.

Brazil now is the largest coffee, sugar, and fruit juice producer, second-largest soybean and beef producer, and third-largest corn and broiler producer. It has overtaken the U.S. in poultry exports, nearly matches the U.S. in soybean exports, and dominates global trade in frozen orange juice. To test and better understand these advances, we draw on decennial farm censuses to examine technical change and efficiency in Brazilian agriculture. Our approach is to estimate a stochastic, multi-product, output distance frontier, using a translog functional form and data disaggregated to the micro-region (sub-state) level. Using two consecutive decennial farm censuses, we combine state-level Fisher productivity-change indexes with state-level translog distance function estimates of growth technical efficiency to impute state-level technical shifts. We find, leading up to the soon-to-be-released 2006 agricultural census, that Brazil's multi-factor productivity growth rate between 1985 and 1996 was 20.2%. Mean state-level growth efficiency was 91.2%, implying the production frontier expanded 22.2% over the reference time period.

International Comparison and Evaluation of Agricultural Productivity Growth

by

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I understand that my dissertation will become part of the permanent collection of Oregon State University Libraries. My signature below authorizes release of my dissertation to any reader upon request.

Nicholas E. Rada, Author

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DEDICATION

To Lucía Belle & Maya Valentina

International Comparison and Evaluation of Agricultural Productivity Growth

Chapter 1: General Introduction

Agriculture has, from an historical perspective, been the keystone to economic growth. In Less Developed Countries (LDCs), agriculture provides labor-intensive employment and generates food for consumption and profit. New agricultural technologies furnish farms with incentives to increase production in the face of rising constraints. Farms are pressured to boost production in light of such constraints as increasing urban populations and decreasing land availability. Rising urban populations force fewer farms to produce greater food quantities. Land scarcity shifts production from extensive to intensive methods – inducing soil exhaustion (e.g., erosion and desertification, salinization, and nutrient depletion), water contamination, pest incidences, and climate change – ensuring that, unless other factors intervene, crop yields will decline. Expanding farm production under such constraints requires technical improvements. Without technical progress, increasing input quantities – to maintain production levels – causes farm costs to escalate, which in turn pressures output prices to climb in order to sustain farm profitability. Thus, new agricultural technologies provide the solution to farm profitability decline by allowing farms to maintain production levels with fewer inputs.

Agricultural productivity growth therefore is a primary determinant of national economic growth and development. New technology dissemination is uneven, affecting regional growth and income differences. If agricultural productivity is to provide a foundation for rapid and balanced economic growth and development, attention must be directed toward adaptive agricultural research, agricultural institution building, rural infrastructure, and farmer education. Understanding agriculture's comparative advantages and improving its international competitiveness are greatly assisted by multi-output assessments of output growth and technical change.

The three essays in the present dissertation have the same focus: a stochastic, multi-output, fixed-effects distance frontier framework employing a translog functional form and disaggregated (sub-national) data. Stochastic frontier models differentiate farm inefficiencies by type: those associated with such exogenous random factors as statistical noise, data measurement error, and weather; and those associated with such endogenous farm factors as information deficiencies, adjustment costs, and farm organization. Shifts in the estimated frontier afford estimates of national technical change, that is secular enlargements in the output possibilities achievable with a given bundle of measurable capital, material, labor, and land inputs. Corresponding examination of the infra-frontier residuals affords estimates of sub-national technical efficiency, that is the proximity of an observation's performance to its own frontier. Technical change may be explained by innovative research, while technical efficiency may be explained by farmer access to that research and by government policies. In each essay, a primal approach is employed which estimates disembodied technical change and technical efficiencies, as farms are assumed to exhibit allocative efficiency and constant-returns-to-scale technology.

Yet each essay also is unique. Essay I, "Productivity Changes in Indonesian Agriculture: Its Sources and Directions," employs 1985 – 2005 province-level data from Indonesian farms. As agriculture's share of the Indonesian economy declines in the post-Green Revolution era, Indonesian government attention increasingly has shifted to the industrial sector and away from agriculture. Government sources of technology improvement are distinguished in Essay I from non-government sources. At a 1.4% per-annum growth rate, technical change has been modest and little of this growth is ascribable to government research efforts. Furthermore, average farm efficiency relative to the best-practice frontier has declined 0.4% per annum, so that mean productivity has risen only 1% per year. Despite this overall lackluster performance, technical change in the Indonesian perennial crop sector has been a vibrant 3.5% per year, suggesting Indonesia has comparative agronomic advantages in cocoa, oil palm, coffee, and rubber production over such annual crops as rice, soybeans, peanuts, and vegetables; annual crop's technical change has been nearly zero.

Virtually all productivity improvements detectable in Indonesian agriculture during the past several decades appear to be coming from outside the government research system, that is from technologies introduced from the private sector and abroad and from farmer's own innovations. Indonesian public expenditures on agricultural research have apparently failed to account for even the modest growth observable in

Indonesian farm performance. Over-centralization of the agricultural research system may partly account for this poor performance.

Essay II, “Brazil’s Rising Agricultural Productivity and World Competitiveness,” employs micro-region- and state-level data from Brazil’s decennial agricultural censuses (1985-1995/1996). State and national total factor productivity (TFP) growth is estimated in Essay II from Fisher index number theory. To complement these productivity growth rates, the multi-output stochastic distance frontier provides state and national mean growth technical efficiency estimates. Because only two observations of decennial censuses are presently available in Brazil, a technical change estimate cannot be derived as in Essay I, but must be imputed as the ratio of a Fisher TFP growth rate to a stochastically estimated growth efficiency measure. Brazilian national TFP growth from 1985 to 1995/1996 is found to have been 20.2%. Brazilian mean growth efficiency was 91.2%, so that the imputed national decennial technical change rate was 22.2%.

Implications of these results are that Brazil can improve the productivity and international competitiveness of its agriculture by focusing on states exhibiting low growth efficiency but strong technical growth rates. Each of the four low-growth-efficiency, high-technical-change states – Acre, Mato Grosso do Sul, Mato Grosso, and the Federal District – draw much of their revenue from annual crops and livestock. Average farm productivity in these four states, and thus nationally, could increase at low marginal cost through improved dissemination of technical information specific to annual crop and livestock production, as the technologies for generating higher growth rates in each of these two output groupings are already available.

Essay III, “Challenged With A Dual? In LDC Productivity Measurement, the Primal May Have the Broader Target,” compares primal and dual stochastic frontier econometric procedures for agricultural productivity estimation, with special attention to LDC data constraints. This essay stresses the importance of measuring multi-output technical change rates in LDC agricultural sectors. Technical change analysis provides insight into the degree to which new technology boosts farm production under *ceteris paribus* conditions. For example, assessment of technical change bias informs the evaluation of development policy and the direction of farm planning. Estimates of technical inefficiencies, in contrast, allow for recognition of geographically sourced technology gaps between average and frontier farms, while explanations of those inefficiencies permit diagnoses that can reduce such gaps. Essay III argues in favor of the primal distance over the dual cost frontier approach in the conduct of international agricultural productivity evaluation and comparison because of the broad availability of quantity data from the Food and Agriculture Organization

Chapter 2: Productivity Changes in Indonesian Agriculture: Its Sources and Directions

2.1 Motivation

Agricultural productivity is a necessary condition for economic growth, as it allows a reallocation of labor from the agricultural to the industrial sector (Hayami and Ruttan, 1985). Labor in developing countries focuses on agriculture to ensure sufficient food supplies. In the present study we look to a model of development in which labor is released from the agricultural sector to the manufacturing sector through increased agricultural productivity. In the case of the United States, the importance of agricultural productivity as a source of economic growth has been well documented (Ball, 1985, Ball, et al., 1997, Jorgenson, Gollop and Fraumeni, 1987). With recent global fluctuations in food prices a renewed emphasis needs to be placed on agricultural production, especially in developing countries. A significant contribution of agricultural productivity is in lowering food prices (Alston, Norton and Pardey, 1995). Secular changes in food prices in the long-run are accounted for by long-run changes in food demand, growth in quasi-fixed and variables factors of production, and agricultural productivity. From a long-run vantage point, investigating agricultural productivity trends is vitally important for consumers in a globalized food-chain. Thus, it is important to look at newly ‘emerging’ economies’ agricultural sectors, such as Indonesia’s.

The Indonesian archipelago is regionalized into five island groups: Sumatra, Java, Kalimantan, Sulawesi, and East Indonesia. Traditionally, an agriculture-first policy has been adopted by the government in Indonesia. In Java, the policy of land extensification for agricultural production gave way to land intensification by the end of the 1930s (van der Eng, 1996). With the population density highest in Java, and increasing throughout the country, balancing food production with an increasing population rate has proven to be the country’s greatest challenge (Booth, 1988).[1] In the

[1] Fuglie and Piggott (2006) report that in 2000, Indonesia had the fourth largest population in the world, a population density of 111 persons per square kilometer, and a population growth rate of 1.4% per annum. 59% of the Indonesian population resides in Java, which boasts a population density of 944 persons per square kilometer.

mid-1960s, Indonesia was the world's largest rice importer (Fuglie and Piggott, 2006). As a result, from the 1970s until the mid-1980s, food crops (mainly rice) were the focus of agricultural production. Yet it took until the 1980s for Indonesia to become nearly self-sufficient in rice production. Emergence of the agricultural sector came about during the 'Green Revolution', when seed-fertilizer technologies and substantial government subsidies allowed increased production through crop intensification. As rice self-sufficiency neared reality, a trend from an agriculture-first policy to an industry-first policy developed from the mid 1980s until the Asian financial crisis hit in 1997. The industry-first policy shifted the focus from food crops to non-food crop production. The Asian financial crisis opened the agricultural sector to competitive global trade. As a result, by the mid-1990s Indonesia had become the second largest exporter of rubber and oil palm, and the third largest exporter of cacao and coffee, yet was again importing record quantities of rice, peaking in 1998 at 4 million metric tons (Fuglie and Piggott, 2006).

The changes in the Indonesian economy from 1985 to 2003 support the notion of a country with an increasing economic growth rate. As the population increased, agriculture's percentage of GDP decreased from 23.2% to 16.6% (Fuglie and Piggott, 2006). This reflects an increasing trend in manufacturing's percentage of GDP. Simultaneously, agriculture's percentage of employment in the Indonesian economy shrank from 54.7% to 46.3% (Fuglie and Piggott, 2006). A decrease in agricultural labor, and a shift from agriculture leading the economy (as a percent of GDP) to manufacturing either echoes the argument from Hayami and Ruttan (1985) of increasing agricultural productivity or that the agricultural sector is lagging behind the non-agricultural sectors. The Indonesian economy grew by 6.7% in 2007, the highest rate of growth in a decade (Bulman, et al., 2008). But from 1993 to 2000, agricultural multi-factor productivity, as measured by a Törnqvist-Thiel chain-weighted index, showed near stagnant growth (-0.1%) (Fuglie, 2004).

Combining food price fluctuations with the current economic growth in Indonesia, it is important to question the role of agriculture in the more-relevant post Green Revolution time-frame. Is increasing agricultural productivity the main driver of this recent economic growth? Or are favorable international prices of exportable commodities (palm oil, cacao, crude oil, etc.) masking stagnant growth in agricultural production? To what extent does Indonesian agricultural research contribute to agricultural productivity? Furthermore, where is the average farmer producing relative to frontier technology?

Fuglie (2004) estimates 1961-2000 total factor productivity (TFP) by applying index number theory to a nationally aggregated data set. Feng and Horrace (2007) compare technical efficiencies of Javanese rice farmers using an aggregated output and fixed-effects stochastic frontier model. The motivation of the present study is, in contrast, to estimate disaggregated rates of technological progress, mean provincial technical efficiencies, and the contributions of policy variables to frontier shifts. To this end, I utilize a flexible functional form and employ a multi-output, fixed-effects stochastic frontier model to distinguish the technical progress specific output categories (annual crops, livestock, and perennial crops) experience. Employing data disaggregated to the provincial level of Indonesian agriculture, 1985 to 2005, I apportion mean technical efficiency by province, providing a geographic account of the relative proximity of producers to the technology employed by the 'best-practice' frontier.

The model includes meta-variables in the technology estimation, thereby explaining the influence of exogenous policy variables on mean technical efficiency. Given the growth in perennial crops exports, I hypothesize these crops to have the highest technical change of all output categories. Building on Fuglie and Piggott (2006), I expect to find technological growth in each of the three output categories to be receiving small, if not insignificant, contributions from Indonesian agricultural research. I also hypothesize province-specific mean technical efficiencies to be increasing over time. Production differences between the average farm and the 'best-practice' frontier likely rest on qualitative differences in farm labor, or human capital. As labor increases its human capital through increased education, disseminated information from international agricultural research spill-ins, and the 'learning-by-doing' process, average farms should converge to the 'best-practice' frontier.

2.2 The Theoretical Specification

To develop our study's output-distance function framework, let $y_{jit} \in \mathbb{R}_{+}^{M},\ j = 1...M$ be a scalar output; $x_{kit} \in \mathbb{R}_{+}^{N},\ k = 1...N$ a scalar conventional input; $t = 1...E$ a technology indicator; and $i = 1...I$ indicate observations defining the technology $T = \{(x_{kit}, y_{jit}):\ x_{kit}$ can produce $y_{jit}\} \in \mathbb{R}_{+}^{\mathrm{N+M}}$. The producible output set identifies the feasible output vectors (y_{jit}) constrained by fixed input vectors (x_{kit}^{o}) and by the technology (T) present in an economy of $M + N$ commodities. Mathematically the producible output set is shown as $P(x_{kit}^{o}) = \{y_{jit} \in \mathbb{R}_{+}^{M}:\ (x_{kit}^{o}, y_{jit}) \in T\}$. From our producible output set, we are able to define the output distance function as (Färe and Primont, 1995)

(1) $$D_O(x_{kit}, y_{jit}, t) = \inf_{\theta}\{\theta > 0:\ {y_{jit}}/{\theta} \in P(x_{kit}^{o}, t)\}\ \forall\ x_{kit} \in \mathbb{R}_{+}^{N}.$$

Distance functions employed in the analysis of production theory are credited to Shephard (1953), (1970). If we assume weak disposability of outputs then from (1), $D_O(x_{kit}, y_{jit}, t) \le 1$ if and only if $y_{jit} \in P(x_{kit}^{o}, t)$ (Färe and Primont, 1995, p.11). The output distance function is less than or equal to unity provided the output vector is within the producible output set. If $D_O(x_{kit}, y_{jit}, t) = 1$ then θ obtains its maximum of unity and outputs y_{jit} are located on the outer isoquant of the producible output set, implying maximized technical efficiency.

An advantage of the distance function technique is the ability to estimate more than one aggregated output, allowing for a more informative model. Moreover as a primal approach, productivity growth is modeled directly in the manner in which productivity is defined, productivity being measured in quantities and the primal approach being a physical relationship rather than a behavioral one. Like all primal or dual approaches to microeconomic theory, the distance function must satisfy certain regularity conditions in order to behave properly. The regularity conditions of most importance in the present study are that the function be monotonic and convex.[2]

2.2.1 Stochastic Frontier Setting

Stochastic frontier estimation was first proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). The stochastic frontier model allows the variation in output to be explained by the variation in inputs, a random shock, and technological inefficiency. Consider production function

(2) $$y_{it} = f(x_{kit}, t, \beta)\exp(\varepsilon_{it}),$$

in which y_{it} is a single output and β are parameters to be estimated. The stochastic production frontier decomposes production function error term ε_{it} in (2) into two errors, v_{it} and u_{it}; that is, $\varepsilon_{it} = v_{it} - u_{it}$. This decomposition gives, from (2),

(3) $$y_{it} = f(x_{kit}, t, \beta)\exp(v_{it} - u_{it}).$$

In equation (3), v_{it} accounts for random noise across time and observations and is assumed independently and identically distributed (iid), symmetric, with mean zero and variance σ_v^2:

(4) $$v_{it} \sim iid\ N(0, \sigma_v^2).$$

Error u_{it} instead is a nonnegative random error term accounting for the distance from each observation to the stochastically estimated frontier. u_{it} is assumed independently and half-normally distributed:

(5) $$u_{it} \sim N^+(0, \sigma_u^2).$$

The two error terms, v_{it} and u_{it}, are assumed distributed independently of each other: $\sigma_{vu} = 0$. Error distribution assumptions follow from Battese and Coelli (1988).

In the case of a single output, the output distance function equals the ratio of actual production to maximum potential production, $E\left({y_{it}} \big/ {f(x_{kit}, t, \beta)} \right)$, which, from

[2] A complete analysis of the distance function's properties and regularity conditions are contained in Färe and Primont (1995)

equation (1), equals $D_O(x_{kit}, y_{it}, t, \beta)$. Generalizing the output distance function to a multiple-output case, we obtain the stochastic distance frontier

(6) $$D_O(x_{kit}, y_{jit}, t, \beta) = \exp(v_{it} - u_{it}).$$

From equation (6) we have

(7) $$D_O(x_{kit}, y_{jit}, t, \beta)\exp(u_{it} - v_{it}) = 1,$$

in which the stochastic output distance frontier is equal to unity when the observation maximizes technical efficiency. To ensure positive numbers for the output distance function, we specify it in exponential form

(8) $$D_O(x_{kit}, y_{jit}, t, \beta) = e^{h(\ln x_{kit}, \ln y_{jit}, t, \beta)},$$

where h is a function of the outputs and inputs. Substituting (8) into (6) provides the stochastic distance frontier in estimable form:

(9) $$e^{h(\ln x_{kit}, \ln y_{jit}, t, \beta)} = e^{(v_{it} - u_{it})}.$$

2.2.2 Incorporating Output Linear Homogeneity and Biased Technical Change

A necessary regularity condition of the output distance function is output homogeneity of degree +1. Output linear homogeneity means scaling the output vector in given positive proportion scales the output distance (i.e., technical efficiency) in the same proportion. It is maintained by requiring that $D_O(x_{kit}, \omega y_{jit}, t, \beta) = \omega D_O(x_{kit}, y_{jit}, t, \beta),$ for any ω>0 (Shephard, 1970). Let $y^*_{jit} = {y_{jit}}/{y_{mit}} \neq +\infty,$ $y_{jit} \neq 0$, and $j = 1...m-1$ in which the m^{th} output is chosen as numeraire (Lovell, et al., 1994). Substituting $\frac{1}{y_{mt}}$ for ω, we have, from (8),

(10) $$e^{h(\ln x_{kit}, \ln y^*_{jit}, t, \beta)} = \frac{1}{y_{mit}} e^{h(\ln x_{kit}, \ln y_{jit}, t, \beta)}.$$

Substituting (9) into (10) gives

(11) $$e^{h(\ln x_{kit}, \ln y^*_{jit}, t, \beta)} = \frac{e^{(v_{it} - u_{it})}}{y_{mit}}.$$

Taking logs of (11) and rearranging terms brings

(12) $$-\ln y_{mit} = h(\ln x_{kit}, \ln y^*_{jit}, t, \beta) + u_{it} - v_{it}.$$

Holding two-sided error term v_{it} in equation (12) at its mean allows us to estimate the expected rate of technical change from input-output relation $h(\ln x_{kit}, \ln y^*_{jit}, t, \beta)$. That is, from (12), technical efficiency estimation employs the predicted logs of the i^{th} observation's output distance:

(13) $$-u_{it} = \ln y_{mit} + h(\ln x_{kit}, \ln y^*_{jit}, t, \beta)$$

or from (9),

(14) $$e^{-u_{it}} = D_O(x_{kit}, y_{jit}, t, \beta).$$

These predicted values are unobservable and must be derived from the composed error term, ε_{it}, expressed either at the technical efficiency mean $\left[E(u_{it} \mid \varepsilon_{it})\right]$ or mode $\left[M(u_{it} \mid \varepsilon_{it})\right]$ (Jondrow, et al., 1982). Depending upon the point estimator required, mean technical efficiency may also estimated as (Battese and Coelli, 1988)

(15) $$E\left[\exp(-u_{it}) \mid \varepsilon_{it}\right].$$

Apart from estimating changes in technology and efficiency, we are interested in the nature or bias of technical change and the influence that exogenous policy variables have on technical efficiency. Antle and Capalbo (1988b) estimate the relative primal bias associated with each input and output category from a transformation function $TF(x_{kit}, y_{jit}, t, \beta) = 0$ using outputs $j = 1,\ldots,M$ and inputs $k = 1,\ldots,N$. To employ their methodology, we formalize the correspondence between the transformation function and the output distance function. From (1), we know $D_O(x_{kit}, y_{jit}, t) \le 1$ if and only if $\left(x_{kit}, y_{jit}\right) \in P(x^o_{kit}, t)$. We also know that $TF(x_{kit}, y_{jit}, t, \beta) \ge 0$ if and only if $\left(x_{kit}, y_{jit}\right) \in P(x^o_{kit}, t)$. Therefore $D_O(x_{kit}, y_{jit}, t, \beta) \le 1$ if and only if $TF(x_{kit}, y_{jit}, t, \beta) \ge 0$. We then have a one-to-one correspondence between the output distance function and the transformation function. From this correspondence we may compute the primal bias, substituting Antle and Capalbo's $TF(x_{kit}, y_{jit}, t, \beta)$ with our $D_O(x_{kit}, y_{jit}, t, \beta)$:

$$RB_{ij} \equiv \partial \ln D_{O,Y_i}(y_j, x_k, t)/\partial t - \partial \ln D_{O,Y_j}(y_j, x_k, t)/\partial t, \quad i \neq j,$$
(16)
$$RB_{kh} \equiv \partial \ln D_{O,X_k}(y_j, x_k, t)/\partial t - \partial \ln D_{O,X_h}(y_j, x_k, t)/\partial t, \quad k \neq h.$$

D_{O,Y_j} and D_{O,Y_i} in equation (16) refer to the derivative of the output distance frontier with respect to the j^{th} and i^{th} output, respectively. D_{O,X_k} and D_{O,X_h} are the derivatives with respect to input x_k and x_h. The *relative* primal output bias (RB_i) or *relative* input bias (RB_k) is defined from (16) as the primal bias between two outputs (RB_{ij}) or two inputs (RB_{kh}), each weighted by its revenue or expenditure share (R_j or R_k)

(17)
$$RB_i = \sum_{j \neq i}^{M} R_j RB_{ij}, \quad RB_k = \sum_{k \neq h}^{N} R_k RB_{kh}.$$

For each output or input category, equation (17) measures the rotation of the production possibilities frontier due to technical change at point (y_j, x_k).

2.2.3 Accounting for Productive Efficiency

The heteroscedastic variance of inefficiency error term u_{it} may be exploited in order to analyze the mean influence of exogenous policy variables on productive efficiency. Theory predicts heteroscedasticity in many situations, especially when resource size is a significant component of production. Indonesian provinces differ in population density and geographic area. The greater the labor and arable land supply, the greater the opportunities for annual production swings. Dividing both sides of (9) by $\exp(v_{it})$ gives

(18)
$$\frac{\exp\left(h(\ln x_{kit}, \ln y_{jit}, t, \beta)\right)}{\exp(v_{it})} = \exp(-u_{it}).$$

In (18), the stochastic transformation of input to output in a given observation has a distance to the 'best-practice' frontier that is assumed unequal to all other observations. By contrast, homoscedasticity in u_{it} would require each observation to have the same production variation. Observations which differ in their resource scarcity and face similar commodity prices choose different variations in their production decisions. This decision-making process allows some observations to form a 'best-practice' frontier while others to produce below the best-practice frontier. Some reasons an observation may not be on the 'best-practice' frontier include poor or obsolete technology, poor management, or other constraints on the producer's resources (Hulten, 2000).

The importance of modeling heteroscedasticity in u_{it} has been shown in Caudill and Ford (1993) and Caudill, Ford, and Gropper (1995). In each of the two studies, Monte Carlo simulations of heteroscedastic stochastic production frontiers are shown to bias parameter estimates by overestimating the intercept and underestimating the slope coefficients (Caudill, Ford and Gropper, 1995). To model heteroscedasticity we following Simar, Lovell, and Vanden Eeckaut (1994), and Caudill, Ford, and Gropper (1995), formalized in Kumbhakar and Lovell (2000). We continue to assume, as in (4), that the distribution of idiosyncratic error term v_{it} is i.i.d. and normal, and that u_{it} and v_{it} are independently distributed ($\sigma_{vu} = 0$). However, rather than the homoscedastic specification in (5), we permit inefficiency to be heteroscedastic by way of the one-sided error term

(19) $$u_{it} \sim N^{+}(0, \sigma^2_{u,it})$$

in which N^{+} indicates the half-normal distribution and $\sigma^2_{u,it}$ is the heteroscedastic variance. Note that $\sigma^2_{u,it}$ generally depends on province *i* and year *t*.

While accounting for heteroscedasticity in u_{it} is important to achieve efficient estimates, a heteroscedastic u_{it} in the present study is merely the vehicle for estimating provincial (thus policy) impacts on mean efficiency. To obtain these policy impacts, we explain the sources of the heteroscedasticity by associating u_{it} with a vector of exogenous policy variables $\ln z_{ait}$ and a vector of parameters Ω. We adopt the multiplicative form

(20) $$u_{it} = g(\ln z_{ait}; \Omega)\eta_{it}, \; a = 1...A,$$

where g is a scaling constant, a represents the policy variables, and η_{it} is an iid random variable such that $\eta_{it} \geq 0$, $E(\eta_{it}) = 1$, and $V(\eta_{it}) = \sigma^2_{\eta}$. Kumbhakar and Lovell (2000) describe (20) as a scale transformation g of an underlying random inefficiency process η_{it}. The insight provided by scaling-factor g is the incorporation of observable characteristics affecting inefficiency. Moreover, because $\ln z_{ait}$ means vary by province, it allows for differing province-specific mean inefficiencies (Alvarez, et al., 2006). Thus if mean inefficiency is province-specific, so also is the variance of inefficiency. Intuitively, η_{it} establishes the basic inefficiency level while policy variables $\ln z_{ait}$ capture differing features of the environment in which the provinces operate.

Incorporating, as in (19), the factors influencing u_{it} alters our characterization (9) of the stochastic frontier to

(21) $$e^{h(\ln x_{kit}, \ln y_{jit}, t, \beta)} = e^{(v_{it} - g(\ln z_{ait}; \Omega)\eta_{it})}.$$

In order to estimate equation (12) in a way that reflects (20) and (21), a parametric specification of $g(\ln z_{ait}; \Omega)\eta_{it}$ is needed. Following (Simar, Lovell and Vanden Eeckaut, 1994), we specify g in exponential form, so that (20) becomes

(22) $$u_{it} = g(\ln z_{ait}; \Omega)\eta_{it} = \exp(\ln z_{ait}{}'\Omega)\eta_{it},$$

where

(23) $$g(\ln z_{ait}; \Omega) = \exp(\ln z_{ait}{}'\Omega).$$

The first two moments of inefficiency error u_{it} therefore become

(24) $$E(u_{it}) = \exp\left\{\ln z_{ait}{}'\Omega\right\} > 0, \text{ and}$$

(25) $$V(u_{it}) = \sigma^2_{u,it} = g(\ln z_{ait}, \Omega)^2 \sigma^2_\eta = \exp\left\{2\ln z_{ait}{}'\Omega\right\}\sigma^2_\eta.$$

Substituting (22)'s parametric specification into (12), we obtain

(26) $$\begin{aligned} -\ln y_{mit} &= h(\ln x_{kit}, \ln y^*_{jit}, t, \beta) + g(\ln z_{ait}; \Omega)\eta_{it} - v_{it}, \\ &= h(\ln x_{kit}, \ln y^*_{jit}, t, \beta) + \exp\left\{\ln z_{ait}{}'\Omega\right\} + \varepsilon_{it}, \end{aligned}$$

where,

(27) $$\varepsilon_{it} = -v_{it} + \exp\left\{\ln z_{ait}{}'\Omega\right\}(\eta_{it} - 1).$$

Taking the variance of the first line of (26), gives

(28) $$Var(-\ln y_{mit}) = \exp\{2\ln z_{ait}{}'\Omega\}\sigma^2_\eta + \sigma^2_v.$$

Equation (28) says the variance of the dependent variable equals the variance of the heteroscedastic inefficiency error term plus the variance of the idiosyncratic error term. Composed error term ε_{it} is independently but not identically distributed, with moments

(29)
$$E(\varepsilon_{it}) = 0,$$
$$V(\varepsilon_{it}) = \sigma_v^2 + \exp\left\{2 \ln z_{ait}{}^{'}\Omega\right\} \sigma_\eta^2,$$

and is useful for estimation purposes.

2.2.4 Policy Impacts on Productive Efficiency

To explain the influence of the exogenous policy variables on mean efficiency, we define a form and parametric specification for inefficiency error term u_{it}, (20) and (22), which maintains a heteroscedastic structure. The source of the heteroscedasticity derives from the provincially indexed policy variables in (27). Our model of u_{it} takes the form:

(30)
$$\ln \sigma_{u,it}^2 = \ln \sigma_\eta^2 + 2 \ln z_{ait}{}^{'}\Omega,$$

where $\ln \sigma_\eta^2$ is an intercept. Equation (30) provides a characterization of the policy factors influencing the variance of u_{it} and thus, through (24), the factors influencing provincial-mean efficiencies. Parameter estimates $\widehat{\Omega}$ in (30) give the elasticities of technical inefficiency variance with respect to the exogenous policy variables. Estimates from models (26) and (30) then are used to obtain the mean technical efficiency via an application of (15):

(31)
$$\widehat{TE}_{it} = E\left[\exp(-u_{it} \mid \varepsilon_{it})\right] = E\left[e^{-\exp\{\ln z_{ait}{}^{'}\Omega\}} \mid \varepsilon_{it}\right].$$

To compute the impact of the exogenous policy variables on mean technical efficiency, we start with the derivative

(32)
$$\frac{\partial \ln \widehat{TE}_{it}}{\partial \ln z_{ait}} = \frac{\partial \ln E\left[e^{-\exp\{\ln z_{ait}{}^{'}\Omega\}} \mid \varepsilon_{it}\right]}{\partial \ln z_{ait}}.$$

Re-arranging linear operators, we obtain

(33)
$$\frac{\partial E \ln\left[e^{-\exp\{\ln z_{ait}{}^{'}\Omega\}} \mid \varepsilon_{it}\right]}{\partial \ln z_{ait}}.$$

Equation (33) allows the influence of each policy variable on mean technical efficiency to be determined as

(34) $$\frac{\partial E(-\exp\{\ln z_{ait}{}^{'}\Omega\} \mid \varepsilon_{it})}{\partial \ln z_{ait}} = -\exp\{\ln z_{ait}{}^{'}\Omega\}\left(\frac{\partial \exp\{\ln z_{ait}{}^{'}\Omega\}}{\partial \ln z_{ait}}\right).$$

The log-likelihood function of (26) is (Kumbhakar and Lovell, 2000, p.120)

(35) $$\ln L = \text{constant} - \frac{1}{2}\sum_i \ln\left[g(\ln z_{ait};\Omega) + \sigma_v^2\right] + \sum_i \ln\Phi\left(-\frac{\varepsilon_{it}\lambda_{it}}{\sigma_{it}}\right) - \frac{1}{2}\sum_i \frac{\varepsilon_{it}^2}{\sigma_{it}^2},$$

where $\Phi(\bullet)$ is the cumulative distribution function of the standard normal distribution. From this log-likelihood function, the variance parameters are given as

(36) $$\sigma_{it}^2 = \sigma_v^2 + \sigma_{u,it}^2 = \sigma_v^2 + g(\ln z_{ait};\Omega),$$

and

(37) $$\lambda_{it} = \frac{\sigma_{u,it}}{\sigma_v} = \frac{\sqrt{g(\ln z_{ait};\Omega)}}{\sigma_v}.$$

Maximizing (35) provides us with estimates of technology parameters β, idiosyncratic error variance σ_v^2, and policy parameters Ω. Estimates of $\sigma_{u,it}^2$ are obtained directly from (25).

2.3 Indonesian Application

Agricultural research has been conducted in Indonesia since the beginning of the 19th century. The most prestigious of many tropical botanical gardens was established in 1817 in Bogor, West Java, by the Dutch colonial authorities. These gardens focused on exploiting tropical plant species for export, adding revenues to the Dutch government (Booth, 1988). By the early 20th Century, the focus of agricultural research rested on crop and disease management for plantation owners, who wished to increase their profitability by improved agricultural productivity (Fuglie and Piggott, 2006). The beginning of the 20th Century also saw the establishment of the Department of Agriculture, which focused its research efforts on alleviating a food shortage problem generated by increasing population growth.

As a result of World War II (1942-1945) and the War of Independence (1945-1949), the 1950s and 1960s saw the nationalization of many foreign-owned plantations, and an exodus of skilled scientists. It wasn't until the New Order government of

President Suharto (1965) that agricultural policy became a national priority. One ramification of the new emphasis was the establishment of the Agency for Agricultural Research and Development (AARD) in 1974. At the time the AARD had 11 Ph.D.'s, and 33 M.S. qualified scientists (Fuglie and Piggott, 2006). In 1994 AARD supported 40 research stations, 64 laboratories, 57 sub-stations, 150 experimental ponds, and 5 research vessels (Evenson, et al., 1994). The national agricultural research system currently includes not only the AARD, but also universities, the Agency for Atomic Energy, and the Agency for Technology Assessment (Evenson, et al., 1994). The efforts of the universities, whose main function has been training scientific and technical personnel for both public and private research, have not been in vain. In 2003 there were 335 Ph.D.'s, 1,095 M.S.'s, and 2,187 B.S. trained scientists employed by the AARD, IPARD, and the Ministry for Marine Resources and Fisheries (Fuglie and Piggott, 2006).

1995 saw a reorganization of the AARD. The most significant impact of the reorganization came from the establishment of the 'Puslit Sosek Pertanian' (PSP), or agricultural socio-economic centers, in each province. These technology assessment centers were established to link agricultural research, extension, and farm-sites engaged in testing new technologies (Fuglie and Piggott, 2006). The establishment of the PSP revealed a government focus to improve the technologies implemented on small holder farms, while also reflecting an emphasis toward non-food crop production.

The most significant problem facing the AARD is financial. Between 1994 and 1999, the Ministry of Agriculture's expenditures on agricultural research and development were cut nearly in half, falling from 125.1 million to 65.7 million 1999 international dollars (Fuglie and Piggott, 2006).[3] The expenditure summary in Appendix A.2 provides a picture of a strengthening agricultural sector combined with a stagnant, if not weakening, research focus.

[3] The Indonesian Rupiah used in the expenditure summary in Appendix A.2 was, using purchasing power parity (PPP) indices, converted to 1999 internationally denominated currency units (dollars).

2.3.1 Econometric Methods

As in the above theoretical specification, let $y_{jit} \in \mathbb{R}^3$ be a output scalar in which $j = 1,...,3,\ i = 1,...,22$, and $t = 1,...,21$. Subscript *j* refers to each of three Fisher output quantity indices representing the three outputs: perennial crops, annual crops, and livestock. *i* subscripts refer to the 22 Indonesian provinces and *t* is a technology indicator accounting for each year in the 1985-2005 time horizon. Let $x_{kit} \in \mathbb{R}^3$ be a conventional input scalar, where $k = 1,...,3$. Subscript *k* refers to each of three Fisher input quantity indices (labor, capital, and intermediates). Let $r_{bit} \in \mathbb{R}^2$ be a meta-variable scalar in which $b = 1,2$. Meta-variables in the present study are: (1) an agricultural research stock variable, and (2) a regional agricultural spillover stock variable. The purpose of the meta-variables is to determine the effects of AARD's and IPARD's agricultural research expenditures on the rate of technical change in the agricultural sector. Agricultural research is, generally speaking, a determinant of agricultural productivity (Huffman and Evenson, 1993). Therefore, excluding agricultural research variables might lead to missing-variable bias in the distance function coefficients (Alston, Norton and Pardey, 1995). Including them, moreover, potentially establishes a direct link between agricultural research and the production technology.

In the present study, we choose the Fisher output index for perennials as the numeraire. The perennials output index has the greatest historical and geographic variation in Indonesia, making it the best dependent variable for econometric estimation. An input-output relation $D_O(\ln x_{kit}, \ln y^*_{jit}, t, \beta)$ incorporating the meta-variables can be specified as

$$
\begin{aligned}
D_O(\ln x_{kit}, \ln y^*_{jit}, \ln r_{bit}, t, \beta) = {} & \beta_0 + \sum_{k=1}^{N} \beta_k \ln x_{kit} + \sum_{j=1}^{M-1} \beta_j \ln y^*_{jit} + \beta \ln AllRD_{it} + \beta \ln SpillRD_{it} \\
& + \frac{1}{2}\sum_{k=1}^{N}\sum_{h=1}^{N} \beta_{kh} \ln x_{kit} \ln x_{hit} + \frac{1}{2}\sum_{j=1}^{M-1}\sum_{l=1}^{M-1} \beta_{jl} \ln y^*_{jit} \ln y^*_{lit} \\
& + \sum_{k=1}^{N}\sum_{j=1}^{M-1} \beta_{kj} \ln x_{kit} \ln y^*_{jit} + \beta_0 t + \frac{1}{2}\beta_{00} t^2 \\
& + \sum_{k=1}^{N} \beta_{kt} t \ln x_{kit} + \sum_{j=1}^{M-1} \beta_{jt} t \ln y^*_{jit} + \beta t \ln AllRD_{it} + \beta t \ln SpillRD_{it}
\end{aligned} \tag{38}
$$

where $AllRD_{it}$ is the agricultural research stock and $SpillRD_{it}$ is the regional agricultural research spillover stock. This function is translog in (x, y, t), so that technical change is assumed constant or smoothly changing (Orea, 2002). Combining the non-meta-variable terms in (38) into $TL(\ln x_{kit}, \ln y^*_{jit}, t, \beta)$, equation (35) can be re-expressed as

$$\begin{aligned} D_O(\ln x_{kit}, \ln y^*_{jit}, \ln r_{bit}, t, \beta) = \beta_0 + TL(\ln x_{kit}, \ln y^*_{jit}, t, \beta) \\ +\beta \ln AllRD_{it} + \beta \ln SpillRD_{it} \\ +\beta t \ln AllRD_{it} + \beta t \ln SpillRD_{it} \end{aligned} \tag{39}$$

Fixed-effects also can be incorporated into the technology specification. In particular, provincial and annual dummy variables may be included to account for unobserved cross-province heterogeneity in the data, but not directly accounted for by the quality-adjusted conventional inputs. In stochastic frontier models, such fixed-effects typically are specified through the inefficiency error term u_{it}. Substituting (39) into (26) gives

$$\begin{aligned} -\ln y_{mit} = \beta_{0it} + TL(\ln x_{kit}, \ln y^*_{jit}, t, \beta) \\ +\beta \ln AllRD_{it} + \beta \ln SpillRD_{it} \\ +\beta t \ln AllRD_{it} + \beta t \ln SpillRD_{it} + \exp\left\{\ln z_{ait}{}'\Omega\right\} \eta_{it} - \nu_{it}, \end{aligned} \tag{40}$$

$$\begin{aligned} = \beta_{it} + TL(\ln x_{kit}, \ln y^*_{jit}, t, \beta) \\ +\chi \ln AllRD_{it} + \varphi \ln SpillRD_{it} \\ +\phi t \ln AllRD_{it} + \kappa t \ln SpillRD_{it} - \nu_{it}, \end{aligned} \tag{41}$$

where $\alpha_{it} = \alpha_{0it} + \exp\left\{\ln z_{ait}{}'\Omega\right\} \eta_{it}$. In equations (40) and (41), the intercept of the fixed-effects model is the intercept common to all observations plus the parametric specification of u_{it}, equation (22). Equation (41) reflects not only provincial and time inefficiency but any unobservable heterogeneity across observations. Unfortunately it confounds provincial and time inefficiency with *all other* unobserved heterogeneity across provinces.[4]

I instead follow a more intuitive approach by including a dummy variable P_i for each province only. Such an approach captures the cross-province, time-invariant,

[4] For a comparative analysis of the two fixed effects models associated with model (38) and (39), the reader is referred to (Greene, 2005)

unobserved heterogeneity while permitting the inefficiency error term to capture the impact of the province-specific $AllRD_{it}$ and $SpillRD_{it}$ variables. Including dummy variables is optimal for measuring inefficiency when employing fixed-effects, provided the time-invariant unobserved heterogeneity which they model is not efficiency-related (Greene, 2005). An example would be that in which variability in local government forms are accounted for by the dummies, while missing data such as soil quality and pesticide use differences are captured by the inefficiency error term. Incorporating the provincial dummy variables into equation (26), inclusive of (39), leads us to the estimable model

$$\begin{aligned} -\ln y_{mit} &= \beta P_i + TL(\ln x_{kit}, \ln y^*_{jit}, t, \beta) \\ &+\beta \ln AllRD_{it} + \beta \ln SpillRD_{it} \\ &+\beta t \ln AllRD_{it} + \beta t \ln SpillRD_{it} \\ &+\exp\left\{\ln z_{ait}{}'\Omega\right\} + \varepsilon_{it}, \end{aligned} \tag{42}$$

Unlike a variable such as age, which would have an expected non-monotonic influence on efficiency (Wang, 2002), both road density and literacy rate are monotonic in their hypothesized effect on agricultural efficiency. Wang (2002) argues that labor efficiency increases with age until a peak-efficiency age is attained, after which efficiency decreases. In a developing country such as Indonesia, road density presumably has yet to reach peak efficiency, implying a monotonic influence on productive efficiency. Literacy also should have a monotonic influence on technical efficiency in both developing and developed countries alike. Increasing education should increase agricultural labor efficiency.

To estimate the factors influencing provincial-mean inefficiencies, we apply the variance characterization of u_{it}, equation (30), and employ the policy variables in log-linear form, so that (30) becomes

$$\ln \sigma^2_{u,it} = \alpha_0 + \alpha_1 \ln RoadDensity_{it} + \alpha_2 \ln Literacy_{it} + \omega_{it}; \ \omega_{it} \sim N(0, \sigma^2). \tag{43}$$

Model (43) says agricultural inefficiency in Indonesia is explained by a constant, road density, and literacy rate.

2.3.2 Data: Outputs, Inputs, and Exogenous Policy variables

Secondary data from government statistical publications are drawn annually from 1985 to 2005, an interval providing a picture of ‘post-green revolution’ agricultural production. Data are taken from six sources, four of which are Indonesian: Buro Pusat Statistik (BPS), or the Central Statistics Office; the Ministry of Agriculture (MOA); the Director General of Estate Crops, or DG Estate; and CBS (Central Bureau of Statistics). The non-Indonesian sources are the Food and Agricultural Organization FAOSTAT/FAO, and Van der Eng (1996).

The Indonesian data are sorted by five regions and 22 provinces, summarized in Appendix A.3. Papua, Maluku, and Nusa Tenggara Timur (NTT) are dropped from Eastern Indonesia, and DKI Jakarta is dropped from Java on account of inadequate data quality. Bali, traditionally part of Eastern Indonesia, is alternatively grouped with Java due to the similarity of their intensive rice-based agriculture. Indonesia’s national currency is the Rupiah. The strength of the Indonesian data set lies in its rich time-series structure and its annually recorded 50 outputs and 6 inputs.

2.3.3 Outputs

Indonesian agricultural production units are recorded in metric tons. The 50 commodities for which data are available are aggregated into annuals, perennials, and livestock. Indonesia’s principal annuals, perennials, and livestock are listed in Appendix A.4. To obtain constant 2002 prices, output prices of each commodity are normalized annually with the World Bank’s GDP price deflator for Indonesia.

2.3.4 Inputs

Recorded inputs in the Indonesian agricultural sector consist of fertilizer, agricultural equipment (tractors, threshers, and animal work), land, labor, and feed. Input prices are recorded in nominal Rupiahs. As with output prices, input prices are converted by the World Bank’s Indonesian GDP price deflator to constant 2002 prices.

Fertilizer

Fertilizer quantities are recorded at the regional level. Three fertilizer types are involved: N (nitrogen), P_2O_5 (phosphate), and K_2O (potash). Fertilizer quantities are given in metric tons of nutrient. Fertilizer price data are recorded only in the Java and North Sumatra regions. Sumatra, Kalimantan, Sulawesi, and East Indonesia are assumed to face the North Sumatran regional fertilizer price.

Agricultural Equipment

Agricultural equipment is comprised of machinery inputs and animal power. Machinery inputs are recorded at the provincial level and composed of the number of agricultural machines and their respective horsepower. Machinery categories are 40 horsepower (hp) 4-wheel large tractors, 30 hp 4-wheel medium tractors, 25 hp 4-wheel small tractors, 5 hp 2-wheel tractors, and 25 hp threshers. Annual total horsepower is calculated as the quantity of machines multiplied by each machine category's respective horsepower. Obtaining agricultural machinery rental prices for a unit of annual horsepower requires estimating the rental rate of a 4-wheel tractor. To this end, we amortize over 10 years at a 10% discount rate the unit price of an imported 4-wheel tractor, obtained from the Food and Agricultural Organization of the United Nations (FAO). The 4-wheel tractor rental rate is then divided by the average horsepower over all machinery categories in that year. No machinery data are recorded for 2003, 2004, and 2005. To redress this problem, I regress machinery factor cost shares against time, obtaining the cost share's average rate of change. From the average rate of change, total machinery expenditures and quantities can be extrapolated because 2003, 2004, and 2005 rental prices are available.

The other component of agricultural equipment is animal power. Animal power is recorded at the provincial level and comprises horses, beef cattle, and buffalo. To obtain the annual value of animal work services, we amortize the (equal) unit price of horses and buffaloes over a 3-year period, using a 10% discount rate and FAO import price data. This allows the computation of the service flow input price for each animal type, in Rupiahs per head per year.

Land

Land inputs are measured in hectares and recorded at the provincial level, quality-differentiated into six classifications. The six classifications are: irrigated cropland, wetland (for growing rice), dry-land, land for permanent crops, temporary fallow land, and meadows. As no land prices are available, they had to be estimated. To obtain an estimated rental value of land, we assume the difference between total revenue and total cost of each of the five inputs for which prices are available (feed, fertilizer, livestock, labor, and machinery) is the residual return to land. This is equivalent to equating total revenues to total costs. The residual return is divided by the total quality-adjusted quantity (hectares) of non-irrigated sawah, or rain-fed wetland equivalents, to obtain a land 'price'. The six land classifications are quality-adjusted, with a separate weight for each classification: irrigated sawah has a weight of 2, non-irrigated sawah 1, dry-land and permanent croplands 0.75, and meadows and fallow land 0.2.

Labor

Labor inputs consist of male and female laborers over the age of 15 in the agricultural sector. Data are collected at the provincial level and include both rural and urban workers. To quality-differentiate them, we assume each laborer receives the same wage but that male laborers work 300 days per year and female laborers work only 250 days per year. Wages are recorded at the national and regional level in Rupiahs per male laborer per day and refer to simple averages across all operations (planting, plowing, and weeding) and across all provinces in each region.

Feed

Feed quantities and expenditures are estimated rather than directly recorded. To estimate the feed input quantities, a time-constant but livestock-specific feed-to-meat conversion factor is estimated from secondary data, then multiplied by the relevant animal output quantity. Feed-to-meat conversion factors are: cattle meat (7.0), buffalo meat (4.0), horse meat (6.0), poultry meat (2.5), duck meat (2.5), sheep meat (0.0), goat meat (0.0), pig meat (3.0), cow's milk (3.0), and hen eggs (3.0). Zero feed weights are associated with small ruminants we assume are fed forages. In the estimation of total feed expenditures, feed price is assumed to be 1.5 times the real (2002 Rupiah basis) price of a metric ton of rice. Rice and livestock feed prices differ from one another on account of feed processing costs.

Exogenous Policy Variables

Metadata are those which explain shifts in technological frontiers or mean efficiencies. As stated earlier, the two meta-variables in the present analysis are (1) national agricultural research stocks and (2) regional agricultural research spillover stocks. Two other exogenous policy variables are included in the estimation of technical efficiency: (a) road density and (b) literacy rate.

Government *expenditures* allocated to agricultural research are available from 1974 to 2003 in 2002 Rupiahs. Those in 2004 and 2005 were forecasted by using 1974-2003 data to regress agricultural research expenditures against time, then extrapolating the results to 2004 and 2005. To procure the provincial data necessary for computing research *stocks*, weighted shares of agricultural scientists (S1, S2, and S3) were estimated for each province. The weights reflect differences in salary.[5] The expenditures on agricultural research are multiplied by the weighted share of agricultural scientists in each province to obtain estimates of province-specific agricultural research expenditures.[6] Agricultural research expenditures are inclusive of those in the AARD (Agency for Agricultural Research and Development) and IPARD (Indonesian Planters Association for Research and Development).

We recognize that although many institutes within any province may have a national research mandate, the developed technologies may be more suited for local environments (Evenson, et al., 1994). As such, agricultural research stocks are constructed by province following Huffman and Evenson (1993). A provincial stock of

[5] The coding for agricultural scientists is: S1-B.Sc., S2-M.Sc., S3-Ph.D.
[6] Weights: S1 – (0.3), S2 – (0.5), and S3 – (1.0)

research ($AllRD_{it}$) is computed using a total lag of 11 years. Referencing observations and time by $i = 1...I$, and $t = 1...E$, respectively, we specify the construction of agricultural research stocks from agricultural expenditures ($AgExp_{it}$) as

$$
\begin{aligned}
AllRD_{it} = {} & 0.025 * AgExp_{i,t=-1} + 0.05 * AgExp_{i,t=-2} + 0.075 * AgExp_{i,t=-3} \\
& + 0.1 * AgExp_{i,t=-4} + 0.125 * AgExp_{i,t=-5,-6,-7,-8} + 0.1 * AgExp_{i,t=-9} \\
& + 0.075 * AgExp_{i,t=-10,-11}.
\end{aligned} \tag{44}
$$

Four increasing weights, four constant weights, and three declining weights constitute the trapezoidal shape employed. Necessarily, the weights sum to unity.

Regional agricultural research spillover stocks are computed in a similar methodology to (44). To obtain the regional agricultural research spillover stock ($ARSpill_{irt}$) in the i^{th} province, expenditures in all provinces in that region ($i \in r = 1...R$) are used, except that the province for which the spillover stock is constructed is excluded ($\sum_{i \in r=1}^{I-1} AgExp_{irt}$). Thus, we have

$$
\begin{aligned}
ARSpill_{irt} = {} & 0.025 * \sum_{i \in r=1}^{I-1} AgExp_{ir,t=-1} + 0.05 * \sum_{i \in r=1}^{I-1} AgExp_{ir,t=-2} \\
& + 0.075 * \sum_{i \in r=1}^{I-1} AgExp_{ir,t=-3} + 0.1 * \sum_{i \in r=1}^{I-1} AgExp_{ir,t=-4} \\
& + 0.125 * \sum_{i \in r=1}^{I-1} AgExp_{ir,t=-5,-6,-7,-8} + 0.1 * \sum_{i \in r=1}^{I-1} AgExp_{ir,t=-9} \\
& + 0.075 * \sum_{i \in r=1}^{I-1} AgExp_{ir,t=-10,-11}.
\end{aligned} \tag{45}
$$

Road density data are available from 1984 to 2002 and are inclusive of all provinces. Year 2003 to 2005 data are forecasted by using 1984-2002 data to regress road density against time, then extrapolating the results to 2003, 2004, and 2005. Road density is defined as the sum of the length of asphalted road, in kilometers, under the responsibility of the province, state, and regency, divided by the area of each province in square kilometers and multiplied by 1,000.

Literacy data are available by province and range from 1985 to 2003. Literacy is defined as the percentage of males and females over the age of 10 who use the Latinbased alphabet. To forecast 2004-2005 literacy data, we regress 1985-2003 data against time and extrapolate the results.

2.4 Empirical Evidence

Estimates of technical change, national mean technical efficiency by year, and the influences of policy variables on technical inefficiency are estimated for a sample of 22 Indonesian provinces to characterize Indonesian farm productivity.[7] Province-specific mean technical efficiencies, with their respective rates of change, also are estimated.

2.4.1 Regularity Conditions

It is often thought that multi-output distance functions should conform to regularity conditions, such as linear homogeneity in the output vector, monotonicity, and convexity, as they are required for rational behavior under certain conditions. For the purpose of examining these regularity conditions, we can rewrite (41), itself an elaboration of equation (12), to reveal the underlying transformation function (TF) of the technology:

$$
\begin{aligned}
0 &= \beta P_i + \ln y_{mit} + TL(\ln x_{kit}, \ln y^*_{jit}, t, \beta) \\
&\quad + \beta \ln AllRD_{it} + \beta \ln SpillRD_{it} \\
&\quad + \beta t \ln AllRD_{it} + \beta t \ln SpillRD + \exp\left\{\ln z_{ait}{}'\Omega\right\} + \varepsilon_{it}, \\
&= TF
\end{aligned} \tag{46}
$$

For (46) to be monotonic, it must be an increasing function of each output quantity and a decreasing function of each input quantity. Appendix A.5 presents the monotonicity results, indicating the transformation function indeed is monotonic: the derivative of (46) is positive with respect to each of the two normalized Fisher output quantity indices (annuals and livestock) and negative with respect to each of the three Fisher input quantity indices (capital, labor, and intermediate inputs).

Technological convexity requires the transformation function have a positive semi-definite Hessian matrix. Appendix A.5 presents the determinants of the Hessian's respective principal minors. For the technology to be convex, the principal minors must

[7] For parameter estimates, see Appendix A.1.

all be nonnegative (Simon and Blume, 1994). In the present case, technology appears to be non-convex because the determinant of the 3rd principal minor is negative. Does such non-convexity imply we have inaccurately characterized Indonesian agriculture's input-output structure? Technologies are convex if agents are profit-maximizing, have perfect information, and can divide outputs and inputs without limit. None of these properties are likely satisfied on many Indonesian farms. For example, when pressed by the government to employ new rice-fertilizer technologies, some farmers have resisted the potentially higher yields in favor of traditional rice varieties (van der Eng, 1996). In fact Van der Eng (1996) concludes that rice profitability would be negative in several areas of Indonesia were it not for effective input subsidies on fertilizer and pesticides. Van der Eng (1996) continues to claim that, while rice remains the most favored food crop among farm households, it is not necessarily the most profitable.

2.4.2 Technological Progress

Our distance function's multi-output structure allows us, impossible in one-output models, to determine which outputs benefit most from technological change. The technical change estimate itself is obtained from time trend variable t, generically capturing every factor, other than formal Indonesian agricultural research, tending to induce technical change over time. If aggregate Indonesian agricultural research expenditures, rather than a time trend, were used to represent the factors inducing such change, no distinction could be made between formal and informal information sources. We therefore need to include a time trend and Indonesian agricultural research stocks to respectively measure the informal and formal contributions to Indonesian agricultural technical change.

We now may apply the implicit function theorem to model (46) in order to decompose total technical change into its informal, direct formal, and indirect formal causes. Informal technical change accounts for knowledge penetration outside the formal agricultural research structure, holding formal agricultural research and agricultural research spillovers fixed. Direct formal technical change explains the contribution of each province's established research structure, holding all other variables constant.

Finally, indirect formal technical change accounts for the contributions of agricultural research spillovers across regions. Taking the total derivative of output with respect to time,

(47) $$\frac{d\ln Y_{jit}}{dt} = \frac{\partial \ln Y_{jit}}{\partial t} + \frac{\partial \ln Y_{jit}}{\partial \ln RD_{it}^{ALL}} \frac{d\ln RD_{it}^{ALL}}{dt} + \frac{\partial \ln Y_{jit}}{\partial \ln RD_{it}^{SPILL}} \frac{d\ln RD_{it}^{SPILL}}{dt}.$$

Informal technical change in (47) is the first right hand side term, $\partial \ln Y_{jit} / \partial t$. Direct formal technical change, the second right hand side term, is the product of output elasticity $\partial \ln Y_{jit} / \partial \ln RD_{it}^{ALL}$ of agricultural research and the time rate of change $d\ln RD_{it}^{ALL} / dt$ of own-province agricultural research. Indirect formal technical change, the last right hand side term, is the product of the output elasticity $\partial \ln Y_{jit} / \partial \ln RD_{it}^{SPILL}$ of agricultural research spill-ins, and the time rate of change $d\ln RD_{it}^{SPILL} / dt$ of cross-province agricultural research. Appendix A.7 formalizes these results separately for each of the three Indonesian output categories.

Two technical change hypotheses were stated in the introduction. First, I hypothesized that perennial crops would enjoy the highest annual technical change rate of the three output groups. Appendix A.7 confirms that hypothesis. At the frontier, annual informal technical change in Indonesian agriculture has been highest (3.42%) among perennials, second highest among livestock at 1.67%, and last among annual crops (0.65%). Annual direct formal technical change has been -0.02% in perennial crop production, -0.01% in livestock, and -0.004% in annual crops. Finally, annual indirect formal technical change has been 0.09% among perennial crops, nearly double that in livestock (0.04%), and far greater than in annual crops (0.01%). As shown in (46), the three sources of annual technical changes sum to annual total technical change in each output category. Annual total technical change in perennial crops was highest at 3.50%, second in livestock at 1.71%, and last in annual crops at 0.66%.

My second hypothesis concerned the significance of the contribution of agricultural research to technical change. This hypothesis is best viewed through the output elasticities with respect to (own-province) agricultural research and with respect to regional (cross-province) agricultural research spillovers. The elasticity of output with respect to agricultural research is defined as the percentage increase in output production given a one percent increase in the agricultural research stock. In counter-intuitive fashion, these elasticities of output with respect to agricultural research are negative: -0.0009% (perennial crops), -0.0004% (livestock), and -0.0001% (annual crops). These elasticities are unexpected, but not completely unreasonable. Obtaining a negative elasticity implies agricultural research, considered as an input to production, acts like and competes with the outputs. A possible explanation for this result is that the model is over-parameterized, implying the full impact of agricultural research is statistically diluted. An over-parameterized model may leave insufficient explanatory power for all parameters in the model to be estimated robustly, thus leaving weak estimates. To determine how sensitive are the output elasticities with respect to agricultural research, I re-estimate (42) without the regional agricultural spillover stock variables. Excluding the cross-province agricultural research stocks made the elasticities of output with respect to agricultural research more negative. Therefore, the negative output elasticities with respect to agricultural research may not be an artifact of an excessive number of parameters.

The next question is whether the agricultural research stock is confounded with the time trend, a collinearity problem. The simple correlation between agricultural research stock and the time trend is 46%, too low to suggest the impacts of these two variables are confounded with one another. One explanation for formal research's weak contribution may be that Indonesian agricultural research staffs were historically concentrated in West Java, especially near Bogor. Gradually, staff and facilities have been extended to other regions, a process accelerated in the mid-1990s by the establishment of provincial research institutes. It may yet be too soon to witness decentralization's effects on local productivity change.

Output elasticities of regional agricultural research spillovers are, conversely, all positive. The elasticity is highest (0.021%) in perennial crops, second (0.010%) in livestock, and last (0.004%) in annual crops. These results were expected; they imply that knowledge obtained in one province of a region spills over into another in the form of boosting its outputs per unit input. The output elasticities (with respect to own-province and cross-province agricultural research) confirm my hypothesis that Indonesian agricultural research has not been contributing to technological growth. Why, however, are own-province output elasticities negative while cross-province output elasticities are positive? Further analysis is needed to precisely answer this question

Obtaining a technical change rate for the entire Indonesian agricultural sector is best accomplished by aggregating the rates across output categories, weighted by the outputs' respective mean shares of Indonesian agricultural revenue. On average, annual crops have had the highest revenue share (67%), followed by perennial crops (22.4%) and livestock (10.6%). The weighted-average annual total technical change rate is 1.41%, implying aggregate agricultural production at given input levels has at the frontier modestly expanded on an annual basis since 1985.

We may compare our weighted-average annual total technical change rate (1.41%) with those estimated in other studies. Fuglie (2004) found the growth in Indonesian total factor productivity, estimated via a chain-weighted Tornqvist-Thiel index, to be 1.70% per annum from 1961 to 2000. Coelli and Rao (2005), employing a Malmquist index of 93 countries from 1980 to 2000, estimated technical change in Indonesian agriculture to be 1.00% per annum during that period. Suhariyanto and Thirtle (2001), in a Malmquist-index-based study of the agricultural industry in eight Southeast Asian countries, found that, from 1965 to 1996, Indonesian agriculture enjoyed a 0.63% annual technical change rate.

2.4.3 Bias of Technical Change

An advantage of using a multi-output, multi-input method in productivity analysis is its ability to assess the magnitude and manner in which technical change influences output and input proportions at given price ratios. Appendix A.8 gives the relative value share changes in inputs and outputs caused by technical progress in the Indonesian agricultural sector - as measured by equation (17) - given transformation function (46). To interpret column (2) in Appendix A.8, we regard each statistic as the annual percentage change in the value share of the given output or input category induced by any annual rotation of the production possibilities, considered at the data mean.

The sign of each output and input in Appendix A.8 indicates whether cost or revenue share is rising or falling in that input's or output's direction as a result of technical change, holding prices constant. In no input or output category has there been a bias greater than 0.0056 in absolute value, implying no value share has changed more than 0.0056% as a result of a year of technical change. That is, the results seem to suggest that the Indonesian agricultural sector has experienced nearly Hicks-neutral technical change. Hicks neutrality implies the expansion paths in both input and output spaces are largely unchanged in the face of technical change. An unchanged expansion path implies technology-induced shifts in the isoquants or production possibility frontiers are in equal proportions in all input or output dimensions.

Appendix A.8 does suggest that technical change is marginally capital- and labor-saving while intermediates-using. It also implies that technical change is relatively annual-crops-favoring and livestock and perennial-crops-disfavoring. For example, from (17), each year of technical change has boosted annual crop revenue share by 0.0002% and reduced perennial-crops and livestock revenue share by 0.0003% and 0.0006%, respectively. Indonesian agriculture's technical change bias in favor of annuals relative to perennial crops and livestock likely is explained by the government's focus on sustaining food levels for an increasing population. That focus would require specialization in intermediate inputs, which tend to be directed toward annual crop production. A result of this focus is an agricultural policy that has engineered technical change bias in the direction of annual crops, despite that its technical progress is the lowest among the three output groups (0.66%) and that technical change bias (0.005%) in its direction has been negligible.

2.4.4 Technological Efficiency

As discussed above, our approach to estimating technical efficiency rests on the assumption of a heteroscedastic inefficiency error term. That assumption is confirmed by the likelihood ratio (LR) test. The output distance frontier estimated with a homoscedastic inefficiency error term has a log-likelihood of 594.46. The homoscedasticity restriction involves holding scale function $g(\ln z_{ait};\Omega)\eta_{it}$ to a constant. The log-likelihood of the output distance frontier estimated with a heteroscedastic error variance, equation (41), is 627.56. Thus, at the 1% level, the Chi-squared likelihood ratio test at two degrees of freedom confirms our hypothesis that technical efficiency in Indonesian agriculture is heteroscedastic and hence heterogeneous across provinces.[8]

Consider next Indonesian technical efficiency at provincial and national levels. Appendix A.9 reports our estimates of mean technical efficiencies by province, and annual mean technical efficiency in the entire sample. Column (2) details the mean provincial technical efficiencies (Mean T.E.) over the two sample decades. Column (3) presents mean provincial logarithmic changes in technical efficiency. Column (5) shows mean national technical efficiencies by year.

Appendix A.9 results are surprising. Although I hypothesized province-specific technical efficiencies to be high, only two provinces reveal a technical efficiency below 90%: Central Kalimantan (83.87%) and East Kalimantan (89.80%). In fact, most provinces appear to be nearly perfectly technically efficient. Bali, Yogyakarta, East Java, South Sulawesi, and NTB all lie within 99% technical efficiency. Furthermore every province, except Jambi (0.07%) and Dista Aceh (0.09%), displays decreasing technical efficiency over time. This contradicts my initial hypothesis that the average farmer is converging to the 'best-practice' frontier.

During the 1985 to 2005 period, Indonesia's agricultural mean technical efficiency was 95.64%.[9] We may compare our 1985-2005 mean technical efficiency level with that found in Coelli and Rao (2005). As stated above, Coelli and Rao estimated, using a Malmquist index, an Indonesian agricultural mean technical efficiency of 97.8% between 1980 and 2000. Computing the mean technical efficiency each year, then the logarithmic mean rates of change between years, implies an average annual mean technical efficiency decrease of -0.39%. This time rate of change implies that, in the aggregate, the average farmer slowly diverges from the frontier, namely at roughly one-half percentage point per year. Suhariyanto and Thirtle (2001) obtained an Indonesian agricultural annual mean technical efficiency change of -0.45% between 1965 and 1996. Their technical efficiency change was estimated relative to the 1965 efficiency level, for which Indonesia was 100% efficient. The latter analysis implies the average farm was diverging from the technological frontier during this period.

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[8] LR chi2(2) = 66.19; Prob > chi2 = 0.0000

[9] The 95 % confidence interval for national mean technical efficiency is (0.95, 0.96).

2.4.5 Explaining Technical Inefficiency

The agricultural productivity literature frequently has employed a two-stage estimation process for explaining, or sourcing, productivity (Ball, et al., 2001, Huffman and Evenson, 1993, Yee, W.E. and Newton, 2002). It involves estimating productivity growth deterministically or stochastically in a first stage, followed by a second in which that growth is explained and hypotheses tested via a stochastic regression. The goal of the second stage is to examine the determinants of productivity growth and thus allow for policy recommendations. The two-stage approach has been utilized to reduce the multicollinearity often found when employing many strongly trended variables. But if the explanatory variables employed in the first stage are correlated with those in the second, the first stage is biased on account of the omitted variables.

In the stochastic frontier literature, in contrast, the model explaining the influence of exogenous policy variables on technical inefficiency is estimated under the same likelihood function, that is simultaneously with, the technical change function. The technical inefficiency model can explain inefficiency through either of the first two moments of the inefficiency error term, u_{it}. Battese and Coelli (1995) employ the first moment; Caudill, Ford, and Gropper (1995) utilize the variance; and Wang (2002), and Alvarez, Amsler et al. (2006) employ both moments for this purpose.

Road density representing transportation infrastructure, and literacy representing education, are used in equation (42) to explain the variance of technical inefficiency. Road density ought to increase producer efficiency because access to paved roads reduces the time necessary for transporting output production to markets, reducing spoilage and thus enhancing profit. Literacy proxies for education. As farmer education increases, farmers should be able to absorb and adapt to disseminated technical information more easily, improving productive efficiency. Results of equation (42) are provided in Appendix A.10. The significant negative road density coefficient estimate in Appendix A.10 indicates that those provinces with higher road density have a lower technical inefficiency variance. The estimated coefficient of literacy, significant at the 2% level, implies those provinces with higher literacy have a higher technical inefficiency variance.

We are also interested in the influence of these exogenous policy variables on the mean technical efficiency of the Indonesian agricultural sector. Using equation (31) and the estimated coefficients from Appendix A.10, we find the impact of road density and literacy on mean technical efficiency is respectively 0.0003 and -0.0098. Increasing road density by one percent thus increases mean technical efficiency by only 0.0003%, and increasing literacy decreases expected technical efficiency by only 0.01%. One may question why these policy variable impacts on mean technical efficiency are so small. The explanation might lie in the structure of the squared-errors. In OLS, total sum squared error (TSS) equals regression sum squared error (RSS) plus error sum squared error (ESS), or TSS = RSS + ESS. In the stochastic frontier framework, in contrast, total sum squared error (TSS) equals model sum squared error (MSS) plus technical inefficiency sum squared error (TISS) plus idiosyncratic sum squared error (ISS), or TSS = MSS + TISS + ISS. Thus if MSS is significantly greater than TISS or ISS, it is possible for the policy variables to significantly explain the technical inefficiency variance yet have a very small impact on its expectation. Post-estimation computation of the respective squared error components obtains a TSS of 302.97, comprising an MSS of 286.11, a TISS of 2.94, and an ISS of 13.91. Confirming my hypothesis, MSS is proportionately much greater than TISS.

2.5 Conclusion

I have examined technical progress and productive efficiency in the Indonesian agricultural sector from 1985 to 2005. The methodology improves on previous agricultural productivity research by utilizing a disaggregated data set and a multi-output fixed-effect stochastic frontier in which both time-invariant unobserved heterogeneity and time-varying inefficiency heterogeneity are accounted for. Our approach provides technical change rates for each of three Indonesian agricultural output categories and province-specific mean technical efficiencies. The empirical analysis suggests aggregate technical change, estimated at the frontier, has been 1.41% per annum, and in perennial crop production 3.50% per annum. The combination of such frontier growth with high but declining mean technical efficiency suggests an agricultural sector in transition. It is changing not only from an agriculture-first policy to an industry-first one, but from a centralized, top-down productivity policy approach to a decentralized one.

Future research should focus on the impact on productive efficiency of Indonesia's provincial technology assessment centers. Through these provincial technology conduits, the Indonesian government has the best opportunity to reverse the growing divergence of the average farmer from the 'best-practice' frontier. To exploit Indonesia's comparative advantages, agricultural policy should continue to redirect its focus toward perennial crop production in order to make best use of the high rate of technical change already occurring in that sector. Pursuing gains from technical change in perennial crop production, accrued by informal information, increasing investments agricultural research, and improving farmers' literacy appear to be the best path for developing Indonesia's agricultural sector. Technological expansion in perennial crops has served to release labor from the geographic areas in which perennial crop production dominates. Some of that excess labor can provide entrepreneurship services such as transportation or inventive perennial crop by-products, while the remainder may be released to search out higher wages in the fast-growing manufacturing sector or education.

Chapter 3: Brazil's Rising Agricultural Productivity and World Competitiveness

3.1 Motivation

Brazilian agriculture historically has been export-oriented, supplying the world market with raw agricultural commodities such as sugar, rubber, cocoa, cotton, and coffee. Cycles of boom-and-bust have occurred periodically in each of these commodities. For example, from 1950 to 1963, coffee constituted 90% of all Brazilian exports (Graham, Gauthier and Mendonca de Barros, 1987). Agricultural production traditionally has taken place on the extensive margin and employed labor-intensive methods of production. Agriculture maintained the highest share of GDP until the mid-1950s, when a government focus on intensive industrialization made manufacturing the economy's dominant sector (Baer, 2008).

From 1945 until the 1980s, Brazilian governments have enacted multiple cycles of free-trade and protectionist policies. Post World War II policies were free-trade oriented, with a focus on controlling inflation (Baer, 2008). A tidal wave of protectionism evolved from the United Nations Economic Commission for Latin America (ECLA), which promoted import-substitution-industrialization (ISI) strategies for Latin American countries. ISI strategies assume balanced growth (imports to equal exports) in their model of development, in which an industrialized center and an agricultural periphery equate differential incomes through an increase in the proportion of capital goods supplied by the agricultural periphery (Prebisch, 1959). Governmental policies that support ISI strategies protect infant domestic industries through high protective barriers, including tariffs, quotas, and licenses (Dornbusch, 1998). During the 1950s and 1960s, Brazil looked to the ISI model to realize an economic growth other industrialized countries had achieved by way of an independent domestic industrial base. In particular, it focused its industrialization towards transportation equipment, machinery, electric machinery & appliances, and chemicals. The ISI strategy intensified under President Juscelino Kubitschek (1956-1961). Kubitschek set a goal of rapid technical change in the industrial sector, which internationalized the Brazilian economy in part by relying on multi-national companies to supply foreign technologies (embodied technical changes) and improve organizational efficiencies (disembodied technical changes) (Baer, 2008).

The Brazilian ISI policies, created to establish capital formation industries while reducing the use of foreign exchange and curbing foreign debt, laid the foundation for modernizing the agricultural sector (Schnepf, Dohlman and Bolling, 2001). Initially, the ISI era was known for dampening agricultural producer incentives through social policies favoring cheap food for an increasingly urban consumer. Such policies disfavored export-oriented agricultural production through export and price controls, import licenses and restrictions, and currency controls (Schnepf, Dohlman and Bolling, 2001).[10] By the 1960s fears of industrial stagnation, attributed to a lack of export revenues and a heavy reliance on imported capital, led the Government to re-embrace free trade opportunities with a focus on exportable agricultural commodities such as soybeans. To this end, governmental policies directly promoted the soybean industry through publicly funded agricultural research, guaranteed minimum price supports, agricultural input subsidies, and public infrastructure programs (Schnepf, Dohlman and Bolling, 2001).[11]

A military *coups d'état* in 1964 altered economic planning toward a more balanced approach between internationalization and protectionism. The approach focused on a rapid increase in international trade via export diversification while concurrently pursuing ISI ideologies focused on boosting domestic capital production. To improve foreign trade, state export taxes were abolished, administrative procedures for exporters were simplified, and export tax incentives and subsidized credit were provided for exporters (Baer, 2008). By the late 1960s, the domestically-focused ISI policies established an industrial foundation for the production of agricultural machinery, fertilizer, and chemical inputs.

In 1965, The National System of Rural Credit was established to quicken new technology adoption, prompt capital formation, and increase foreign exchange through growth in exportable agricultural commodities (Schnepf, Dohlman and Bolling, 2001). Adding an inflationary policy of cheap rural credit to the domestic industrial foundation

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[10] By the mid-1960s, 84% of agricultural exports were unprocessed raw commodities, whereas by the early 1990s these primary commodities declined to be only 20% of agricultural exports (Baer, 2008)
[11] Schnepf, Dohlman, and Bolling (2001) report that only in 2 of the last 30 years has the national average soybean price fallen below the governmental minimum price support price.

created the first of two agricultural transformation phases: that of mechanized agricultural production, increased land concentration, and rural-to-urban labor migration (Graham, Gauthier and Mendonca de Barros, 1987). This first phase of agricultural transformation created a high demand for food production (Baer, 2008). A pre-existing food shortage problem was aggravated by the displacement of food-crop production to frontier areas. Increasing in the distance between urban consumers and food-crop production lifted food prices and strained the country's poor transportation infrastructure.[12]

The second phase of agricultural transformation came in the 1970s and early 1980s. Three factors of this phase have played critical roles in the growth Brazilian agriculture is presently experiencing. The first factor was a continued opening of the economy, in which soybeans drove an expansion of processed and semi-processed agricultural exports. Graham, Gauthier, and Mendonca de Barros (1987) estimate that metric tonnage of soybeans grew 17.88% from 1961 to 1970, and 18.61% from 1971 to 1980. A second study shows soybean production between 1966 and 1977 grew at a rate of 37.6% per annum, making Brazil the third largest soybean producer and second largest soybean exporter by the mid-1970s (Baer, 2008). Export subsidies to promote processed agricultural exports, specifically soybeans, coincided with trade controls and quotas to discriminate against agricultural producers of other primary commodities in favor of agro-industrial processors (Graham, Gauthier and Mendonca de Barros, 1987). One such example was a 50% export-tax imposed on coffee producers in the late 1970s (Helfand and Rezende, 2001). With growth in selected agricultural commodities for export, food-crop production was continually marginalized to frontier areas. In keeping with the previous era's mechanized production transformation, land holdings were increasingly consolidated, land prices rose, and labor was altered from tenancy and shareholding arrangements to seasonal, temporary opportunities (Graham, Gauthier and Mendonca de Barros, 1987). Subsidized rural credit became the primary policy instrument for initiating agricultural growth, with total agricultural credit as a proportion of agricultural

[12] As of 2001, only an estimated 10% of Brazil's highways were paved (Schnepf, Dohlman and Bolling, 2001). In the state of Mato Grasso, the least-cost mode of transportation was by river, with costs increasing if producers chose to transport by rail or road. (Matthey, Fabiosa and Fuller, 2004).

GDP peaking at 94.1% in 1976 (Graham, Gauthier and Mendonca de Barros, 1987). Unfortunately the dispersion of rural credit was highly skewed to the larger, more technically advanced farms, and the success of rural credit programs became questionable as the demand for automobile credit rose (Baer, 2008).

A continuation of import-substitution strategies in the 1970s and early 1980s was an additional factor in the second phase of Brazil's agricultural transformation. One such ISI strategy was energy independence, denoted by the establishment of PROALCOOL in 1977. PROALCOOL is a government program designed to substitute sugarcane ethanol for imported petroleum (Baer, 2008). This initiative further pushed agricultural production to the frontier, this time driving livestock and soybean production toward the center-west region (Graham, Gauthier and Mendonca de Barros, 1987, Schnepf, Dohlman and Bolling, 2001).

The third factor contributing to Brazil's second phase of agricultural transformation was the establishment of Embrapa (Empresa Brasileira de Pesquisa Agrpecuaria) in 1973, under the Ministry of Agriculture and Food Supply. Embrapa is a national agricultural research agency, organized along federal lines and involving cooperation between federal and state experiment stations, created to increase human capital investments, provide regionalized research and development to improve small land-holder productivity, and increase yields in the acidic soils of the frontier regions of the southeast and center-west (Graham, Gauthier and Mendonca de Barros, 1987). Embrapa employs a decentralized model of agricultural research that allows localized research into crops and ecosystems and cooperation on product development with private seed producers and farm organizations (Matthey, Fabiosa and Fuller, 2004). Prior to the re-organization of the national agricultural research system creating Embrapa, agricultural development focused on exportable crops, agricultural research was underfinanced and poorly managed, and investment in human capital formation and rural extension services was lacking (Graham, Gauthier and Mendonca de Barros, 1987).[13]

Embrapa has enjoyed significant success in adapting tropical soybeans, corn, and cotton varieties to the acidic soils and climate of the center-west, along with some areas

[13] Graham, Gautheir, and Mendonca de Barros (1987) do note the exception of Sao Paulo's research efforts on exportable commodities coffee and cotton.

in the north and northeastern regions (Schnepf, Dohlman and Bolling, 2001). Moreover, from 1983 to 2007, Baer (2008) cites Embrapa's agricultural research and development as an important determinant of the observed increase in land productivity (measured in kilograms per hectare) of cotton, rice, sugarcane, corn, wheat, and soybeans.

Brazil has largely transformed its agricultural sector into a world agricultural powerhouse. As the U.S. share of world soybean exports declined from 79% to 32% from the 1970s through 1990s, Brazil's share rose from 9% to 28% (Schnepf, Dohlman and Bolling, 2001). Brazil now is the largest coffee, sugar, and fruit juice producer, second-largest soybean and beef producer, and third-largest corn and broiler producer (Production Supply and Distribution Database, 2008). It has overtaken the U.S. in poultry exports, nearly matches the U.S. in soybean exports, and dominates global trade in frozen orange juice. The Brazilian agricultural transformation, founded in the ISI era, developed a traditional agricultural system into an agro-industrial complex. The transformation was sustained through large-scale production of exportable agricultural commodities, favorable international prices and governmental policies, and rapid technical change in the agro-industrial sector (Baer, 2008). With the removal of discriminatory policies against food producers in the mid-1980s, sufficient incentives allowed the agro-industrial complex to modernize food production. One example is rice production in Rio Grande do Sul and Santa Catarina.[14] These states employ modern irrigation technologies that allow a higher quality and quantity of rice to be produced (Helfand and Rezende, 2001). By the late 1980s, policies that liberalized international trade, stabilized domestic prices, and attempted to eliminate state agricultural monopolies in sugar, alcohol, coffee, and wheat allowed agribusinesses to become increasingly influential in the agricultural sector (Baer, 2008). Agriculture's share of GDP from 1985 to 2005 is provided in Appendix B.2. These shares provide insight into the stability of the agricultural sector, its share of the economy averaging 8.25% from 1985 to 1995, and 8.34% from 1985 to 2005.

The interest of the present analysis is to examine agricultural productivity growth from 1985 to 2006. Unfortunately the 2006 agricultural census, scheduled to be publicly available in July of 2008, has yet to be entirely published. We therefore focus on the

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[14] Rio Grande do Sul accounted for 40% of Brazilian rice production in 1991 (Baer, 2008).

Post-Green revolution timeframe of 1985 to 1995/1996. We estimate state and national total factor productivity (TFP) growth via Fisher index number theory. The analysis employs 19 output commodities and 9 conventional inputs. To complement the productivity analysis, we use a stochastic multi-product output distance frontier to estimate state and national mean growth technical efficiency from 1985 to 1995/1996. These state-level growth inefficiency estimates allow an examination of the proportion of productivity growth achieved by average farms. In the absence of adequate time-series of panel data for directly estimating state and national technical change rates from the stochastic output distance frontier, I impute technical change as the ratio of a Fisher TFP growth rate to a stochastically estimated growth efficiency measure. Such TFP decomposition assumes allocative efficiency on Brazilian farms and a constant-returns-to-scale technology. We find the national decennial total factor productivity growth from 1985 to 1995/1996 to have been 20.2%. In light of a Brazilian mean growth efficiency of 91.2%, the imputed national decennial Brazilian agricultural technical change rate was 22.2%.

3.2 The Theoretical Specification

For measuring multi-input and multi-product productivity growth, the Fisher productivity quantity index best satisfies index number theory's axiomatic approach (Diewert, 1992). The index, developed originally as a price index by Fisher (1922 & 1927 , p. 360), is the ratio of a Fisher ideal output quantity index to a Fisher ideal input quantity index. The Fisher ideal index is defined as the geometric mean of the Laspreyes and Paasche quantity indices. The Laspreyes quantity index is defined as,

$Q_L(p^{t+1}, p^t, x^{t+1}, x^t) = \dfrac{p^t x^{t+1}}{p^t x^t}$, where $p^t, p^{t+1}, x^t, x^{t+1} \gg 0$, are strictly positive price and quantity vectors $\left(p, x \in \mathbb{R}_+^M\right)$, respectively, and t refers to the time period. Alternatively, the Paasche quantity index is defined as $Q_P(p^t, p^{t+1}, x^t, x^{t+1}) = \dfrac{p^{t+1}x^{t+1}}{p^{t+1}x^t}$, with the same definitions as in the Laspreyes quantity index. Thus, the Fisher ideal quantity index is defined as,

(1) $$Q_F(p^t, p^{t+1}, x^t, x^{t+1}) = \left[\frac{p^t x^{t+1}}{p^t x^t} \cdot \frac{p^{t+1} x^{t+1}}{p^{t+1} x^t} \right]^{1/2}.$$

The Fisher ideal quantity index is superlative, or a quantity index which corresponds to a functional form capable of providing a second-order approximation to an arbitrarily twice differentiable linear homogenous function (Diewert, 1976).

3.2.1 From Output Distance Function to Frontier

To develop our econometrically tractable multi-product output distance frontier, let $y_{ji} \in \mathbb{R}_+^M$, $j = 1...M$ be an output scalar; $x_{ki} \in \mathbb{R}_+^N$, $k = 1...N$ a conventional input scalar; and $i = 1...I$ indicate observations defining the technology $T = \{(x_{ki}, y_{ji}) : x_{ki}$ can produce $y_{ji}\} \in \mathbb{R}_+^{N+M}$. The producible output set, a subset of technology T, identifies the feasible output vectors (y_{ji}) constrained by fixed input vectors (x_{ki}^o) in an economy of $M + N$ commodities, indicated as $P(x_{ki}^o) = \{y_{ji} \in \mathbb{R}_+^M : (x_{ki}^o, y_{ji}) \in T\}$. We define the output distance function from the producible output set as (Färe and Primont, 1995),

(2) $$D_O(x_{ki}, y_{ji}) = \inf_{\theta}\{\theta > 0 : y_{ji}/\theta \in P(x_{ki}^o)\} \ \forall\ x_{ki} \in \mathbb{R}_+^N.$$

Distance functions are credited to Shephard (1953), (1970). From (2), $D_O(x_{ki}, y_{ji}) \le 1$ if and only if $(x_{ki}^o, y_{ji}) \in T$, assuming weak disposability of outputs (Färe and Primont, 1995). If outputs are located on the outer boundary of $P(x_{ki}^\circ)$, then $D_O(x_{ki}, y_{ji}) = 1$ implying technical efficiency is maximized.

Stochastic frontier estimation was first proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) and prescribes output variation to be explained by input variation, an idiosyncratic error term, and a technical inefficiency error term. Consider a stochastic expression of the Shephard multi-product distance function

(3) $$D_O(x_{ki}, y_{ji}, \beta) = e^{\varepsilon_i},$$

where β is a vector of parameters to be estimated and ε_i is an observation-specific error specified in exponential form. In (3) the stochastic distance frontier decomposes error term ε_i into the difference of two errors, $v_i - u_i$, so that with manipulation, the stochastic output distance frontier is

(4) $$e^{-u_i} = \frac{D_O(x_{ki}, y_{ji}, \beta)}{e^{v_i}}.$$

The idiosyncratic error term in (4), v_i, is assumed independently and identically distributed (iid), symmetric, with mean zero and variance σ_v^2 $\left(v_i \sim iid\ N(0, \sigma_v^2)\right)$. The inefficiency error u_i is a nonnegative random error term accounting for each observation's distance to the stochastically estimated frontier. u_i is assumed independently and half-normally distributed $\left(u_i \sim N^+(0, \sigma_u^2)\right)$. The two error terms, v_i and u_i, are assumed distributed independently of each other: $\sigma_{vu} = 0$. Error distributional assumptions follow from Battese and Coelli (1988).

Technical efficiency of the output distance frontier is obtained by dividing by e^{-u_i}, such that (4) becomes

(5) $$D_O(x_{ki}, y_{ji}, \beta) e^{(u_i - v_i)} = 1.$$

Moreover, to evaluate the data at its mean implies the stochastic output distance frontier is no greater than unity:

(6) $$D_O(x_{ki}, y_{ji}, \beta) e^{-u_i} \leq 1.$$

To guarantee positive numbers for the Shephard output distance frontier, we parameterize input-output relation $D_O(x_{ki}, y_{ji}, \beta)$ as $e^{h(\ln x_{ki}, \ln y_{ji}, \beta)}$. If we substitute the exponential form of $D_O(x_{ki}, y_{ji}, \beta)$ into (5), we have

(7) $$e^{h(\ln x_{ki}, \ln y_{ji}, \beta)} e^{(u_i - v_i)} = 1.$$

We obtain an estimable stochastic distance frontier by rearranging terms:

(8) $$e^{h(\ln x_{ki}, \ln y_{ji}, \beta)} = e^{(v_i - u_i)}.$$

A required property of any output distance function is that of linear homogeneity of degree +1in outputs. Therefore to ensure $e^{h(\ln x_{ki}, \ln y_{ji}, \beta)}$ is a distance function, we impose linear homogeneity on (8) by normalizing each of the outputs with a numeraire output.[15] Imposing output linear homogeneity through normalization is an elegant approach to estimation as it provides a dependent variable naturally lacking in distance functions. Output linear homogeneity of degree +1 is maintained by requiring that $D_O(x_{ki}, \omega y_{ji}, \beta) = \omega D_O(x_{ki}, y_{ji}, \beta),$ for any $\omega>0$ (Shephard, 1970). Let $y^*_{ji} = {y_{ji}}\big/{y_{mi}} \neq +\infty,$ $y_{ji} \neq 0$, and $j = 1...m-1$, in which the m^{th} output is chosen as numeraire (Lovell, et al., 1994). Substituting $\frac{1}{y_m}$ for ω, we then have from (8)

$$e^{h(\ln x_{ki}, \ln y^*_{ji}, \beta)} = \frac{1}{y_{mi}} e^{h(\ln x_{ki}, \ln y_{ji}, \beta)}, \tag{9}$$

and by substituting (8) into (9) provides

$$e^{h(\ln x_{ki}, \ln y^*_{ji}, \beta)} = \frac{e^{(v_i - u_i)}}{y_{mi}}. \tag{10}$$

Taking logs of (10) and rearranging terms brings

$$-\ln y_{mi} = h(\ln x_{ki}, \ln y^*_{ji}, \beta) + u_i - v_i. \tag{11}$$

From (11), technical efficiency estimation employs the predicted logs of the i^{th} observation's output distance:

$$e^{-u_i} = D_O(x_{ki}, y_{ji}, \beta). \tag{12}$$

These predicted values are unobservable and must be derived from the composed error term, ε_i. In the present analysis, observation-specific predicted values are expressed as (Battese and Coelli, 1988)

$$\widehat{TE}_i = E\left[\exp(-u_i) \mid \varepsilon_i\right]. \tag{13}$$

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[15] In the production frontier framework, output linear homogeneity of degree +1 means scaling the output vector in given positive proportion scales output distance, or technical efficiency, in the same proportion.

3.2.3 Explaining Productive Efficiency

To estimate productive efficiency in a manner that allows inefficiency to be explained by policy variables, the variance of technical inefficiency error u_i is allowed to be heteroscedastic. Heteroscedasticity is theoretically prevalent for multiple reasons, but especially when resource size is a significant component of production. In the present study, rather than the homoscedastic u_i employed in the equations above, the model permits inefficiency error u_i to be heteroscedastic by way of a one-sided error term

(14) $$u_i \sim N^+(0, \sigma^2_{u,i}),$$

in which N^+ indicates the half-normal distribution and $\sigma^2_{u,i}$ is a heteroscedastic variance dependent upon micro-region *i*.

To estimate mean impacts of state-level policy variables on inefficiency error variance $\sigma^2_{u,i}$, and thus on mean technical efficiency, we associate u_i with a vector of exogenous policy variables $\ln z_{ai}$ and a vector of parameters Ω in multiplicative form

(15) $$u_i = g(\ln z_{ai}; \Omega)\eta_i,\ a = 1...A.$$

g in equation (15) is a scaling function, a represents the a^{th} policy variable, and η_i is an iid random variable such that $\eta_i \geq 0$, $E(\eta_i) = 1$, and $V(\eta_i) = \sigma^2_\eta$. Scaling-factor g integrates observable characteristics that affect observation-specific inefficiency. η_i establishes the basic inefficiency level while policy variables $\ln z_{ai}$ capture differing features of the environment in which micro-regions operate. Including such observable characteristics alters equation (8) to become

(16) $$e^{h(\ln x_{ki}, \ln y_{ji}, \beta)} = e^{(\nu_i - g(\ln z_{ai}; \Omega)\eta_i)}.$$

A parametric specification of $g(\ln z_{ait}; \Omega)\eta_{it}$ is required to estimate equation (11) in a manner incorporating (15) and (16). Following (Simar, Lovell and Vanden Eeckaut, 1994), we specify g in exponential form, so that (15) becomes

(17) $$u_i = g(\ln z_{ai}; \Omega)\eta_i = \exp(\ln z_{ai}'\Omega)\eta_i.$$

The mean and variance of inefficiency error u_i then are

(18) $$E(u_i) = \exp\left\{\ln z_{ai}{}^{'}\Omega\right\} > 0, \text{ and}$$

(19) $$V(u_i) = \sigma_{u,i}^2 = g(\ln z_{ai}, \Omega)^2 \sigma_\eta^2 = \exp\left\{2\ln z_{ai}{}^{'}\Omega\right\}\sigma_\eta^2.$$

Substituting (16)'s parametric specification into (11), we obtain

(20) $$\begin{aligned} -\ln y_{mi} &= h(\ln x_{ki}, \ln y_{ji}^*, \beta) + g(\ln z_{ai}; \Omega)\eta_i - v_i, \\ &= h(\ln x_{ki}, \ln y_{ji}^*, \beta) + \exp\left\{\ln z_{ai}{}^{'}\Omega\right\} + \varepsilon_i, \end{aligned}$$

where,

(21) $$\varepsilon_i = -v_i + \exp\left\{\ln z_{ai}{}^{'}\Omega\right\}(\eta_i - 1).$$

To estimate policy impacts on technical inefficiency variance $\sigma_{u,i}^2$, we constrain u_i such that from (19) we have

(22) $$\ln \sigma_{u,i}^2 = \ln \sigma_\eta^2 + 2\ln z_{ai}{}^{'}\Omega,$$

where $\ln \sigma_\eta^2$ is an intercept, and estimates $\widehat{\Omega}$ provide the elasticities of technical inefficiency variance with respect to the exogenous policy variables. To obtain mean technical efficiency estimates, we apply equation (23):

(23) $$\widehat{TE}_i = E\left[\exp(-u_i \mid \varepsilon_i)\right] = E\left[e^{-\exp\{\ln z_{ai}{}^{'}\Omega\}} \mid \varepsilon_i\right].$$

While equation (22) allows exogenous policy variables to explain variations in technical inefficiency variance $\sigma_{u,i}^2$, our interest is drawn to how these exogenous policy variables impact, or shift, national mean technical efficiency. To this end, we differentiate the national-level mean predicted technical efficiency with respect to the exogenous policy variables, shown as

(24)

$$\frac{\partial \ln \widehat{TE}_i}{\partial \ln z_{ai}} = \frac{\partial \ln E\left[e^{-\exp\{\ln z_{ai}{}^{'}\Omega\}} \mid \varepsilon_{it}\right]}{\partial \ln z_{ai}} = -\exp\{\ln z_{ai}{}^{'}\Omega\}\left(\frac{\partial \exp\{\ln z_{ai}{}^{'}\Omega\}}{\partial \ln z_{ai}}\right).$$

3.3 Brazilian Application

Brazil’s land mass encompasses 27 states in 5 regions and covers over half of the South American continent (Baer, 2008). Details of the respective states and regions are presented in Appendix B.4. As United States’ global share of major field crops increasingly erodes, understanding Brazil’s agriculture productivity, and more generally their agricultural competitiveness, is imperative in allowing U.S. policy makers to assess and act upon these changes.

Structural changes in the agricultural sector provide insight into factor share changes. The number of farm establishments, land area, labor counts, and tractor counts are detailed in Appendix B.3 for agricultural census years 1975, 1985, 1995/1996, and 2006. Column 7 of of Appendix B.3 suggests surprising changes in the number of establishments (-17.7%), total agricultural area (-5.9%), cropland (-22.1%), labor (-26.6%), and tractor inventories (18.9%). Land consolidation may be a major reason for the decrease in the number of farm establishments between 1985 and 1995/1996. Furthermore, mean increases in agricultural productivity may have induced inefficient farms to exit the sector. A decrease in total agricultural cropland suggests a shift from producing on the extensive margin to increasing yields. A decline in labor, with an increase in the number of tractors, suggests a labor-saving and capital-using bias in technical change.

But Helfand and Brunstein (2000) argue that these structural change indicators overestimate actual change. Helfand and Brunstein emphasize two problems with the 1995/1996 census: weak comparability with previous censuses, and weak representation of mid-1990s agricultural production (Helfand and Brunstein, 2000). Weak comparability of the 1995/1996 census to previous census studies is particularly owing to the reference-period which, between census years 1985 and 1995/1996, changed from January 1 – December 31 to August 1 – July 31. Thus the planting and harvesting periods differ between the pre-1995/1996 censuses and the 1995/1996 census, altering data continuity. Compounding the problems associated with the 1995/1996 census, 1994 was the start of an increasingly rationed agricultural credit regime which, in turn, influenced plantings in 1995 (Baer, 2008). Helfand and Rezende (2001) add that with implementation of the Real Plan and the introduction of the new Real in 1994, high interest rates created an incentive for producers to buy capital assets.[16] That in turn pushed land, cattle, and agricultural commodity prices downward in early 1995. With an increase in agricultural investment and credit, the price declines resulted in the most severe agricultural financial crisis in Brazilian history (Helfand and Rezende, 2001).

Brazilian agricultural productivity analyses generally have followed non-stochastic methods of estimation. Avila and Evenson (1995) employ a Törnqvist-Thiel index number approach from 1970 to 1985 to obtain regional TFP growth rates per annum of: north (1.31%), northeast (1.60%), southeast (3.06%), south (1.46%), and the center-west (3.80%). Helfand and Rezende (2001) cite Barros (1999), whose Brazilian agricultural productivity dissertation employed a growth accounting approach. Barros (1999) concluded that Brazil's agricultural TFP grew by 20% between 1975 and 1995, most of the growth coming in the 1990s (Helfand and Rezende, 2001). da Silva Dias and Amaral (2000) estimated agricultural productivity levels by index number theory from 1987 to 1998. The percentage change estimated from their crop- and livestock-composed 1987 – 1996 agricultural productivity index was 22.8%. Pereira, da Silveira, Lanzer, and Samohyl (2002) employ a Malmquist productivity index to estimate state, regional, and national agricultural TFP. Their analysis accounts only for states existing in 1970, thus excluding two important states in frontier agricultural production: Mato Grosso do Sul and Tocantins (Pereira, et al., 2002). They estimate annual TFP growth rates from 1970 to 1996 of: north (-0.71%), northeast (-0.62%), southeast (5.00%), south (4.63%), center-west (7.30%), and Brazil (4.81%). Lastly, Vicente (2004) estimated mean state, regional, and national technical efficiency levels for agricultural crop production in 1995. Fisher quantity output indices were employed in Data Envelopment Analysis (DEA) estimation to obtain regional and national technical efficiencies of: northeast (0.51%), north (0.84%), southeast (0.89%), south (0.69%), center-west (0.92%), and Brazil (0.72%).

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[16] For a comprehensive analysis of the Real Plan, please see Chapter 7 of Baer (2008).

3.3.1 Applied Methodology

The present analysis estimates, from 1985 to 1995/1996, state and national Fisher quantity TFP growth rates, along with output- and input-growth from each of the three Fisher output and input indices. To obtain growth technical efficiency estimates, three output and input Fisher quantity-growth indices are used to econometrically estimate output distance frontier (20). Such estimates have implications for government agricultural research and extension policy. We highlight those states which exhibit high technical changes and low growth efficiencies. Enhancing agricultural extension services and local adaptive-research capacity allows farmers to make better use of existing technology and hence move closer to their own technological possibilities. The marginal cost of these improvements likely will be low because the technology for realizing them is already in place.

To apply our theoretical model, let $y_{ji} \in \mathbb{R}_{+}^{3}$ be an output scalar, with $j = 1,...,3$ representing the Fisher output growth indices for perennial crops, annual crops, and livestock. Let $x_{ki} \in \mathbb{R}_{+}^{3}$ be a conventional input scalar, with $k = 1,...,3$ representing the Fisher input growth indices for labor, capital, and material inputs. Lastly, let $i = 1,...,557$ indicate the Brazilian micro-regions. Our growth efficiency analysis uses the livestock Fisher output quantity growth index as the numeraire output because the livestock growth index recorded the largest increase between 1985 and 1995/1996.

The translog quadratic input-output distance relation $D_O(\ln x_{ki}, \ln y_{ji}^{*}, \beta)$ is expressed as

(25)
$$D_O(\ln x_{ki}, \ln y_{ji}^{*}, \beta) = \beta_0 + \sum_{k=1}^{N} \beta_k \ln x_{ki} + \sum_{j=1}^{M-1} \beta_j \ln y_{ji}^{*} + \frac{1}{2} \sum_{k=1}^{N} \sum_{h=1}^{N} \beta_{kh} \ln x_{ki} \ln x_{hi} + \frac{1}{2} \sum_{j=1}^{M-1} \sum_{l=1}^{M-1} \beta_{jl} \ln y_{ji}^{*} \ln y_{li}^{*} + \sum_{k=1}^{N} \sum_{j=1}^{M-1} \beta_{kj} \ln x_{ki} \ln y_{ji}^{*},$$

or more simply as

(26)
$$D_O(\ln x_{ki}, \ln y_{ji}^{*}, \beta) = \beta_0 + TL(\ln x_{ki}, \ln y_{ji}^{*}, \beta).$$

To incorporate fixed-effects into the multi-output distance frontier, dummy variables are included for each of the 27 states. Fixed-effects capture unobserved cross-state heterogeneity present in the data, yet not accounted for in the quality-adjusted conventional inputs. Including dummy variables to account for fixed-effects in stochastic frontier models is recommended provided the time-invariant unobserved heterogeneity modeled is not efficiency-related (Greene, 2005). Specifying (26) to include fixed-effects allows us to write

$$D_O(\ln x_{ki}, \ln y^*_{ji}, \beta) = \beta P_s + TL(\ln x_{ki}, \ln y^*_{ji}, \beta), \tag{27}$$

where subscript $s = 1,....,27$ represents the state dummy variables. To obtain an estimable model, substitute (27) into (20):

$$-\ln y_{mi} = \beta P_s + TL(\ln x_{ki}, \ln y^*_{ji}, \beta) + \exp\left\{\ln z_{ai}{}'\Omega\right\} + \varepsilon_i. \tag{28}$$

To estimate the factors impacting state-level mean growth inefficiencies, we apply the variance characterization of u_{it}, equation (22), and employ the policy variables in log-linear form, so that (22) becomes

$$\ln \sigma^2_{u,i} = \alpha_0 + \alpha_1 \ln PublicEducation_i + \alpha_2 \ln RuralEduction_i + \omega_i;\ \omega_i \sim N(0, \sigma^2). \tag{29}$$

Model (29) explains agriculture's growth inefficiency variance in Brazil by a constant, real per-capita state-level expenditure on public education, and the average number of schooling years of the rural population over the age of 10. For estimation purposes, we assume per-capita state-level expenditures in each state are equally divided amongst all micro-regions in that state. Equations (28) and (29), employing functional form (27) are estimated jointly with Full Information Maximum Likelihood (Stata Version 2008).

3.3.2 Data: Outputs, Inputs, and Exogenous Policy variables

The data employed in the present analysis come from the 1985 and 1995/1996 Brazilian agricultural censuses. Census data are obtained from the Instituto Brasileiro de Geografia e Estatística (IBGE, 2009), while supplementary data is also obtained from the Food and Agricultural Organization of the United Nations (FAO, 2009), and the World Bank. The farm-level survey data collected in the agricultural censuses are recorded at two levels: the micro-region and the state. The 557 micro-regions vary in number within each of the 27 states. The strength of the Brazilian agricultural census data lies in its structure; with 28 outputs, 9 inputs, and 557 observations in the 1995/1996 census year and 554 observations in the 1985 census year, it provides a very rich cross-section of 554 observations.

3.3.3 Outputs

The 19 outputs cover three categories: annual crops, perennial crops, and livestock. Annual crops in the data are green beans, cotton, maize, manioc, onion, peanuts, rice, soybeans, and tomatoes. The perennial crops are bananas, cocoa, coffee, oranges, and sugarcane. Livestock data is comprised of cattle meat, pig meat, poultry meat, cow milk, and hen's eggs. Each commodity's quantity and output revenue is available at the micro-region level. All output commodities are measured in metric tons. The Brazilian currency changed five times between 1984 and 1994 and is detailed in Appendix B.5. To create the Fisher output quantity index, 1985 prices were converted to *Reais*. Both 1985 and 1995/1996 prices then were deflated by the World Bank's Brazilian GDP deflator to constant 1989 prices. Poultry quantities were unavailable at the micro-region level in the 1985 census, but were available at the national level. To obtain data at the micro-region level in 1985, each micro-region's share of national production in the 1995/1996 census is employed assuming a constant growth rate.

3.3.4 Inputs

Labor, land, fertilizers, pesticides, feed, vaccines, seed, tractors, and animal power are the conventional inputs employed in the present analysis. Input expenditure data are recorded at the micro-region level. To obtain quantities, we assume each micro-region in a given state faces the same input price, as only state-level input prices are available. To create the Fisher input quantity index, 1985 prices are converted to *Reais*. Both 1985 and 1995/1996 prices then were deflated by the World Bank's Brazilian GDP deflator to constant 1989 prices.

Fertilizers, Pesticides, Feed, Vaccines, & Seed

Fertilizers, chemicals, feed, vaccines, and seed expenditures are recorded at the micro-region level, with prices recorded at the state level. The state-level price of each input is the price of its most commonly used form in that state (Avila and Evenson, 1995). For example, the fertilizer price is the price of the most commonly used compound in that state. We assume each micro-region in each state faces the same input price. Using micro-region input expenditures and state-level prices, we interpolate input quantities for each micro-region.

Agricultural Equipment

In the present analysis, tractors and horses employed in agriculture comprise the agricultural equipment input. The count of horses in agriculture is recorded at the state level. To obtain the agricultural work horse rental rate, we divide the total agricultural work animal value by the total horse count, and apply a 2.5% discount rate. We then deflate the rental rate by the World Bank's GDP deflator specific to Brazil to obtain constant 1989 prices. We assume that every micro-region in a given state utilizes the same share of horses and faces the same service rental rate.

Tractor usage in the Brazilian data is recorded at the micro-region level. Tractor counts are recorded within specific ranges of horsepower (hp) into five classifications: <10 hp, 10-20 hp, 20-50 hp, 50-100 hp, and >110 hp. The tractor counts are converted to 75-horsepower-equivalent tractors within each micro-region. To obtain the tractor service rental price, the imported tractor wholesale unit price, obtained from the FAO, is marked up by 50%, converted to *Reais*, amortized over 10 years at a 10% discount rate, and deflated by the World Bank's Brazilian GDP deflator to constant 1989 prices. The 50% markup adjusts the wholesale price to be consistent with farm-level prices observed with other inputs.

Land

Cropland and pasture-land are recorded at the micro-region level in hectares. Each micro-region's expenditures on, and hectare-quantity of, rented lands are also reported in the census. We assume rented lands have equivalent quality as owned land. To obtain the land rental rate, rented land expenditures are divided by total hectares of rented land. The land rental rates are then deflated by the World Bank's Brazilian GDP deflator to constant 1989 prices.

Labor

Labor quantity is recorded at the state level by labor sector and labor class. Three sectors (crop labor, livestock labor, and forestry labor) and three classes (family labor, permanent labor, and temporary labor) are recorded in the census. To estimate the contribution of labor to agricultural productivity, a single labor count – quality-adjusting all labor classes into permanent-labor equivalents and accounting only for crop- and livestock-sector labor – projected from the state to the micro-region is required. Let our characterization of total agricultural labor count in a given state be

(30) $$\sum_{r=f,p,t} L_{rs} = C_{rs} + A_{rs} + F_{rs}, \quad s = 1,\ldots,27 .$$

Subscripts $r = f, p, t$ represent family labor $(f = 1,\ldots,F)$, permanent labor $(p = 1,\ldots,P)$, and temporary labor $(t = 1,\ldots,T)$, respectively. As before, subscript $s = 1,\ldots,27$ refers to the Brazilian states. C_{rs} represents the labor count in crops, A_{rs} the labor count in livestock, and F_{rs} the labor count in forestry.

To differentiate the labor count in (30) among its micro-regions in a given state, each sector must be share-weighted. To estimate each micro-region's share of cropland (measured as hectares, and defined as permanently and temporarily cultivated land) in a state's crop sector, we define ρ_i, $i = 1,\ldots,557$ as a micro-region's cropland share. To obtain the micro-region's labor count in the livestock sector, the value of nonworking livestock in a given state is share-weighted by the number of micro-regions in that state.

The nonworking livestock value, θ_i, is defined as the value of swine and cattle. Reliable data on the forestry sector are unavailable for accurately projecting state-level data to the micro-region. Therefore, each state's total forestry labor count is estimated by share-weighting the state-level data by the number of micro-regions in that state (Avila and Evenson, 1995). To project labor in the s^{th} micro-region, by class and sector, we have

$$\sum_{r=f,p,t} L_{rs} = \rho_i C_{rs} + \theta_i A_{rs} + \delta_i F_{rs} \tag{31}$$

In equation (31), $\rho_i C_{rs}$ represents the s^{th} micro-region's labor share (family, permanent, and temporary) accounted for in the crop sector, $\theta_i A_{rs}$ represents the s^{th} micro-region's labor share in the livestock sector, and $\delta_i F_{rs}$ represents the s^{th} micro-region's labor share in the forestry sector.

To obtain permanent-labor equivalents in (31), each labor class is quality-adjusted. We assume two-thirds of family labor is permanent labor. Family labor consists of women and children who do not work full-time. Permanent labor is considered full-time labor. Temporary labor is assumed to work less regularly than permanent labor, as in much of Brazil they are a seasonal labor force. To quality-adjust temporary labor to permanent-labor equivalents in each micro-region, we follow Avila and Evenson (1995) and weight the temporary labor count by the ratio of average temporary-labor expenditure to average permanent-labor expenditure. This ratio provides a measure of temporary labor quantity relative to permanent labor and is defined as

$$\frac{Exp_{ti} / labor_{ti}}{Exp_{pi} / labor_{pi}}, \tag{32}$$

where Exp_{ri} represents labor expenditure in a r^{th} class and i^{th} observation, and $labor_{ri}$ represents the r^{th} and i^{th} labor count. Because labor expenditure is identical to per hour wage rate multiplied by the average number of labor hours worked times the labor count, and because we assume temporary and permanent labor receive equal wage rates, we have

(33) $$Exp = (wage/hr.)*(Avg.\ hrs.\ worked/labor)*(labor)\ .$$

Substituting (32) into (31), we have

(34) $$\frac{(wage/hr.)*(Avg.\ hrs.\ worked/labor_t)*(labor_t)\Big/ labor_t}{(wage/hr.)*(Avg.\ hrs.\ worked/labor_p)*(labor_p)\Big/ labor_p}\ .$$

Canceling terms obtains

(35) $$\frac{(Avg.\ hrs.\ worked/labor_t)}{(Avg.\ hrs.\ worked/labor_p)}\ .$$

Equation (35) is then multiplied by the temporary labor count to obtain temporary labor in permanent-labor equivalents:

(36) $$\frac{(Avg.\ hrs.\ worked/labor_t)}{(Avg.\ hrs.\ worked/labor_p)}*labor_t = labor_p\ .$$

Exogenous Policy Variables

The exogenous policy variables used in this analysis to explain the variance of growth inefficiency are rural education and state-level per-capita public education expenditures. Rural education data are available by state and consist of the average number of years of schooling of the rural population over 10 years of age (Avila and Evenson, 1995). Expenditure data are available from 1996 to 2002. 1995 state-level expenditures are estimated by using 1996-2002 data to regress state-specific expenditures against time, then extrapolating the results to each state in 1995. Public expenditures on education entail funding for administration and support, special education, primary, secondary, and higher education, research, and student aid. Due to wide variations in state populations, gross state expenditures are expressed in a per-capita basis.[17] State population data from the IBGE are employed to generate per-capita public education expenditures. To distribute public expenditures among micro-regions, we assumed every micro-region in a

[17] Baer (2008) reports the 1980 and 1996 regional distributions of population: North (4.9% in 1980, 7.1% in 1996), Northeast (29.3% in 1980, 28.5% in 1996), Southeast (43.4% in 1980, 42.7% in 1996), South (16% in 1980, 15% in 1996), and Center-West (6.4% in 1980, 6.7% in 1996).

given state receives an equal share of education payments. All expenditures are converted to *Reais* and deflated by the World Bank's Brazilian GDP deflator to obtain constant 1989 state-level per-capita education expenditures.

3.4 Empirical Evidence

In light of insufficient panel data to directly estimate Brazilian agricultural technical changes from the stochastic output distance frontier, the present analysis employs Brazilian state and national Fisher TFP estimates, in conjunction with state and national growth efficiency estimates, to impute state and national technical changes. To this end, we assume Brazilian farms operate under constant-returns-to-scale technology and allocative efficiency such that TFP is equal to the product of technical change (TC) and growth efficiency (GE). Technical changes may therefore be imputed as

$$TC = \frac{TFP}{GE}. \tag{37}$$

Equation (1) is used to obtain state and national TFP estimates, while state and national mean growth efficiencies are estimated, given a sample of 550 micro-regions, from the stochastic multi-output distance frontier in (28). We then obtain the impact of each policy variable on the average farm's growth efficiency. Finally, a focus is kept on those states which have experienced relatively high technical changes and relatively low growth efficiencies. Farmers in these states have the potential to rapidly improve productivity through enhanced agricultural extension services and local adaptive-research because the marginal cost of implementing existing technologies likely is low given that they are already in place.

Some may question the consistency of employing a Fisher index approach with a translog functional form in (28) to impute technical changes. In the aggregate (country-level) there was virtually no difference between Fisher TFP growth estimates and those obtained from the Törnqvist-Thiel approach.[18] A random sample taken at a more disaggregated level (state-level) shows no significant difference (exact to the hundredths

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[18] Relative to base 1.00, the aggregate Tornqüist-Thiel approach obtained a 1.19 measure of agricultural productivity, while the aggregate Fisher approach obtained a 1.20 measure.

decimal place) between the two index approaches. Furthermore, Acquaye, Alston, and Pardey (2002) find no difference in productivity levels when employing the same data set to each approach; they obtained a 0.9999 simple correlation between the Törnqvist-Thiel and Fisher TFP estimates.

3.4.1 Output Growth

To better understand the state and national Fisher TFP estimates, it is necessary to review the growth in each of the three output (annual crops, perennial crops, and livestock) and input (labor, materials, and capital) categories. Appendix B.6 presents the Fisher output growth indices from 1985 to 1995/1996 for each output category and state in Brazil. The northern state of Rondônia experienced exceptional output growth in its livestock sector, with a seven-fold increase in production. Rondônia's livestock growth was led by cattle and milk production, followed closely by that of poultry and swine. Roraima, a second northern state to experience considerable output growth, observed a three-fold increase in perennial crops, led by banana production.

The state of most interest in Appendix B.6 is Mato Grosso, located in the center-west region. Unlike most states in Brazil, Mato Grosso experienced production growth in all three output categories. Annual crop production doubled, led by cotton, corn, and soybeans. Perennial crop production observed the most growth, with contributions mainly from sugarcane and orange/citrus products. Livestock production, especially in swine and poultry, grew nearly as much as in perennial crops.

3.4.2 Input Growth

Appendix B.7 presents the Fisher input growth indices for each state and input category. The states immediately standing out are once again the northern ones of Rondônia and Roraima, and the center-west state of Mato Grosso. Rondônia experienced an over four-fold increase in material inputs, largely attributed to an increase in the application of animal vaccines, although pesticide and fertilizer use also grew. Roraima showed a nearly-four-fold increase in material inputs, with fertilizer use leading the way but seed, pesticides, and animal vaccines contributing. Mato Grosso likewise experienced an increase in material input application, with seed, fertilizer, and pesticide use growing the most. Only four states did not exhibit labor declines: Acre, Roraima, Espírito Santo, and Mato Grosso do Sul. Only in eight states did capital inputs grow: Rondônia, Acre, Amazonas, Roraima, Pará, Paraná, Mato Grosso do Sul, and Mato Grosso. Overall, the Brazilian input Fisher growth indices show very small declines in inputs, largely attributed to capital and labor reductions.

3.4.3 TFP Growth

The Brazilian agricultural Fisher TFP growth index, presented in Appendix B.8, grew by 20.2% over the decennial reference period of 1985 to 1995/1996. With an 11.3% increase, Roraima experienced the lowest decennial productivity growth of all northern states, while at 66.7% Amazonas achieved the highest decennial productivity growth. The northeastern states varied widely in productivity growth. Piauí observed a robust decennial growth of 73.4%, while on the other end of the spectrum Pernambuco achieved the poorest decennial growth: -10.6%. In the southeastern region, no state had a decennial productivity growth greater than 17%. The southern region contained only one state (Santa Catarina) with exceptional decennial productivity growth (49.4%). Santa Catarina's TFP growth may be a product of the new irrigation technologies employed to boost food crop production. The center-west region, the epicenter of recent agricultural interest in Brazil (Hecht and Mann, 2008, Helfand and Levine, 2004, Matthey, Fabiosa and Fuller, 2004), observed decennial growth of 51% in Mato Grosso do Sul, 71.8% in Mato Grosso, 22.6% in Goiás, and 52.2% in the Federal Distracit (Brasilia).

Other studies of Brazil's agricultural technical change include Helfand and Rezende (2001) who cite Barros (1999). Barros employs a Törnqvist-Thiel approach from 1985/1986 to 1994/1995 to obtain 15% TFP growth. Gasquez, Bastos, and Bacchi (2008) also employ a Törnqvist-Thiel index using national-level data, with base 1.00 in 1985, to obtain a 1.24 index measure in 1995, or 24.2% decennial productivity growth. Baer (2008) cites Guilherme Leite da Silva Dias and Cicely Moitinho Amaral (2000), who estimate 22.8% decennial growth in agricultural TFP from 1987 to 1998.

da Silva Dias and Amaral (2000) attribute Brazil's agricultural productivity growth to weak infrastructure investments in the 1980s, forcing production to occur on the intensive margin in the 1990s; Embrapa's contribution to embodied and disembodied technical changes; migration transferring human capital from the southern and center-west states to northern ones; and trade liberalization's effect on improving the availability of material inputs at lower prices. While each of these determinants have undoubtedly played a part in the substantial increase Brazil experienced in agricultural productivity growth, the state-wide agricultural TFP growth disparities displayed in Appendix B.8 should be a warning to both Brazilian policy makers and Brazilian agriculture's competitors. Negative agricultural productivity growth affects local and regional development by reducing, or even eliminating, a significant revenue source from the rural population. Improvements in states with low or negative productivity growth would further boost Brazil's agricultural supply to both domestic and international markets. Such improvements would either have the direct welfare impact of cheaper domestic food, or the indirect impact of improving Brazil's macro-economic stability by way of the rising currency reserves from exporting to international markets.

3.4.4 Technology Regularity Conditions

Linear homogeneity, monotonicity, and convexity are important regularity conditions required of multi-output distance functions to ensure rational behavior. Linear homogeneity was imposed on the output distance frontier through the normalization of outputs given a numeraire output, shown by equations (9) and (10). To test for monotonicity and convexity, it is first necessary to rewrite (28) in a way which reveals the underlying transformation function (TF):

(38)
$$\begin{aligned} 0 &= \mu' P_s + TL(\ln x_{ki}, \ln y^*_{ji}, \beta) + \ln y_{mi} + \exp\left\{\ln z_{ai}'\Omega\right\} + \varepsilon_i, \\ &= TF. \end{aligned}$$

Transformation function (38) must be an increasing function of each output quantity and a decreasing function of each input quantity to be monotonic. Appendix B.9 confirms the transformation function is monotonic, as the derivative of (38) with respect to each of the two normalized Fisher output quantity indices (annual crops and perennial crops) is positive, while the derivative of (38) with respect to each of the three Fisher input quantity indices (labor, materials, and capital) is negative.

Technological convexity requires a positive semi-definite Hessian matrix, in turn requiring that each principal minor be nonnegative (Simon and Blume, 1994). Appendix B.10 presents the case that the technology is nearly convex, as the fourth principal minor is negative. Non-convexity of the Brazilian agricultural technology is to be expected, as convexity requires farm agents to maximize profits, have perfect information, and be able to divide outputs and inputs without limit. While profit-maximizing behavior is questionable for any developing country's agricultural sector, weather fluctuations and natural disasters such as fire and flood make perfect information a generally unrealistic assertion for agricultural production.

3.4.5 Growth Efficiency

As production technologies evolve, the dissemination of technical information and farm organization strategies determine the proportion of the productivity growth achieved by average farms. Thus, to assume a heteroscedastic inefficiency error is to assume the dissemination of technical information and farm organization strategies vary across observations. Our assumption of a heterscedastic inefficiency error is confirmed by the Chi-squared likelihood ratio (LR) test, which at the 1% level with two degrees of freedom.[19] This result confirms that scale function $g(\ln z_{ai};\Omega)\eta_i$ from equation (20) is not constant and growth efficiency in Brazilian agriculture is heterogeneous across micro-regions.

Mean growth efficiencies provide evidence of how well observations internalize the productivity growth. Appendix B.11 presents state and national mean growth efficiency estimates. The national mean growth efficiency is 91.2%.[20] Therefore, from 1985 to 1995/1996, average Brazilian farmers internalized (or achieved) 91.2% of the productivity growth that occured. An interesting result from table 10 involves the northeast region. Of the nine states in the northeast, seven have observed nearly 100%

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[19] LR chi2(2) = 13.47; Prob > chi2 = 0.0012
[20] The 95% confidence interval for national mean technical efficiency is (0.904, 0.921).

growth efficiency: Piauí (99.4%), Ceará (99.9%), Paraiba (99.7%), Pernambuco (99.4%), Alagoas (99.1%), Sergipe (99.0%), and Bahia (99.8%). In fact, only two other states – Rondônia (99.3%) and Amazonas (99.9%), each located in the north region – also achieved nearly 100% mean growth efficiency. Brazil's lowest mean growth efficiency estimates are from the Federal District (63.7%) and Amapá (68.4%). Apart from Amapá, table 10 raises the question of why the highest mean growth efficiencies are observed in the northern regions. One possible explanation comes from differing complexity in the relative technologies employed. Generally, simple technologies need lower understanding and education levels to obtain optimal utilization. It is thus possible that the technologies employed in the northern regions agricultural sectors are of less complex nature than those employed in the southern and center-west regions. Another more feasible explanation could be the significant public expenditures, relative to the rest of the country, funneling into the northern regions to improve agricultural productivity (Baer, 2008).

To explain growth inefficiency error variance $\sigma_{u,i}^2$, education data representing human capital are employed. Those micro-regions with higher rural education and state-level per-capita public education expenditures are expected to experience lower growth inefficiency variances because education improves human capital, a primary determinant of agricultural productivity growth (Schultz, 1998). The results of equation (29) are presented in Appendix B.12. The significant positive coefficients on both state-level per-capita public education expenditures (significant at the 5% level) and rural education (significant at the 3% level) suggest that micro-regions with higher human capital tend to have higher growth inefficiency variances. While these results are not expected, a possible explanation may be that farmers with more education leave the agricultural sector in search of higher wages, or profits, in non-farm activities. Agricultural production is then left to the remaining farmers who have lower human capital.

Because inefficiency error u_i is specified in a half-normal distribution, to increase the variance of technical inefficiency is to increase mean technical inefficiency, and to increase mean technical inefficiency is to decrease mean technical efficiency. Our results from Appendix B.12 indicate that, indeed, micro-regions with more human capital have higher growth inefficiency variances. To determine the associated shift in national-level mean growth efficiency, we employ equation (24). We find that a marginal increase in real state-level per-capita public education expenditures implies a 0.00003% decrease in mean growth efficiency, while a marginal increase in the average number of years of schooling in the rural population implies a 0.0025% decrease. So while the education variables significantly impact technical inefficiency's variance, their impact on mean growth efficiency is very small.

3.5 Conclusion

We have examined Brazil's agricultural sector employing micro-region and state-level data from the agricultural censuses conducted in 1985 and 1995/1996. In light of insufficient panel data to obtain technical change estimates directly from the stochastic output distance frontier, state and national technical changes are imputed as the ratio of agricultural Fisher TFP growth estimates to stochastically estimated growth efficiencies. The empirical evidence indicates, at the national level, agricultural total factor productivity to have grown 20.2% from 1985 to 1995/1996. The average Brazilian farmer was able to internalize – or experience – only 91.2% of the agricultural productivity growth, implying the production frontier expanded 22.2% over the reference time period.

Brazil could improve agricultural productivity, and thus international competitiveness, by focusing on states with low growth efficiency and high imputed technical growth. Such states are: Acre, Mato Grosso do Sul, Mato Grosso, and the Federal District. Acre's agricultural Fisher TFP decennial growth was nearly 42%, while the average farmer in Acre was only 81.1% efficient in that growth. Acre's imputed decennial technical change therefore was 51.7%, second-best among states in the northern region. In 1995, Acre's revenue shares were dominated by manioc (35.7%), cattle meat (23.0%), and milk production (10.4%). Mato Grosso do Sul experienced decennial Fisher TFP productivity growth of 51%, growth efficiency of 84.1%, and an imputed technical change of 60.6%. Mato Grosso do Sul's revenue shares were predominately comprised of cattle meat (60.8%) and soy production (16.2%). Mato Grosso's decennial TFP growth of 71.8% -- the national high -- and its growth efficiency of 88.4% imply an imputed decennial technical change of 81.2%. Mato Grosso's revenue shares in 1995 favored rice (38.6%), cattle meat (27.8%), and sugarcane production (10.7%). The Federal District's decennial TFP growth of 52.2% and national-low 63.7% growth efficiency generated an imputed decennial technical change of 82%. Eggs (32%), poultry (13.6%), and maize (13.1%) constituted the largest shares of the Federal District's revenues in 1995. Amazingly, the results show Mato Grosso's and the Federal District's frontier producers nearly doubled production from 1985 to 1995/1996.

Apart from Mato Grosso's sugarcane revenues, each of the four high-technical-change low-growth-efficiency states obtained significant shares of their revenues from annual crops and livestock production. These four states should be able to improve average-farm productivity at low marginal cost through improved dissemination of technical information, as the technologies to produce at higher growth rates are already available. In order to maximize agricultural production in these four states, that is to push the average farmer up to the technical frontier, Brazil should emphasize disseminating technical information about annual crop and livestock production. Technical information sources available to farmers include, but are not limited to, national extension services, input suppliers, consultants, farmer organizations, and non-governmental organizations (NGOs) (Morris and Byerlee, 1998).

Future research should focus on the role of extension services and their contribution to improving technical inefficiencies in Brazilian agriculture. Our results show that improving the education of the average Brazilian farmer most likely comes at a small cost to agricultural productivity. Thus any policy efforts to improve farmer knowledge of available production technologies may simultaneously need to provide incentives to hold farmers in the agricultural sector.

Chapter 4: Challenged with A Dual? In LDC Productivity Measurement, the Primal May Have the Broader Target

4.1 Motivation

Productivity is universally defined as output per unit of input, the measurement and explanation (or decomposition) of which varies by researcher. The most simplified approach for measuring productivity is the ratio of an output growth rate to an input growth rate (Diewert, 1992). Productivity growth measures are formulated as primal measures in order to demonstrate increasing production possibilities with given inputs, or as dual measures in order to demonstrate decreasing costs of producing given outputs, itself reflecting technological change (Morrison Paul, 1999). Productivity – along with real exchange rates, past and present trade policies, the economic system, and a country's characteristics (such as natural endowments, geographic location, culture, and history) – is a primary factor in any country's measure of competitiveness (Ofer, 1992). On a macro-economic scale, productivity growth analyses provide unique opportunities to understand the determinants of a country's economic growth and international trade, while on a micro-economic scale, they provide opportunities to evaluate management and profits. As international trade barriers continue to decline, productivity will become an increasingly important measure of developing countries' agricultural competitiveness.

McCalla (1998) estimated 75.1% of the world's population in 1985 lived in developing countries, and projected the percentage to grow to 83.2% by 2025. By 2050, 86.5% of the world's population will live in developing countries (United Nations 2003). As population pressures intensify in these nations, a renewed call is being made for agriculture to provide a leading development role by achieving rapid technical change (Mellor, 1998). Understanding agriculture's role in any developing country's economic development requires identifying the sources, dynamics, and impact of such agricultural technical change (Timmer, 1998). In the present essay we analyze stochastic frontier models of multi-output productivity, our focus being their application to Less Developed Countries (LDCs) in the face of agricultural data constraints.

In order for a developing nation to make informed decisions about its optimal development path, multi-output productivity models are needed to provide insight into where their own agricultural comparative advantages lie. To this end, we focus the present essay on the input distance function and cost function, as each stochastically measures a technology dual to the other. Multi-output models provide information single-output models cannot supply. If the focus of the analysis is on food security, one may, for example, distinguish between food crop and non-food crop production indices and technical change estimates. If agricultural production is highly regionalized, one may characterize such output classes as annual crops, perennial crops, and livestock.

The present analysis concentrates on stochastic multi-output productivity models applied to agriculture. To decompose total factor productivity into its disembodied technical change and technical efficiency change components we assume allocative efficiency and constant-returns-to-scale technology. One might conduct a similar stochastic primal-dual multi-output productivity analysis from the output distance function and revenue function.

4.2 The Economic Model

Single-output production functions historically have been the primal workhorse for economic production theory. But single-output models lack multi-output technical change estimates which developing countries require. When only single-output models are employed, it is impossible to identify where comparative output advantages lie. Moreover, multi-output models may provide insight into a developing country's food supply and thus, in the long-run, insight into national food security. To provide this information, we develop a primal and a dual multi-output stochastic frontier models for measuring productivity growth. Primal multi-output models employ distance functions, credited to Shephard (1953), (1970). Defined in a primal manner, distance functions allow productivity to arise from technical changes, technical efficiency changes, and scale elasticities. Technical change is modeled by shifts in the frontier given a fixed set of inputs, that is from secular changes in the output possibilities achievable given a bundle of measurable inputs. Technical efficiency change is modeled by an observation's movement toward or away from the production frontier. Scale elasticities provide insight into the percentage change in production possibilities or total cost given a 1-percent total output increase.

The primal multi-output model we develop is an input distance frontier. An input-based distance function affords an examination of how inputs may be proportionally reduced given a fixed output vector. To characterize the technology T, let $y_{jit} \in \mathbb{R}_{+}^{M}$, $j = 1...M$ be a scalar output; $x_{kit} \in \mathbb{R}_{+}^{N}$, $k = 1...N$ a scalar input; $t = 1...E$ a technology indicator; and $i = 1...I$ indicate observations such that

(1) $$T = \{(x_{kit}, y_{jit}, t): x_{kit} \text{ can produce } y_{jit}\} \in \mathbb{R}_{+}^{N+M}.$$

Observations in (1) lie within the technology if transformation function (TF) is no greater than zero: $TF(x_{kit}, y_{jit}, t) \leq 0 \Leftrightarrow (x_{kit}, y_{jit}, t) \in T$. Moreover, if and only if the inputs and outputs lie on the boundary of T then $TF(x_{kit}, y_{jit}, t) = 0$. From (1), technology T is restricted by holding output vector y_{jit} fixed to obtain the input requirement set

(2) $$L(y_{jit}^{\circ}, t) = \{x_{kit} \in \mathbb{R}_{+}^{N}: (x_{kit}, y_{jit}^{\circ}, t) \in T\}.$$

In (2), the input requirement set is defined as the set of all inputs such that a fixed output level is feasible. We assume the production technology is non-null. From (2), the input distance function is

(3) $$D_I(x_{kit}, y_{jit}, t) = \underset{\lambda}{Sup}\{\lambda > 0: x_{kit}/\lambda \in L(y_{jit}^{\circ}, t)\} \forall y_{jit} \in \mathbb{R}_{+}^{M},$$

where $D_I(x_{kit}, y_{jit}, t) \geq 1$ if and only if $x_{kit} \in L(y_{jit}^{\circ}, t)$ and weak disposability of inputs is assumed (Färe and Primont, 1995). If $D_I(x_{kit}, y_{jit}, t) = 1$ then λ has a maximum at unity and the inputs are on the outer boundary of $L\left(y_{jit}^{\circ}, t\right)$ implying maximized technical efficiency. To complete the one-to-one correspondence between the input distance and input requirement set, we have

(4) $$L(y_{jit}^{\circ}, t) = \left\{x_{kit} \in \mathbb{R}_{+}^{M}: D_I(x_{kit}, y_{jit}, t) \geq 1\right\},$$

in which the input requirement set binds the input distance function to be no less than unity.

An alternative to defining input distance function as in (3) is to define it in terms of cost:

(5) $$D_I(x_{kit}, y_{jit}, t) = \inf_w (w_{kit} x_{kit} : TC(w_{kit}, y_{kit}, t) \geq 1).$$

Equation (5) says that the input distance function is equal to the ratio of actual cost $[w_{kit} x_{kit}]$ to minimized total cost $[TC(w_{kit}, y_{kit}, t)]$ such that minimum total cost is no less than unity (Färe and Primont, 1995).

To express a change in the input distance function over time, adapting to the distance function approach the method Morrison Paul (1999, p.41) employed with a production function, we differentiate $D_I(x_{kit}, y_{jit}, t)$ with respect to t:

(6) $$\begin{aligned}\frac{dD_I(x_{kit}, y_{jit})}{dt} &= \sum_{k=1} \frac{\partial D_I(x_{kit}, y_{jit}, t)}{\partial x_{kit}} \cdot \frac{dx_{kit}}{dt} + \sum_{j=1} \frac{\partial D_I(x_{kit}, y_{jit}, t)}{\partial y_{jit}} \cdot \frac{dy_{jit}}{dt} \\ &+ \frac{\partial D_I(x_{kit}, y_{jit}, t)}{\partial t}.\end{aligned}$$

To obtain this expression in elasticity form, divide each term in (6) by input distance $D_I(x_{kit}, y_{jit}, t)$:

(7) $$\begin{aligned}\frac{\frac{dD_I(x_{kit}, y_{jit}, t)}{dt}}{D_I(x_{kit}, y_{jit}, t)} &= \frac{\sum_{k=1} \frac{\partial D_I(x_{kit}, y_{jit}, t)}{\partial x_{kit}} \cdot \frac{dx_{kit}}{dt}}{D_I(x_{kit}, y_{jit}, t)} \cdot \frac{x_{kit}}{x_{kit}} + \frac{\sum_{j=1} \frac{\partial D_I(x_{kit}, y_{jit}, t)}{\partial y_{jit}} \cdot \frac{dy_{jit}}{dt}}{D_I(x_{kit}, y_{jit}, t)} \cdot \frac{y_{jit}}{y_{jit}} \\ &+ \frac{\frac{\partial \ln D_I(x_{kit}, y_{jit}, t)}{\partial t}}{D_I(x_{kit}, y_{jit}, t)}.\end{aligned}$$

Manipulate (7) to obtain

(8) $$\begin{aligned}\frac{d \ln D_I(x_{kit}, y_{jit}, t)}{dt} &= \sum_{k=1} \frac{\partial D_I(x_{kit}, y_{jit}, t)}{\partial x_{kit}} \cdot \frac{x_{kit}}{D_I(x_{kit}, y_{jit}, t)} \cdot \frac{d \ln x_{kit}}{dt} \\ &+ \sum_{j=1} \frac{\partial D_I(x_{kit}, y_{jit}, t)}{\partial y_{jit}} \cdot \frac{y_{jit}}{D_I(x_{kit}, y_{jit}, t)} \cdot \frac{d \ln y_{jit}}{dt} \\ &+ \frac{\partial \ln D_I(x_{kit}, y_{jit}, t)}{\partial t}.\end{aligned}$$

Further manipulation of (8) gives

$$\text{(9)}\quad \begin{aligned}\frac{d\ln D_I(x_{kit},y_{jit},t)}{dt} &= \sum_{k=1} \frac{w_{kit}^r x_{kit}}{D_I(x_{kit},y_{jit},t)}\cdot\frac{d\ln x_{kit}}{dt} + \\ &\sum_{j=1}\frac{\partial D_I(x_{kit},y_{jit},t)}{\partial y_{jit}}\cdot\frac{y_{jit}}{D_I(x_{kit},y_{jit},t)}\cdot\frac{d\ln y_{jit}}{dt} \\ &+\frac{\partial \ln D_I(x_{kit},y_{jit},t)}{\partial t},\end{aligned}$$

where

$$\text{(10)}\quad \sum_{k=1}\frac{\partial D_I(x_{kit},y_{jit},t)}{\partial x_{kit}} = w_{kit}^r .$$

Equation (10) exploits input distance function definition (5) by showing the derivative of the input distance function taken with respect to factor demand $\left(x_{kit}\right)$ provides the inputs' relative price vector w_{kit}^r (Färe and Primont, 1995, p.55).

To simplify terms in (9), we first assume $d\ln y_{jit}/dt$ is equal for all j. Such an assumption implies that the total logarithmic change with respect to time of each output is constant over time. It also allows (9) to be rewritten as

$$\text{(11)}\quad \begin{aligned}\frac{d\ln D_I(x_{kit},y_{jit},t)}{dt} &= \sum_{k=1} \frac{w_{kit}^r x_{kit}}{D_I(x_{kit},y_{jit},t)}\cdot\frac{d\ln x_{kit}}{dt} + \\ &\frac{d\ln y_{jit}}{dt}\cdot\sum_{j=1}\frac{\partial D_I(x_{kit},y_{jit},t)}{\partial y_{jit}}\cdot\frac{y_{jit}}{D_I(x_{kit},y_{jit},t)} \\ &+\frac{\partial \ln D_I(x_{kit},y_{jit},t)}{\partial t}.\end{aligned}$$

Consider now the second line of (11), in which we have

$$\text{(12)}\quad \sum_{j=1}\frac{\partial D_I(x_{kit},y_{jit},t)}{\partial y_{jit}}\cdot\frac{y_{jit}}{D_I(x_{kit},y_{jit},t)} .$$

Färe and Primont (1995) have shown that if the value of the input distance in the denominator of (12) maximizes efficiency, we have

$$\text{(13)}\quad \sum_{j=1}\frac{\partial D_I(x_{kit},y_{jit},t)}{\partial y_{jit}}\cdot\frac{y_{jit}}{1} = -\frac{1}{\varepsilon_{Y.Scale}^p},$$

where $\varepsilon_{Y.Scale}^p$ is the primal output scale elasticity. The primal output scale elasticity is the percentage change in input distance $D_I(x_{kit},y_{jit},t)$ given a 1-percent increase in total output. On the assumption of a constant-returns-to-scale technology, (13) is negative unity. Inserting the result from (12) into (10) and rearranging terms provides

$$(14)\qquad \frac{\partial \ln D_I(x_{kit}, y_{jit}, t)}{\partial t} = \frac{d \ln D_I(x_{kit}, y_{jit}, t)}{dt} - \sum_{k=1} \frac{w^r_{kit} x_{kit}}{D_I(x_{kit}, y_{jit}, t)} \cdot \frac{d \ln x_{kit}}{dt} + \frac{d \ln y_{jit}}{dt}.$$

Equation (14) shows the primal multi-product technical change rate to be the total change in the input distance over time, net of the input change over time, and plus the change in outputs over time.

4.2.1 Economic Model: The Dual Approach

To develop a second approach to multi-output productivity growth measurement, we define productivity in a dual manner, allowing productivity growth to arise from technology changes, technical and allocative efficiency changes, and scale economies. Technical change induces a downward shift in the cost function. Technical efficiency change is an observation's movement toward or away from the boundary of the technology. Allocative efficiency requires that the firm operate with a mix of inputs that lie upon the scale expansion path (SEP), and as such minimize cost at given output. The presence of economies of scale implies an increase in output requires a less than proportionate increase in cost (i.e., doubling output less than doubles cost).

Figure 1 graphically characterizes productivity using non-constant-returns-to-scale technology and average cost curves (Morrison Paul, 1999). In time period 0, point A lies on short-run average cost curve (SAC_0) and long-run average cost curve (LAC_0), incurs average cost AC_A, and produces output Y_0. Evidence of scale economies between time periods 0 and 1 is shown as a move from point A to point B, demonstrating an increase in production from Y_0 to Y_1 as a movement to the minimum point of the $LAC_{0,1}$. Productivity gains from technical change can be seen as the movement from point B to point C, in which between time period 1 and 2, there is a shift from $LAC_{0,1}$ to LAC_2. From points A to C, productivity improves on account of producing a given output quantity with fewer inputs, and therefore at lower unit cost.

The cost function is unique in that it can represent farm technical change not through changes in output and input quantities but through output quantity changes and farm costs. If output and input prices are fixed, and costs of producing a given output vector decrease over time, then fewer inputs will be utilized. The cost function is defined as the solution to the cost minimizing problem of producing maximum feasible output given the technology (4) and input price vector w_{kit}:

$$TC(y_{jit}, w_{kit}, t) = \min_{x} \left\{ w_{kit} x_{kit} : x_{kit} \in L(y^{\circ}_{jit}, t) \right\} \forall y_{jit} \in \mathbb{R}^{M}_{+} \neq 0, w_{kit} > 0 . \tag{15}$$

Equation (15), when it exists, shows total cost $TC(\cdot)$ to be a function of output scalar $y_{jit} \in \mathbb{R}^{M}_{+}$, input price scalar $w_{kit} \in \mathbb{R}^{N}_{+}$, and technology indicator t. If we assume producing each output scalar y_{jit} requires some non-negative input quantity, and that the input requirement set is nonempty, closed, convex, and exhibits strong disposability, then from (15) we can complete the one-to-one correspondence between the cost function and the input requirement set with (Färe and Primont, 1995, p.45)

$$L(y^{\circ}_{jit}, t) = \left\{ x_{kit} : w_{kit} x_{kit} \geq TC(y_{jit}, w_{kit}, t), \forall w_{kit} > 0 \right\} . \tag{16}$$

Equation (16) shows the input requirement set binds actual costs to be no less than minimized total costs at all positive input prices.

To obtain the dual cost function's technical change measure, differentiate (16) with respect to t to obtain (Morrison Paul, 1999)

$$\begin{aligned} \frac{dTC(y_{jit}, w_{kit}, t)}{dt} &= \sum_{k=1} \frac{\partial TC(y_{jit}, w_{kit}, t)}{\partial w_{kit}} \cdot \frac{dw_{kit}}{dt} + \sum_{j=1} \frac{\partial TC(y_{jit}, w_{kit}, t)}{\partial y_{jit}} \cdot \frac{dy_{jit}}{dt} \\ &+ \frac{\partial TC(y_{jit}, w_{kit}, t)}{\partial t} . \end{aligned} \tag{17}$$

Dividing each term by total cost $TC(y_{jit}, w_{kit}, t)$ transforms (17) into elasticities,

$$\begin{aligned} \frac{d \ln TC(y_{jit}, w_{kit}, t)}{dt} &= \sum_{k=1} \frac{w_{kit} x_{kit}}{TC(y_{jit}, w_{kit}, t)} \cdot \frac{d \ln w_{kit}}{dt} + \sum_{j} \frac{\partial \ln TC(y_{jit}, w_{kit}, t)}{\partial \ln y_{jt}} \cdot \frac{d \ln y_{jit}}{dt} \\ &+ \frac{\partial \ln TC(y_{jit}, w_{kit}, t)}{\partial t} . \end{aligned} \tag{18}$$

Notice in (18) we employ Shephard's Lemma, $\partial TC / \partial w_{kit} = x_{kit}$, where x_{kit} is the cost minimizing demand of input k in observation i and at time t. To simplify equation

(18), assume $d\ln y_{jit}/dt$ is equal for all j, implying the logarithmic change with respect to time is constant for each output. We then may replace $\sum_j \partial \ln TC/\partial \ln y_{jit}$ with the dual total cost scale elasticity measure $\varepsilon^d_{TC.Scale}$ (Morrison Paul, 1999). The dual cost scale elasticity is the percentage change in total cost given a 1-percent increase in total output. By the assumption of constant-returns-to-scale technology, $\varepsilon^d_{TC.Scale} = 1$. Given this assumption, we can re-define equation (18) in terms of the dual measure of multi-output technical change (Morrison Paul, 1999)

$$(19) \qquad \frac{\partial \ln TC(y_{jit}, w_{kit}, t)}{\partial t} = \frac{d\ln TC(y_{jit}, w_{kit}, t)}{dt} - \frac{d\ln y_{jit}}{dt} - \sum_{k=1} \frac{w_{kit}x_{kit}}{TC(y_{jit}, w_{kit}, t)} \cdot \frac{d\ln w_{kit}}{dt}.$$

Equation (19) explains net total cost technical change to be equal to the total cost change over time less output and input changes over time.

4.2.2 Economic Model: The Duality

Diewert (1993) explains duality between technology and minimized cost as, "…under certain conditions, [a] closed convex set…can be represented as the intersection of the half-spaces generated by the iso-cost surfaces tangent to the production possibilities set." (p. 117). Shephard (1953) developed the duality theorem between the input distance function and the cost function, whereas his (1970) work developed the duality between the output distance function and the revenue function (Färe and Primont, 1994). To ensure duality between cost function (15) and input distance function (3), we assume input set convexity and a weak form of free disposability.[21] To theoretically establish the duality between the cost function and input distance function, it was necessary to first establish the one-to-one relation between the cost function and input requirement set, (15) and (16), and the one-to-one relation between the input distance function and the input requirement set, (3) and (4). The total-cost-input-distance duality is (Färe and Primont, 1995, p.47-8):

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[21] A weak form of free disposability is defined as: If vectors $\left(x_{it}, y_{it}\right) \in T$ then $\left(ax_{it}^{'}, ay_{it}^{'}\right) \in T \forall a \in (0,1]$.

$$\text{(20)}\qquad \begin{aligned} &TC(y_{jit}, w_{kit}, t) = \min_{x} \left\{ w_{kit} x_{kit} : D_I(x_{kit}, y_{jit}, t) \geq 1 \right\}, w_{kit} > 0 \\ &\textit{if and only if} \\ &D_I(x_{kit}, y_{jit}, t) = \inf_{w} \left\{ w_{kit} x_{kit} : TC(y_{jit}, w_{kit}, t) \geq 1 \right\}, x_{kit} \in \mathbb{R}^N_+ . \end{aligned}$$

Equations (20) state that the duality between the total cost function and the input distance function exists only when total cost is equal to actual costs normalized by input distance $D_I(x_{kit}, y_{jit}, t)$ at positive input prices, and the input distance is equal to actual costs normalized by minimized total cost $TC(y_{jit}, w_{kit}, t)$ at positive input quantities.

While (20) shows the duality between the total cost function and the input distance function, we now provide an example when there exists equality between each function's technical change measure. To present the equality between the primal technical change measure and the dual technical change measure, we follow the method proposed by Morrison Paul (1999), who cites Ohta (1975). This methodology requires totally differentiating the total cost function with respect to time in two different manners. The first manner, seen in equation (19), treats the total cost function as a function of output quantities, input prices, and a time trend. The second manner, seen in equation (21), treats the total cost function as some function of input prices and quantities. As such, in equation (21) below, we take the differential of the logarithmic change in total cost with respect to time

$$\text{(21)}\qquad \frac{d \ln TC(y_{jit}, w_{kit}, t)}{dt} = \sum_{k=1} \frac{w_{kit} x_{kit}}{TC(y_{jit}, w_{kit}, t)} \cdot \frac{d \ln w_{kit}}{dt} + \sum_{k=1} \frac{w_{kit} x_{kit}}{TC(y_{jit}, w_{kit}, t)} \cdot \frac{d \ln x_{kit}}{dt} .$$

If we then substitute (21) into (19) and cancel terms, we obtain a dual technical change measure free of a total derivative fraction

$$\text{(22)}\qquad \frac{\partial \ln TC(y_{jit}, w_{kit}, t)}{\partial t} = \sum_{k=1} \frac{w_{kit} x_{kit}}{TC(y_{jit}, w_{kit}, t)} \cdot \frac{d \ln x_{kit}}{dt} - \frac{d \ln y_{jit}}{dt} .$$

To derive the equality between the primal and dual technical change measures, we assume them to be equal by equating equations (14) and (22). We then look to define the primal technical change measure in terms of dual measure (22). Note we employ technical change measures from functions that already assume constant-returns-to-scale technology. If we equate equations (14) and (22), and rearrange terms, we obtain

$$\text{(23)} \qquad \frac{d\ln D_I(x_{kit}, y_{jit}, t)}{dt} = \sum_{k=1} \frac{w_{kit} x_{kit}}{TC(y_{jit}, w_{kit}, t)} \cdot \frac{d\ln x_{kit}}{dt} - \frac{d\ln y_{jit}}{dt}$$
$$+ \sum_{k=1} \frac{w^s_{kit} x_{kit}}{D_I(x_{kit}, y_{jit}, t)} \cdot \frac{d\ln x_{kit}}{dt} - \frac{d\ln y_{jit}}{dt}.$$

By rearranging terms in (14) we obtain

$$\text{(24)} \qquad \frac{d\ln y_{jit}}{dt} = \frac{\partial \ln D_I(x_{kit}, y_{jit}, t)}{\partial t} - \frac{d\ln D_I(x_{kit}, y_{jit}, t)}{dt} + \sum_{k=1} \frac{w^s_{kit} x_{kit}}{D_I(x_{kit}, y_{jit}, t)} \cdot \frac{d\ln x_{kit}}{dt}.$$

If we then substitute (24) into the last term of (23) and cancel terms, we obtain the primal technical change measure defined in terms of dual technical change measure (22):

$$\text{(25)} \qquad \frac{\partial \ln D_I(x_{kit}, y_{jit}, t)}{\partial t} = \sum_{k=1} \frac{w_{kit} x_{kit}}{TC(y_{jit}, w_{kit}, t)} \cdot \frac{d\ln x_{kit}}{dt} - \frac{d\ln y_{jit}}{dt}.$$

After presenting the duality between the input distance function and total cost function, we have shown that under certain assumptions the primal technical change rate is equal to the dual technical change rate by defining the primal in terms of the dual.

4.3 Primal Stochastic Frontier Estimation

In estimating a developing country's agricultural productivity, importance should be placed not only on modeling it in a multi-output setting, but also accounting for changes in both technologies and efficiencies across time and space. While multi-output analyses provide more detailed information pertaining to output growth sources, it is the potentially wide variation of production technologies employed in developing countries that requires any productivity analysis to differentiate between production innovators and imitators. Innovators are those farms that expand the production possibilities through technological advances. Imitators utilize available information along with disseminated spillover information to catch up to production front-runners. Agriculture's inefficiencies provide information essential for optimal and balanced economic development policies in poor countries (Johnston and Mellor, 1961).

To obtain an estimable model for the primal input distance function, alter (3)'s definition to include a vector of unknown parameters β and set it equal to an exponentially specified idiosyncratic normally distributed error term ε_{it} :

(26) $$D_I(x_{kit}, y_{jit}, t, \beta) = e^{\varepsilon_{it}},.$$

In (26) the input distance is expressed as a function of input quantity scalar $\left(x_{kit} \in \mathbb{R}_+^N\right)$, output quantity scalar $\left(y_{jit} \in \mathbb{R}_+^M\right)$, technology indicator $t = 1,..., E$, and unknown parameter vector β. The input distance in (26) is given an exponential form to ensure it remains positive:

(27) $$D_I(x_{kit}, y_{jit}, t, \beta) = e^{f(\ln x_{kit}, \ln y_{jit}, t, \beta)}.$$

Equation (27) specifies the input distance as the exponentiation of a translog function of outputs and inputs. Thus from (27)

(28) $$\begin{aligned} f(\ln x_{kit}, \ln y_{jit}, t, \beta) = \beta_0 &+ \sum_{k=1}^{N} \beta_k \ln x_{kit} + \sum_{j=1}^{M} \beta_j \ln y_{jit} + \frac{1}{2}\sum_{k=1}^{N}\sum_{h=1}^{N} \beta_{kh} \ln x_{kit} \ln x_{hit} \\ &+ \frac{1}{2}\sum_{j=1}^{M}\sum_{l=1}^{M} \beta_{jl} \ln y_{jit} \ln y_{lit} + \sum_{k=1}^{N}\sum_{j=1}^{M} \beta_{kj} \ln x_{kit} \ln y_{jit} \\ &+ \beta_0 t + \frac{1}{2}\beta_{00} t^2 + \sum_{k=1}^{N} \beta_{kt} t \ln x_{kit} + \sum_{j=1}^{M} \beta_{jt} t \ln y_{jit}. \end{aligned}$$

Linear homogeneity of degree +1 in input quantities is a necessary input distance function property. An elegant way of imposing linear homogeneity follows from Lovell, Richardson, Travers, and Wood (1994). Shephard (1953) first identified the linear homogeneity property of input distance functions, shown as:

$D_I(\varphi x_{kit}, y_{jit}, t) = \varphi D_I(x_{kit}, y_{jit}, t)$ for any $\varphi > 0$. Thus if $x_{kit}^* = \dfrac{x_{kit}}{x_{nit}} \neq 0$ and $x_{kit}^* = \dfrac{x_{kit}}{x_{nit}} \neq +\infty$, $k = 1,..., N-1$, with the n^{th} input chosen as the numeraire, from (24) we then have

(29) $$e^{f(\ln x_{kit}^*, \ln y_{jit}, t, \beta)} = \frac{e^{f(\ln x_{kit}, \ln y_{jit}, t, \beta)}}{x_{nit}}.$$

Substituting (27) into (26), then (26) into (29), we have

(30) $$e^{f(\ln x_{kit}^*, \ln y_{jit}, t, \beta)} = \frac{e^{\varepsilon_{it}}}{x_{nit}}.$$

Taking logs and rearranging terms, an econometrically estimable model reveals itself as

(31)
$$\begin{aligned} -\ln x_{nit} &= \beta_0 + \sum_{k=1}^{N-1}\beta_k \ln x^*_{kit} + \sum_{j=1}^{M}\beta_j \ln y_{jit} + \frac{1}{2}\sum_{k=1}^{N-1}\sum_{h=1}^{N-1}\beta_{kh}\ln x^*_{kit}\ln x^*_{hit} \\ &+\frac{1}{2}\sum_{j=1}^{M}\sum_{l=1}^{M}\beta_{jl}\ln y_{jit}\ln y_{lit} + \sum_{k=1}^{N-1}\sum_{j=1}^{M}\beta_{kj}\ln x^*_{kit}\ln y_{jit} \\ &+\beta_0 t + \frac{1}{2}\beta_{00}t^2 + \sum_{k=1}^{N-1}\beta_{kt} t \ln x^*_{kit} + \sum_{j=1}^{M}\beta_{jt} t \ln y_{jit} - \varepsilon_{it}, \end{aligned}$$

or more simply as

(32)
$$-\ln x_{nit} = f(\ln x^*_{kit}, \ln y_{jit}, t, \beta) - \varepsilon_{it}.$$

Residual ε_{it} in (31) and (32) is an idiosyncratic error accounting for random shocks in production. OLS estimates of input-output relation $f(\ln x^*_{kit}, \ln y_{jit}, t, \beta)$ in (32) provide information about technical change and technical change bias as evaluated at the data means. Unfortunately error ε_{it} in (32) confounds inefficiencies related to exogenous random factors, such as statistical noise, data measurement error, and weather, with inefficiencies related to endogenous farm factors, such as information deficiencies, adjustment costs, and farm organization (Marschak and Andrews, 1944, Zellner, Kmenta and Dreze, 1966).

Decomposing error ε_{it} into the two components which reflect inefficiencies attributed to exogenous and endogenous farm factors requires a model that fits a line bounding the data. A bounding function allows the most efficient firms to lie upon the frontier, forming a ‘best-practice’ with which one can compare other, less efficient firms (i.e., those lying above the frontier). With such fragmentation of error ε_{it} in mind, Aigner, Lovell, and Schmidt (1977) and Meeusen and Van den Broeck (1977) independently developed the stochastic frontier model. The stochastic frontier model decomposes error ε_{it} to reveal both an inefficiency error u_{it} (related to endogenous random factors) and an idiosyncratic error v_{it} (related to exogenous farm factors), shown as

(33)
$$\varepsilon_{it} = v_{it} + u_{it}.$$

Idiosyncratic error v_{it} accounts for random noise across time or other observations, and is assumed independently and identically distributed (iid), symmetric, with mean zero and variance σ_v^2: $v_{it} \sim iid\ N(0, \sigma_v^2)$. Inefficiency error u_{it} in (33), rather, is a nonnegative random error term accounting for the distance from each observation to the stochastically estimated frontier. u_{it} is assumed independently and half-normally distributed: $u_{it} \sim N^{+}(0,\sigma_u^2)$. The two error terms, v_{it} and u_{it}, are assumed distributed independently of each other: $\sigma_{vu} = 0$. Error distributional assumptions follow from Battese and Coelli (1995, 1988).

To obtain the primal stochastic input distance frontier, substitute (33) into (32) to obtain

(34) $$-\ln x_N = f(\ln x^{*}_{kit}, \ln y_{jit}, t, \beta) + u_{it} + v_{it}.$$

While equations (34) and (32) provide equally important information about agricultural sector structure, only model (34) provides geographically-sourced (or location-based) relative agricultural performances. Structure refers to which outputs incur technical change and how technical change alters output and input choices. Performance refers to changes in an observation's position relative to the 'best-practice' frontier, thereby providing policy information about both geographic and historical inequalities. Technical change, as measured by models (32) and (34), reflects a contraction of the input requirement set over time given a fixed output set. Only model (34) includes observation-specific technical inefficiencies, shown as

(35) $$-u_{it} = f(\ln x^{*}_{kit}, \ln y_{jit}, t, \beta) + \ln x_N + v_{it}.$$

Observation-specific mean technical efficiencies $\left(\widehat{TE_{it}}\right)$ are estimated through (Battese and Coelli, 1988)

(36) $$\widehat{TE_{it}} = E\left[\exp(-u_{it}) \mid \varepsilon_{it}\right].$$

Technical inefficiency reflects the extent to which any observation lies off the input requirement set's frontier. Thus, technical inefficiency changes imply that a firm increases or decreases its relative distance to the frontier. Graphically, inward-oriented technical efficiency can be seen in figure 2. Figure 2 shows the stochastic input distance frontier that maximizes efficiency. Technical efficiency is obtained by substituting (33) into (26)

(37) $$D_I(x_{kit}, y_{jit}, t, \beta)e^{-u_{it}-v_{it}} = 1$$

In figure 2, point $x_{kit}^{'}$ is technically inefficient by measure $e^{u_{x_{kit}^{'}}} = D_I(x_{kit}^{'}, y_{jit}, t, \beta)e^{-v_{it}}$.

To obtain the frontier, shown by x_{kit}^{*}, inefficient point $x_{kit}^{'}$ must be deflated by stochastic input distance $D_I(y_{jit}, x_{kit}^{'}, t, \beta)e^{-v_{it}}$, or $x_{kit}^{*} = \dfrac{x_{kit}^{'}}{D_I(y_{jit}, x_{kit}^{'}, t, \beta)e^{v_{it}}}$.

4.3.1 Simultaneity Bias

A disadvantage of the production function approach relative to the dual approach derives from the fact that statistical estimation of unknown parameters which characterize the technology may not be consistent, i.e., production functions are prone to simultaneity bias (Diewert, 1992). Simultaneity bias may arise on account of the 'two-way' decision relationship between output quantity and that which explains output, the inputs. To characterize the simultaneity bias present in multi-output models of production, we first review the simultaneity bias associated with single-output production functions.

Simultaneity bias was initially discussed by Marschak and Andrews (1944), who show that when firms are assumed to exhibit profit maximizing behavior, classical least-squares Cobb-Douglas production function estimates are generally biased and inconsistent due to the dependence of the stochastically estimated production functions' input levels with the production function's error. Stated another way, producer optimization errors are correlated with the production function's error (e.g., variations in labor quality and quantity directly affect variations in yield output; or given a weather expectation, producers implement new irrigation technologies, which in turn impact farm yields). To avoid simultaneity bias in Cobb-Douglas production functions, a number of feasible methods are available: a) assume farms exhibit deterministic profit maximization behavior, then estimate the conditional factor demands and production function as a system of equations (Marschak and Andrews, 1944); b) assume farms exhibit expected profit maximization behavior, then directly estimate the production function (Zellner, Kmenta and Dreze, 1966); or c) assume inputs are already chosen (i.e., inputs are fixed and as such are exogenous), then maximize outputs given input quantities (Coelli, 1995).

If a developing country exhibits much subsistence-based agricultural production, it may not be possible to assume either deterministic or expected profit maximizing behavior. Profit maximization requires agents to maximize revenues over output choices and minimize costs over input choices. While cost minimizing behavior may be a feasible assumption, revenue maximization requires agents to choose those outputs which provide the highest income. Given producer uncertainty about future crop yield and market prices, farmers may make output-choice decisions that do not maximize revenues (e.g., may choose to grow a specific food crop even if it receives lower market prices than do other marketable crops). Such decisions may be due to cultural and historical factors or to the tendency of developing country governments to provide income stability through government support prices for specific food crops. Thus to measure developing nation agricultural productivity from a primal platform may require applying option c), which assumes inputs are predetermined by the farmer. This option raises interesting economic questions. Provided a sufficient length of run in the data, can a subsistence-based farmer predetermine the measurable inputs in his agricultural operation? Do developing countries have efficient and fully-functioning markets to supply all farms with the latest technologies? Moreover, are farmers' supplies of consistent quality (e.g., do fertilizers consistently contain the correct, or purchased, level of nutrient)?

There has yet to be a sufficient examination of the simultaneity bias possibly prevalent in the recent stochastic distance function literature. While Coelli (1995) cites expected profit maximization as the assumption most commonly made in characterizing agricultural production, Preckel, Akridge, and Boland (1997) find little evidence of profit maximization in U.S. farm supply cooperatives. Expected profit maximization in developing countries may therefore be the wrong behavioral assumption. Rather, it is more reasonable to think of developing country farmers as maximizing utility in a primal-dual model. A primal-dual model is necessary given the multiple outputs modeled and the simultaneous decisions farmers make about inputs and outputs.

In the most basic of such settings, we assume a subsistence farmer has a small plot of land producing food crops for home consumption and cash crops for profit. The farmer's utility is assumed to be a function of a farmer's expected profit, variance of profit (which entails both price risk and yield risk), and home food consumption. Only the first two moments of the farmer's utility of profit are modeled as we assume profits are normally distributed (Hirshleifer and Riley, 1992). In the presence of a farmer's risk preferences, the expectation and variance of profit combine to form expected utility of profit. To model the utility function, consider

(38) $$U\left(x_k, y_j\right) = E\left[U(\pi)\right] + \phi(y_j)$$

where the farmer's utility of inputs and outputs $U\left(x_k, y_j\right)$ is a function of the expected utility of profit $E\left[U(\pi)\right]$ plus the utility $\phi(y_j)$ of home food consumption, where output $\left(y_j \in \mathbb{R}_+^M\right)$ and input $\left(x_k \in \mathbb{R}_+^N\right)$ are in scalar notation. Note all observation and time subscripts have been suppressed. Under certain regularity conditions, expected utility of profit is approximately (Hirshleifer and Riley, 1992)

(39) $$E\left[U(\pi)\right] = E(\pi) + \chi\sigma_\pi^2 .$$

In equation (39), $E(\pi)$ is expected profit; $\chi = -\frac{U^{"}(x,y)}{U^{'}(x,y)}$ is the Arrow-Pratt coefficient of absolute risk aversion, a measure of utility curvature ($U^{'}$ is the utility function's first derivative and $U^{"}$ is its second derivative); and σ_π^2 is profit variance. Product $\chi\sigma_\pi^2$ provides a measure of the risk premium. If $\chi\sigma_\pi^2 > 0$, the farmer exhibits risk aversion (Anderson, Dillon and Hardaker, 1977).

To maximize utility over outputs and inputs in Lagrangian form, we have

(40) $$L(x_k, y_j, \lambda) = \underset{x,y}{Max}\left\{E(\pi) + \chi\sigma_\pi^2 + \phi(y_j) - \lambda\left[T(x_k, y_j)\right]\right\},$$

where λ is the marginal cost (benefit) of altering the technology constraint, which from (1) is $T(x,y) = 0$. The Lagrangian function in (40) maximizes the utility of profit and home food consumption in the face of the technology constraint.

The primal-dual method presented above broadens the scope of assumptions one may employ when the goal is to estimate a developing country's agricultural productivity in a primal multi-output manner. Assuming farmers maximize utility rather than profits may more accurately depict economic reality.

4.3.2 Data Constraints

The largest obstacles in estimating multi-factor productivity in a developing country are the quality and quantity of data. Because primal approaches require only quantity levels, secondary governmental public resources, such as the Foreign Agricultural Organization of the United Nations (FAO), the United Nations Educational, Scientific, and Cultural Organizations (UNESCO), the World Bank, and the International Labor Organization (ILO), are popular data sources (Coelli and Rao, 2005, Craig, Pardey and Roseboom, 1994, Fuglie, 2008, Hayami and Ruttan, 1985, Trueblood and Coggins, 2003).

The FAO has been the primary data source in most international agricultural productivity studies. They record production data on crops (primary and processed) and livestock (live animal stocks, and primary & processed commodities), and provide production indices (disaggregated into cereals, crops, and livestock, or as food and non-food) and production values. The FAO standard data base records data for 239 countries, territories, or economic areas over 47 years (1961-2007) (FAO, 2009). Primary crop production, measured in metric tons, accounts for 159 commodities; processed crops include 16 agricultural items, mainly oils, beer, and wine. Live animal stocks and beehives are recorded by count (in 'head' where applicable). Poultry, birds, and rabbits are recorded in 1,000 head. Primary and processed livestock commodities are measured in metric tons. The FAO records 17 live animal stocks, 41 primary livestock commodities, and 3 processed livestock commodities.

The FAO also reports output production indices, each measured as a price-weighted Laspreyes quantity index. The indices are estimated, net of feed and seed, relative to base year 1999-2001 in each calendar year. The prices employed to weight the Laspreyes quantity index are 'international prices' derived from the Geary-Khamis method, that is they are net of exchange rates to allow multilateral comparisons that maintain such properties as transitivity and base invariance.[22] Production indices are estimated for all agriculture, all cereals, crops, livestock, food, and non-food categories.

The FAO also records input quantity data pertaining to fertilizers, pesticides, labor, land, and machinery. Water resource data may soon be publicly available from the

[22] See Rao (1993)

FAO. Fertilizer consumption data typically centers on N, P205, and K20 (Nitrogen, Phosphate, and Potash respectively), although 20 other nutrients (such as urea, ammonia, and DAP) and classifications (i.e., <=10 kg., or >10 kg. NPK complex) are recorded, subject to data availability. While the FAO provides recorded fertilizer data, Fuglie (2008) says more up-to-date and accurate fertilizer consumption data, by country, may be found at the International Fertilizer Association website (www.fertilizer.org). Pesticide data are recorded for fungicides, herbicides, insecticides, and disinfectants. Labor estimates are in thousands of economically active population in 2004 and 2006. Land data are recorded by area (hectares) and by type (arable, temporary cropland, fallow land, permanent crops, meadows and pastures, and forests). Machinery data include tractors, balers, threshers, combine harvesters, manure spreaders, milking and dairy machinery, ploughs, roots & tuber harvesters, and seeders by count in use, imported, and exported.

Thus, whether research focuses on a single country or a multilateral approach to multi-factor productivity, the FAO provides extensive production data for primal productivity analysis. While the FAO attempts to record data for each country, it may be necessary to supplement FAO data with country-specific data, through either surveys or governmental censuses. As with all productivity research, farm resources, or input data, are more difficult to measure and obtain. Such price data may not always be available and border prices may be employed to supplement them. Border prices are wholesale prices and as such may need to be adjusted to accurately represent local retail prices (Hayami and Ruttan, 1985).

4.4 Dual Stochastic Frontier Estimation

Equation (34) shows that all deviations from the input distance frontier not accounted for by idiosyncratic error v_{it} are technical inefficiencies attributed to inefficiency error u_{it}. Stochastic cost estimation, on the other hand, includes as arguments output quantity and input price vectors rather than input quantities, so that any deviation from the minimum feasible cost is attributed to cost inefficiency. To obtain the cost inefficiency error associated with the stochastic cost frontier model, we start by showing that any farm's actual expenditures in exponential translog form $\left(e^{\ln \sum_k w_{kit} x_{kit}} \right)$ must be equal to the

exponential translog stochastic cost function $\left(e^{TC(\ln y_{jit}, \ln w_{kit}, t, \varpi)} e^{\mu_{it}} \right)$ which consists of

predicted costs $\left(e^{TC(\ln y_{jit}, \ln w_{kit}, t, \varpi)} \right)$ multiplied times an error $\left(e^{\mu_{it}} \right)$. That is,

(41) $$e^{\ln \sum_k w_{kit} x_{kit}} = e^{TC(\ln y_{jit}, \ln w_{kit}, t, \varpi)} \cdot e^{\mu_{it}} .$$

Residual μ_{it} is assumed to be an idiosyncratic error accounting for random production shocks. The deterministic kernel $e^{TC(\ln y_{jit}, \ln w_{kit}, t, \varpi)}$ is comprised of an output quantity scalar $\left(y_{jit} \in \mathbb{R}_+^M \right)$, input price scalar $\left(w_{kit} \in \mathbb{R}_+^N \right)$, technology indicator $t = 1, ..., E$, and unknown parameter vector ϖ . Requirements for estimating (44) are total expenditure, output quantity, and input price data.

Error μ_{it} is similar to primal composed error ε_{it} in (32) in that it may be decomposed into inefficiency error u_{it}^d and idiosyncratic error v_{it}^d , shown as

(42) $$\mu_{it} = u_{it}^d + v_{it}^d .$$

Superscript d denotes the dual approach, so as not to confuse readers with primal technical inefficiency error u_{it}. Substitute (42) into (41) to provide the stochastic cost frontier

(43) $$e^{\ln \sum_k w_{kit} x_{kit}} = e^{TC(\ln y_{jit}, \ln w_{kit}, t, \varpi)} \cdot e^{u_{it}^d + v_{it}^d} .$$

Distributional assumptions regarding the error components in equation (43) are drawn from Kumbhakar and Lovell (2000). Error v_{it}^d accounts for random noise across time and observations and is assumed independently and identically distributed (iid), symmetric, with mean zero and variance $\sigma_{v^d}^2$: $v_{it}^d \sim iid\ N(0, \sigma_{v^d}^2)$. Cost inefficiency error u_{it}^d is a nonnegative random error accounting for both technical inefficiency and input allocative inefficiency. u_{it}^d is assumed independently and half-normally distributed: $u_{it}^d \sim N^+(0, \sigma_{u^d}^2)$. As in the primal approach, the two error terms v_{it}^d and u_{it}^d are assumed distributed independently of each other: $\sigma_{v^d u^d} = 0$.

To obtain the stochastic cost frontier from (43), take logs across all terms to obtain

(44) $$\ln \sum_k w_{kit} x_{kit} = TC(\ln y_{jit}, \ln w_{kit}, t, \varpi) + u_{it}^d + v_{it}^d \,,$$

where the deterministic translog kernel $TC(\ln y_{jit}, \ln w_{kit}, t, \varpi)$ is presented in log-linear form

(45) $$\begin{aligned} TC_{it}(\ln y_{jit}, \ln w_{kit}, t, \varpi) &= \varpi_0 + \sum_{k=1}^{N} \varpi_k \ln w_{kit} + \sum_{j=1}^{M} \varpi_j \ln y_{jit} + \frac{1}{2}\sum_{k=1}^{N}\sum_{h=1}^{N} \varpi_{kh} \ln x_{kit} \ln x_{hit} \\ &+ \frac{1}{2}\sum_{j=1}^{M}\sum_{l=1}^{M} \varpi_{jl} \ln y_{jit} \ln y_{lit} + \sum_{k=1}^{N}\sum_{j=1}^{M} \varpi_{kj} \ln w_{kit} \ln y_{jit} \\ &+ \varpi_0 t + \frac{1}{2}\varpi_{00} t^2 + \sum_{k=1}^{N} \varpi_{kt} t \ln w_{kit} + \sum_{j=1}^{M} \varpi_{jt} t \ln y_{jit}. \end{aligned}$$

Equations (44) and (45) embody the technology of the primal (the production function) and the behavioral structure of the dual (that of cost minimization). Moreover, they provide the minimum cost to produce a given quantity of outputs. Alternatively defined, they provide the conditional factor demands necessary to minimize total production cost.

The cost function is homogeneous of degree +1 in input prices; that is $TC(y_{jit}, \iota w_{kit}, t, \varpi) = \iota TC(y_{jit}, \iota w_{kit}, t, \varpi) \;\forall\; \iota > 0$. Linear homogeneity of the cost function implies that any proportionate increase in farm input prices proportionately increases farm total cost. To constrain (45) for linear homogeneity of degree +1 in input prices, the following restrictions are imposed (Kumbhakar and Lovell, 2000, p.144):

(46) $$\sum_k \varpi_k = 1,\; \sum_k \varpi_{kh} = 0 \;\forall\; h = 1,\ldots,N, \text{ and } \sum_k \varpi_{kj} = 0 \;\forall\; j = 1,\ldots,M \,.$$

Equation (43) provides structural estimates of technical change and technical change bias through deterministic kernel $TC(\ln y_{jit}, \ln w_{kit}, t, \varpi)$. Performance estimates derive from cost inefficiency error u_{it}^d, which may be described in (47) as the negative of the difference between minimized total cost and actual farm cost plus idiosyncratic error v_{it}^d:

(47) $$-u_{it}^d = TC(\ln y_{jit}, \ln w_{kit}, t, \varpi) - (\ln \sum_k w_{kit} x_{kit}) + v_{it}^d \,.$$

To estimate a farm's cost inefficiency $\left(\widehat{CE_{it}}\right)$, the i^{th} observation's predicted cost inefficiency error u_{it}^{d} is used to derive the conditional expectation of cost inefficiency from composed error μ_{it} (Battese and Coelli, 1988)

(48) $$\widehat{CE_{it}} = E\left[\exp\left(-u_{it}^{d}\right) \mid \mu_{it}\right].$$

Cost inefficiency is indicated when $e^{-u_{it}^{d}} \leq 1$ and ruled out when $e^{-u_{it}^{d}} = 1$ (Kumbhakar and Lovell, 2000).

4.4.1 Cost Inefficiency Decomposition

Unfortunately, there is no consensus in the literature on the best multi-output stochastic frontier model for obtaining estimates of cost technical inefficiencies and cost allocative inefficiencies. An analytical and graphical decomposition of cost inefficiency error into its technical and allocative components is provided in figure 3 (Farrell, 1957).

Cost-efficient point A in figure 3 lies on the iso-cost line, determined by prevailing input price ratio $-w_1 / w_2$, tangent to the frontier of technology $T(y^{\circ})$. Any farm operating at point B should be able to improve its technical efficiency to point C by making better use of theoretically available technologies to reduce input usage (and as such farm cost) while maintaining production at current output levels. Any farm operating at point C is inefficiently allocating inputs at given price ratio $-w_1 / w_2$. If a farm operating at point C wished to improve allocative efficiency, it would substitute the relatively more expensive input x_1 for relatively cheaper input x_2 until it finds its marginal rate of substitution (MRTS) equal to the prevailing input price vector $-w_1 / w_2$. The MRTS is the ratio of inputs $\partial x_2 / \partial x_1$. Reallocating inputs to production point A places the farm on the scale expansion path (SEP), indicated by the tangency of the iso-cost line with the input requirement set, which implies farm cost minimization given input price ratio $-w_1 / w_2$ and input requirement set $T(y^{\circ})$.

A stochastic decomposition of cost inefficiency is provided in Kumbhakar and Lovell (2000).[23] They cite a stochastic translog cost frontier system of equations developed by Kumbhakar (1997), which is itself an adaptation of a stochastic Cobb-Douglas production frontier developed by Schmidt and Lovell (1979). While there are a number of methods for decomposing the cost inefficiency error into its technical and allocative inefficiency components, Kumbhakar's (1997) method is especially useful because it allows for the most variation in the allocative inefficiency estimates. For example, Kumbhakar's (1997) model provides allocative inefficiency estimates that vary by time, producer, and inputs; other models either lack an error for capturing statistical noise in the input share equations, assume allocative inefficiency to be constant across producers, or require numerical solutions of a system of nonlinear equations (Kumbhakar and Lovell, 2000, p. 165-166).

Econometrically differentiating cost inefficiency error u_{it}^{d} into its technical inefficiency and allocative inefficiency components requires input demand or cost share equations to be estimated along with a stochastic cost frontier (43) in a system of equations. We decompose cost inefficiency error term u_{it}^{d} as (Kumbhakar and Lovell, 2000)

(49) $$u_{it}^{d} = u_{it}^{d,te} \cdot u_{it}^{d,ae},$$

where the multiplicative inefficiency error u_{it}^{d} is the product of technical inefficiency error $u_{it}^{d,te}$ and allocative inefficiency error $u_{it}^{d,ae}$.

Substituting (49) into (44) and taking logs obtains

(50) $$\ln \sum_{k} w_{kit} x_{kit} = TC(\ln y_{jit}, \ln w_{kit}, t, \varpi) + v_{it}^{d} + u_{it}^{d,te} + u_{it}^{d,ae}.$$

The cost share, or factor demand, equations may be defined as

(51) $$CS_{kit} = \Phi_{k} + \sum_{h} \Phi_{kh} \ln w_{hit} + \sum_{m} \Gamma_{km} \ln y_{jit} + A\eta_{nit} + \mathrm{E}_{nit},$$

where each cost share is, from Shephard's Lemma, defined as the input price elasticity $CS_{kit} = \partial \ln TC_{it} / \partial \ln w_{kit}$. Subscript $k = 2,...,N$ refers to the kth factor, deleting one of

[23] For a complete review of the different feasible estimation procedures inclusive of the advantages and disadvantages associated with each method, the reader is directed to Kumbhakar and Lovell's Chapter 4.

them to avoid perfect multicollinearity (Kumbhakar and Lovell, 2000). Subscript $h = 1, ..., N$ refers to input price vector $w \in \mathbb{R}_+^N$, defined over time periods $t = 1, ..., E$ and observations $i = 1, ..., N$. $j = 1, ..., M$ refers to output vector $y \in \mathbb{R}_+^M$. A parametric specification of allocative inefficiency's impact on cost is imbedded via $A\eta_{nit}$ in each cost share equation. Allocative inefficiency parameters η_{nit} themselves are modeled as parametric functions of time, $\eta_{nit} = \eta_{ni} \cdot \Lambda(t)$. To obtain estimates of the impact of allocative inefficiency on total cost, allocative inefficiency error $u_{it}^{d,ae}$ is defined as the deterministic version of model (51) and estimates are obtained from those estimated parameters. Distributional assumptions for errors associated with equations (50) and (51) are (Kumbhakar and Lovell, 2000):

(52) $$v_{it}^d \sim iid\ N(0, \sigma_v^2),$$

(53) $$u_{it}^{d,te} \sim iid\ N^+(0, \sigma_u^2), \text{ and}$$

(54) $$\mathrm{E}_{nit} \sim iid\ N(0, \Sigma_{\mathrm{E}}).$$

To estimate technical inefficiency, we have (Jondrow, et al., 1982)

(55) $$E\left[u_{it} \mid \mu_{it}\right].$$

The model above improves on other inefficiency models by not only including technical inefficiency estimates but allowing both producer- and input-specific estimates of allocative inefficiency to vary over time.

An alternative method of obtaining allocative inefficiency estimates is to employ shadow prices. A shadow price reflects the opportunity cost to a producer of not equating his MRS with the respective ratio of input prices. Generalizing equations (44) and (51), Cornwell and Schmidt (1996) show the shadow cost minimization problem to be

(56) $$\begin{gathered} \ln \sum_k w_{kit} x_{kit} = TC(\ln y_{jit}, \ln z_{kit}, t, \varpi) + u_{it}^d + v_{it}^d \\ CS_{kit} = \Phi_k + \sum_h \Phi_{kh} \ln z_{hit} + \sum_m \Gamma_{km} \ln y_{jit} + \mathrm{E}_{kit}, \end{gathered}$$

in which the shadow input price vector is $z_{kit} = \gamma_{ki} w_{kit}$. Allocative inefficiency is determined from the estimated values $\widehat{\gamma_{ki}}$. If $\widehat{\gamma_{ki}}$ is less (more) than unity for a specific input, that input is relatively over- (under-) utilized (Cornwell and Schmidt, 1996).

Estimates of $\widehat{\gamma_{ki}}$ therefore provide an alternative method of estimating allocative inefficiency. When $\widehat{\gamma_{ki}}$ completely captures allocative inefficiency, u_{it}^{d} represents unbiased technical inefficiency (provided the model is otherwise unbiased). If, on the other hand, $\widehat{\gamma_{ki}}$ does not capture all of the allocative inefficiency present in the model then parameter estimates and the error terms u_{it}^{d} and v_{it}^{d} would be biased.

4.4.2 Data Constraints

Färe and Primont (1996) cite Shephard (1953) in describing the benefit of a dual approach over the primal, namely that the cost function's generally greater accessibility given that empirical investigations most frequently employ economic data in price and monetary terms. As stated above, the cost frontier is a function of output quantity and input price data. When conducting a micro-analysis of an LDC's agricultural productivity, the opposite may be true. At the disaggregate level, an LDC's quantity data often are more accessible than are price data. Inasmuch as this is true, the primal approach provides a broader target area for poor countries to analyze. This thought is epitomized by Fuglie (2008), who notes that there is no internationally comparable information on agricultural input prices, a requisite for the dual approach. For example, in his FAO paper on inter-country agricultural productivity comparisons, Rao (1993) was forced to employ a special survey to obtain input prices. It was conducted by the Statistical Analysis Service of the FAO's Statistics Division and is not publicly available (Rao, 1993). Barring general access to farm-level input-price survey data, the dearth of public input-price data thus is the major roadblock to a cost-based micro-approach to LDC multi-factor productivity analysis.

4.5 Conclusions

We have examined agricultural productivity estimation by highlighting the stochastic frontier approach in both a primal and dual model, with special attention to procedures, assumptions, and data constraints in LDCs. The emphasis of this essay has been on obtaining more information than may be derived from a single-output model. The information provided by applying these methods will assist LDCs in achieving their development goals. Analysis of technical change, a long studied contributor to agricultural development, provides insight into the impact of new technologies on farm production. Assessments of technical change bias allow policy makers and farmers alike to understand how technology alters farmer choices among inputs and outputs. Estimates of an agricultural sector's inefficiencies provide geographically sourced technology gaps between average and frontier farms.

In conclusion, our analysis has evaluated alternatives for implementing stochastic multi-output productivity analysis for LDC agricultural sectors, focusing on structural and performance estimates and in light of data constraints. Given the broad availability of quantity data from the FAO, the primal distance frontier approach provides a broader spectrum of countries than does the dual cost frontier for conducting agricultural productivity evaluation.

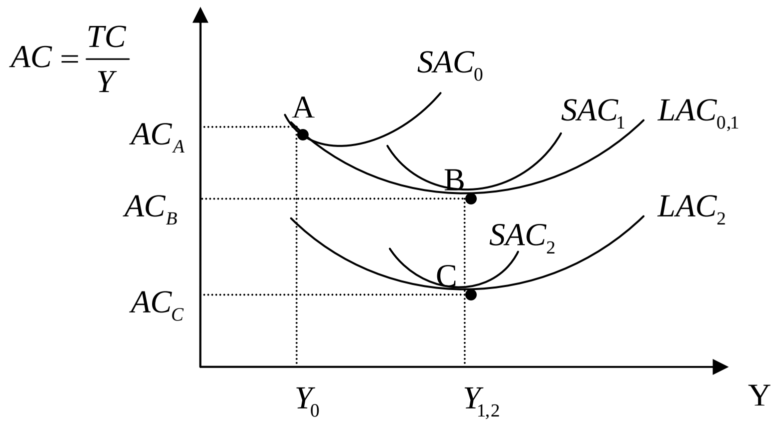

Figure 1. Characterizing Productivity in Terms of Average Cost, Assuming Non-Constant-Returns-To-Scale Technology

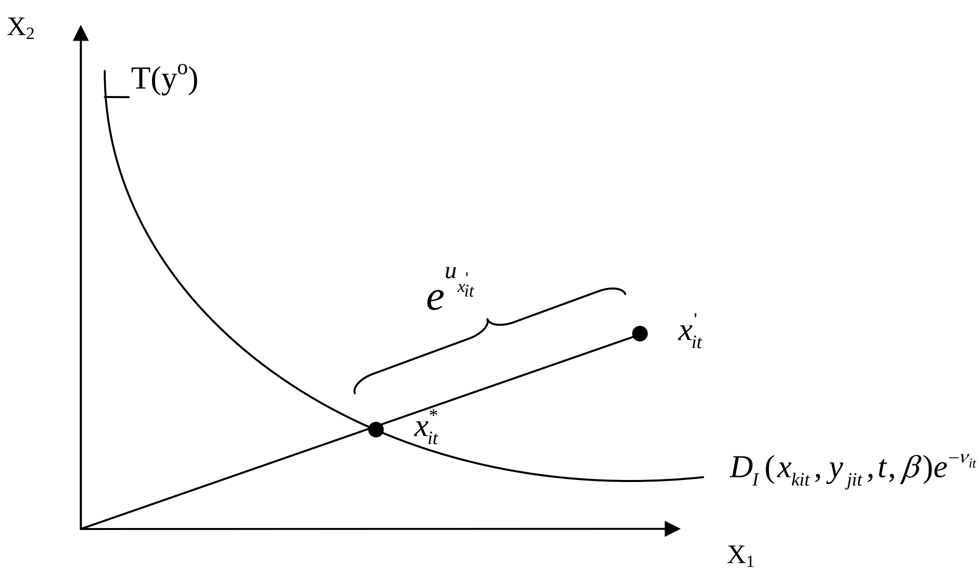

Figure 2. Inward-Oriented Technical Inefficiency with 2 inputs

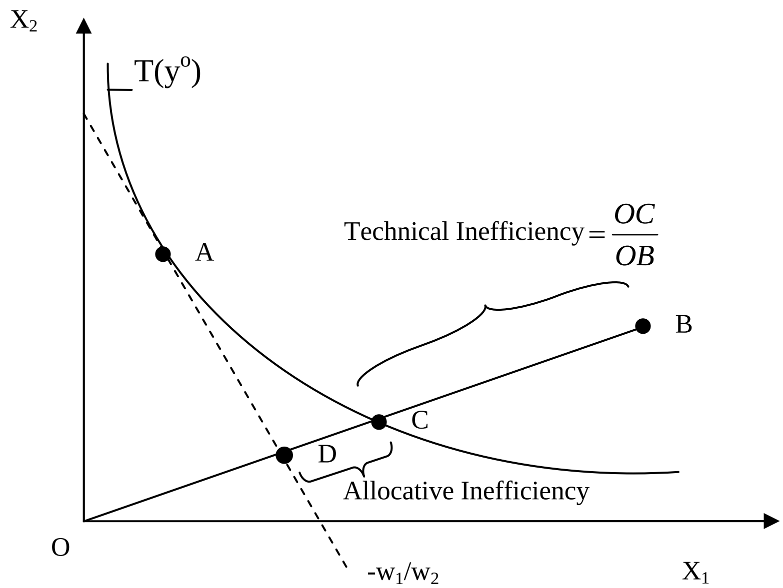

Figure 3. Cost Inefficiency with 2 Inputs

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APPENDICES

Appendix A: Indonesian Empirical Results

A.1 Parameter Estimates

DEP. VAR.: -LnPerennials	COEFFICIENTS	STANDARD ERROR	Z	P > |Z|
t	-0.0238676	.0044959	-5.31	0.00
LnAnnuals	0.7926849	.0404592	19.59	0.000
LnLivestock	0.1381265	.0300058	4.60	0.000
LnCapital	-0.1598463	0.060096	-2.66	0.008
LnIntermediates	-0.3774629	0.060376	-6.25	0.00
LnLabor	-0.0973661	0.069155	-1.41	0.159
LnAll_RD	-0.0009288	.0009093	-1.02	0.307
LnRegionalSpill_RD	-0.0070738	.0013053	-5.42	0.000
t_2	-0.0000598	.0004344	-0.14	0.891
LnAnnuals_2	0.1550812	0.077025	2.01	0.044
LnLivestock_2	0.147295	0.052702	2.79	0.005
LnCapital_2	-0.2920034	.220309	-1.33	0.185
LnIntermediates_2	-0.2769394	.1081915	-2.56	0.010
LnLabor_2	-0.0564542	.2605994	-0.22	0.828
LnCapital_LnIntermediates	-0.1458342	.158936	-0.92	0.359
LnCapital_LnLabor	0.1497109	.1866182	0.80	0.422
LnIntermediates_LnLabor	-0.3278083	.1449794	-2.26	0.024
LnAnnuals_LnLivestock	-0.1937048	.0519234	-3.73	0.000
LnAnnuals_LnCapital	-0.2326893	.1066319	-2.18	0.029
LnAnnuals_LnIntermediates	-0.0382586	.0746029	-0.51	0.608
LnAnnuals_LnLabor	-0.2279611	.1016073	-2.24	0.025
LnLivestock_LnCapital	0.1642983	.104831	1.57	0.117
LnLivestock_LnIntermediates	0.0725241	.0728493	1.00	0.319
LnLivestock_LnLabor	0.1869084	.0930002	2.01	0.044
t_LnAnnuals	0.0004915	0.0037822	0.13	0.897
t_LnLivestock	-0.0003553	0.0029958	-0.12	0.906
t_LnCapital	0.0082865	0.0077503	1.07	0.285
t_LnIntermediates	0.0146283	0.0055699	2.63	0.009
t_LnLabor	0.0071595	0.0064298	1.11	0.266

t_LnAll_RD	0.00010	0.000072	1.32	0.187
t_LnRegionalSpill_RD	0.0004048	0.000156	2.6	0.009
Bali – Java	0.2341477	0.038672	6.05	0.00
Central Java – Java	0.2297569	0.036199	6.35	0.00
Yogyakarta – Java	0.1250696	0.035575	3.52	0.00
East Java – Java	0.2598652	0.037471	6.94	0.00
West Java – Java	0.2335263	0.039553	5.9	0.00
Dista Aceh – Sumatra	0.333509	0.034199	9.75	0.00
N. Sumatra – Sumatra	0.2348827	0.038165	6.15	0.00
W. Sumatra – Sumatra	0.2708541	0.036206	7.48	0.00
Riau – Sumatra	0.2736961	0.043557	6.28	0.00
Jambi – Sumatra	0.3183176	0.041231	7.72	0.00
S. Sumatra – Sumatra	0.260258	0.040034	6.5	0.00
Bengkulu – Sumatra	0.1769858	0.039404	4.49	0.00
Lampung – Sumatra	0.2165377	0.038315	5.65	0.00
W. Kali. – Kalimantan	0.1159825	0.035118	3.3	0.001
C. Kali. – Kalimantan	0.189666	0.049642	3.82	0.00
S. Kali. – Kalimantan	0.0396722	0.033929	1.17	0.242
E. Kali. – Kalimantan	0.203085	0.053577	3.79	0.00
C. Sulawesi – Sulawesi	0.1877051	0.041324	4.54	0.00
N. Sulawesi – Sulawesi	0.237929	0.040688	5.85	0.00
S. Sulawesi – Sulawesi	0.166402	0.039828	4.18	0.00
SE. Sulawesi – Sulawesi	0.0314366	0.042865	0.73	0.463
NTB – East Indonesia	0.0920825	0.027706	3.32	0.001
LnSigma_2: v				
constant	-5.981611	0.205722	-29.08	0.0000
LnSigma_2: u				
constant	-115.1626	47.94879	-2.4	0.016
LnRoad	-0.7684447	0.246411	-3.12	0.002
LnLiteracy	25.18222	10.69301	2.36	0.019

Log Likelihood: 627.56; number of observations = 462

A.2 Indonesian Agricultural Research Financial Trends, Measured in 1999 International Dollars

	1981-1985	1991-1995	2001-2003
Ag. Research spending per farm	10.7	10.6	9.4
Ag. Research expenditures % of Ag.GDP	0.3 %	0.3 %	0.2 %
Ag.GDP (billions)	60.3	88.6	110.3

A.3 Regions and Provinces of Indonesia

Regions:	Provinces:							
Sumatra	Dista Aceh	North Sumatra	West Sumatra	Riau	Jambi	South Sumatra	Bengkulu	Lampung
Java/Bali	Bali	Central Java	Yogyakarta	East Java	West Java			
Sulawesi	Central Sulawesi	North Sulawesi	South Sulawesi	South East Sulawesi				
Kalimantan	West Kalimantan	Central Kalimantan	South Kalimantan	East Kalimantan				
E. Indonesia	Nusa Tenggara Barat (NTB)							

A.4 Indonesian Output Commodities

Annuals	rice, corn, soybeans, peanuts, pulses, cassava, sweet potatoes, potatoes, green beans, cabbages, carrots, chilies, cucumbers and gherkins, eggplants, garlic, shallots, pumpkins and squash, spinach, tomatoes, swamp cabbage, and tobacco.
Perennials	avocados, bananas, mangos, oranges, papayas, pineapples, fruit n.e.s. (not elsewhere specified), dried coconut, palm oil, cocoa beans, coffee, tea, natural rubber, cane sugar, primary fiber crops, cinnamon, cloves, nutmeg and mace and cardamoms, pepper (white and black), and vanilla.
Livestock	cattle meat, buffalo meat, horse meat, poultry meat, sheep meat, goat meat, pig meat, cow milk, and hen eggs.

A.5 Regularity Condition: Monotonicity

MONOTONICITY			
Outputs		Inputs	
$\frac{\partial TF}{\partial \ln Y_{Annuals}}$	0.63	$\frac{\partial TF}{\partial \ln X_{Capital}}$	-0.25
$\frac{\partial TF}{\partial \ln Y_{Livestock}}$	0.25	$\frac{\partial TF}{\partial \ln X_{Intermediates}}$	-0.55
		$\frac{\partial TF}{\partial \ln X_{Labor}}$	-0.15

A.6 Regularity Condition: Convexity

CONVEXITY	
Hessian Principal Minors:	Determinant
1	0.310162
2	0.053849
3	-0.026382
4	0.013156
5	0.000194

A.7 Technical Change Rates

	Informal Technical Change Rates (TCR)	Output elasticity of agricultural research	Time rate change in own-province agricultural research	Direct Formal TCR	Output elasticity of cross-province agricultural research	Time rate change in cross-province agricultural research	Indirect Formal TCR	Total TCR
Perennials	0.034	-0.0009		-0.0002	0.021		0.0009	0.035
Livestock	0.016	-0.0004	0.19	-0.0001	0.010	0.04	0.0004	0.017
Annuals	0.006	-0.0001		-0.00004	0.004		0.0001	0.006

A.8 Output & Input Bias to Technical Change

Input Bias	RB_k
Capital	-0.0007
Intermediates	0.0056
Labor	-0.0018
Output Bias	RB_i
Annuals	0.0002
Perennials	-0.0003
Livestock	-0.0006

A.9 Mean Technical Efficiencies (T.E.) by Province and Year

Provinces	Mean T.E. by Province, 1985-2005	Mean Logarithmic Rate of Change by Province, 1985-2005	YEARS	Mean T.E. by Year, All Provinces
Bali	0.996	-0.0003	1985-2005	0.956
C. Java	0.992	-0.0006	1985	0.975
Yogyakarta	0.997	-0.0001	1986	0.970
E. Java	0.997	-0.0003	1987	0.976
W. Java	0.979	-0.0028	1988	0.970
Dista Aceh	0.967	0.0009	1989	0.973
N. Sumatra	0.944	-0.0025	1990	0.972
W. Sumatra	0.954	-0.0015	1991	0.971
Riau	0.935	-0.0030	1992	0.969
Jambi	0.957	0.0007	1993	0.957
S. Sumatra	0.940	-0.0065	1994	0.958
Bengkulu	0.958	-0.0011	1995	0.954
Lampung	0.962	-0.0001	1996	0.950
W. Kalimantan	0.968	-0.0069	1997	0.960
C. Kalimantan	0.838	-0.0264	1998	0.970
S. Kalimantan	0.958	-0.0072	1999	0.946
E. Kalimantan	0.898	-0.0122	2000	0.950
C. Sulawesi	0.930	-0.0076	2001	0.964
N. Sulawesi	0.900	-0.0182	2002	0.946
S. Sulawesi	0.994	-0.0003	2003	0.928
SE. Sulawesi	0.970	-0.0012	2004	0.916
NTB	0.998	-0.0002	2005	0.901
			Mean Logarithmic Rate of Change	-0.0039

A.10 Explaining Technical Inefficiency

DEP. VAR.: $\ln\sigma_{uit}^{2}$	Estimated Coefficients	P > |Z|
Constant	-115.1626	0.016
LnRoad	-0.7684447	0.002
LnLiteracy	25.18222	0.019

Appendix B: Brazilian Empirical Results

B.1 Parameter Estimates

DEP. VAR.: -LnLivestock	COEFFICIENTS	STANDARD ERROR	Z	P > |Z|
LnAnnuals	0.38288	0.05574	6.870	0.000
LnPerennials	0.07018	0.02374	2.960	0.003
LnCapital	-0.10319	0.11113	-0.930	0.353
LnMaterials	-0.12643	0.05988	-2.110	0.035
LnLabor	-0.63013	0.08907	-7.070	0.000
LnCapital_2	0.27740	0.16356	1.700	0.090
LnMaterials_2	-0.11486	0.05498	-2.090	0.037
LnLabor_2	-0.04735	0.08142	-0.580	0.561
LnAnnuals_2	0.12611	0.03742	3.370	0.001
LnPerennials_2	0.02188	0.00786	2.780	0.005
LnCapital_LnMaterials	0.01421	0.06832	0.210	0.835
LnCapital_LnLabor	-0.07562	0.10685	-0.710	0.479
LnMaterials_LnLabor	0.05136	0.06871	0.750	0.455
LnAnnuals_LnPerennials	-0.04971	0.01282	-3.880	0.000
LnAnnuals_LnCapital	0.26819	0.05759	4.660	0.000
LnAnnuals_LnMaterials	-0.07085	0.03555	-1.990	0.046
LnAnnuals_LnLabor	-0.04836	0.04820	-1.000	0.316
LnPerennials_LnCapital	-0.09537	0.03241	-2.940	0.003
LnPerennials_LnMaterials	0.00444	0.01633	0.270	0.786
LnPerennials_LnLabor	0.04760	0.03091	1.540	0.124
Rondônia	-0.78591	0.11161	-7.040	0.000
Acre	-0.10048	0.16629	-0.600	0.546
Amazonas	-0.75576	0.07788	-9.700	0.000
Roraima	-0.08833	0.14910	-0.590	0.554
Pará	-0.50218	0.07406	-6.780	0.000
Amapá	0.12394	0.25327	0.490	0.625
Tocantins	-0.16774	0.11015	-1.520	0.128
Maranhão	-0.50832	0.07786	-6.530	0.000
Piauí	-0.46962	0.08489	-5.530	0.000
Ceará	-0.34068	0.06180	-5.510	0.000
Rio Grande Do Norte	-0.29859	0.08169	-3.660	0.000
Paraiba	-0.27280	0.06572	-4.150	0.000
Pernambuco	-0.24608	0.07286	-3.380	0.001

Alagoas	-0.51936	0.07969	-6.520	0.000
Sergipe	-0.14822	0.08352	-1.770	0.076
Bahia	-0.00323	0.06516	-0.050	0.960
Minas Gerais	-0.17550	0.06003	-2.920	0.003
Espírito Santo	0.29464	0.09916	2.970	0.003
Rio De Janeiro	-0.11443	0.09081	-1.260	0.208
São Paulo	0.09602	0.08672	1.110	0.268
Paraná	-0.48910	0.07577	-6.450	0.000
Santa Catarina	-0.35338	0.09192	-3.840	0.000
Rio Grande Do Sul	-0.20505	0.07932	-2.590	0.010
Mato Grosso Do Sul	-0.36936	0.11377	-3.250	0.001
Mato Grosso	-0.64233	0.09801	-6.550	0.000
Goiás	-0.25969	0.07862	-3.300	0.001
Federal District (Brasilia)	-0.36617	0.65943	-0.560	0.579
LnSigma_2: v				
constant	-2.893175	0.0793149	-36.48	0.00
LnSigma_2: u				
constant	-18.389440	7.400423	-2.480	0.013
LnEducationExpenditures	1.5880	0.7949212	2.000	0.046
LnRuralEducation	10.2248	4.709389	2.170	0.030

Log Likelihood: -31.475; number of observations = 550

A.2 Agriculture's Share of GDP (Current Prices, US$)

Year	Agriculture's GDP share	Year	Agriculture's GDP share
1985	9.00%	1996	8.32%
1986	9.24%	1997	7.96%
1987	7.73%	1998	8.23%
1988	7.60%	1999	8.25%
1989	7.20%	2000	7.97%
1990	8.10%	2001	8.39%
1991	7.79%	2002	8.75%
1992	7.72%	2003	9.90%
1993	7.56%	2004	9.05%
1994	9.85%	2005	7.53%
1995	9.01%	2006	n/a
1985-1995 Avg.	8.25%	1985-2005 Avg.	8.34%

Source: (Baer, 2008); n/a implies unavailable data

B.3 Structural Changes of the Agricultural Sector

	1975	1985	1995/1996	2006	1975-1985 Growth Rate	1985-1996 Growth Rate	1996-2006 Growth Rate
Establishments	4,993,252	5,801,809	4,859,865	5,204,130	0.150	-0.177	0.068
Total Land (Ha)	323,896,082	374,924,929	353,611,246	354,865,534	0.146	-0.059	0.004
Crop Lands (Ha)	40,001,358	52,147,708	41,794,455	76,697,324	0.265	-0.221	0.607
Pastures (Ha)	165,652,250	179,188,431	177,700,472	172,333,073	0.079	-0.008	-0.031
Forests (Ha)	70,721,929	88,983,599	94,293,598	99,887,620	0.230	0.058	0.058
Labor	20,345,692	23,394,919	17,930,890	16,414,728	0.140	-0.266	-0.088
Tractors	323,113	665,280	803,742	788,053	0.722	0.189	-0.020

Source: IBGE website

B.4 Regions and States of Brazil

Regions:	States:							
North	Rondônia	Acre	Amazonas	Roraima	Pará	Amapá	Tocantins		
Northeast	Maranhão	Piauí	Ceará	Rio Grande do Norte	Paraiba	Pernambuco	Alagoas	Sergipe	Bahia
Southeast	Minas Gerais	Espírito Santo	Rio de Janeiro	São Paulo					
South	Paraná	Santa Catarina	Rio Grande do Sul						
Center-West	Mato Grosso do Sul	Mato Grosso	Goiás	Federal District (Brasilia)					

B.5 Currency Changes in Brazil 1984-Present

Currency	Period	Equivalence
Cruzeiro (Cr$)	08/1984 to 02/1986	
Cruzado (Cz$)	02/1986 to 01/1989	Cz$1 = Cr$1,000
Cruzado Novo (NCz$)	01/1989 to 03/1990	NCz$1 = Cz$1,000
Cruzeiro (Cr$)	03/1990 to 08/1993	Cr$1 = NCz$1
Cruzeiro Real (CR$)	08/1993 to 05/1994	CR$1 = Cr$1,000
Real (R$)	05/1994 to Present	R$1 = CR$2,750

Source: IBGE

B.6 Agricultural Output Growth (Relative to 1.00 in Base Year 1985)

Regions	State	Annual Crops	Perennial Crops	Livestock	Output Fisher
North	Rondônia	0.73	1.15	7.01	1.67
North	Acre	1.47	1.59	2.89	1.99
North	Amazonas	1.12	1.39	1.87	1.25
North	Roraima	1.44	3.27	1.80	1.74
North	Pará	0.72	1.08	2.40	1.19
North	Amapá	0.63	2.01	2.47	1.11
North	Tocantins	0.67	0.62	1.99	1.36
Northeast	Maranhão	0.81	1.11	2.05	1.15
Northeast	Piauí	0.98	1.57	2.00	1.33
Northeast	Ceará	0.91	1.13	1.59	1.16
Northeast	Rio Grande Do Norte	0.66	1.25	1.55	1.15
Northeast	Paraiba	0.64	0.66	1.33	0.75
Northeast	Pernambuco	0.80	0.67	1.50	0.76
Northeast	Alagoas	1.10	0.83	2.02	0.88
Northeast	Sergipe	0.62	1.15	1.59	1.11
Northeast	Bahia	0.94	0.72	1.28	0.91
Southeast	Minas Gerais	1.03	1.13	1.34	1.18
Southeast	Espírito Santo	0.54	1.24	1.25	1.18
Southeast	Rio De Janeiro	0.61	0.61	1.30	0.73
Southeast	São Paulo	0.70	1.07	1.62	1.07
South	Paraná	1.26	0.84	2.22	1.25
South	Santa Catarina	1.16	0.96	2.76	1.73
South	Rio Grande Do Sul	1.00	1.12	1.96	1.26
Center-West	Mato Grosso Do Sul	1.27	1.81	2.76	2.04
Center-West	Mato Grosso	2.35	3.53	3.39	2.82
Center-West	Goiás	1.41	1.41	1.57	1.48
Center-West	Federal District (Brasilia)	1.63	1.85	2.76	2.01
	Brazil	1.07	1.03	1.90	1.20

B.7 Agricultural Input Growth (Relative to 1.00 in Base Year 1985)

Region	State	Labor	Materials	Capital	Input Fisher
North	Rondônia	0.92	4.33	2.06	1.50
North	Acre	1.38	1.52	1.56	1.40
North	Amazonas	0.70	1.22	1.04	0.75
North	Roraima	1.50	3.96	1.31	1.57
North	Pará	0.70	1.95	1.02	0.87
North	Amapá	0.87	1.68	0.82	0.93
North	Tocantins	0.84	2.25	0.99	1.03
Northeast	Maranhão	0.78	2.37	0.85	0.81
Northeast	Piauí	0.79	2.27	0.68	0.77
Northeast	Ceará	0.92	1.43	0.68	0.85
Northeast	Rio Grande Do Norte	0.82	2.18	0.76	0.88
Northeast	Paraiba	0.72	1.42	0.76	0.76
Northeast	Pernambuco	0.73	1.59	0.91	0.85
Northeast	Alagoas	0.69	1.97	0.93	0.84
Northeast	Sergipe	0.85	2.15	0.90	0.91
Northeast	Bahia	0.79	2.97	0.97	0.94
Southeast	Minas Gerais	0.79	2.33	0.93	1.08
Southeast	Espírito Santo	1.18	1.74	0.88	1.02
Southeast	Rio De Janeiro	0.52	1.35	0.67	0.70
Southeast	São Paulo	0.73	2.00	0.72	0.92
South	Paraná	0.70	2.24	1.00	1.06
South	Santa Catarina	0.85	1.99	0.96	1.16
South	Rio Grande Do Sul	0.76	2.43	0.93	1.11
Center-West	Mato Grosso Do Sul	1.19	2.59	1.02	1.35
Center-West	Mato Grosso	0.89	3.68	1.58	1.64
Center-West	Goiás	0.77	3.15	0.95	1.21
Center-West	Federal District (Brasilia)	0.83	1.76	1.11	1.32
	Brazil	0.783	2.247	0.916	0.998

B.8 Agricultural Fisher TFP Indices (Relative to 1.00 in Base Year 1985) and Logarithmic TFP Growth Rates from 1985 to 1995/1996

Region	State	Fisher TFP Index	Fisher TFP Change
North	Rondônia	1.117	0.117
North	Acre	1.419	0.419
North	Amazonas	1.667	0.667
North	Roraima	1.113	0.113
North	Pará	1.369	0.369
North	Amapá	1.192	0.192
North	Tocantins	1.327	0.327
Northeast	Maranhão	1.417	0.417
Northeast	Piauí	1.734	0.734
Northeast	Ceará	1.372	0.372
Northeast	Rio Grande Do Norte	1.315	0.315
Northeast	Paraiba	0.989	-0.011
Northeast	Pernambuco	0.894	-0.106
Northeast	Alagoas	1.040	0.040
Northeast	Sergipe	1.216	0.216
Northeast	Bahia	0.966	-0.034
Southeast	Minas Gerais	1.099	0.099
Southeast	Espírito Santo	1.154	0.154
Southeast	Rio De Janeiro	1.034	0.034
Southeast	São Paulo	1.165	0.165
South	Paraná	1.184	0.184
South	Santa Catarina	1.494	0.494
South	Rio Grande Do Sul	1.132	0.132
Center-West	Mato Grosso Do Sul	1.510	0.510
Center-West	Mato Grosso	1.718	0.718
Center-West	Goiás	1.226	0.226
Center-West	Federal District (Brasilia)	1.522	0.522
	Brazil	1.202	0.202

B.9 Regularity Condition: Monotonicity

MONOTONICITY			
Outputs		Inputs	
$\dfrac{\partial TF}{\partial \ln Y_{Annuals}}$	0.26	$\dfrac{\partial TF}{\partial \ln X_{Capital}}$	-0.17
$\dfrac{\partial TF}{\partial \ln Y_{Perennials}}$	0.08	$\dfrac{\partial TF}{\partial \ln X_{Materials}}$	-0.19
		$\dfrac{\partial TF}{\partial \ln X_{Labor}}$	-0.58

B.10 Regularity Condition: Convexity

CONVEXITY	
Hessian Principal Minors:	Determinant
1	0.252224
2	0.008565
3	0.001853
4	-0.000519
5	0.000074

B.11 Growth Efficiencies and Imputed Technical Changes from 1985 to 1995/1996

Region	State	Technical Efficiency Changes	Imputed Techincal Changes
North	Rondônia	0.993	0.117
North	Acre	0.811	0.517
North	Amazonas	0.999	0.668
North	Roraima	0.912	0.124
North	Pará	0.980	0.377
North	Amapá	0.684	0.281
North	Tocantins	0.931	0.351
Northeast	Maranhão	0.979	0.426
Northeast	Piauí	0.994	0.738
Northeast	Ceará	0.999	0.373
Northeast	Rio Grande Do Norte	0.955	0.330
Northeast	Paraiba	0.997	-0.011
Northeast	Pernambuco	0.994	-0.107
Northeast	Alagoas	0.991	0.040
Northeast	Sergipe	0.990	0.218
Northeast	Bahia	0.998	-0.034
Southeast	Minas Gerais	0.971	0.102
Southeast	Espírito Santo	0.848	0.182
Southeast	Rio De Janeiro	0.854	0.040
Southeast	São Paulo	0.767	0.215
South	Paraná	0.862	0.213
South	Santa Catarina	0.790	0.625
South	Rio Grande Do Sul	0.791	0.167
Center-West	Mato Grosso Do Sul	0.841	0.606
Center-West	Mato Grosso	0.884	0.812
Center-West	Goiás	0.979	0.231
Center-West	Federal District (Brasilia)	0.637	0.820
	Brazil	0.912	0.222

B.12 Explaining Technical Inefficiency

Dep. Variable: $\ln \sigma^2_{u,it}$	Estimated Coefficients	P > |Z|
Constant	-18.38901	0.013
LnPublicEducation	1.587913	0.046
LnRuralEducation	10.22454	0.030