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# Explaining Agricultural Productivity Levels and Growth: An International Perspective

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## Abstract

With persistent population growth, a dwindling supply of arable land per capita, and the relatively high income elasticity of demand for food in developing countries, there is a growing need for food supply increases to originate from growth in productivity rather than expansions in inputs. In this paper the authors construct levels of total factor productivity in agriculture for 111 countries covering the years 1970 to 2000. Employing this data in panel and cross-sectional regressions, the authors seek to explain levels and trends in total factor productivity (TFP) in world agriculture, examining the relative roles of environmental and geographical factors, human capital, macroeconomic factors, technological processes resulting from globalization and the Green Revolution, and institutional factors such as measures of land inequality and proxies for urban biases in public and private expenditure. The authors conclude that, in addition to standard explanations of productivity improvements such as human capital, openness and environmental factors, both urban biases and inequality have been major impediments to successful rural development.

**Key words**: Total factor productivity; labour productivity; world agriculture; multi-output distance function; institutional factors; environmental factors; urban bias; Green Revolution.

**JEL Classification:** O13, O18, O31, Q16, Q18.

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## 1. INTRODUCTION

The striking feature of the process of development of world agriculture over the last hundred or so years is the transition from a land-based to a productivity-based agricultural system underpinned by scientific and technological advances. Although this transition commenced in the second half of the $19^{th}$ century in most of the developed world, it only began a century later in much of the contemporary developing world (Ruttan, 2002), and some of the least developed countries are still yet to experience this technical revolution[1].

Over the last five decades to 2000 the world population has increased by 140 per cent from 2.5 billion to 6 billion. By the middle of this century the world is likely to witness a population growth of between 3 and 4 billion with most of this increase occurring in the poorest regions where the income elasticity of demand for food is at its highest.

Though there has been a significant reduction in global poverty in the last decade, there are still an estimated 1.1 billion people living under $1/per day and 2.1 billion people under $2/day, two thirds to three fourths of whom live in rural areas in Asia and Sub-Saharan Africa (Thirtle et al. 2002).

These three phenomena - low levels of technology, high population growth and high levels of rural poverty - are intimately interrelated. Low levels of technology in conjunction with high population growth (and therefore a dwindling supply of arable land per capita) cause low levels of food supply. This in turn may adversely affect both the rural and urban sector. On the one hand, the rural sector may, ceteris paribus, receive higher prices, but the reduction in output will more than likely offset this and lead to lower real income. The urban sector more

[1] Advances in science and technology following the Industrial Revolution have underpinned this change. On the other hand, as colonies the countries of the contemporary developing world benefited little from these advances except through the trickle down mechanism or where the direct interest of the colonial powers was paramount.

unambiguously faces higher food prices and lower real income.[2] Thus the importance of inducing technological innovations and greater efficiency in developing countries can hardly be overstated, particularly in terms of poverty reduction (see Thirtle et al. (2002) for a review).

Unsurprisingly, then, explaining productivity growth in agriculture has been the subject matter of extensive research. Colin Clark (1940), in his pioneering study Conditions of Economic Progress, first examined productivities per unit of land area and per unit of labour over time and across countries. Almost three decades later Hayami (1969) and Hayami and Inagi (1969) revived interests in cross-country time series analysis of land and labour productivity in agriculture. Subsequent research in this area involved estimation of cross-country production functions and multifactor productivity estimates (see for example, Trueblood and Ruttan 1995). Hayami and Ruttan (1970), Kawagoe et al (1985) and Lau and Yotopoulos (1989) employed meta-production function analyses in growth accounting frameworks to account for differences in agricultural labour and land productivity among individual countries and between developed and developing countries. Findings resulting from these studies rather unsurprisingly identified internal resource endowments (land and livestock), modern technical inputs (machinery and fertilisers) and human capital (general and technical education) as sources of variation among countries (Ruttan 2002).

More recently, researchers have elaborated on the question of resource constraints and sources of technical change. Hayami (2002) and Ruttan (2002) identify sources and constraints to productivity growth, van Ark (2002) attempts to measure the influence of information and communication technologies on productivity growth, and Craig et al. (1997)

[2] Of course, the open economy effects may be even worse for the rural sector if it cannot compete against cheaper imports.

and Thirtle et al. (2002) gauge the influence of research and development (R&D) expenditure on growth in productivity.

In sharp contrast to much of the earlier work on productivity in agriculture, with an emphasis on labour productivity, the present study focuses on multi- or total factor productivity growth, which takes into account all the important measurable inputs into agriculture. In addition to labour, the current study considers land, fertilizer, tractors and livestock inputs into agricultural production with productivity growth measured as the Solow residual. Much of the past work on agricultural productivity was based on estimated production functions which in the recent literature have been termed "augmented neoclassical" production functions or index number calculations (see, for example, Ruttan 2002; Pingali and Heisey 2001). In contrast, the current study takes advantage of more appropriate non-parametric frontier methods to estimate productivity change over time (Coelli et al. 2004).

Once the traditional quantitative inputs into agriculture are taken into account, any productivity growth (or change) has to be explained using other factors: either the quality of inputs or unmeasured inputs (such as publicly provided goods). In similar studies, Craig et al. (1997) have investigated the role of input quality, infrastructure and research in explaining total factor productivity growth, but these two studies suffer from the same limitations as the previous ones given that they only employ partial productivity measures. On the whole, therefore, the present study contrasts with previous studies in the literature both in terms of methodology and empirics, a difference epitomised by the use of a stochastic frontier approach and a total factor productivity measure, greater spatial coverage (111 countries), longer time series (more than three decades) and the inclusion of a significantly more expansive list of explanatory variables (particularly institutional and environmental variables).

Thus the second contribution of this paper is theoretical in that we explicitly test the linkages between TFP in agriculture and various aspects of development theory and historical experience.

With regard to the latter, we were particularly interested in the relationship of agricultural TFP to three phenomena: the Green Revolution, land inequality and urban biases in government expenditure.

The Green Revolution in many Asian countries, since the mid-1960s, has been canvassed as a major source of the transformation of agricultural production in the developing world (see fro example, Hayami and Ruttan 1985). However, the qualitative benefits of the Green Revolution have been questioned by numerous researchers, particularly with regard to the distributional consequences (Pearse, 1980, Griffin, 1979) and the effects on the environment and labour (Alauddin, 2004; Wilson, 2002). In this study we take account of arguably two 'Green' inputs, fertilisers and tractors. By assessing the impact of the Green Revolution on the TFP residual, we hope to estimate the productivity benefits of the Revolution.

Our second area of theoretical interest concerns the linkages between agricultural TFP and the evolution of both the rural and urban sectors. Early development thinkers, such as the highly influential Sir Arthur Lewis (1954), viewed development as virtually synonymous with industrialisation. The influence of this class of dualist models has been substantial[3]. Development policies for most of the post-war era have centred around industrialization plans[4] which, contrary to the assumptions of the Lewis model, have certainly come at some

[3] Formulated originally by W. Arthur Lewis in the mid-1950s (Lewis, 1954) , and later modified, formalized and extended by Fei and Ranis (1964), the "Lewis two-sector model became the received "general" theory of the development in labor-surplus Third World nations during most of the 1960s and early 1970s " (Todaro 1992, p.69).
[4] As Meier (1976, p.5) put it "As a result of their colonial history and newly acquired political independence, many poor countries have expressed discontent with their "dependence" on export markets and foreign capital… to be avoided now by import substitution policies and restrictions on the inflow of foreign capital ". India was a

direct or indirect cost to the development of the rural sector[5] – a sector in which, as we have already noted, the majority of the world's poor still inhabit. The most vocal critic of urban biases in development is Lipton (1977), who identified a myriad of ways in which resource allocation is disproportionately and inefficiently biased towards the urban sector at the expense of productivity and poverty alleviation in the rural sector. Other studies which have identified biases against the agricultural sector include Little et al. (1970), Krueger et al (1991) and Binswanger and Deininger (1997). The first two studies mostly attempt to gauge the policy biases against agriculture in the form of direct and indirect taxes (such as overvalued exchange rates, import duties, and industrial protection), while Binswanger and Deininger place greater emphasis on political constraints to rural action. In some contrast, this study gauges the effects of urban biases on productivity levels and growth, with a particular emphasis on biases within government expenditure.

A final issue much discussed in the development literature is the existence of equity-efficiency tradeoffs in the agricultural sector. This was an area of heated debate during the 1960s and the 1970s when it took the form of establishing an inverse relationship between productivity and farm size[6], with some authors arguing that land reform would in fact increase productivity (Berry and Cline 1979). Other authors highlight the political implications of greater equality: inequality may lead to a greater collective action potential and in fact reduce urban biases (Binswanger and Deininger, 1997). More recently there has been considerable

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glaring example of this type of policy stance on industrialization emphasizing heavy and capital intensive industries embodied in the second and third five year plans.

[5]A common example implicit discrimination of the rural sector is the protection of the industrial sector in the form of artificially overvalued exchange rates and subsidies, which often amount to a large effective tax on the agro-rural sector (see for example, Little et al. 1970). Another widely cited example was pre-separation Pakistan, in which the industrialization in the western part was largely financed through such mechanisms was at the expense of agriculture in the eastern wing (see for example, Khan 1972).

[6] For a summary of this debate see Bhagwati and Chakravarty (1969) and Bhalla and Roy (1988). Later studies e.g. Bhalla and Roy (1988) introduced the role of land quality as a factor in the size productivity debate rather than absolute size per se. For a comprehensive review of the relevant literature see Berry and Cline (1979).

interest in the effects of inequality on economic growth. Establishing a relationship between land inequality and TFP is therefore a pursuit of persistently topical interest.

The structure of the paper is as follows. Section 2 describes the methodology employed to construct estimates of agricultural TFP. Section 3 describes the basic data used in the analysis and an exposition of the underlying conceptual framework. Some basic features of the data, including the levels and shares of global agricultural production, are briefly described, while the output and input variables used in productivity measurement are described in greater detail. Section 4 presents the empirical results and highlights the characteristic features of productivity performance in global and regional agriculture. This section identifies political, institutional, geographic and macro-economic factors that can explain inter-country differences in agricultural productivity levels and growth performance. Section 5 provides a discussion of the main findings and some concluding comments. In this paper the authors conclude that a wide range of conventional factors (human capital, geography, the Green Revolution) play their expected roles, albeit to varying degrees, but perhaps most significantly, land inequality (in poorer countries only) and urban biases in government expenditure have been major obstacles to productivity improvements in the agricultural sector.

## 2. METHODOLOGY[7]

Most studies to date have used the index number approach to measure productivity growth in agriculture. This approach is consistent with the general interpretation of the Solow residual and the use of Cobb-Douglas production technology. The measurement and interpretation of TFP growth from the index number approach was adequately addressed by Caves et al (1982) who established an analytical link between TFP growth measured based on the index number

[7] This section draws heavily on Coelli et al (2004).

approach and the conceptual framework underlying the Malmquist TFP index ( see Coelli et al. (1998) for more details). The empirical application of the Malmquist TFP index requires more data than just output and input information on two countries. If panel data with a reasonable size cross-section of observations are available then the Malmquist TFP index can be applied. For example, Färe et al. (1994) and Coelli and Rao (2004) use the Malmquist TFP index for a comparative analysis of productivity performance across countries.

The Malmquist TFP index is used in the current study for 111 countries over the time period 1970 to 2000. The data set is rich and sizeable allowing us to undertake a more sophisticated econometric estimation of the production technologies which are in turn used in obtaining measures of TFP levels and trends in agriculture.

### 2.1 The Malmquist TFP Index

The Malmquist TFP index is defined using an output distance function.[8] For further details of this approach, including the technology axioms associated with the output function, see Coelli, Rao and Battese (1998, Ch. 3). The Malmquist TFP index itself measures the TFP change between two data points (e.g., those of a particular country in two adjacent time periods) by calculating the ratio of the distances of each data point relative to a common technology. Following Färe et al (1994), the Malmquist (output-orientated) TFP change index between period s (the base period) and period t is given by

$$m_o(y_s, x_s, y_t, x_t) = \left[ \frac{d_o^s(y_t, x_t)}{d_o^s(y_s, x_s)} \times \frac{d_o^t(y_t, x_t)}{d_o^t(y_s, x_s)} \right]^{1/2}, \qquad (1)$$

[8] The main reason for this approach is that countries have limited capacity to alter the input endowments when it comes to agriculture – factors like land, irrigation and to some extent labour, as measured by population actively employed in agriculture, are treated as endowments. Thus productivity is based on measures technically feasible maximum output for given inputs – an output-orientated Malmquist productivity index based on output distance functions are more appropriate.

where the notation $d_o^s(y_t, x_t)$ represents the output distance from the period t observation to the period s technology. A value of $m_o$ greater than one will indicate positive TFP growth from period s to period t while a value less than one indicates a TFP decline. Note that equation (3) is, in fact, the geometric mean of two TFP indices. The first is evaluated with respect to period s technology and the second with respect to period t technology.

An equivalent way of writing this productivity index is

$$m_o(y_s, x_s, y_t, x_t) = \frac{d_o^t(y_t, x_t)}{d_o^s(y_s, x_s)}\left[\frac{d_o^s(y_t, x_t)}{d_o^t(y_t, x_t)} \times \frac{d_o^s(y_s, x_s)}{d_o^t(y_s, x_s)}\right]^{1/2}, \qquad (2)$$

where the ratio outside the square brackets measures the change in the output-orientated measure of Farrell technical efficiency between periods s and t. That is, the efficiency change is equivalent to the ratio of the technical efficiency in period t to the technical efficiency in period s. The remaining part of the index in equation (4) is a measure of technical change. It is the geometric mean of the shift in technology between the two periods, evaluated at $x_t$ and also at $x_s$. Thus we have the decomposition:

$$\text{Malmquist index} = m_o(y_s, x_s, y_t, x_t) = \text{Efficiency Change} \times \text{Technical Change} \qquad (3)$$

Equation (5) shows an important property of the Malmquist index which makes it possible to decompose the productivity growth, measured using Malmquist TFP index, into efficiency change and technical change components. Efficiency change component here refers to the improved ability of a country to adopt the global technology available at different points of time where as technical change measures the effect of shift in the production frontier resulting from technological advances on agricultural output.

Distance functions can be estimated using various methods. Each method differs according to type of techniques used, type of data available, and the assumptions made regarding the economic behaviour of decision makers and the structure of the production technology. In this study, the distance functions used are directly estimated using the stochastic frontier estimation of multi-output and multi-input distance function. Empirical estimates of the parameters of the distance function are drawn from a recent study conducted by Coelli et al (2004), details of the model specification and econometric estimation are not included here.

The translog output distance function for the case of M output and K inputs estimated in Coelli at el (2004) is shown as:

$$\begin{aligned}\ln D_{oit} &= \beta_0 + \sum_{m=1}^{M} \beta_{y_m} \ln y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{y_m y_n} \ln y_{mit} \ln y_{nit} + \sum_{k=1}^{K} \beta_{x_k} \ln x_{kit} \\ &+ \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{x_k x_l} \ln x_{kit} \ln x_{lit} + \sum_{k=1}^{K}\sum_{m=1}^{M} \beta_{x_k y_m} \ln x_{kit} \ln y_{mit} + \beta_z z + \frac{1}{2}\beta_{zz} z^2 \\ &+ \sum_{k=1}^{K} \beta_{x_k z} \ln x_{kit} z + \sum_{m=1}^{M} \beta_{y_m z} \ln y_{mit} z\end{aligned} \tag{4}$$

where $i = 1,...,I$ index of country; $t = 1,...,T$ index of time period; $k,l = 1,...,K$ index of input quantities; $m,n = 1,...,M$ index of output quantities; $D_o$ is the output distance; $x_k$ is the k-th input quantity; $y_m$ is the m-th output quantity; $z$ represents time trend; and βs are unknown parameters to be estimated. In the current study M=2 and K=5, since there are two outputs and five inputs.

Equation (5) is estimated after imposing the symmetry restrictions, $\beta_{x_k x_l} = \beta_{x_l x_k} \ (\forall k,l = 1,...,5)$ and $\beta_{y_m y_n} = \beta_{y_n y_m} \ (\forall m,n = 1,2)$, and the additional restrictions required for homogeneity of degree +1 in outputs given by:

$$\sum_{m=1}^{2} \beta_{y_m} = 1,\ \sum_{n=1}^{2} \beta_{y_m y_n} = 0 \ \ (m = 1,2),\ \sum_{m=1}^{2} \beta_{x_k y_m} = 0 \ \ (k = 1,...,5) \text{ and } \sum_{m=1}^{2} \beta_{y_m z} = 0 \tag{5}$$

Equation (6) can be estimated as a standard stochastic frontier function where $v_{it}$ s are the random errors, assumed to be i.i.d. and have $N(0,\sigma_v^2)$ -distribution, independent of the $u_{it}$ , the technical inefficiency effects.

In order to guarantee constant returns to scale (CRTS) upon the output distance function, the additional restriction of homogeneity of degree -1 in inputs must be imposed upon equation (6) which requires:

$$\sum_{k=1}^{5}\beta_{x_k} = -1,\ \sum_{l=1}^{5}\beta_{x_k x_l} = 0\ \left(k = 1,...,5\right),\ \sum_{k=1}^{5}\beta_{x_k y_m} = 0\ \left(m = 1,2\right),\ \sum_{k=1}^{5}\beta_{x_k z} = 0\,. \tag{6}$$

These restrictions can be imposed by estimating a model where the K-1 input quantities are normalized by the K-th input quantity.

Once the output distance function is estimated, measures of technical efficiency and technical change between adjacent periods s and t to calculate the Malmquist TFP index are calculated as follows.

$$\text{Efficiency Change} = \frac{TE_{it}}{TE_{is}} = \frac{E\left(\exp\left(-u_{it}\right)\middle|e_{it}\right)}{E\left(\exp\left(-u_{is}\right)\middle|e_{is}\right)} \tag{7}$$

$$\text{Technical Change} = \left\{\left[1+\frac{\partial d(\cdot)}{\partial s}\right]\times\left[1+\frac{\partial d(\cdot)}{\partial t}\right]\right\}^{0.5} \tag{8}$$

where $d(\cdot)$ is the translog functional form of the output distance functions defined in equation (6).

### 2.3. Calculating Implicit Value Shares in Malmquist TFP Index

While the output distance function described in Section 2.2 can be employed in measuring TFP growth for each country along with its components, results from the output distance function cannot readily be used in making TFP level comparisons. In the study, TFP levels are computed using multilateral-index number methods using the Tornqvist binary index as the basis. However, application of Tornqvist index requires output and input shares which are not readily available due to lack of price data for inputs. The current study makes use of implicit value shares derived from the estimated output distance function. Färe et al. (1993) showed that if the output sets are convex, the duality between the output distance function and the revenue function can be exploited to retrieve information on output shadow prices. The first partial derivative of the output distance function with respect to the m-th output represents a revenue-deflated shadow price:

$$\frac{\partial D_o}{\partial y_m} = \frac{p_m^*}{R} \tag{9}$$

where $p_m^*$ is the shadow price of the m-th output and R is total revenue. The ratio of the revenue-deflated shadow prices of two outputs will reflect the slope of the production possibility curve (i.e. the marginal rate of transformation). Färe et al. (1994) showed that the first partial derivative of the output distance function with respect to the k-th input provides a measure of the shadow price of the k-th input deflated by total cost. Ratios of these partial derivatives (i.e. shadow prices) reflect the slope of the isoquant (i.e. the marginal rate of technical substitution). Coelli et al (2004) derive implicit value shares and the underlying shadow prices for all the inputs and the two outputs considered here. These are used along with quantity data to derive TFP level indexes used in the empirical analysis here.

### 2.4 Comparison of Levels of Total Factor Productivity

The multi-output production technology representation based on multi-output and multi-input distance function is used in compiling trends in total factor productivity for each of the countries included in the study for the period under consideration. In order to construct a panel data set comprising of total factor productivity comparisons across countries and over time, it is necessary to construct index numbers of TFP to make comparisons of levels of TFP across countries.

In this paper, TFP levels across countries are compared using multilateral index number methodology similar to that described in Caves et al (1982) with slight modifications. The TFP index is defined as

$$\text{TFP index} = \frac{\text{Output index}}{\text{Input index}} \tag{10}$$

where the output and input indices are computed using the following steps. For any pair of countries j and k, the output index, $O_{jk}$, and the input index, $I_{jk}$, are given by

$$O_{jk} = \prod_{i=1}^{M} \left[ \frac{y_{ik}}{y_{ij}} \right]^{\frac{v_{ij}+v_{ik}}{2}} \quad \text{and} \quad I_{jk} = \prod_{n=1}^{N} \left[ \frac{x_{nk}}{x_{nj}} \right]^{\frac{w_{nj}+w_{nk}}{2}} \tag{11}$$

where y's and x's represent outputs and inputs and v's and w's respectively denote the output and input shares respectively. For given j, k and i and n the output and input shares are the average shadow shares derived from the multi-output distance functions estimated using actual data. The shadow shares are derived for each of the years in the sample and averaged over time for each country. This averaging process is designed to retain the cross-country differences in output and input shares and at the same time eliminate fluctuations over time.

The index numbers used in (2) are essentially binary Tornqvist index numbers similar to those used in Caves et al (1982), the only difference is that the shares used here are not the observed shares but the shadow shares derived from the estimated multi-output and multi-input distance function. Since the binary index numbers in (2) are not transitive, the approach outlined in Caves et al (1982) is followed in this paper in deriving transitive multilateral index numbers, denoted by $O_{jk}^{*}$ and $I_{jk}^{*}$. These are computed as:

$$O^*_{jk} = \prod_{\ell=1}^{C} \left[O_{j\ell} * O_{\ell k}\right]^{\frac{1}{C}} \text{ and } I^*_{jk} = \prod_{\ell=1}^{C} \left[I_{j\ell} * I_{\ell k}\right]^{\frac{1}{C}} \qquad (12)$$

where C represents the number of countries in the study. The indices in (3) are usually referred to as the EKS index numbers as they are based on a formula suggested by Elteto and Koves (1964) and Szulc (1964).[9]

The multilateral output and input index numbers are used in deriving TFP level index numbers. In this study, TFP level comparisons are derived for the year 1970 using the United States as the base country.[10] The TFP growth estimates derived from the multi-output multi-input distance function are applied to the TFP levels computed using the formulae discussed here leading to a complete panel of TFP estimates that are used in further regression work.

## 3. THE DATA

The primary calculations for this study were carried out on panel data on 111 countries over the time period of 1960-2000 (see Table 1). These countries account for more than 95 percent of global agricultural output and 98 percent of world's population. Thus the coverage of the study is truly global in character. For the cross-country regressions presented in the next section we used 1970-2000 data only, and a handful of countries were excluded due to either insufficient data, measurement error (denoted *) or because they were transition countries. We also run regressions with a developing country set which excludes OECD countries (denoted #).

[insert Table 1]

[9] For further details on these index numbers see Rao (2001).
[10] As the index numbers used here satisfy the transitivity property, the choice of the reference or *numeraire* country does not affect relative productivity level comparisons between pairs of countries.

### 3.1 The TFP Data

The primary source of TFP data is obtained from the website of the Food and Agriculture Organization of the United Nations (www.fao.org) and, in particular, the agricultural statistics provided by the AGROSTAT system, supported by the Statistics Division of the FAO[11]. The data used to estimate the TFP measurement and decomposition contain the measurements of agricultural output and input quantities. In this study, the production technology is presented by two output variables (i.e. crops and livestock output variables) and five input variables (i.e. land, tractors, labour, fertiliser, and livestock input variables). The definitions of these variables are summarized as follows.

#### 3.1.1 Output Series

The output series for the two output variables are derived by aggregating detailed output quantity data on 185 agricultural commodities[12]. Construction of output data series uses the following steps.

First, output aggregates for the year 1990 are drawn from Table 5.4 in Rao (1993). These aggregates are constructed using international average prices (expressed in US dollars) derived using the Geary-Khamis method (see Rao 1993, Chapter 4 for details) for the benchmark year 1990.[13] Since the crop and livestock aggregates are all formed using Geary-Khamis method it is possible to aggregate these two to form total agricultural output, where necessary. Thus the output series for 1990 are at constant prices, expressed in a single currency unit. Data for the transition countries are based on the results from a recent study

[11] We are grateful to the FAO for maintaining an excellent site and for devoting resources to the compilation and dissemination of data through the internet.
[12] The output series are based on 1990 international average prices. So the output series could change slightly when the base is shifted from 1990 to another period, thus potentially influencing the final results. Even though results are available for more recent benchmark year, 1995, it was decided that 1990 comparisons would form a more appropriate basis for the current project.
[13] The Geary-Khamis international average prices are based on prices (in national currency units) and quantities of 185 agricultural commodities in 103 countries.

(Rao, Ypma and van Ark, 2004) which uses 1995 as benchmark, the results of which are spliced to express the series in 1990 prices.

The next step is to extend the 1990 output series to cover the whole study period 1961-2000. This is achieved using the FAO production index number series for crops and livestock separately[14]. The production index number series show growth in output (for crops and livestock separately) using 1990 as the base. The series derived using this approach are essentially equivalent to the series constructed using 1990 international average prices and the actual quantities produced in different countries in various years.

### 3.1.2 Input Series

Because of data constraints on additional inputs, we have opted to consider only five input variables, though this is considerably more than many other studies. The land input variable represents the arable land, land under permanent crops as well as the area under permanent pasture. The tractor input variable represents the total number of wheel and crawler tractors, but excluding garden tractors, used in agriculture. Labour input variable refers to economically active population in agriculture which is defined as all persons engaged or seeking employment in an economic activity, whether as employers, own-account workers, salaried employees or unpaid workers assisting in the operation of a family farm or business. Following other studies (Hayami and Ruttan 1970, Fulginiti and Perrin 1997) of inter-country comparisons of agricultural productivity, the fertiliser input variable represents the sum of Nitrogen (N), Potassium (K) and Phosphate (P) contained in the commercial fertilizers consumed. It is expressed in thousands of metric tons. Livestock input variable used in the study is the sheep-equivalent of the five categories of animals used in constructing this variable. The categories considered are: buffaloes, cattle, pigs, sheep and goats. Raw numbers

[14] See the 1997 FAO Production Yearbook for details regarding the construction of production index numbers.

of these animals are converted into sheep equivalents using conversion factors: 8.0 for buffalos and cattle; and 1.00 for sheep, goats and pigs.[15]

The resulting data set is an unbalanced panel of 111 countries for the years 1970 to 2000 with a total of 3099 observations, though we transform this data for our regression analysis (see below). Table 2 represents a summary of the data used in this study. The table implies large variation in the output and input variables across the countries. Figure 1 shows input growth from 1970 to 2000 aggregated over all the 111 countries in the study and contrasts it with output growth. The graph shows a phenomenal increase in the use of fertilisers over the period. A similar trend can be observed for tractors as well. Thus we already observe two rather spectacular measures of the effect of the Green Revolution – the adoption of complementary inputs. Table 2 also shows significant growth rates in labour and land productivity over this period, indicating modest total factor productivity (TFP) growth.

[Insert Table 2]

[Insert Figure 1]

We now look at TFP data for our regression sample (see Table 1). The total sample (ALL) can be split up into advanced countries (including Israel), developing countries (DEV), East Asia (EASIA), South Asia (SASIA), Latin America and the Caribbean (LAT), sub-Saharan Africa (SSA), and the Middle East and North Africa (MENA). Figure 2 shows mean, minimum and maximum TFP levels in 1970 for the whole sample and each sub-sample.

[Insert Figure 2]

[15] The conversion figures used in this study correspond very closely with those used in the 1970 study of Hayami and Ruttan. Chicken numbers are not included in the livestock estimates.

TFP levels are lowest in South Asia and MENA, higher in the Latin American region, East Asia and, unsurprisingly, highest in the OECD sample. The spreads also make for interesting viewing. The OECD sample has the widest spread, ranging from Israel which has by far the highest TFP level at 1.94 (almost twice that of U.S. TFP levels) down to Norway at 0.49 (less than half the U.S. TFP level). South Asia and MENA are relatively small samples with similar TFP levels. There is greater variation in East Asia, with China and Myanmar beginning from very low levels (0.42 and 0.44 respectively) while South Korea had already reached a TFP level comparable to the OECD countries (1.05). Latin America presents even more variety with Brazil beginning with a TFP level half that of the U.S., while Argentina began with a TFP significantly greater than the U.S. (1.31).[16]

The broad picture that emerges from TFP growth performance is markedly different. Figure 3 presents data on average annual change in TFP from 1970 to 2000.

[Insert Figure 3]

Here, the mean growth rates do not vary significantly by sample, though there are perhaps two exceptions to this conclusion. East Asia and South Asia – two regions containing countries which were early beneficiaries of the Green Revolution - both have markedly lower TFP levels. Indeed, the econometric analysis (Section 4) confirms that TFP growth levels in major rice- and wheat-producing countries (the two crops most affected by Green Revolution technologies) were not significantly different from growth levels in other countries. Of course, since TFP levels implicitly incorporate increases in inputs, including Green Revolution inputs such as fertilisers, this result is not entirely counterintuitive. Nevertheless, our inputs do not include genetically modified high-yield crop varieties such that it is somewhat surprising that

[16] As we will see, our regression analysis required us to explicitly account for two major outlier countries mentioned here, Israel and Argentina. We also find that Bangladesh to be an outlier for at least one of the explanatory variables.

rice and wheat producing nations have not recorded significantly higher TFP growth rates. It is perhaps also surprising that sub-Saharan Africa, the worst performing region in terms of GDP growth and supposedly not a major beneficiary of the Green Revolution[17] has not shown lower TFP growth. Indeed, sub-Saharan Africa seems to have performed relatively well in terms of TFP growth.

### 3.2. Regression Data and Methodology

This study seeks to test hypotheses concerning both TFP levels and TFP growth. From the raw yearly panel data described above, we constrcuted two different data sets: a panel data set for the TFP levels analysis employs 5 years averages, with the last period (1995-2000) covering six years (hereafter referred as the panel data set); and a cross-sectional data set in which TFP growth is defined as the 1995-2000 average less the 1970-1974 average (hereafter referred as the cross-sectional data set). The need to employ 5 year averages is dictated by the data itself, which is subject to cyclical variations as well as measurement error, both of which are reduced by averaging.

We now turn to modelling TFP levels. As noted in earlier sections, the measure of productivity in this paper differs from the majority of previous research (Craig et al., 1997; Thirtle et al., 2002; Hayami, 2002), this paper uses a measure of multi- or total factor productivity (TFP), which can be thought of as the Solow residual of an agricultural production function. Specifically, the dependent variable (TFP) can be thought of as the Solow residual (A) from an agricultural output (Y) function with the five inputs we have used to construct the TFP measure, the quantities of tractors (K), fertilizers (F), arable farm land (M), and livestock (H):

[17] Note that Green Revolution is primarily confined to cereals such as rice and wheat which are not the dominant cropping patterns in sub-Saharan Africa.

$$Y = Af(K, L, F, M, H) \tag{13}$$

The central question of this paper concerns the determinants of A. We can think of A as consisting of four types of components:

1. Unmeasured input quantities which, because of data unavailability, were not used for the construction of our TFP measure (such as publicly provided inputs);
2. unmeasured quality of inputs (which cannot be precisely measured);
3. “technology”, where in this case technology refers to the efficiency with which inputs are combined; and
4. measurement error.

Because of either data limitations or the inherently intangible nature of some of these components, our explanatory variables are typically proxies for the component of A which we seek to account for. We discuss each component and the corresponding proxies in turn. Table A1 in our appendix gives details and definitions of all our variables, while Table A2 presents descriptive statistics and Table A3 shows cross-correlations.

### 3.2.1. Unmeasured Input Quantities

The first component of A includes inputs into agricultural production which were not included among our five measurable inputs above because of specific data limitations (such as lack of time series data) or because such inputs are semi-collectively consumed or public goods (e.g. climate factors or publicly provided goods such as basic infrastructure). Measures of excluded quantitative inputs therefore include: the proportion of arable land which is irrigated (IRRG) from the FAO AGROSTAT database; rainfall levels (which we use with a quadratic term for excessive rainfall), derived from data from Mitchell (2001); proxies for the provision of infrastructure or other relevant inputs, including gross domestic product per capita (GDP), gross domestic investment over GDP (GDI), and government consumption over GDP (GCON). We also looked to explicitly measure transport and communications infrastructure, but these turned out to be consistently insignificant.

Finally, the aforementioned macroeconomic expenditures may not increase agricultural output if they are heavily directed towards the urban sector. Thus we also employ two measures of urban bias. The first is an oil producers' dummy (OIL). There is a significant body of literature which addresses the means by which natural resource abundance may hinder overall development (see Sachs and Warner 1995, for example). In this case we posit that both government and private resources are simply diverted towards oil production. Furthermore, oil revenues provides a means of financing food imports rather than relying on domestic production, perhaps relieving the need to use agricultural inputs more efficiently. We also tested other indicators of natural resources from the Sachs and Warner (1995) database, but none of these proved to be significant.

The second variable in this category is a more direct proxy for the differential provision of infrastructure. We took the WDI measures of the proportions of urban and rural populations with access to safe water and subtracted the latter from the former to create an urban bias variable (UBIAS) which is hypothesized to be negatively related to TFP levels and TFP growth. The data were only available in the 1990s, such that we were forced to assume that these biases were relatively persistent.[18]

#### 3.2.2 Input Qualities

[18] Furthermore we suspect that if this is not the case, the variable still captures the intended effects since countries which reduced urban biases over this period will end up having reasonably low measures by the end of our sample.

Standard neoclassical production functions typically assume homogeneity of inputs in terms of their quality or, in the case of labour, they augment the standard function with a human capital variable. In the construction of our TFP measure we have only incorporated quantities of inputs. A significant amount of variation in TFP levels, however, may be explained by variations in the quality of these inputs. Measures of land quality included a time invariant measure of soil quality (SOIL) from Harvard University's Centre for International Development (CID) geography dataset, and the proportion of land in the tropics which capture soil quality as well as human capital (Gallup et al., 1999). More direct measures of labour quality (or human capital) include illiteracy rates, and age-dependency ratio (ratio of non-working age to working age people), malaria prevalence (MAL) and the change in malaria prevalence (ΔMAL), though the last three variables were insignificant and thus dropped from analysis.

Finally, we were interested in trying to gauge the effects of the Green Revolution on TFP. Some of the inputs to this revolution are already implicitly within the TFP index – for example, the enormous increase in the use of fertilizers in developing countries. The key input which was not captured by our TFP calculations was the use of new high-yield crops. The two crops which benefited most from the first round of the Green Revolution were rice and wheat[19]. We, therefore, hypothesized that countries with higher rice or wheat intensity in their cropping patterns would display higher TFP growth rates. We therefore used FAO data on rice and wheat production for 1970 (in metric tonnes), multiplied this by international prices for each commodity, and divided by GDP to obtain our two 'Green' measures, RICE70 and WHEAT70, and a third, the sum of the two, WHRICE70.

[19] We are indebted to Dr Clevo Wilson for suggesting this idea.

It should be noted that these are hardly ideal measures of the Green Revolution for several reasons. First, countries may have invested resources into rice and wheat production after 1970. For some countries then, this measure may be biased downwards. Second, several of the more economically successful rice or wheat producing economies in 1970 later were in the process of industrialisation, such that very few resources may have been devoted to agricultural output thereafter (for example, South Korea and Thailand). For these countries, our two measures are biased upwards.

### 3.2.3 Technology Factors

After controlling for excluded quantities and qualities of inputs (that is, 1. and 2.), the residual variation in *A* should comprise measured error and what we term technological factors. However, in a sense, technology here refers to total factor productivity in its most literal sense: the efficiency with which inputs (quantitatively and qualitatively measured) are combined. Not surprisingly, it is the technological determinants of *A* which are most difficult to measure, though theories of the nature and determinants of technological growth have become increasingly abundant in recent years. The economic growth literature suggests that technological growth can be promoted by learning-by-doing, investment in R&D, and human capital accumulation. To some extent we have already accounted for human capital, thus we ask the reader to bear in mind that high levels of literacy and age dependency ratios can also be interpreted in this fashion (the latter, for example, may be a reasonable proxy for labour force experience and hence learning-by-doing). Furthermore, if there are increasing returns to scale larger countries should be able to generate and reap the rewards from increases in inputs. We therefore expect a positive coefficient on the log of population size (POP). The growth of technology may also be affected by obstacles to the free diffusion of knowledge. We consider three variables that fall under this category: trade openness (OPEN) as measured by exports plus imports over GDP, foreign direct investment over GDP (FDI), and the geographical isolation of the country, measured as the distance from core (developed) economies (CDIST).

A key objective of this paper was to identify the institutional determinants of TFP, particularly insofar as they affected economies of scale and labour arrangements. First, we used a measure of inequality of land ownership (LGINI) which, because of the relative paucity of data on this variable, we were forced to use in separate regression models. We also interacted LGINI with GDP on the prior expectation that inequality has different effects in different stages of development. This is consistent with studies in the existibg literature (see, for example, Lundberg and Squire, 2003). A priori, unequal land distribution had an adverse effect in developing countries, but actually be an indicator of higher levels of technology (through returns to scale, increased specialisation, higher levels of R&D) in developed countries which are, in any case, highly urbanized.

Second, we considered how political factors might affect TFP. While a more even distribution of technology and resources (e.g. less urban bias) may be correlated with the degree of democracy in a country (DEMOC), a variable taken from the POLITYIV database (2002), democracies may also pay more attention to urban centres depending on country-specific demographic and political structures, or address equity issues at the expense of efficiency. Thus we had no strong a priori expectation about the sign of the DEMOC coefficient. We also used a dummy variable if the country has had a socialist regime (SOCIALIST) at any stage during the period under consideration.

Third, we expected the incidence and severity of conflict to negatively affect technological growth through interruption to human capital accumulation or investment in R&D, loss of knowledge and diversion of resources away from agriculture. Indeed, a recent World Bank research has estimated that the cost of war, particularly civil war, in developing countries is extremely high indeed (Murdoch and Sandler, 2001). We therefore employed a measure of war intensity (WAR) from The Oslo International Peace Research Institute (2002).

### 3.2.4. Measurement Error

Given the difficulties in accounting for all inputs (quantitative and qualitative) into the production process, and the indirect manner in which we gauge the level of technology and technological growth, measurement error is likely to be a significant component of our regressions. Unlike many cross-country regression analyses in which endogeneity of right hand side variables is of significant concern, we were more worried about heteroskedasticity, particularly, for the growth equations. We attempted to minimize this problem in several ways. First, we employ five-year averages (and one six year average, 1995-2000) for all our variables in order to minimize year to year errors (which are presumably distributed around a zero mean). We then used these five year averages to explain TFP levels using pooled OLS panel regressions. Appropriate econometric tests revealed that the residuals from these regressions were not obviously heteroskedastic so we used OLS. However, TFP growth regressions using five year data appeared to be comprised of significant measurement error and heteroskedastic residuals. We therefore opted to employ cross-sectional rather than panel regressions of change in TFP levels between the 1970-74 period to the 1995-2000 period. We used the average values rather than the yearly values because this reduced the probability of generating additional error by not smoothing out cyclical components of TFP levels, which, after eyeballing the data, were quite pronounced for some countries. This approach appeared to eliminate a large amount of measurement error and rendered the residuals homoskedastic. Of course, it comes at the cost of a smaller sample size, such that we emphasise the results from our panel-based TFP levels regressions somewhat more so than the cross-sectional TFP growth regressions, though most of our results are consistent across the two models.

## 4. RESULTS

This section focuses on four major issues within the agricultural sector in development literature: the general causes of productivity levels and, somewhat more ambitiously, productivity improvements; the interactions between the rural and urban/industrial sectors, with particular emphasis on gauging the potential influence of urban biases; the identification of possible equity-efficiency tradeoffs in the rural sector; and the potential benefits of the Green Revolution.

### 4.1 Explaining TFP Levels

In order to explain cross-country variation in TFP levels we first employ a full country sample from the panel data set. Using all the countries in our data set has the advantage of permitting greater variation in the data, and it also allows us to draw inferences from developed to developing countries. Regression 1 shows our specific regression model. Five variables were dropped from the general model on the basis of insignificant t-values: GDI, TRADE, FDI, WAR, and distance from the core economies, CDIST. However, we keep GDI in the model for reasons that will be made clear later on. The results are set out in Table 3.

[insert Table 3]

Statistically, our specific model performs remarkably well, with an explanatory power of around 0.65. We also report the $\chi^2$ statistic for a White test of heteroskedasticity of the residuals. This statistic is marginally significant for some but not all of our regressions, so we do not consider heteroskedasticity to be a cause for major concern. In any event, we report heteroskedastic t-values for all our regressions.

From a theoretical point of view, our final specification (Regression 1) is also quite encouraging, though not entirely consistent with all prior expectations. As expected, GDP, IRRG, SOIL, and RAIN are all positively associated with TFP levels, while RURAL, SOCIALIST, $RAIN^2$, OIL and UBIAS are all negatively correlated. Less consistent with prior expectations, GCON and DEMOC[20] are negatively correlated TFP levels, while TROP is positively correlated, though only after controlling for soil quality (SOIL), rainfall (RAIN), excessive rainfall ($RAIN^2$) and irrigation (IRRG).

The specific model for the developing country (DEV) sample (regression 4) is somewhat different. First, the reduced variation appears to lead to a slightly worse fit, with the R-squared dropping to 0.45. Second, GDI is now significant and negative – which is again counterintuitive – while TRADE is now positive and significant, and WAR and CDIST are negative and significant, as expected. Interestingly, soil suitability (SOIL) and the rainfall variables are now insignificant, suggesting that rainfall may explain some of the productivity differences between advanced and developing countries, but not differences between developing countries.

To summarise our results up to this point, we have achieved our first aim – a general identification of factors which underpin TFP levels - quite successfully. One residual puzzle, however, is the negative sign of the GDI, GCON and the DEMOC variables. Though the latter two factors have been known to enter negatively into cross-country growth regressions[21], this is not normally the case with GDI. We now try to merge this explanation with our second area of interest – the interaction between the rural and urban/industrial sectors. One problem with

[20]Together, these two results would suggest that more right wing illiberal regimes generally have higher TFP levels. Examples of such regimes are Argentina 1975-1985, The Philippines, pre-1985, Malaysia, Ecuador (various years), Cameroon, 1986-90 and Ghana, 1986-90. Whether these countries are mere statistical outliers in the democracy-TFP relationship, or whether they genuinely represent a causal linkage between the political system and the agriculture sector is an interesting question, but one which cannot be resolved here.

[21] In fact, the negative sign on both SOCIALIST and DEMOC would tend to indicate that more right wing regimes are associated with higher TFP levels.

the two macroeconomic variables, GDI and GCON, is that they may be explicitly biased towards the urban sector. In regression 1 we have already observed a negative sign on the urban bias (UBIAS) coefficient.

To test whether urban biases are manifested in these macroeconomic and political variables, we interacted GDI, GCON and DEMOC with UBIAS. Regression 2 reports that the GDI*UBIAS and GCON*UBIAS interactions bear coefficients which are significant and negative, suggesting that urban biases are prevalent with government expenditure in many countries and that these adversely affect agricultural TFP (this may also be true with private investment which is also included in GDI). Furthermore, regression 2 indicates that coefficients of GDI and GCON are now positive and significant. When we ran a similar model for the developing countries (regression 5) we found the interaction between GDI and WAR to also be significant and negative. Thus our results appear to indicate that governments whose expenditures are biased towards the urban or military sectors tend to have lower agricultural productivity levels.

We now turn to addressing our third area of interest, inequality and TFP. Regression 3 adds LGINI to the full sample. We were required to exclude LGINI from regression 1 due the relative paucity of data for this variable (note the reduction in sample size). Adding LGINI to the model does not markedly affect the significance of other variables, though when we added LGINI by itself we did not derive a significant result. A scatterplot of LGINI against TFP levels (not reported, but available on request) appeared to indicate a non-linear relationship. Previous research into inequality and growth relationships (Lundberg and Squire, 2003) has tested interactions between inequality measures and GDP. On the one hand this is broadly within the spirit of the Kuznet's (1955, 1963) approach, though Lundberg and Squire consider a contrary hypothesis: inequality does not adversely affect development (e.g. growth) in advanced economies, but is an obstacle to growth in developing countries. We consider a similar hypothesis. Employing an LGINI*GDP interaction (Regression 3) we find the coefficient on the interaction term to be positive and significant, but the LGINI coefficient is negative and significant, while the GDP variable loses its significance altogether. This tends to suggest that land inequality is negatively associated with TFP levels in developing countries but, if anything, the opposite is the case for developed countries.

### 4.2 Explaining TFP Growth

In this section we employ our cross-sectional data set in an attempt to explain TFP change (growth) in the period 1970 to 2000, as measured by the difference in levels between the 1995-2000 average level and the 1970-74 average level. Our explanatory variables are roughly the same as before, though we now include two new explanatory variables: a convergence term (TFP levels in 1970, TFP70) and the change in illiteracy levels (ΔILLIT). A second difference is that we now have now an opportunity to attempt an identification of the effects of the Green Revolution, which was not possible with the case with TFP levels data.

Regression 1 in Table 4 reports our specific model. It does not come as a surprise that, given the smaller sample size of a cross-sectional regression and the difference engendered by moving from a level to a growth regression, a number of previously significant variables disappear. For these reasons we decided to retain several variables that were only marginally insignificant at conventional levels, including the urban bias variable (UBIAS), GCON and SOCIALIST, all of which had the same signs as the corresponding TFP level regressions.

Perhaps the three most interesting new features of this specific growth regression is the large and significant coefficients on TFP70 (negative), ΔILLIT (negative) and FDI (positive), indicating respectively that in terms of TFP levels poor countries have tended to catch up to rich countries (conditional convergence) and that countries which have managed to increase literacy (human capital) and attract FDI (investment, technology) have also witnessed increases in TFP.

[Insert Table 4]

Regression 2 attempts to confirm our findings from the previous sub-section by interacting GCON (which is positive but insignificant in regression 1) with UBIAS: the coefficient on the interaction term is significant and negative and the coefficient on GCON is now significantly positive. This strengthens our previous conclusion: governments which biased their expenditures towards the urban sectors were those with lower TFP growth.

We do not report any new results for LGINI which entered insignificantly into all regressions: perhaps not surprisingly, land inequality explains TFP levels but not TFP growth. Instead we turn to testing the effects of the Green Revolution. We entered RICE70 and WHEAT70 into the specific model, but both terms proved to be insignificant. However, one problem with these variables (see Section 3) is that many of the most successful newly industrializing economies (NIEs) such as Korea, Thailand and Malaysia, tended to move away from agriculture. Thus the fact that they had high levels of rice production in 1970 is no indication that they were active participants in the Green Revolution. We therefore interact RICE70 with average GDP per capita on the grounds that the NIEs have higher income per capita than the Green Revolution countries. Regression 3 indicates that the coefficient on this interaction is negative and significant, while the coefficient of RICE70 is positive and significant. Thus we have some tentative signs that the Green Revolution was of greater benefit to poorer countries, though our study, unlike most, suggests that the productivity improvements of the Green Revolution era were relatively small, since our TFP measure already accounts for some "Green" inputs such as tractors and fertilizers. Of course, we also remind the reader that we still consider our two Green Revolution variables somewhat unsatisfactory proxies.

## 5. DISCUSSION AND CONCLUDING COMMENTS

This study constructed TFP estimates for a wide range of countries for the years 1970 to 2000. Despite some significant technological improvements in this era, average growth in agricultural productivity has been modest at best. Though we identify some degree of conditional convergence in productivity, the specified conditions under which catch-up takes place are extensive and in many (but not all) cases, determined by natural endowments. These conditions include favourable climatic and geographical conditions, high levels of human capital (literacy and the age distribution of workers), and open economies that promote FDI and trade.

However, some of our other results are both more surprising and more complex.

First, and in contrast to many other studies, we estimate the productivity benefits of the Green Revolution to be quite small. Much of the massive increase in output for Green Revolution (Hayami and Ruttan, 1985; Alauddin and Hossain, 2001) was simply achieved by increases in inputs (refer back to Figure 1). Because our measure of TFP is broader than those considered by previous studies in that it includes several "Green Revolution" inputs, it should not be entirely surprising that TFP levels have not changed considerably for all Green Revolution countries (though several, such as The Philippines, Malaysia, Colombia, Peru, Bolivia, and Costa Rica, have certainly done well in productivity terms). Of course, it is also possible that the returns to Green Technologies are inhibited by institutional and policy constraints (Jahan 1998, p.80), their extension to marginal areas (Alauddin and Tisdell 1991), and environmental degradation (see, for example, Alauddin 2004).

Second, our study has re-established what is fast becoming something of a stylized fact in the inequality and growth literature – the differential effects of inequality across different income levels (Lundberg and Squire 2003; Iyugen and Owen 2004), with inequality having adverse consequences in lower income countries and either zero or positive effects in higher income countries. There are a variety of ways in which this result can be explained in terms of economic theory. It could be that larger farms in capital-abundant (labour-scarce) developed countries may be able to generate economies of scale, so that inequality of land distribution may be subsumed in the scale effect. On the other hand, in the labour-abundant (capital-scarce) developing countries the opposite may be the case: a heavier reliance on labour in relatively large farms may imply poor incentives for wage labourers, resulting in low productivity of labour. In contrast to this, workers on smaller scale farms face more direct incentives to innovate and adopt new technologies. Likewise, subsistence pressure has been found to be an important underlying factor in previous studies (Alauddin and Tisdell 1991; Asaduzzaman 1978; Jones 1984; Ruttan 1977). Alternative arguments invoke political factors. Binswanger and Deininger (1997), for example, argue that land inequality weakens the collective action potential of the rural poor, thus inducing policies which favour urban centres and/or the rural elite (see also Lipton, 1977). Macroeconomic evidence, however, cannot distinguish between the empirical validity of these various explanations. In policy terms, the issue of land reform is contentious and well beyond the scope of this article (see, for example, Berry and Cline 1979; Bardhan 1984). Our results, at least, do provide some evidence of the potential for productivity-enhancing land reforms, without assessing the empirical evidence of the success of past reforms (Binswanger and Deininger (1997) provide such an assessment).

Finally, our results provide strong evidence that urban biases adversely affect agricultural productivity. These biases appear to have direct and indirect effects. Our urban bias proxy is not only negatively correlated with TFP levels, it also explains the negative sign on measures of government expenditure[22], as does the incidence of war, which presumably biases government expenditure towards the military sector. Furthermore, the negative sign on the oil production dummy also suggests a more particular case of urban bias[23].

These results appear to support the arguments put forth by Lipton (1977)[24], though there are potential caveats to this conclusion. First, our regression analysis also revealed that the size of the rural population adversely affects agricultural productivity, a result consistent with the surplus labour models of Lewis and others, which advocate an industrialization process justified by low rural labour productivity. In fact, it can easily be shown that the Lewis model mechanically implies increasing agricultural productivity based entirely on the emigration of unproductive rural labour (see Denison (1967) for similar conclusions regarding productivity trends in postwar Europe). Thus, it could be argued that urbanisation, a process potentially driven by urban biases[25], can also benefit rural productivity, *ceteris paribus*. In contrast to this view, however, Krueger et al. (1991), suggest that most of the countries which have successfully industrialized (South Korea, Taiwan, Malaysia, Indonesia, Thailand) reduced effective taxation of the agricultural sector at relatively early stages of their industrialization and that most countries which engaged in urban bias policies did so against their long run comparative advantage. Thus, if urbanization is driven by taxing the rural poor such that urbanization occurs not because of a high absolute benefit to urban migration, but because

[22] As noted, however, GDI includes private investment. Interacting FDI with UBIAS did not produce any significant results. This tends to suggest that the bias is primarily manifested within the public purse.

[23] We also tested other indicators of natural resources calculated by Sachs and Warner (1995), none of which displayed a significant negative association with TFP levels or growth.

[24] In this particular case we take the term "inefficient" to mean poverty-inefficient, in that we assume that agricultural productivity increases have a greater impact on poverty reduction than policies geared towards increasing industrial output growth, at least in the short run. Though this assumption is not explicitly tested, much of the previous research on poverty reduction lends credence to this assumption (for example, Hayami and Ruttan, 1985). One important caveat is that many East Asian countries have successfully industrialized and reduced poverty, and much of this industrialization was led by their governments. The size of the government sector, however, was not large. Our results indicate that it is both the size of the government sector as well as the degree of urban bias which adversely affect the agricultural sector.

[25] The correlation between UBIAS and the average urbanization rate is 0.26.

expected urban wages are high relative to the poverty of the highly taxed rural sector (Harris and Todaro, 1970), then the widely observed problems of urban unemployment and congestion may occur. It is therefore perfectly possible that urban biases can stunt the long-run development of both the rural and urban sectors.[26]

Perhaps a final objection to the Lipton critique is simply that attitudes towards rural development have changed significantly since the 1960s and 70s such that the Lipton critique is largely obsolete.[27] There is ample evidence that researchers, aid agencies and LDC governments are aware of the magnitude of rural poverty. But is this rhetoric matched by resources? The answer is a definitive "No". There is very little cross-country data on the allocation of domestic resources to the agricultural sector, but in 2001, foreign aid resources to this sector, in relative terms, were around half their 1978 level (around the time at which Lipton published his critique), while absolute aid to agriculture fell by two-thirds in the period 1989-1999 (World Bank 2003a). Given that the 70 percent of the world's poor who live in rural areas only receive 25 per cent of World Bank aid, it is hard to argue that even multilateral donors, whose motivations are relatively non-strategic (Burnside and Dollar, 2000), have really allocated their resources to where they are most needed.[28]

In conclusion, the challenges to productivity growth and poverty alleviation in the rural sector are substantial. The paper concludes that many of the obstacles to agricultural

[26] Binswanger and Deininger (1997) and Litpon (1977) also note that urban biases and land inequality may be manifestations of the same underlying imbalance of power. When resources are devoted to the rural sector, they are often devoted to the rural elite, an elite with closer ties to the urban centres of power.

[27] Or even before. Lipton notes that in 1971, World Bank President, Robert McNamara, delivered a series of speeches which focused attention on the stagnant or worsening lives of the rural poor.

[28] Nevertheless, it is heartening to observe that the World Bank, upon cognizance of these trends, has begun to reverse their own urban biases by substantially increasing aid to the rural sector in 2003 and 2004 for the first time in many years. It could be argued, however, that our knowledge of urban biases, and therefore our ability to address them, is still hindered by the very biases themselves (Lipton, 1977). We note, for example, that of the 197 social indicators measured in the World Bank's WDI 2003 database, there are 23 measures of the gender dichotomy, but only 3 indicators of the rural-urban dichotomy. Thus, cross-country researchers and aid donors alike remain largely in the dark as to the exact magnitude of this very serious problem.

development appear to be endowment-based, determined largely by geography and climate[29]. However, our results also suggest that LDC governments and aid agencies can increase productivity and reduce poverty by investing in human capital, actively engaging in the global economy, and redressing biases in the distribution of both land ownership and government expenditure. With the vast majority of the World's poor living in rural areas, the importance of these reforms can be neither overstated nor overlooked, especially if we are to achieve the kind of large-scale poverty reduction targeted in the Millennium Goals and elsewhere.

[29]Though the effect of these factors is certainly mitigated by human intervention, particularly the construction of appropriate infrastructure (irrigation, roads, ports, etc.).

## Tables and Figures

### Table 1: Distribution of Countries by Region

| **Advanced Countries** | | **Asia & Pacific** | **South Asia** | **Transition** | |
|---|---|---|---|---|---|
| Australia# | Italy# | Cambodia | Bangladesh | Belarus* | Romania* |
| Austria# | Netherlands# | China | China | Bulgaria* | Romania* |
| Belgium# | New Zealand# | India | India | Czech Rep.* | Russian Fed.* |
| Canada# | Norway# | Indonesia | Indonesia | Czechoslovakia | Slovakia* |
| Denmark# | Portugal# | Japan | Myanmar | Georgia* | Slovenia* |
| Finland# | Spain# | Korea Rep. | Sri Lanka | Hungary* | Tajikistan* |
| France# | Sweden# | Laos | | Kazakhstan* | Turkmenistan* |
| Germany# | Switzerland# | Malaysia | | Kyrgyzstan* | Ukraine* |
| Greece# | UK# | Mongolia | | Latvia* | USSR* |
| Ireland# | USA# | Myanmar | | Lithuania* | Uzbekistan* |
| Israel# | | Nepal | | Poland* | Yugoslav SFR* |
| | | Sri Lanka | | | |

| **Middle East & North Africa** | **Sub-Saharan Africa** | | **Latin America & Caribbean** | |
|---|---|---|---|---|
| Algeria | Burkina Faso* | Mali | Argentina | El Salvador |
| Egypt | Burundi | Mozambique | Bolivia | Guatemala |
| Iran | Cameroon | Níger* Nigeria | Brazil | Haiti* |
| Iraq | Chad | Rwanda* | Chile | Hondurus |
| Morocco | Cote d'Ivoire | Senegal | Columbia | Mexico |
| Saudi Arabia | Ethiopia PDR | South Africa | Costa Rica | Nicaragua |
| Syria | Ghana | Sudan | Cuba* | Paraguay |
| Tunisia | Guinea* | Tanzania | Dominican Rep.* | Peru |
| Turkey | Kenya | Uganda* | Ecuador | Uruguay |
| | Madagascar | Zimbabwe | | Venezuela |
| | Malawi | | | |

**Table 2: Data summary for 111 countries over the periods of 1970-2000**

| Variable | Units | Mean | S. D. | Minimum | Maximum |
|---|---|---|---|---|---|
| Crop Output | (× $10^3$ dollars) | 5441727 | 14181736 | 21496 | 174725194 |
| Livestock Output | (× $10^3$ dollars) | 3887306 | 9666120 | 34066 | 112736478 |
| Area Input | (× $10^3$ hectares) | 44449 | 94682 | 466 | 558425 |
| Tractor Input | (tractors) | 227684 | 607962 | 3 | 5270000 |
| Labor Input | (× $10^3$) | 11042 | 49360 | 20 | 516712 |
| Fertilizer Input | (metric tons) | 1160278 | 3527434 | 67 | 36439000 |
| Livestock Input | (heads) | 130560489 | 305675191 | 1320024 | 2698476000 |

**Fig. 1. Growth of TFP components: 1970-2000**

(Base year=1970)

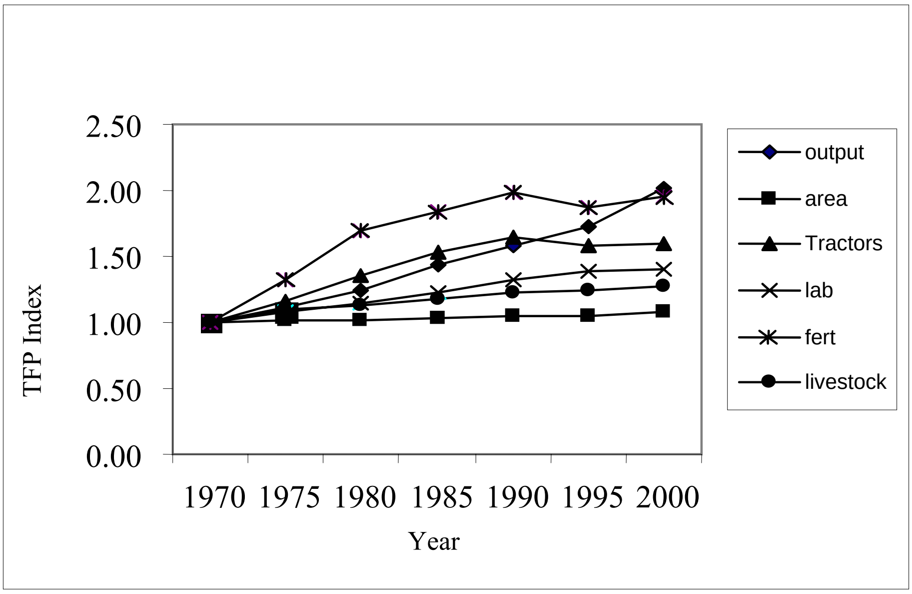

**Fig. 2. TFP Levels in 1970: Mean, Minimum and Maximum by Sample**

(USA=1.00)

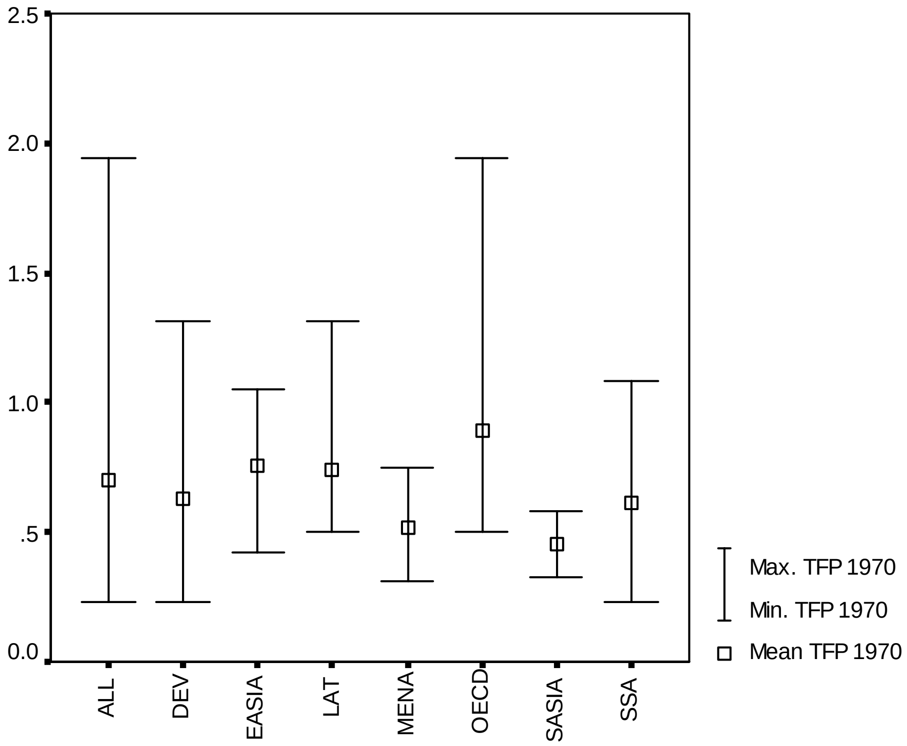

**Fig. 3. TFP Change, 1970-1974 to 1995-2000: Mean, Minimum and Maximum by Sample**

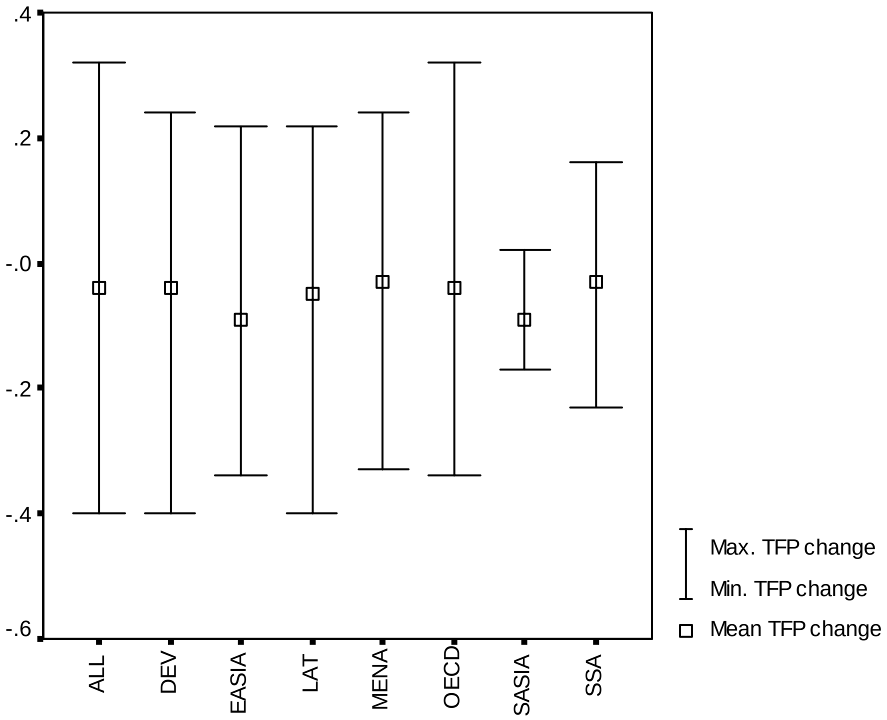

Table 3. Explaining TFP Levels

| **Reg. No.** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| Sample | Full | Full | Full | Dev | Dev |
| Model | Specific# | UBIAS | LGINI | Specific | UBIAS |
| N | 414 | 273 | 330 | 273 | 271 |
| GDP | 0.30*** | 0.24** | -0.18 | -0.20** | -0.21** |
| TRADE | -- | -- | -- | 0.34*** | 0.27*** |
| GDI | -0.03 | 0.12*** | -- | -0.18*** | 0.16* |
| GCON | -0.08** | 0.09*** | -0.03 | -0.25*** | 0.08 |
| RURAL | -0.28*** | -0.31*** | -0.34*** | -0.35*** | -0.40*** |
| DEMOC | -0.26*** | -0.13*** | -0.25*** | -0.15*** | -0.16*** |
| SOCIALIST | -0.13*** | -0.13*** | -0.05* | -0.15*** | -0.29*** |
| WAR | -- | -- | | -0.06* | -0.15** |
| CDIST | -- | | | -0.10* | -0.18*** |
| TROP | 0.12** | 0.13*** | 0.17*** | -- | -- |
| IRRG | 0.20*** | 0.18*** | 0.14** | 0.29*** | 0.30*** |
| IRRG*SAS | -0.34*** | -0.30*** | -0.36*** | -0.50*** | -0.45** |
| IRRG*ISR | 0.46*** | 0.38*** | 0.44*** | -- | -- |
| SOIL | 0.13*** | 0.17*** | 0.21*** | -- | |
| RAIN | 0.30*** | 0.30*** | 0.41*** | -- | -- |
| $RAIN^2$ | -0.22*** | -0.24*** | -0.27*** | -- | -- |
| OIL | -0.13*** | 0.14*** | -0.15*** | 0.16*** | -0.22*** |
| UBIAS | 0.15*** | 0.66** | -0.13** | -0.12** | 0.76*** |
| GDI*UBIAS | | -0.37*** | | -- | -0.65*** |
| GCON*UBIAS | | -0.48*** | | -- | -0.30*** |
| GDI*WAR | | -- | | -- | -0.21* |
| LGINI | | -- | -0.16** | -- | -- |
| LGINI*GDP | | -- | 0.45*** | -- | -- |
| CONSTANT | 0.75*** | 0.55*** | 0.91 | 1.00*** | 0.78*** |
| $R^2$ | 0.64 | 0.67 | 0.69 | 0.55 | 0.48 |
| $R_a^2$ | 0.63 | 0.65 | 0.68 | 0.51 | 0.44 |
| $\chi^2$ | 11.36** | 3.19 | | 8.49 | 2.45 |
| p-value | 0.001 | 0.071 | | 0.004 | 0.121 |

Notes:

Heteroskedastic-consistent t-values reported.

*, ** and *** refer to 10%, 5% and 1% significance levels respectively.

Chi-squared refers to heteroskedasticity test based on regression of squared residuals on squared predicted

| |
|---|
| values, with * indicating rejection of null hypothesis of homoskedasticity, with p-value. |
| #Variables dropped from general specification were GDI, FDI, TRADE, WAR and CDIST. |
| “Dev” indicates developing country sample with Argentina excluded. |
| Heteroskedastic-consistent t-values reported. Chi-squared refers to heteroskedasticity test based on regression of squared residuals on squared predicted values, with * indicating rejection of null hypothesis of homoskedasticity. The p-value for this test is also reported. |

Table 4: Explaining TFP Growth

| **Reg. No.** | **1** | **2** | **3** |
|---|---|---|---|
| Sample | Full | Full | Full |
| Model | Specific[#] | UBIAS | GREEN |
| N | 73 | 73 | 73 |
| TFP70 | -0.68*** | -0.78*** | -0.68*** |
| GDP | 0.21 | 0.16 | 0.28 |
| FDI | 0.31*** | 0.30** | 0.28** |
| GCON | 0.15 | 0.43** | 0.17** |
| RURAL | -0.48*** | -0.46*** | -0.61*** |
| ΔILLIT | -0.55*** | -0.58*** | -0.61*** |
| SOCIALIST | -0.15 | -0.13 | -0.16 |
| TROP | 0.31** | 0.35** | 0.39** |
| SOIL | 0.31*** | 0.37*** | 0.32*** |
| OIL | -0.19*** | -0.18*** | -0.20*** |
| UBIAS | -0.13 | -0.91*** | -0.08*** |
| GCON*UBIAS | -- | -1.10** | -- |
| RICE70 | | | 0.49 |
| RICE70*GDP | | | -0.46 |
| CONSTANT | -0.01 | -0.12 | 0.91 |
| $R^2$ | 0.53 | 0.56 | 0.56 |
| $R_a^2$ | 0.44 | 0.46 | 0.46 |
| $\chi^2$ | 0.03 | 0.19 | 0.11 |
| p-value | 0.875 | 0.665 | 0.738 |

Notes: Heteroskedastic-consistent t-values reported.

*, ** and *** refer to 10%, 5% and 1% significance levels respectively. Chi-squared refers to heteroskedasticity test based on regression of squared residuals on squared predicted values, with * indicating rejection of null hypothesis of homoskedasticity, with p-value.

#Variables dropped from general specification were GDI, FDI, TRADE, WAR and CDIST. Heteroskedastic-consistent t-values reported. Chi-squared refers to heteroskedasticity test based on regression of squared residuals on squared predicted values, with * indicating rejection of null hypothesis of homoskedasticity, with p-value.

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## Appendix

### Table A1. Data definitions

| Code | Definition | Source | Notes |
|---|---|---|---|
| bgd | Bangladesh dummy variable. | | |
| cdist | Distance from the core economies (Europe, USA, Japan). | Centre of International Development at Harvard University. | |
| code | World Bank Country Code | World Bank | |
| democ | democracy score 1-10 | POLITY IV PROJECT: Political Regime Characteristics | |
| $\Delta$illit | Change in illiteracy. | WDI | |
| dmal | change in malaria from 1966 to 1994 | | |
| eas | east asia dummy | WDI | |
| eu | Europe dummy variable | WDI | |
| fdi | Foreign Direct Investment over GDP | WDI | |
| GCON | General government final consumption expenditure over GDP | WDI | |
| gdi | Gross domestic investment over GDP | WDI | |
| gdppc85 | Real GDP Per Capita in constant dollars (international prices, base year 1985) | Penn World Table 5.6. | |
| gtfp | growth in TFP is 1995-2000 value less 1970-1974 value. | Rao, Coelli, and Alauddin (2003) | |
| illit | Illiteracy rate, adult total (% of people ages 15 and above) | WDI | |
| irrg | Mean irrigation suitability, very suitable (%) | Centre of International Development at Harvard University; FAO. 1995. The Digital Soils Map of the World, Version 3.5. Rome:FAO. | From the crop-specific soil suitability indices, the maximum percent of each soil type across six rainfed crops that was very suitable. Maps of these four values were then summarized by country. |
| isr | Israel dummy variable. | | |
| landgini | Gini coefficient for land: average of surveys after 1950 | Klaus Deininger, Heng-fu Zou, FAO. | Averaged data from several different sources. We treat this variable as fixed. |
| lat | Latin America and Caribbean dummy | WDI | |
| ltropics | percentage of area which is in tropics | Centre of International Development at Harvard University. | |

| Code | Definition | Source | Notes |
| --- | --- | --- | --- |
| mal | % of country area with malaria | Centre of International Development at Harvard University. WHO. | Data covers years, 1966, 1982 and 1994. Linear extrapolation used to fill in periods. |
| mena | Middle East and North Africa dummy variable | WDI | |
| oil | An oil dummy variable. | World Bank classifications. | |
| pop | The natural log of population, total | WDI | |
| rain | Rainfall (mm) divided by arable land (hectares) | Mitchell, 2002 | |
| rice70 | Value of rice production over GDP in 1970 | FAO | We multiplied output data (metric tonnes) by international prices in 1970 US$ and divided by GDP in US$. |
| rural | Rural population (% of total population) | WDI | |
| sas | south asia dummy variable | WDI | |
| soc | socialist dummy variable | Centre of International Development at Harvard University. | |
| soil | mean soil suitability 1, very suitable (%) | Centre of International Development at Harvard University. FAO. 1995. The Digital Soils Map of the World, Version 3.5. Rome:FAO. | From crop-specific soil suitability indices, the maximum percent of each soil type across six rainfed crops and two irrigated rice crops that was very suitable. Maps of these values were then summarized by country. |
| ssa | sub-Saharan Africa dummy | WDI | |
| tfp | Total factor productivity in agriculture, stochastic frontier analysis | Rao, Coelli, and Alauddin (2003) | |
| tfp70 | TFP in 1970 | Rao, Coelli, and Alauddin (2003) | Convergence term. |
| trade | Total trade (imports+exports) over GDP | WDI | |
| trade | Exports plus imports over GDP | WDI | |
| ubias | Proportion of the urban population with access to safe water less rural proportion. | Source data from WDI | |
| war | War Intensity | PRIO (2003) | We scaled war by population size. |
| wheat70 | Value of wheat production over GDP in 1970 | FAO | Multiplied output data (metric tonnes) by international prices in 1970 US$ and divided by GDP in US$. |

**able A2. Descriptive statistics – TFP levels and growth**

| Code | Units | N=549 | Mean | Min. | Max. | Std. Dev. |
|---|---|---|---|---|---|---|
| GDP | US$ 1985 | 513 | 7073 | 464 | 30721 | 6780 |
| TRADE | %GDP | 505 | 51.15 | 2.70 | 203.42 | 25.97 |
| GDI | %GDP | 510 | 21.33 | 2.95 | 45.90 | 6.22 |
| FDI | %GDP | 416 | 1.16 | -1.02 | 12.16 | 1.57 |
| GCON | %GDP | 498 | 14.97 | 4.51 | 58.31 | 6.06 |
| RURAL | % | 546 | 51.47 | 2.84 | 96.34 | 25.15 |
| DEMOC | (0-10) | 534 | 4.65 | 0.00 | 10.00 | 4.29 |
| WAR | (0-3)/POP | 549 | 0.44 | 0.00 | 8.69 | 1.23 |
| ILLIT | % | 463 | 29.77 | 1.71 | 92.35 | 26.03 |
| CDIST | km | 549 | 4080 | 140 | 9280 | 2625 |
| TROP | % | 549 | 49.00 | 0.00 | 100.00 | 14.00 |
| SOC | % | 549 | 14.00 | 0.00 | 100.00 | 35.00 |
| IRRG | % arable | 549 | 4.27 | 0.32 | 24.28 | 3.59 |
| SOIL | % arable | 549 | 12.97 | 1.13 | 36.07 | 7.66 |
| DMAL | Δ in % | 549 | -0.13 | -1.00 | 0.78 | 0.35 |
| RAIN | mm/arable | 549 | 707 | 3 | 8742 | 1249 |
| OIL | (0,1) | 549 | 0.09 | 0.00 | 1.00 | 0.28 |
| UBIAS | % | 549 | 18.86 | -6.00 | 66.00 | 17.40 |
| LGINI | (0-1) | 431 | 64.25 | 31.21 | 93.31 | 15.76 |
| RICE70 | %GDP | 549 | 3.45 | 0.00 | 58.18 | 9.20 |
| WHEAT70 | %GDP | 549 | 1.38 | 0.00 | 51.99 | 5.99 |
| POP | millions | 549 | 50.81 | 1.56 | 1229.66 | 141.80 |

## Table A3. Cross-correlations – Selected variables, all countries

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| TFP | 1.00 | | | | | | | | | | | | | | | | | | | | |
| G_TFP | -.32 | 1.00 | | | | | | | | | | | | | | | | | | | |
| TFP70 | .91 | -.32 | 1.00 | | | | | | | | | | | | | | | | | | |
| GDP | .47 | .06 | .42 | 1.00 | | | | | | | | | | | | | | | | | |
| TRADE | .24 | .08 | .22 | .22 | 1.00 | | | | | | | | | | | | | | | | |
| POP | -.14 | .03 | -.10 | -.01 | -.43 | 1.00 | | | | | | | | | | | | | | | |
| GDI | .05 | .03 | .05 | .21 | .25 | .15 | 1.00 | | | | | | | | | | | | | | |
| FDI | .16 | .00 | .12 | .22 | .52 | -.07 | .11 | 1.00 | | | | | | | | | | | | | |
| GCON | .28 | .15 | .27 | .48 | .36 | -.16 | .06 | .09 | 1.00 | | | | | | | | | | | | |
| RURAL | -.53 | -.08 | -.47 | -.77 | -.24 | .07 | -.24 | -.21 | -.43 | 1.00 | | | | | | | | | | | |
| DEMOC | .38 | .12 | .34 | .73 | .19 | .00 | .18 | .18 | .28 | -.62 | 1.00 | | | | | | | | | | |
| WAR | .15 | -.09 | .17 | -.14 | .02 | -.23 | -.19 | -.05 | .18 | .10 | -.12 | 1.00 | | | | | | | | | |
| ILLIT | -.41 | -.06 | -.34 | -.69 | -.20 | -.02 | -.28 | -.27 | -.25 | .70 | -.66 | .19 | 1.00 | | | | | | | | |
| TROP | -.27 | .04 | -.23 | -.63 | -.03 | -.13 | -.30 | .00 | -.35 | .57 | -.44 | .17 | .35 | 1.00 | | | | | | | |
| SOC | -.29 | -.14 | -.24 | -.25 | -.01 | .03 | .06 | .06 | .07 | .22 | -.36 | .17 | .20 | .14 | 1.00 | | | | | | |
| IRRG | .02 | -.01 | .04 | -.09 | -.05 | .13 | -.09 | .05 | -.21 | .03 | .03 | -.05 | -.05 | .19 | -.07 | 1.00 | | | | | |
| SOIL | .22 | .10 | .14 | .19 | -.11 | .15 | .00 | -.09 | .10 | -.27 | .18 | -.03 | -.16 | -.42 | -.01 | .17 | 1.00 | | | | |
| RAIN | .20 | .07 | .17 | .04 | .31 | -.33 | -.02 | .08 | -.01 | -.05 | .20 | .18 | -.16 | .12 | -.11 | .19 | .13 | 1.00 | | | |
| OIL | -.23 | -.02 | -.17 | -.11 | .10 | .02 | .10 | .04 | .11 | -.04 | -.21 | .09 | .20 | .01 | .26 | -.09 | -.10 | -.16 | 1.00 | | |
| UBIAS | -.34 | -.11 | -.28 | -.63 | -.18 | .04 | -.24 | -.17 | -.29 | .46 | -.61 | -.03 | .47 | .48 | .28 | .00 | -.08 | -.11 | .06 | 1.00 | |
| LGINI | .10 | .16 | .04 | -.12 | -.11 | -.11 | -.07 | .04 | -.03 | -.25 | .00 | .16 | -.13 | .15 | .03 | -.01 | .17 | -.06 | .23 | .29 | 1.00 |
| | TFP | GTFP | TFP70 | GDP | TRADE | POP | GDI | FDI | GCON | RURAL | DEMOC | WAR | ILLIT | TROP | SOC | IRRG | SOIL | RAIN | OIL | UBIAS | LGINI |