IMPACT OF AGRICULTURAL PRODUCTIVITY CHANGES ON POVERTY IN DEVELOPING COUNTRIES

by

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(Under the Direction of Lewell F. Gunter and Octavio A. Ramirez)

ABSTRACT

Agricultural productivity growth has long been recognized as pro-poor and as a crucial determinant of poverty reduction, but empirical estimates of this relationship are still limited. Earlier studies primarily focus on partial productivity measures, such as land and labor productivity, to explain poverty reduction. A few recent studies use frontier based total factor productivity (TFP) measures while examining its impact on poverty. The frontier based TFP measures are calculated using distance functions and are relative to the most efficient country's TFP. Theory on agricultural productivity growth, however, emphasizes the impact of productivity growth within a country over time on poverty in that country. This study compares the impact of single factor productivity growth, as well as frontier and non-frontier TFP growth estimates, on poverty reduction in developing countries. We estimate multiple measures of agricultural total factor productivity growth employing frontier approach for 108 developing countries. We then make alternative groupings of countries to allow for the possibility of different production frontiers for countries with different income level and countries based on different regions. We compare these various measures of agricultural TFP with TFP measures obtained by Fuglie (2011) using a non-frontier growth accounting approach. Results from the

TFP analysis show that TFP change estimates by income groups differ from those estimated using all countries in a pooled model. This indicates that agricultural technology and production frontiers may differ across countries based on income levels. For most of the countries, TFP measures from the pooled model, from income groups and groups based on regions are found to be notably different from those obtained using growth accounting approach. We then use these various measures of agricultural productivity growth in a poverty model. Using the Two-Step System Generalized Method of Moments estimation technique in a dynamic panel data framework, we find that single productivity measures as well as TFP measures based on growth accounting approach are significantly poverty reducing. The point estimate of growth accounting TFP growth is found to be higher than that of land productivity, but lower than that of labor productivity on poverty reduction. Most of the frontier based TFP measures are found to be both ambiguous in sign and weaker in the sense that they are not significant.

INDEX WORDS: Agricultural Productivity, Growth Accounting, Stochastic Frontier Analysis (SFA), Data Envelopment Analysis (DEA), Distance Function, Growth, Inequality, Poverty, Developing Countries

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DEDICATION

I dedicate this dissertation to my beloved husband.

Ranjan K. Behera: It's all for you…

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CHAPTER 1

INTRODUCTION

1.1. Motivation

Agricultural growth plays an important role in the economic development of developing countries. In much of the early development literature, agriculture was seen as a backward, unproductive and subsistence sector. As a consequence, resources were diverted from the agricultural sector to support the non-agricultural sector. This was done mostly by means of taxing the agricultural sector, leading to an urban bias strategy in developing countries. Later, Johnston and Mellor (1961) emphasized the role of agricultural growth, implying investment in agriculture might actually lead to faster overall economic growth. More recently, focus has been shifted from enhancing economic growth to attaining poverty reduction through agricultural growth, as about 75% of the world's poor still live in rural areas and primarily depend on agriculture for their livelihood. According to the recent World Bank report, the number of people living on less than $1.25 per day in the developing world has decreased dramatically in the past three decades, from about 52% of the total population in 1981 to 21% in 2010. Despite this progress, the number of people living in extreme poverty remains high. There are still 1.2 billion people around the world living in extreme poverty. While poverty rates have declined globally, the rate of decline has been slow and progress has been uneven across regions. Accelerating extreme poverty reduction is a huge challenge in both Sub-Saharan Africa and South Asia, given that approximately one-third of the extreme poor live in these regions.

This slow progress in eradicating poverty from the developing world has drawn attention to the role of agriculture in enhancing economic growth, reducing inequality, and alleviating poverty. The World Development Report (2008) emphasizes the role of agricultural productivity growth for agricultural growth and poverty reduction in developing regions. Agricultural productivity growth leads to a rural growth process that can be fundamentally pro-poor. It can benefit poor farmers directly by increasing agricultural production and benefit all consumers through lower food prices. It can also benefit small farmers and landless laborers by increasing employment and benefit the rural and urban poor through growth in the rural and urban non-farm economy. All the direct and indirect benefits from increasing agricultural productivity lead to increase real income and hence reduce poverty (Thirtle et al., 2001).

Although theory on productivity-poverty suggests that agricultural productivity has special power to enhance agricultural growth and poverty alleviation, the appropriate methodology for measuring agricultural productivity has been the subject of debate among researchers. Agricultural productivity is measured several ways throughout the poverty literature including agricultural yield per hectare (or acre), total output per worker, total output per unit of input and recently total factor productivity (TFP). Partial productivity measures relate output to a single input and are better suited theoretically for identifying bias in technology. To get correct measures of single factor productivity, however, it is required to control for changes in other inputs. They are likely to overstate the overall improvement in efficiency if they don't account for other inputs changing (Fuglie, 2010). On the other hand, multi-factor productivity measures attempt to account for simultaneous change in efficiencies of all inputs. These multi-factor productivity measures are better for identifying technological change, input substitution, and technological improvements embodied in other inputs. Land and labor productivity measures are widely used because land and labor are regarded as the two most important factors of production, and also the associated productivity measures are easy to calculate. Measuring total factor productivity, on the other hand, requires aggregation of a broad range of outputs and inputs and therefore involves many conceptual and methodological issues.

A careful look at the poverty literature reveals that agricultural growth has long been characterized as pro-poor and as a crucial determinant of poverty reduction, but empirical estimates of this relationship are still limited (De Janvry & Sadoulet, 2009). Earlier studies primarily focus on partial productivity measures such as land and labor productivity to explain poverty reduction. Some of them account for change in other inputs by estimating partial productivity after controlling for other inputs. Only a small number of studies have dealt with the impact of TFP on poverty reduction, and those use frontier based TFP measures or are based on a single country study. The frontier based TFP measures are calculated using distance functions and are relative to the most efficient country's TFP. Efficiency of one country is determined based on how efficiently it produces relative to the so called 'best practice' frontier. Efficiency change in a country hence represents the change in its efficiency relative to other countries over time. Theory on agricultural productivity and poverty, however, emphasizes the impact of productivity growth within a country over time on poverty in that country. The need for within-country measures of productivity growth, rather than productivity growth relative to other countries, suggests the need for non-frontier methods for measuring TFP growth for each individual country over time relative to its own past TFP measures.

The literature reveals quite varied measurements and analytical approaches for measuring total factor productivity. Variability in the methods used sometimes makes it difficult for policy makers to compare and evaluate the results of productivity studies. The measures used to estimate productivity growth affect the magnitude of the estimates, and furthermore, the magnitude and direction of effects on poverty. This study compares the impacts of single factor productivity growth as well as frontier and non-frontier TFP growth on poverty reduction in developing countries. For our non-frontier TFP growth estimates, we use Fuglie's (2011) growth accounting approach to find TFP growth rates. Unlike the frontier approach, this method uses output and input growth within a country and finds TFP growth rates over time for each individual country. These TFP growth rates are theoretically better suited than frontier based TFP to assess the impact of agricultural productivity growth within countries on poverty.

1.2. Objectives

The primary objective of this study is to examine the impact of agricultural productivity growth on poverty reduction in developing countries. Specific objectives are to

- Discuss different methodologies used in the literature to estimate agricultural productivity
- Estimate single factor productivity growth as well as multifactor productivity growth measures in agriculture
- Investigate the differences in multi factor productivity measures obtained using different methods
- Empirically examine the impact of various agricultural productivity measures on poverty reduction

1.3. Organization of the Dissertation

The organization of this study is as follows. Chapter 1 presents a background and motivation for the study and outlines the specific research objectives. Chapter 2 provides theoretical background for agricultural productivity growth models found in the literature. Chapter 3 uses empirical models to estimate various total factor productivity measures in developing countries' agriculture and analyze the results. Chapter 4 discusses the theoretical background for the poverty model and uses various measures of single as well as multi-factor productivity measures to investigate their impacts on poverty reduction. The study concludes with a summary and policy implications in Chapter 5.

CHAPTER 2

THEORETICAL FOUNDATIONS OF PRODUCTIVITY MEASUREMENT

2.1. Introduction and Background

Agricultural productivity growth is important for policy making in pursuing development objectives such as poverty reduction and food security in developing countries. Thus, it is essential to use appropriate measures of agricultural productivity. Broadly, productivity is measured by an index of output divided by inputs. Two measures of productivity are frequently used in the literature: partial factor productivity (PFP) and total factor productivity (TFP). Partial or Single factor productivity is defined simply as a ratio of a measure of total output to a measure of a single input used in the production process. Land and labor are regarded as the two most important factors of production in the agricultural sector in the developing world. Land productivity as a proxy for improved efficiency has been used for comparisons between locations and time periods. It is also used to assess the performance of new agricultural technology. Increased labor productivity is generally used as a measure of improved living standard or welfare, as it indicates the capacity to acquire higher income (Block, 1994). These partial productivity measures are no doubt useful, but at times could be misleading. For example, if output increases due to increase in other inputs, the issue of factor substitution might lead partial productivity measures to provide a misleading picture of agricultural performance (Capalbo & Antle, 1988). Moreover, the policy implications of changes in partial productivity measures are not clear because of uncertainty about their determinants. A more comprehensive measure of productivity takes into account all the inputs used in the production process, which can be done by measuring total factor productivity (Ludena et al., 2006). Total factor productivity is defined as the ratio of aggregate output to aggregate input. TFP measures attempt to account for simultaneous change in efficiencies of all inputs. It is required, therefore, to account for the sum total of changes in outputs and in all the inputs in the production process to measure changes in agricultural TFP. However, the measurement of TFP growth involves many conceptual and methodological issues. Literature reveals quite varied measurements and analytical approaches. Variability in the methods used sometimes makes it difficult for the policy makers to compare and evaluate the results of productivity studies. The purpose of this chapter is to review various methods that are used to measure agricultural TFP growth, focusing on the strengths and weaknesses of the different approaches. The next section presents theoretical approaches to measure TFP growth. A comparison of the various approaches is discussed in section 2.3. A brief summary and conclusions from the productivity study are presented in the last section.

2.2. Agricultural TFP Measuring Techniques: A review

While the concept of TFP is reasonably straight forward, choosing an appropriate method to measure it is not. Measuring TFP involves aggregation of broad types of outputs and inputs to form total outputs and inputs. Several methods are used to overcome this problem. Among them, the growth accounting approach and the frontier approach are the two most widely accepted methods.

2.2.1. Growth Accounting Approach

Growth accounting involves assembling detailed accounts of quantity and price data of inputs and outputs to aggregate them into a total output index and a total input index to derive a TFP index. Solow (1957) was the first to propose a growth accounting framework, where growth in aggregate production is considered as a contribution of the growth rates of the all the factors of production and a residual (also known as “Solow residual”) part that reflects growth in TFP. In other words, growth in TFP is attributed to that part of growth in output which cannot be explained by growth in factor inputs. This methodology gradually reached a high level of sophistication due to the efforts by Kendrick (1961, 1973), Denison (1967, 1987), and Jorgenson (1995). The theoretical model under this approach is as follows.

In a production function of the form $Y_{i,t} = A_{i,t} F(X_{i,t})$, where, Y is a vector of outputs of a country at time t, and X is a vector of inputs used, TFP is given by $A_{i,t.}$

$$TFP_{i,t} = A_{i,t} = \frac{Y_{i,t}}{F(X_{i,t})} \quad (2.1)$$

Change in TFP can be calculated as

$$\frac{TFP_{i,t}}{TFP_{i,t-1}} = \frac{A_{i,t}}{A_{i,t-1}} \quad (2.2)$$

Alternatively, it can be calculated as:

$$\frac{dln(TFP)}{dt} = \frac{dln(Y)}{dt} - \frac{dln(X)}{dt}, \quad (2.3)$$

which states that the rate of change in TFP is equal to the difference between the rate of change in aggregate output and the rate of change in aggregate input. Chambers (1988) shows that if production technology can be represented by a Cobb-Douglas production function with constant returns to scale technology, and if we assume that producer maximizes profits and in the long run total revenue equals total cost, then the above equation can be written as:

$$\ln \frac{TFP_{i,t}}{TFP_{i,t-1}} = \Sigma\, R_m \ln \frac{Y_{i,t}}{Y_{i,t-1}} - \Sigma\, S_n \ln \frac{X_{i,t}}{X_{i,t-1}} \quad (2.4)$$

where, R_m is the revenue share of the m^{th} output and S_n is the cost share of the n^{th} input of country ‘i’. Output growth is estimated by summing over growth of each output weighted by its revenue share. Similarly, input growth is calculated by summing the growth rate of each input weighted by its cost share. TFP growth is then the difference between growth in aggregate output and growth in aggregate inputs with in a country. This approach focuses on the time series dimension of the data. Time series data of individual countries are analyzed without relating these to data of other countries so growth-accounting calculated TFP gives TFP growth rates within a country rather than growth relative to other countries. This method requires data on output and input prices. However, data on input prices for developing countries are seldom available. Primarily because of data constraints, application of this methodology remains limited to small samples of developed countries (Islam, 1999). This is one of the important reasons why frontier methods have been widely used to obtain TFP based on distance functions to compare productivity among group of countries over time.

2.2.2. Frontier Approach

The Frontier approach assumes the presence of inefficiency in the production process. The terms efficiency and productivity are often used interchangeably; however, they do not precisely represent the same things. To illustrate the distinction between the two terms, let’s take an example of a production frontier for a group of countries producing the same type of agricultural outputs using the same type of inputs. Each country would presently be operating either on that frontier, if they are fully efficient or below the frontier if they are not perfectly efficient. In such a situation, improvement in productivity can be achieved in two ways: a more efficient use of resources of land, labor, capital and other intermediate inputs or through advances in technology of production through which higher output is obtained. While the former refers to efficiency change, the later is termed as technical change in the production process. Efficiency is represented by the country operating more closely to the existing frontier. Thus, productivity growth may be achieved through either technological progress or efficiency improvement.

The presence of inefficiency in the production process leads to discrepancy between observed output and maximum feasible output

$$[Y_{i,t} = A_{i,t} F(X_{i,t})] < [Y_{j,t} = A_{j,t} F(X_{i,t})] \qquad (2.5)$$

where $Y_{j,t}$ is the frontier output produced by country 'j' with the same level of input $X_{i,t}$ as used by country 'i'. $Y_{i,t}$ is observed output of a country 'i' and $Y_{j,t}$ is the maximum potential output. Country 'j', being able to produce the maximum potential output, lies on the frontier. The subscript j may represent a different country at any time t. $\frac{Y_{i,t}}{Y_{j,t}}$ is defined as the distance function $D^0_{ij,t}(X_{i,t}, Y_{i,t})$, and represents the distance between observed and maximum potential output. Using the distance function, TFP growth of country 'i' can be obtained from equation (4) as follows:

$$A_{i,t} F(X_{i,t}) < A_{j,t} F(X_{i,t})$$

$$A_{i,t} F(X_{i,t}) = A_{j,t} F(X_{i,t}) * D^0_{ij,t}(X_{i,t}, Y_{i,t})$$

$$A_{i,t} = A_{j,t} \; D^0_{ij,t}(X_{i,t}, Y_{i,t})$$

$$TFP_{i,t} = A_{j,t} \; D^0_{ij,t}(X_{i,t}, Y_{i,t})$$

Assuming j produces the maximum potential output in period t-1, TFP in period t-1 is

$$TFP_{i,t-1} = A_{j,t-1} \; D^0_{ij,t-1}(X_{i,t-1}, Y_{i,t-1})$$

TFP change from period t-1 to t can be calculated as

$$\frac{TFP_{i,t}}{TFP_{i,t-1}} = \frac{A_{j,t}}{A_{j,t-1}} \; \frac{D^0_{ij,t}(X_{i,t},Y_{i,t})}{D^0_{ij,t-1}(X_{i,t-1},Y_{i,t-1})} \qquad (2.6)$$

The first ratio of the right hand side of (2.6) represents technical change, which provides an indication of pushing out the production frontier. The second term (the distance functions ratio) represents efficiency change, which measures whether production is getting closer or farther from the frontier (Fare et al., 1994). The resulting TFP change is also known as Malmquist Productivity index that represents the change in TFP relative to the most efficient country or the best practice frontier.

Distance functions can be estimated using multi-output multi-input production technology. An output distance function is defined as the maximum feasible expansion of a output vector for a given input vector. Suppose the output set, P(x) represents the set of all output vectors, $y \in R^{+}$, which can be produced using the input vector $x \in R^{+}$. Then $P(x) = \{y \in R^{+}$: X can produce y. The output distance function introduced by Shephard (1970) is defined on the output set P(x) as: $D_0(x,y) = \min \{\theta: (y/ \theta) \in P(x)\}$. $D_0(x,y)$ is non-decreasing, positively linearly homogenous and convex in y, and non-increasing and quasi-convex in x (Lovell et al., 1994). Given the input vector, the value of the function Do(x,y) places y/ Do(x,y) on the outer boundary of P(x) and on the ray through y . The output distance function can take values less than or equal to one if the output vector y is an element of the feasible production set P(x). It takes value of 1 if y is located on the outer boundary of the feasible production set. A graphical representation for estimating change in TFP using distance function is given in figure 2.1.

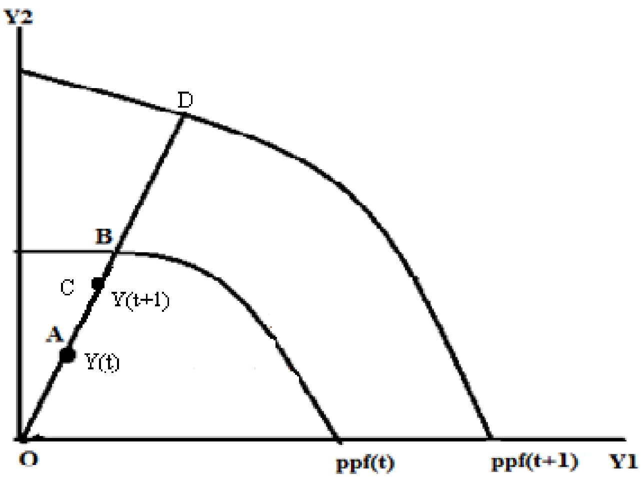

Figure 2.1: Graphical Representation of Malmquist Index with Distance Function

In the above diagram, output distance function can be illustrated where two outputs y1 and y2 are produced using the input vector x. The production possibility set P(x) is bounded by the production possibility frontier (ppf) and the two axes. At time period t, the value of the output distance function is: $D^t (x^t,y^t) =$ OA/OB. Similarly, in time period t+1, the distance function is: $D^{t+1} (x^{t+1},y^{t+1})$ = OC/OD. The rate of growth in the output can be measured by ln(OC/OA). The change in the distance function from $D^t (x^{t+1},y^{t+1})$ to $D^{t+1} (x^{t+1},y^{t+1})$ contributes to technical change and is represented by ln (OD/OB). On the other hand, the change from $D^t (x^t,y^t)$ to $D^{t+1} (x^{t+1},y^{t+1})$ contributes to efficiency change and is represented by ln $\frac{OD/OC}{OB/OA}$. Technical change and efficiency change give rise to change in TFP.

An important problem associated with the frontier based approach is to find out the reference frontier and, alternatively, the distance function. Two different techniques are adopted to find it; one is Data Envelopment Analysis (DEA) method and another is Stochastic Frontier

Analysis (SFA) method. The theoretical procedures involved in DEA and SFA to estimate TFP change are discussed below.

Data Envelopment Analysis (DEA): DEA has been originated from the work of Farrell (1957) and presented to the literature by Charnes et al. (1978). DEA is a non-parametric method aiming to identify relative efficiency of counties producing multiple outputs using multiple inputs. One of the main properties of DEA is that it does not require any assumptions about the functional form of the production frontier. It is a linear programming technique, which uses input and output data for a set of countries to construct a non-parametric piece-wise linear production frontier for each year in the sample. The frontier surface is constructed by the solution of a sequence of linear programming problems for each country in the sample. Any country that lies below the frontier is considered to be inefficient. DEA permits to construct a best-practice benchmark from the data on inputs and outputs. Suppose data on K inputs and M outputs are available for each of N countries. For the i-th country these are represented by the vectors X_i and Y_i, respectively. The KX x N input matrix, X, and the MX x N output matrix, Y, represent the data of all N firms. The DEA application constructs a non-parametric envelopment frontier over the data points such that all observed points lie on or below the production frontier. The distance between the observed point and the frontier is then produced to calculate the Malmquist index.

The Malmquist TFP index is the TFP change (TFPC) between two data points of a particular country in two adjacent time periods. It is calculated as the ratio of the distances of each data point relative to a common technology as follows:

$$m_0(y_s, x_s, y_t, x_t) = \left[\frac{D0^s(Yt,Xt)}{D0^s(Ys,Xs)} \times \frac{D0^t(Yt,Xt)}{D0^t(Ys,Xs)}\right]^{½}$$

where Y is a vector of outputs, X is a vector of inputs, s and t represent time, d_0 is the distance function. This TFP change index can be decomposed into efficiency change (EC) and technical change (TC) as:

$$m_0(y_s, x_s, y_t, x_t) = \frac{D0^t(Yt,Xt)}{D0^s(Ys,Xs)} \left[\frac{D0^s(Yt,Xt)}{D0^t(Yt,Xt)} \times \frac{D0^s(Ys,Xs)}{D0^t(Ys,Xs)}\right]^{½} \qquad (2.8)$$

The first ratio in the right hand side measures a country's efficiency change between period s and t. It provides information about the extent to which a country is able catching-up to the production frontier. The second part in the brackets measures the technical change between the two periods which provides an indication of pushing out the production frontier.

Stochastic Frontier Analysis (SFA): SFA is a parametric approach and the production frontier is estimated econometrically. It requires prior specification of the functional form for the production function. A production frontier defines the technological relationship between the level of inputs and the level of outputs. A stochastic frontier allows for deviations from the frontier to represent both inefficiency and an inevitable random noise. SFA has its origins in the work by Aigner, Lovell, and Schmidt (1977) and Meeusen and Van den Broeck (1977), followed by the works by Battese and Corra (1977). The stochastic production frontier addresses technical efficiency and implies that random shocks beyond the control of producers may affect the production output. Therefore, in these models, the impact of random shocks on the product can be separated from the impact of technical efficiency variation. A number of functional forms, including Cobb-Douglas production functions (Hannesson, 1983), CES production functions (Campbell and Lindner, 1990) and translog production functions (Squires, 1987; Pascoe & Robinson, 1998) have been used to estimate stochastic frontiers using agricultural inputs and outputs data.

A general output oriented stochastic production frontier model is defined as:

$$\ln Y = F(X,t) + V - U \tag{2.9}$$

where Y represents vector of output, X is a vector of inputs, V is random error term, and U is a stochastic non-negative error term represents inefficiency.

Alternatively, the stochastic distance function model is given by

$$\ln D(y, x, t) = -U = \ln\hat{Y} - \ln Y^* \tag{2.10}$$

where, $\hat{Y}$ is the frontier output and Y* is the observed output of a country. The distance function represents technical efficiency and is constrained to be between zero and one in value. The frontier output set corresponds to: $D_0(y, x, t) = 1$ and the interior points to: $0 < D(y, x, t) \leq 1$ which represents inefficiency. Alternatively, if *U* equals zero, then production is said to be technically efficient. Technical efficiency of a country is therefore a relative measure of its output as a proportion of the corresponding frontier output. Technical change is captured by shift in the frontier over time.

2.3. Growth Accounting, SFA, and DEA: Comparison

DEA was widely used to measure and compare agricultural TFP growth among countries, mainly because of its apparent computational simplicity. DEA is a non-parametric technique, and so it doesn't require any prior specification on the functional form of the production function. It only requires the production technology to satisfy some basic axioms of production functions. DEA can also be used to decompose TFP change into technical change and efficiency change using the Malmquist index (Coelli et al., 2005) by estimating input or output distance functions. Despite the practical advantages, the TFP growth rates estimated by DEA often obtain anomalous results (Headey et al., 2010) because it doesn't take account of the possible influence of measurement error and other noise in the data. It has been found that DEA-based TFP results often show that many countries experience contractions of the frontier, in other words, technical regress over time. DEA seems to produce sometimes contrasting results, e.g. high rates of TFP growth in countries that have performed poorly in agricultural development. This kind of finding looks unusual and may be resulting from measurement errors along the frontier due to the non-stochastic nature of the methodology. To deal with the measurement problem, recent studies prefer SFA over DEA to compute TFP change.

The advantage of SFA over DEA approach is that the non-parametric DEA approach attributes all measurement error and omitted variables into inefficiency, but SFA can separate noise in the data from variations in inefficiency. However, it is possible that SFA can go in the other direction by ascribing too much variation in the data to measurement error rather than to real determinants of agricultural production. Imputing the effect of any omitted variable into the error term might result in excessive smoothing of measured productivity (Headey et al., 2010). Also, the estimation of a stochastic frontier model requires specific distributional assumptions to be made on the error term U that represents inefficiency. Coelli (1995) argues that the main criticism of SFA is that there is no a priori justification for the selection of any particular distributional form for the U and that the resulting efficiency measures may be sensitive to distributional assumptions. In addition, except for the level of efficiency, the coefficients of the frontier function hold for all observations equally. The same parametrically given production function is applicable to all sample units. Technological progress is given by a time trend and therefore same for the whole sample. The difference in TFP among countries arises primarily out of inefficiencies. Thus, the stochastic frontier approach implies a technology as well as a smooth and continuous path of technological progress common to all countries in the sample. This is why recent studies on SFA models focus on estimating TFP by grouping countries facing similar technological conditions.

The main difference between the traditional growth-accounting method and the production frontier technique is that the latter depends on a changing external measure of the production frontier and compares each country in the sample with it. TFP is estimated relative to the most efficient country (or frontier) in any particular year. Hence, the resulting TFP estimates are sensitive to the group of countries selected for study (Thirtle et al., 2003). Based on which sets of countries are selected, results will be different. This is why different authors have found different TFP estimates for the same country in the literature. The growth accounting approach is criticized because it assumes each country is fully efficient, and that in the presence of inefficiency it may lead to biased results. Headey et al. (2010) argue that growth accounting approach does not take into account production inefficiency, which implies the only source of productivity growth is through technical change. Recently, Fuglie (2011) has estimated agricultural TFP growth for a large number of countries using a growth accounting approach where he tries to account for sources of inefficiency by adjusting the outputs and inputs data. He considers smoothing the output series for weather and other disturbances and by using quality adjusted land inputs, which are believed to be the major sources of inefficiency. Another limitation of the growth accounting approach is that it requires data on output and input prices or revenue/cost shares. As we already mentioned, getting these data for developing countries is difficult. Fuglie compiles estimates of input cost shares or production elasticities for individual countries or regions from previous studies. For countries lacking data on cost shares, he approximates these by applying cost shares from a 'like' country and calculates TFP growth rates for each country separately over time. If the problem with inefficiency in data and price data can be eliminated, the growth accounting approach could be very useful in studying the behavior of TFP growth over time and in studying the impact of TFP growth on other economic variables.

2.4. Conclusions

This chapter compared the methodologies of three different approaches to TFP measurement, namely the growth accounting approach, the Data Envelopment Analysis (DEA) approach, and the Stochastic Frontier Analysis (SFA) approach. The growth accounting approach is of most long standing and has attained a great degree of sophistication as it has evolved. The sophistication and data-intensity of this approach limits its application to countries where the required data are available (Islam, 1999). The DEA and SFA approaches are used when input and output price data are unavailable, but produce relative TFP indices for samples of countries and so are sensitive to the selection of the sample. Both can contribute to international or cross-country comparison related to TFP and technology. The growth accounting based TFP growth emphasizes the evolution of productivity changes over time in a within-country context.

CHAPTER 3

EMPIRICAL MODELING FOR ESTIMATING AGRICULTURAL PRODUCTIVITY IN DEVELOPING COUNTRIES

3.1. Introduction

In chapter 2 we discussed the theoretical background for different methodologies used to estimate total factor productivity. We conclude that the frontier based TFP measures enable the understanding of cross-country comparisons in TFP growth over time where TFP measures based on the growth accounting approach measure the evolution of productivity change over time for each individual country. Since our primary objective is to study the impact of productivity growth within a country over time on poverty reduction in that country, TFP estimates based on a growth accounting approach are more appropriate for our needs than TFP measures obtained from frontier methods. We estimate various measures of agricultural TFP change for developing countries using different techniques discussed in chapter 2.

The sensitivity of frontier methods to the choice of sample of countries is well known. Recent frontier studies focus on estimating TFP by grouping countries facing similar technological conditions. We estimate TFP change in a whole sample and sub-samples using frontier techniques. For the sub-samples, countries are grouped based on their income level and based on which geographical regions they belong. More discussion on grouping of countries is presented in the next sub-section. We investigate the similarity of each of these TFP measures to Fuglie's single-country estimates based on growth accounting method. Fuglie's TFP estimates serve as a baseline for this productivity study.

3.2. Growth Accounting Approach

The empirical model used in Fuglie (2011) to estimate TFP growth rate for each country is as follows:

$$\ln \frac{TFP_{i,t}}{TFP_{i,t-1}} = \Sigma\, R_m \ln \frac{Y_{i,t}}{Y_{i,t-1}} - \Sigma\, S_n \ln \frac{X_{i,t}}{X_{i,t-1}} \qquad (3.1)$$

where, Y represents output and X represents input. R_m is the revenue share of the m^{th} output and S_n is the cost share of the n^{th} input of country 'i'. Output growth is estimated by summing over growth of each output weighted by its revenue share. Similarly, input growth is calculated by summing the growth rate of each input weighted by its cost share. TFP growth is then the difference between growth in aggregate output and growth in aggregate inputs within a country.

3.3. Data Envelopment Analysis (DEA)

Following Färe et al. (1994), we can calculate the required distance measures for the Malmquist TFP index using DEA-like linear programs using panel data. For the i-th country, four distance functions need to be estimated to measure the TFP change between two periods, s and t. This requires the solving of four linear programming problems. For a group of N countries, the linear programming problems to find the distance functions for the i-th country in a output oriented DEA model are as follows:

$$[\, D_0^t\, (X_t,Y_t)]^{-1} = \max \theta,$$

$$\text{st} \quad -\theta y_{it} + Y_t\, \lambda \geq 0,$$

$$x_{it} - X_t\, \lambda \geq 0,$$

$$\lambda \geq 0 \qquad (3.2.1)$$

$$[\, D_0^s\, (X_s,Y_s)]^{-1} = \max \theta,$$

$$\text{st} \quad -\theta y_{is} + Y_s\, \lambda \geq 0,$$

$$x_{is} – X_s \lambda \geq 0,$$

$$\lambda \geq 0 \tag{3.2.2}$$

$$[D_0^t (X_s,Y_s)]^{-1} = \max \theta,$$

$$\text{st} \quad -\theta y_{is} + Y_t \lambda \geq 0,$$

$$x_{is} – X_t \lambda \geq 0,$$

$$\lambda \geq 0 \tag{3.2.3}$$

$$[D_0^s (X_t,Y_t)]^{-1} = \max \theta,$$

$$\text{st} \quad -\theta y_{it} + Y_s \lambda \geq 0,$$

$$x_{it} – X_s \lambda \geq 0,$$

$$\lambda \geq 0 \tag{3.2.4}$$

where, D_0 is the distance function. y_i is a M×1 vector of output quantities for the i-th country, x_i is a K×1 vector of input quantities for the i-th country, Y is a N×M matrix of output quantities for all N countries, X is a N×K matrix of input quantities for all N countries, λ is a N×1 vector of weights, and θ is a scalar. The value of 1/θ obtained is the efficiency score for the i-th country and it varies between 0 and 1, with a value of 1 indicates a point on the frontier and the i-th country will be technically efficient. Assuming constant returns to scale, the linear programming problem is solved N times and a value of θ is obtained for each country in the sample (Coelli, et al., 2005). This TFP change between two periods, s and t can be estimated and decomposed into efficiency change (EC) and technical change (TC) as in (2.8) as:

$$m_0(y_s, x_s, y_t, x_t) = \frac{D0^t(Yt,Xt)}{D0^s(Ys,Xs)} \left[\frac{D0^s(Yt,Xt)}{D0^t(Yt,Xt)} \times \frac{D0^s(Ys,Xs)}{D0^t(Ys,Xs)}\right]^{½}$$

One important issue in estimating DEA is the returns to scale properties of the production technology. Grifell-Tatje´ and Lovell (1995) show that DEA Malmquist index in the presence of nonconstant return to scale does not accurately measure productivity. They argue that that the imposition of a variable returns to scale technology creates a systematic bias on the productivity measurement derived unless the variable returns to scale technology is identical to constant returns to scale technology. We use constant returns to scale technology for DEA estimation.

3.4. Stochastic Frontier Analysis (SFA)

SFA is a parametric approach and the production frontier is estimated econometrically. In order to estimate a parametric distance function, a functional form for the production function or the transformed distance function has to be chosen which should be flexible, easy to derive and permit the imposition of homogeneity (Coelli and Perelman, 1999). The translog function developed by Christensen et al. (1970) satisfies these properties, and hence has been used in productivity studies over last two decades. The output distance function is defined below in a logarithmic form for panel N countries over T periods. Following Headey et al. (2010), a translog specification of an output distance function involving a multi-output multi-input technology is presented below.

$$\ln D_0(y, x, t) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=1}^{K} \alpha_k \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \alpha_{kl} \ln x_{kit} \ln x_{lit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{m=1}^{M} \alpha_{km} \ln x_{kit} \ln y_{mit} + \delta_t t + \sum_{m=1}^{M} \alpha_{ym} \ln y_{mit}\, t + \sum_{k=1}^{K} \alpha_{xk} \ln X_{kit}\, t + \frac{1}{2}\delta_{tt} t^2 \qquad (3.3.1)$$

where D_0 is the unobservable value of the output distance function. i is index of countries, t represents time period, X is a vector of inputs, and Y is a vector of outputs. Technical change (TC) is captured in the form of a trend variable t. The frontier output set corresponds to: $D_0(y, x, t) = 1$ and the interior points to: $0 < D_0(y, x, t) \leq 1$ which represents inefficiency. The reciprocal of the output distance function is equal to the output orientated measure of technical efficiency (TE). Symbolically,

$D_0(y, x, t) = 1/TE$

To simplify the exposition, we replace the output measure of technical efficiency TE with an exponential non-negative error term u and write the above equation as

$D_0(y, x, t)\exp(u) = 1$

$\Rightarrow \ln D_0(y, x, t) + u = 0$

$\Rightarrow \ln D_0(y, x, t) = -u$

To write the equation (3.3.1) in a standard stochastic frontier framework, impositions of homogeneity and symmetry restrictions are required. The restrictions required for homogeneity of degree 1 in outputs are: $\sum_{m=1}^{M}\alpha_m = 1$, $\sum_{n=1}^{M}\alpha_{mn} = 0$, $\sum_{m=1}^{M}\alpha_{km} = 0$. The symmetry restriction requires: $\alpha_{mn} = \alpha_{nm}$, $\alpha_{kl} = \alpha_{lk.}$ A convenient method of imposing homogeneity restriction in the above equation is to normalize the function by one output, as described in Lovell et al. (1994). Replacing $\ln D_0(y, x, t)$ with $-u_{it}$, the output distance function can be written as:

$$-\ln y_{1i} = \alpha_0 + \sum_{m=1}^{M}\alpha_m \ln y_{mit}/y_{1it} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn}\ln y_{mit}/y_{1it}\ln y_{nit}/y_{1it} + \sum_{k=1}^{K}\alpha_k \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\alpha_{kl}\ln x_{kit}\ln x_{lit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{m=1}^{M}\alpha_{km}\ln x_{kit}\ln y_{mit}/y_{1it} + \delta_t t + \sum_{m=1}^{M}\alpha_{ym}\ln y_{mit}/y_{1it}\, t + \sum_{k=1}^{K}\alpha_{xk}\ln X_{kit}\, t + \frac{1}{2}\delta_{tt}t^2 + u_{it} \qquad (3.3.2)$$

Adding an additional random error term v_{it}, alternatively it can be written as

$$\ln y_{1i} = -(\alpha_0 + \sum_{m=1}^{M}\alpha_m \ln y_{mit}/y_{1it} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn}\ln y_{mit}/y_{1it}\ln y_{nit}/y_{1it} + \sum_{k=1}^{K}\alpha_k \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\alpha_{kl}\ln x_{kit}\ln x_{lit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{m=1}^{M}\alpha_{km}\ln x_{kit}\ln y_{mit}/y_{1it} + \delta_t t + \sum_{m=1}^{M}\alpha_{ym}\ln y_{mit}/y_{1it}\, t + \sum_{k=1}^{K}\alpha_{xk}\ln X_{kit}\, t + \frac{1}{2}\delta_{tt}t^2) + v_{it} - u_{it} \qquad (3.3.3)$$

"v_{it} -u_{it}" is the composite error term allowing for inefficiency in the production function and for noise. Both terms are assumed to be independently distributed. The noise term v_{it} is symmetrically distributed and assumed to be iid N(0, σ_v^2). The u_{it} is non-negative technical inefficiency component of the composite error term, independently distributed and follows a half normal distribution with $N^+(0, \sigma_u^2)$. The non-negative technical inefficiency implies that the composite error term is negatively skewed and that there is evidence of inefficiencies in the data. On the other hand, a positive skewed distribution of composite error term indicates that the data do not support inefficiency. Once the output distance function is estimated, the Malmquist index of total factor productivity change (TFPC) between two adjacent periods is calculated following Kumbhakar et al. (2005) as:

TFPC = EC * TC, where (3.4)

Efficiency change (EC) = $\frac{E(\exp(-u_{it})|e_{it})}{E(\exp(-u_{is})|e_{is})}$, where $e_{it} = v_{it} - u_{it}$.

Technical change (TC) = $\frac{1}{2}\left\{\frac{\partial \ln y_{is}}{\partial s} + \frac{\partial \ln y_{it}}{\partial t}\right\}$

3.5. Data and Estimation:

3.5.1. Data:

Since we are trying to assess the difference between within-country productivity change and panel data estimates of productivity change, Fuglie's TFP estimates serve as our baseline. We use the same data used by Fuglie (2011) as much as possible in frontier TFP calculations for developing countries.

As Craig et al. (1997) points out that although decades have passed since Griliches and Kuznets emphasized issues relating to producing meaningful productivity measures, empirical problems have not been resolved. The problem is more prominent in computing productivity growth at the international level. The foremost problem associated with measuring productivity is insuperable data constraints as productivity measurement requires aggregation of broad range of outputs and inputs. We discuss below the issues with aggregating inputs and outputs and how they are handled in Fuglie's study.

Outputs: All data used for this study are taken from Fuglie (2011). Fuglie relies primarily on FAO data for his study. He uses two outputs, i.e. crop and livestock outputs. To measure output growth in agriculture, he uses the FAO total agricultural output that includes 195 crop and livestock commodities valued at a set of average international prices expressed in US dollars (Rao, 1993) derived using the Stone-Geary method. These prices are used as weights to calculate value of total agricultural output for each country. Fuglie points out that the FAO commodity prices are close to the "wheat equivalent" prices developed by Hayami and Ruttan (1985) in their study on international agricultural productivity. The growth rate in agricultural output in an individual country at the national level is usually found to be close to the growth rate in the FAO output. In addition, he smoothes the output series for each country using the Hodrick-Prescott filter setting (λ=6.25) as recommended by Ravn and Uhlig (2002) for annual data to remove trends from short-run fluctuations in output due to weather and other disturbances, which are believed to be the major source of apparent inefficiencies.

Inputs: Five agricultural inputs, land, labor, live animals, machinery, and fertilizers from FAO database are used in Fuglie's study. He supplements these data with more accurate and up-to-date data from national or industry sources whenever available.

Land: Agricultural land covers permanent crops, annual crops and the area in permanent pasture. Cropland (permanent and annual crops) is further divided into rain-fed cropland and cropland equipped for irrigation. The importance of land quality in productivity studies has been pointed out by many authors, but few international studies empirically account for land quality diffeences. Land quality is potentially a major source of inefficiency in the production process. Fuglie derives a quality-adjusted measure of agricultural land that gives greater weight to irrigated cropland and less weight to permanent pasture in assessing agricultural land changes over time. Quality adjusted land is used as an input throughout our productivity estimations.

Labor: Labor refers to total economically active population in agriculture. Economically active population is defined as all persons engaged or seeking employment in agricultural sector.

Live animals: The livestock input variable used in the study is the aggregate number of animals in “cattle equivalents” held in farm inventories that includes cattle, camels, water buffalos, horses and other equine species (asses, mules, and hinnies), small ruminants (sheep and goats), pigs, and poultry species (chickens, ducks, and turkeys). Numbers of these animals are converted into cattle equivalents using conversion factors based on the study by Hayami and Ruttan (1985). The weights used are 1.38 for camels, 1.25 for water buffalo and horses, 1.00 for cattle and other equine species, 0.25 for pigs, 0.13 for small ruminants, and 12.50 per 1,000 head of poultry.

Fertilizer: Fertilizer is the amount of major inorganic nutrients applied to agricultural land annually, measured as sum of Nitrogen, Potassium and Phosphate contained in the commercial fertilizers consumed, expressed in metric tons.

Machinery: Machinery is the number of tractors in use calculated as the total stock of farm machinery in "4-wheel tractor equivalents." This includes 2-wheel tractors, 4-wheel tractors, and combine-harvesters. For aggregation, Fuglie assumes 2 wheel tractors average 12 CV, 4-wheel tractors 40 CV, and combine-harvesters 20 CV.

Input Cost Shares: Fuglie uses the growth accounting approach, so he needs inputs cost shares in order to get TFP estimates for different countries. However, price or cost share data are not available for all the countries. Due to limited data availability, he assigns cost shares available for one country to a group of similar countries. The table below shows the regions to which the various cost-share estimates were applied for constructing the aggregate input indices.

Table 3.1: Agricultural Input Cost Share Assignment

Country of input shares	Assigned to regional country group
South Africa	South Africa
Sub Saharan Africa	Sub Saharan Africa
Mexico	Central America + Caribbean
Brazil	South America + Middle East & North Africa (MENA)
China	North East Asia
Indonesia	South East Asia + Oceania
India	South Asia
USSR	EU Transition

Source: Fuglie(2011)

These assignments were basically done because of resemblance among the agricultural sectors of these countries. Countries that are assigned cost shares from India are usually countries using relatively few modern inputs. Countries that are assigned the cost shares from Brazil are generally countries having relatively large livestock sectors, and so on.

Country and time period coverage:

108 developing countries are included in the whole sample covering the period from 1961 to 2009. The whole sample is then divided into three subsamples based on their income level. We follow the World Bank's current grouping of countries (2010), i.e low income group (with GNI[1] less than $1045), lower middle income group (with GNI more than $1046 but less

[1] GNI per capita is the gross national income, converted to U.S. dollars after adjusting for fluctuations in prices and exchange rates using the World Bank Atlas method, divided by the midyear population. GNI is the sum of value added by all resident producers plus any product taxes (less subsidies) not included in the valuation of output plus net receipts of primary income (compensation of employees and property income) from abroad.

than $4125), and upper middle income group (with GNI more than $4125) in our sample. We have 32 low income countries, 38 lower middle income and 38 upper middle income countries in our sample. We also group countries based on regions used in Fuglie's (2011) study. It is, however, not feasible to estimate frontier TFP for exactly the same regional group of countries as above, especially when the group is very small. We estimate frontier TFP change for three groups based on Fuglie's regional groupings for input cost share assignment. One regional group consists of 45 Sub-Saharan African countries where cost shares from SSA study are assigned. Another regional group consists of 20 countries from South Asia, South East Asia, and Oceania, where cost shares from India and Indonesia are assigned. The two countries' cost shares are not exactly the same, but quite similar. A third set of countries comprised of 22 countries from South America and MENA regions, where Fuglie assigns input cost share from Brazil. We estimate frontier based TFP change using both smoothed and unsmoothed output for the whole sample and sub-samples to investigate the extent of difference in the productivity change and the sensitivity of sample used to the methods used. We then compare these TFP measures with TFP change obtained using growth accounting approach by Fuglie to see if any of these estimates are close to Fuglie's estimates of TFP change.

3.5.2. Estimation

First we estimate TFP change index for 108 developing countries using DEA and SFA for the pooled sample as well as sub-samples based on income level. We use smoothed outputs in this analysis. DEA-Pooled and DEA by Income Group were estimated solving linear programming problems from 3.2.1 to 3.2.4 were solved to estimate annual the TFP change index and cumulative TFP index (base 1961=1) for each country. The stochastic translog distance function in (3.3.3) was estimated using the maximum likelihood method for the pooled sample as well as for the three sub-samples. All the variables were normalized by their respective sample means prior to estimation. We obtain annual TFP change index and cumulative TFP index (base 1961=1) for each country each year from SFA-pooled and SFA-by Income group estimation. Results from these analysis are discussed below.

3.5.2.1. Productivity Estimates: Results from DEA and SFA Estimations for Countries Groups Based on Income Level Using Smoothed Data

Once we estimate annual TFP change index and cumulative TFP index (base 1961=1) for each country each year, mean TFP growth rate for each country is obtained by taking the geometric mean of the annual TFP change indices over the whole period. The mean TFP growth rate for each income group calculated from estimation of SFA pooled, SFA by Income Group, DEA pooled, DEA by Income Group, and results from Fuglie's growth accounting approach are presented below.

Table 3.2: Mean TFP Growth Rate for the Period 1961-2009: Fuglie vs. SFA vs. DEA - Smoothed Data

Countries Group	Fuglie	SFA Pooled	SFA by Income group	DEA Pooled	DEA by Income group
Low income	0.274	0.654	0.674	0.142	-0.095
Lower Middle income	0.796	0.647	0.867	0.067	0.079
Upper Middle Income	1.297	0.706	1.196	1.047	0.407

For each income group, mean TFP growth rate obtained from different methodology are discussed here. For low income group, SFA Pooled and SFA by Income Group give similar mean TFP growth rate, 0.654% and 0.674%, respectively. DEA Pooled yields very low mean TFP growth rate, whereas DEA by Income group show a negative mean TFP growth rate. . Average TFP growth rate for lower middle income group is 0.647% based on the estimation of SFA-pooled. SFA-by Income group yields a slightly higher average TFP growth rate, i.e.

0.867%. Again, DEA Pooled and DEA by Income group show very low mean TFP growth for this group. The difference between average TFP growth rate from SFA Pooled and SFA by Income Group is substantial for upper middle income countries where SFA by Income group yields an average TFP growth rate of 1.196%, while SFA Pooled gives an average TFP growth rate of 0.706% over the sample period. On the other hand, in DEA estimation, DEA pooled obtained a higher growth rate of 1.047% as compared to 0.407% obtained from DEA by Income Group.

We now evaluate results from each of the estimation methodologies. For the SFA-pooled case, there is not much difference in the average growth rate for the three income groups. As we discussed in an earlier chapter, the same parametrically given production function is applicable to all sample countries and SFA results in technological progress are common to all countries in the sample. Grouping of countries has allowed for a different frontier for each income group and the resulting mean TFP growth rates are different for each income group. Both SFA-by Income group and Fuglie report the lowest mean TFP growth rate for low income group, a higher growth rate than this for lower middle income group, while the upper middle income group has the highest average TFP growth rate. Comparing estimates from DEA-pooled and DEA-by Income Group, noticeable difference in mean TFP growth rates are found for upper middle income countries. In addition, mean TFP growth rates for low income and lower middle income group are found to be substantially lower than those obtained using SFA and growth accounting approach. The lower mean growth rates obtained with DEA estimation supports findings from the literature. As Nin et al. (2003) have noted, several “unrealistic” characteristics of DEA-based estimates of TFP growth, notably their low average TFP growth, the large number of countries recording negative TFP growth and particularly negative technical change or technical regress, and considerable volatility of year-to-year TFP growth rates.

It can be summarized from the above analysis that the SFA Pooled estimation gives a similar mean TFP growth rate for each income group. The average TFP growth rates obtained from SFA by Income Group are somewhat similar to those obtained by Fuglie using growth accounting approach. Results from both DEA Pooled and DEA by Income group seem to be quite unrealistic.

In order to assess to what extent TFP estimates deviate for a country over time when calculated using different techniques, we also measure the difference in annual TFP growth rates for each country produced by pairs of TFP estimation techniques. For example, the difference in annual TFP growth rates from SFA by Income Group and SFA Pooled for each of the low income countries each year is obtained. We then square the differences and sum them over time to get "Sum of Squared Differences" for each country. "Sum of Squared Differences" for all countries in that group are added up and divided by the number of countries in the group to get "Average Sum of Squared Differences" for the low income group. In this way, "Average Sum of Squared Differences" in annual TFP growth rates for each income group are obtained while comparing DEA by Income Group and DEA Pooled, Fuglie and SFA by Income Group, Fuglie and SFA Pooled, Fuglie and DEA by Income Group, and Fuglie and DEA Pooled. The results are presented in figures 3.1a, 3.1b, and 3.1c. Total Sum of Squared Differences is shown on the Y axis for each comparison.

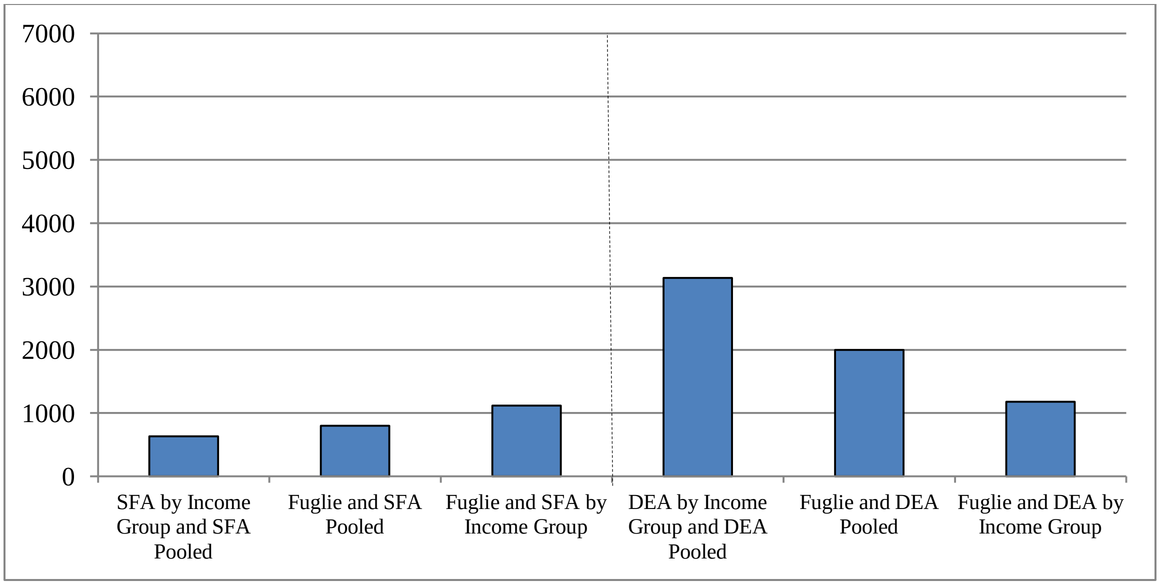

Fig. 3.1a. Average Sum of Squared Differences between Estimated Annual TFP Changes for Low Income Countries: Fuglie, SFA, and DEA - Smoothed Data

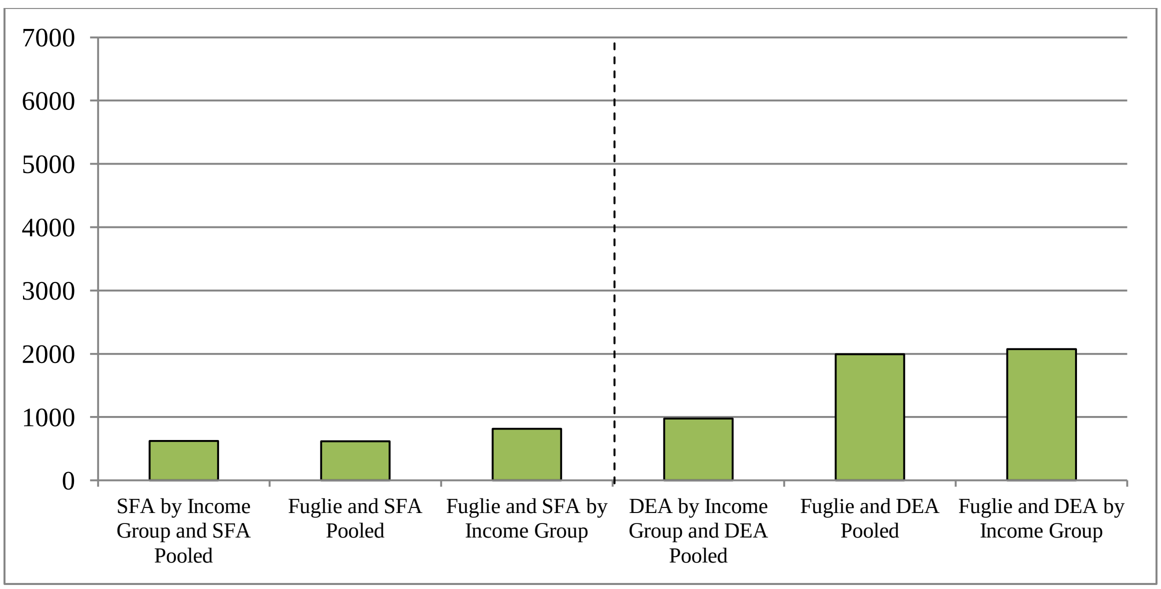

Fig. 3.1b. Average Sum of Squared Differences between Estimated Annual TFP Changes for Lower Middle Income Countries: Fuglie, SFA, and DEA - Smoothed Data

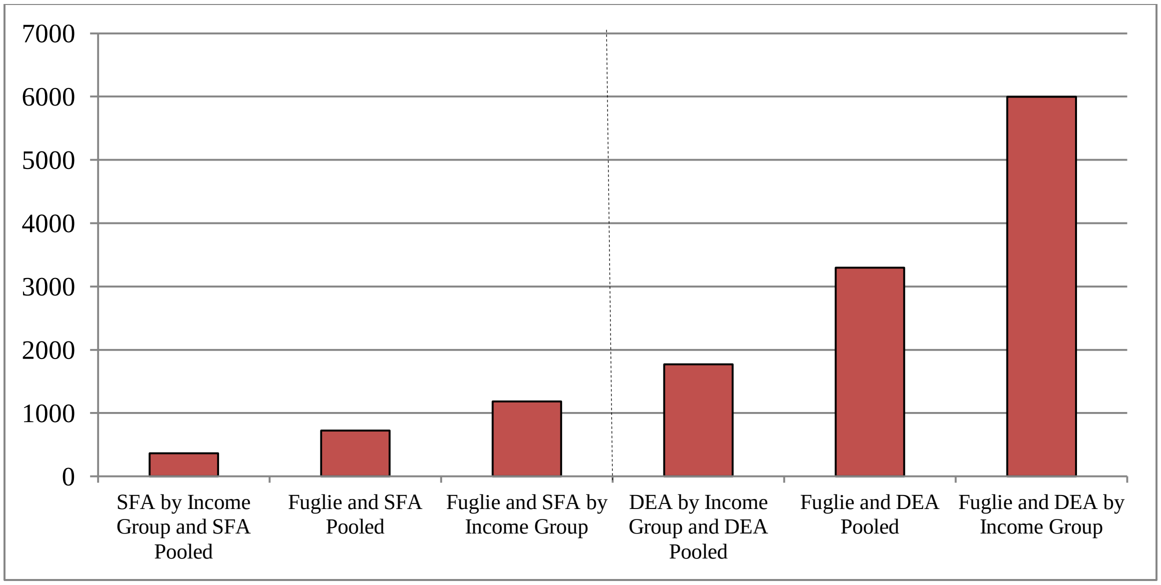

Fig. 3.1c. Average Sum of Squared Differences between Estimated Annual TFP Changes for Upper Middle Income Countries: Fuglie, SFA, and DEA - Smoothed Data

In each figure above, the three bars using DEA measures show higher "Average Sum of Squared Differences" compared to the three bars associated with SFA measures. The differences in annual TFP growth rates are higher between DEA by Income Group and DEA pooled than those between SFA by Income Group and SFA pooled. Also, DEA estimates show greater deviations from Fuglie's estimates than SFA estimates do. Moreover, for all the income groups, TFP growth rates estimated from SFA-pooled seem to be closer to Fuglie's estimate than the growth rates obtained by DEA. If we just look at the mean TFP growth rate obtained using SFA-pooled and SFA-By Income Group, it is clear that differences between estimates of TFP growth between these estimates are greatest for the Upper middle income group. But looking at the average sum of squared differences in the annual TFP growth rates seems to be lowest among all these income groups. Whereas Mean TFP growth rate shows the average growth in TFP for all the countries in the group over the whole sample period, the sum of squared differences represents sum of squared differences in TFP growth rate for each country observed every year.

It is possible that two different methods can give similar mean TFP growth rates for a same country over a long period of time, but still have substantial differences in growth rates in individual years.

Analysis from the DEA and SFA estimation reveals that both DEA and SFA are affected by selection of countries. The annual TFP change indices and cumulative TFP indices obtained for each country from the sub-samples and whole sample are different. For few countries the differences are smaller, but most of the countries the difference is noticeable. Among the two approaches, DEA seems to be most sensitive to selection of countries. In spite of the adjustment in outputs and some inputs that account for any inefficiency, DEA based results still show high differences when compared with growth accounting based TFP growth rates. In addition, DEA is more restrictive on its assumptions compared to SFA. For these reasons, we will drop the consideration of DEA-based TFP estimates from this point forward and will confine our analysis to SFA and Fuglie-type estimates of TFP growth.

3.5.2.2. Productivity Estimates: Results from SFA Estimation for Countries Groups Based on Income Level Using Unsmoothed Data

We now consider TFP estimates using unsmoothed output data. SFA estimates are for the pooled sample and sub-samples based on income level. It is possible that actual output per worker affects poverty more than trends in productivity. So theoretically it might be better to use unadjusted output. If output increases for, say, favorable weather conditions, output per worker will increase. Demand for labor will increase and possibly increase labor income in the short run. However, when we talk about TFP, we mean productivity change due to technical change and efficiency change. If output increases due to favorable weather condition, that’s not because resources are used more efficiently. We obtain annual TFP change index and cumulative TFP index (base 1961=1) for each country each year. The mean TFP growth rate for each income group calculated from estimation of SFA pooled, SFA by Income Group, and results from Fuglie's growth accounting approach are presented below. We compare the results with those obtained from SFA using smoothed output. (Please see Appendix A for more detailed graphs on annual and cumulative TFP indices)

Table 3.3: Mean TFP Growth Rate for the Period 1961-2009: Fuglie vs. SFA Pooled vs. SFA by Income Group - Smoothed Data vs. Unsmoothed Data

	Smoothed Output			Unsmoothed Output		
Countries Group	Fuglie	SFA Pooled	SFA by Income group	Fuglie	SFA Pooled	SFA by Income group
Low income	0.274	0.654	0.674	0.268	0.651	0.692
Lower Middle income	0.796	0.647	0.867	0.795	0.648	0.862
Upper Middle Income	1.297	0.706	1.196	1.269	0.705	1.175

For each estimation method, we didn't find much difference in the mean TFP growth rates for each income group obtained using smoothed and unsmoothed output. This might be due to the behavioral assumption made on the inefficiency term U with mean 0. It could also be due to the very nature of SFA that describes that SFA can ascribe too much variation in the data to measurement error and might result in excessive smoothing of measured productivity as argued by Headey et al. (2010). However, differences are observed on the annual TFP growth rates for countries over time. We again sum the squared differences in annual TFP growth rates for each income group by comparing two different techniques as described earlier. Panel A shows the average sum of squared differences in annual TFP growth rates for each income group comparing TFP measures from SFA by income group, SFA pooled, and Fuglie's growth accounting approach using smoothed output. Panel B shows the average sum of squared differences in annual TFP growth rates for each income group comparing TFP measures from

SFA by income group, SFA pooled, and Fuglie's growth accounting approach using unsmoothed output. Panel C compares TFP measures for smoothed and unsmoothed output for each estimation method for the same income group.

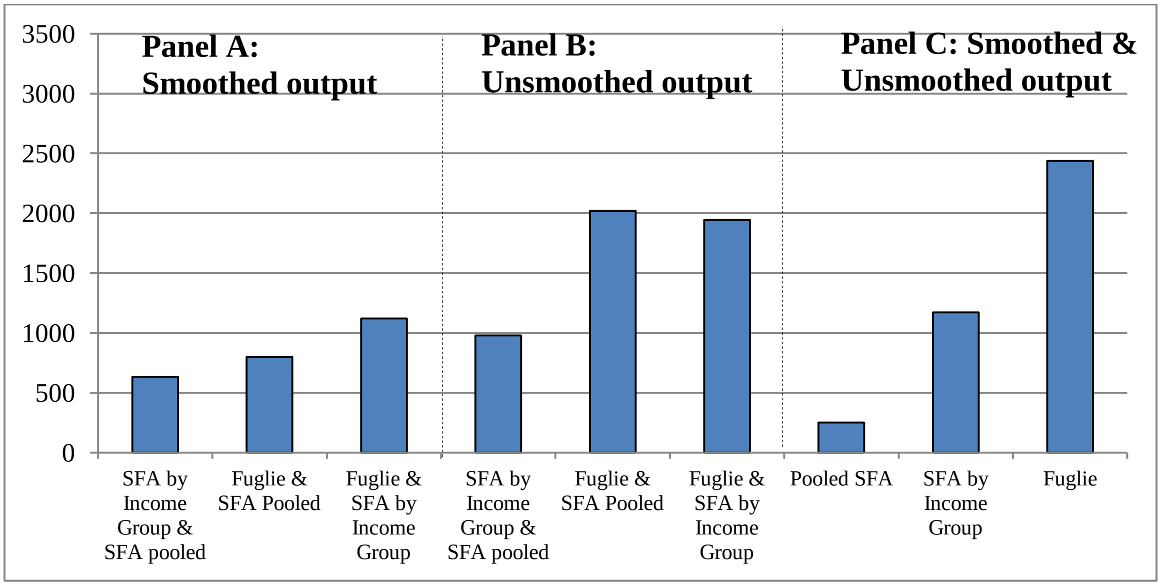

Figure 3.2a. Average Sum of Squared Differences between Estimated Annual TFP Changes for Low Income Countries: Fuglie, SFA Pooled, and SFA by Income Group - Smoothed Data and Unsmoothed Data

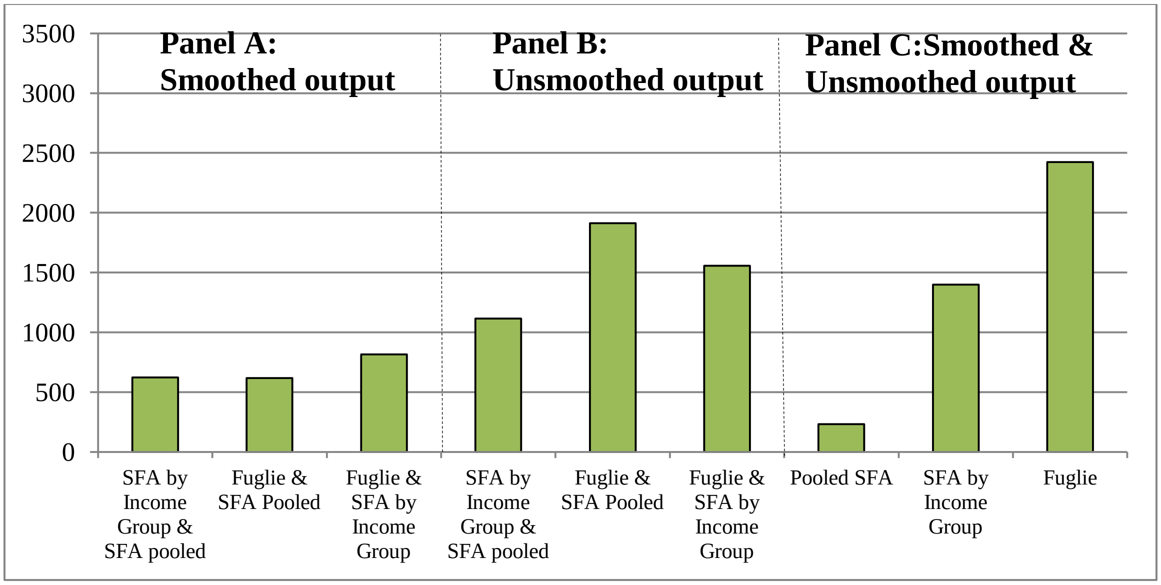

Figure 3.2b. Average Sum of Squared Differences between Estimated Annual TFP Changes for Lower Middle Income Countries: Fuglie, SFA Pooled, and SFA by Income Group - Smoothed Data and Unsmoothed Data

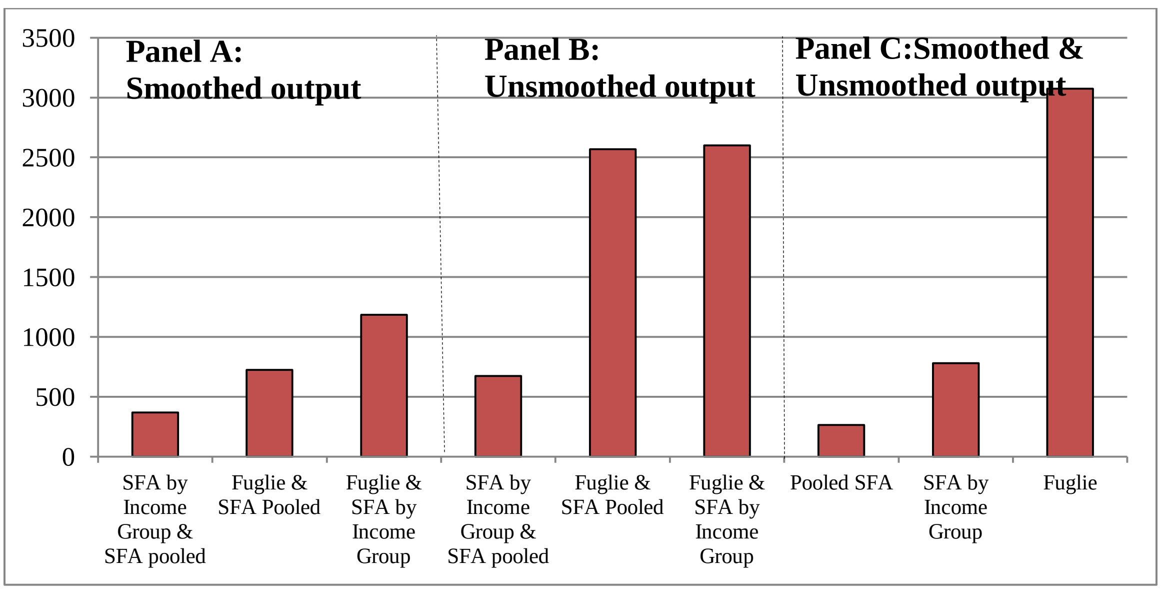

Figure 3.2c. Average Sum of Squared Differences between Estimated Annual TFP Changes for Upper Middle Income Countries: Fuglie, SFA Pooled, and SFA by Income Group - Smoothed Data and Unsmoothed Data

For the low income countries, it is clear from Figure 3.2a that smoothing of output leads to less discrepancy between the annual growth rates for countries than the case if output is not smoothed. This is true for lower middle and upper middle income groups too. In case of unsmoothed output, the differences between growth accounting and SFA based TFP measures are higher compared to the smoothed output case. The annual TFP growth rates seem to be less affected when all the countries are included in the SFA model. The differences between annual growth rates estimates based on smoothed and unsmoothed data are especially pronounced for Fuglie's growth accounting approach.

3.5.2.3. Productivity Estimates: Results from SFA Estimation for Countries Groups Based on Geographical Regions Using Smoothed and Unsmoothed Data

Finally, we estimate SFA using both smoothed and unsmoothed output for the three groups based on Fuglie's regional grouping as described earlier in the data section. One group consists of 45 Sub-Saharan African countries; the second group comprises 20 countries from South Asia, South East Asia and Oceania; and the third group includes 22 countries from South America and MENA regions. The calculated Mean TFP growth rates for each region are presented in the table below. (Please see appendix for more detailed graphs on annual and cumulative TFP indices)

Table 3.4: Mean TFP Growth Rate for the Period 1961-2009: Fuglie vs. SFA by Region - Smoothed vs. Unsmoothed Data

	Smoothed Output		Unsmoothed output	
Countries Group	Fuglie	SFA	Fuglie	SFA
SSA	0.250	0.705	0.239	0.713
South Asia + SE Asia + Oceania	0.876	0.712	0.861	0.699
South America + Mena	1.636	0.813	1.637	0.843

Once again, smoothed and unsmoothed outputs do not seem to alter the mean TFP growth rates a lot. In SFA, the average TFP growth rates for each regional group don't vary dramatically. For SSA, S. Asia and Oceania countries it is found to be quite similar. The similar mean TFP growth rates for all different regions seem quite unreasonable, given the fact that the agricultural performance of each region has been found to be unequal over time as reported in World Development Report, 2008. In that sense, Fuglie's estimates look reasonable with variation in TFP growth rate in different regions.

Smoothing of output does affect the annual TFP growth rates however. In Figures 3.3 we show the average sum of squared differences in annual TFP growth rates obtained by comparing Fuglie's TFP estimates with TFP estimates from SFA using smoothed and unsmoothed output, along with comparisons of TFP estimates for smoothed and unsmoothed output for each estimation method.

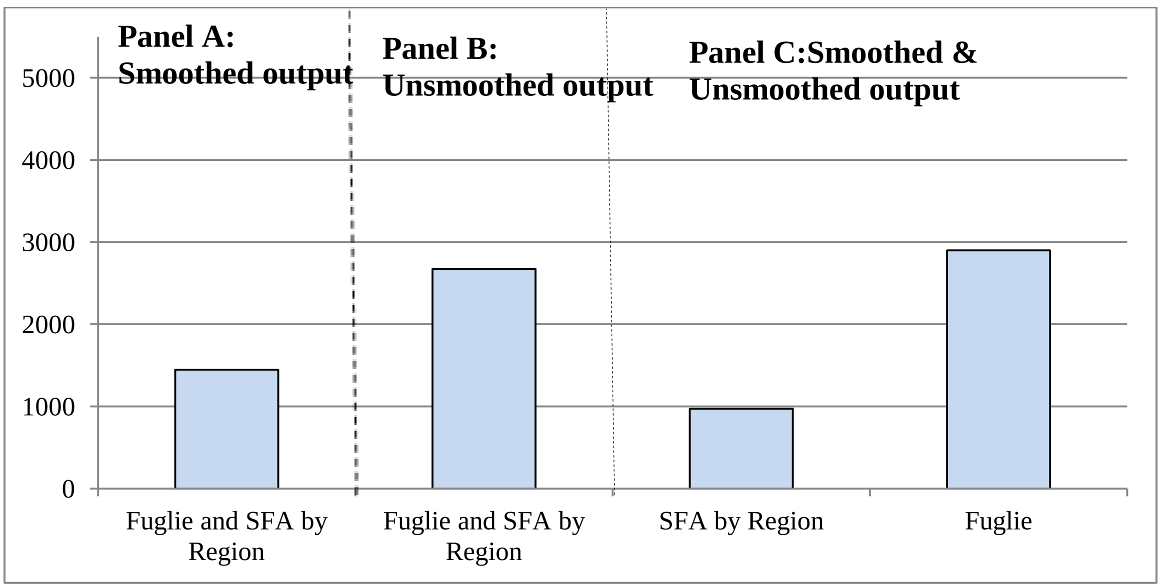

Figure 3.3a. Average Sum of Squared Differences between Estimated Annual TFP Changes for SSA Countries: Fuglie and SFA by Region - Smoothed Data and Unsmoothed Data

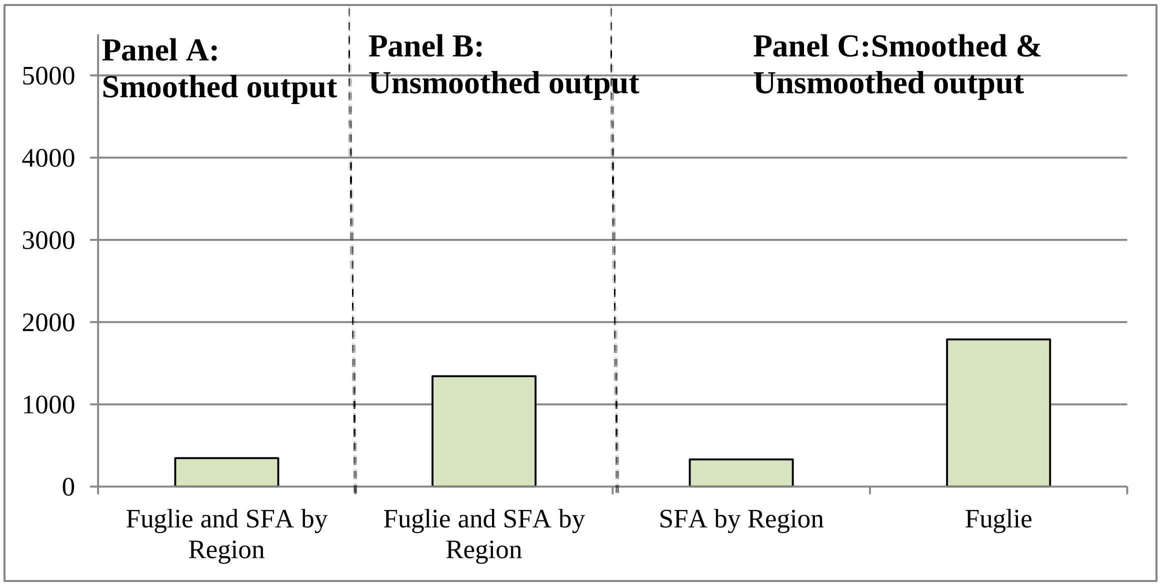

Figure 3.3b. Average Sum of Squared Differences between Estimated Annual TFP Changes for S. Asia & Oceania Countries: Fuglie and SFA by Region - Smoothed Data and Unsmoothed Data

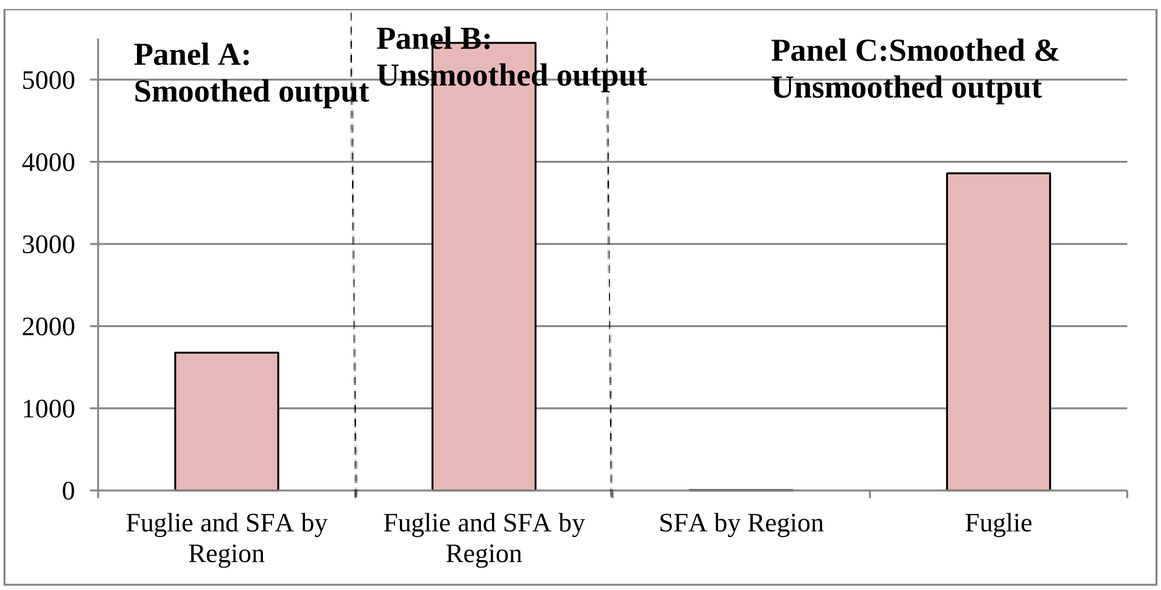

Figure 3.3c. Average Sum of Squared Differences between Estimated Annual TFP Changes for S. America and Mena Countries: Fuglie and SFA by Region - Smoothed Data and Unsmoothed Data

Fig 3.3a and 3.3b show that the differences in annual TFP growth rates are higher if estimated for unsmoothed output. The differences are substantial in case of Fuglie's growth accounting estimation. The estimation of stochastic distance function for S. America and MENA region indicated no inefficiency in the data which implies that all the countries are fully efficient. In the absence of inefficiency, the resulting TFP change is only due to technical change. Smoothing of output doesn't seem to affect TFP estimates much. The difference found in the annual TFP growth rates for each country is found to be negligible. When differences in annual TFP growth rates for smooth and unsmooth output case are compared, Fuglie's estimates show higher differences in TFP growth compared to SFA.

3.5.2.4. List of Countries with Highest Sum of Squared Differences (SSD's) between Estimated Annual TFP Changes: Comparing Fuglie, SFA by Income Group, and SFA by Region, Smoothed vs. Unsmoothed Data

We examine Sum of squared Differences (SSD's) for income groups and regions to see if there is an apparent relationship between SSD and these characteristics. We include 36 countries with highest SSD (in descending order) by comparing Fuglie and SFA by income group for smoothed and unsmoothed data; comparing Fuglie and SFA by Region for smoothed and unsmoothed data; comparing SSD using smoothed and unsmoothed data for SFA by Income group, SFA by Region, and Fuglie. The countries are listed in the tables 3.5-3.11 from each comparison.

Table 3.5. Sum of Squared Differences between Estimated Annual TFP Changes: Fuglie vs. SFA by Income Group – Smoothed Data

Country	Income Group	Regional Group	SSD
Seychelles	Upper Middle Income	SSA	11940.3
Jordan	Upper Middle Income	S. America & MENA	5461.462
Cape Verde	Lower Middle Income	SSA	3238.199
Albania	Upper Middle Income	European Union	2922.719
Burundi	Low Income	SSA	2732.005
Rwanda	Low Income	SSA	2703.821
Somalia	Low Income	SSA	2613.632
Iraq	Upper Middle Income	S. America & MENA	2482.268
Laos	Lower Middle Income	S. Asia & Oceania	2326.582
Benin	Low Income	SSA	2286.641
Mozambique	Low Income	SSA	2267.079
Belize	Upper Middle Income	Central America	2173.555
Namibia	Upper Middle Income	SSA	2142.694
Congo	Lower Middle Income	SSA	1983.345
Yemen	Lower Middle Income	S. America & MENA	1804.031
Papua New Guinea	Lower Middle Income	S. Asia & Oceania	1662.002
Cambodia	Low Income	S. Asia & Oceania	1620.253
Central African Republic	Low Income	SSA	1608.446
Sierra Leone	Low Income	SSA	1589.024
Uganda	Low Income	SSA	1572.406
Gabon	Upper Middle Income	SSA	1521.499
Niger	Low Income	SSA	1512.124
Burkina Faso	Low Income	SSA	1435.532
Fiji	Upper Middle Income	S. Asia & Oceania	1408.524
Congo, DR	Low Income	SSA	1264.516
Angola	Upper Middle Income	SSA	1262.44
Libya	Upper Middle Income	S. America & MENA	1259.918
Honduras	Lower Middle Income	Central America	1258.557
Lesotho	Lower Middle Income	SSA	1234.608
Swaziland	Lower Middle Income	SSA	1148.031
Mongolia	Lower Middle Income	NE Asia	1136.005
Ethiopia, former	Low Income	SSA	1132.687
Haiti	Low Income	Central America	1125.018
Vietnam	Lower Middle Income	S. Asia & Oceania	1092.989
Cuba	Upper Middle Income	Central America	1059.859
Botswana	Upper Middle Income	SSA	1039.705

Note: Table 3.5 only includes 36 countries with the highest SSD's. Regional grouping is based on Fuglie (2011).

Table 3.6. Sum of Squared Differences between Estimated Annual TFP Changes: Fuglie vs. SFA by Geographic Region - Smoothed Data

Country	Income Group	Regional Group	SSD
Niger	Low Income	SSA	9069.442
Somalia	Low Income	SSA	6528.59
Jordan	Upper Middle Income	S. America & MENA	6363.213
Iraq	Upper Middle Income	S. America & MENA	5800.861
Suriname	Upper Middle Income	S. America & MENA	5260.976
Seychelles	Upper Middle Income	SSA	4679.51
Yemen	Lower Middle Income	S. America & MENA	4183.15
Mauritania	Lower Middle Income	SSA	4051.064
Burkina Faso	Low Income	SSA	3914.022
Congo, DR	Low Income	SSA	3661.463
Djibouti	Lower Middle Income	SSA	3322.391
Sao Tome and Principe	Lower Middle Income	SSA	2790.989
Guyana	Lower Middle Income	S. America & MENA	2387.883
Ethiopia, former	Low Income	SSA	2249.999
Libya	Upper Middle Income	S. America & MENA	2177.899
Bolivia	Lower Middle Income	S. America & MENA	2029.469
Gabon	Upper Middle Income	SSA	1815.791
Rwanda	Low Income	SSA	1655.525
Mali	Low Income	SSA	1654.045
Mozambique	Low Income	SSA	1602.606
Cape Verde	Lower Middle Income	SSA	1572.089
Chad	Low Income	SSA	1414.352
Algeria	Upper Middle Income	S. America & MENA	1326.476
Lebanon	Upper Middle Income	S. America & MENA	1202.316
Swaziland	Lower Middle Income	SSA	1018.766
Central African Republic	Low Income	SSA	1001.94
Botswana	Upper Middle Income	SSA	931.441
Nigeria	Lower Middle Income	SSA	918.234
Paraguay	Lower Middle Income	S. America & MENA	912.389
Congo	Lower Middle Income	SSA	895.859
Uganda	Low Income	SSA	868.821
Laos	Lower Middle Income	S. Asia & Oceania	855.505
Angola	Upper Middle Income	SSA	847.286
Syria	Lower Middle Income	S. America & MENA	818.607
Liberia	Low Income	SSA	673.563
Burundi	Low Income	SSA	671.024

Note: Table 3.6 only includes 36 countries with the highest SSD’s. Regional grouping is based on Fuglie (2011).

Table 3.7. Sum of Squared Differences between Estimated Annual TFP Changes: Fuglie vs. SFA by Income Group - Unsmoothed Data

Country	Income Group	Regional Group	SSD
Jordan	Upper Middle Income	S. America & MENA	15897.36
Tunisia	Upper Middle Income	S. America & MENA	10118.45
Seychelles	Upper Middle Income	SSA	9624.151
Cambodia	Low Income	S. Asia & Oceania	6277.172
Libya	Upper Middle Income	S. America & MENA	4881.749
Mongolia	Lower Middle Income	NE Asia	4865.204
Niger	Low Income	SSA	4800.137
Iraq	Upper Middle Income	S. America & MENA	4671.284
Burundi	Low Income	SSA	4426.698
Benin	Low Income	SSA	4404.262
Mauritius	Upper Middle Income	SSA	4284.796
Fiji	Upper Middle Income	S. Asia & Oceania	4216.947
Belize	Upper Middle Income	Central America	4062.761
Cuba	Upper Middle Income	Central America	4008.427
Rwanda	Low Income	SSA	4008.121
Paraguay	Lower Middle Income	S. America & MENA	3839.18
Lebanon	Upper Middle Income	S. America & MENA	3204.441
Syria	Lower Middle Income	S. America & MENA	3153.058
Albania	Upper Middle Income	European Union	3128.172
Uganda	Low Income	SSA	3050.499
Laos	Lower Middle Income	S. Asia & Oceania	3039.889
Namibia	Upper Middle Income	SSA	3016.425
Vanuatu	Lower Middle Income	S. Asia & Oceania	2994.43
Djibouti	Lower Middle Income	SSA	2784.443
Nicaragua	Lower Middle Income	Central America	2779.55
Mozambique	Low Income	SSA	2775.208
Somalia	Low Income	SSA	2720.232
Cape Verde	Lower Middle Income	SSA	2496.134
Burkina Faso	Low Income	SSA	2458.899
Morocco	Lower Middle Income	S. America & MENA	2222.383
Central African Republic	Low Income	SSA	2179.154
Lesotho	Lower Middle Income	SSA	2150.632
Sierra Leone	Low Income	SSA	2114.994
Sudan	Lower Middle Income	SSA	2079.165
Senegal	Lower Middle Income	SSA	2011.16
Congo	Lower Middle Income	SSA	1989.171

Note: Table 3.7 only includes 36 countries with the highest SSD's. Regional grouping is based on Fuglie (2011).

Table 3.8. Sum of Squared Differences between Estimated Annual TFP Changes: Fuglie vs. SFA by Geographic Region - Unsmoothed Data

Country	Income Group	Regional Group	SSD
Jordan	Upper Middle Income	S. America & MENA	23005
Tunisia	Upper Middle Income	S. America & MENA	17366.15
Niger	Low Income	SSA	11131.56
Syria	Lower Middle Income	S. America & MENA	10575.43
Morocco	Lower Middle Income	S. America & MENA	9869.083
Libya	Upper Middle Income	S. America & MENA	9531.524
Senegal	Lower Middle Income	SSA	8547.335
Seychelles	Upper Middle Income	SSA	7237.731
Suriname	Upper Middle Income	S. America & MENA	7025.593
Algeria	Upper Middle Income	S. America & MENA	6856.695
Mauritius	Upper Middle Income	SSA	6654.663
Somalia	Low Income	SSA	5774.397
Iraq	Upper Middle Income	S. America & MENA	5714.211
Burkina Faso	Low Income	SSA	5593.097
Gambia	Low Income	SSA	5534.33
Vanuatu	Lower Middle Income	S. Asia & Oceania	5433.533
Djibouti	Lower Middle Income	SSA	4992.815
Yemen	Lower Middle Income	S. America & MENA	4870.599
Zimbabwe	Low Income	SSA	4746.729
Guyana	Lower Middle Income	S. America & MENA	4070.856
Lebanon	Upper Middle Income	S. America & MENA	4012.483
Fiji	Upper Middle Income	S. Asia & Oceania	3890.994
Congo, DR	Low Income	SSA	3858.583
Bolivia	Lower Middle Income	S. America & MENA	3854.006
Rwanda	Low Income	SSA	3598.038
Mauritania	Lower Middle Income	SSA	3417.123
Cambodia	Low Income	S. Asia & Oceania	3186.156
Cape Verde	Lower Middle Income	SSA	2802.783
Mali	Low Income	SSA	2675.632
Burundi	Low Income	SSA	2599.131
Ghana	Lower Middle Income	SSA	2598.96
Namibia	Upper Middle Income	SSA	2556.746
Paraguay	Lower Middle Income	S. America & MENA	2548.162
Mozambique	Low Income	SSA	2474.084
Sao Tome and Principe	Lower Middle Income	SSA	2451.78
Laos	Lower Middle Income	S. Asia & Oceania	2447.679

Note: Table 3.8 only includes 36 countries with the highest SSD's. Regional grouping is based on Fuglie (2011).

Table 3.9. Sum of Squared Differences between Estimated Annual TFP Changes: SFA by Income Group - Smoothed Data vs. Unsmoothed Data.

Country	Income Group	Regional Group	SSD
Senegal	Lower Middle Income	SSA	9624.505
Namibia	Upper Middle Income	SSA	7387.293
Mongolia	Lower Middle Income	NE Asia	6659.204
Gambia	Low Income	SSA	6490.694
Malawi	Low Income	SSA	3738.336
Cambodia	Low Income	S. Asia & Oceania	3690.182
Sao Tome and Principe	Lower Middle Income	SSA	3186.661
Cape Verde	Lower Middle Income	SSA	3069.065
Syria	Lower Middle Income	S. America & MENA	3007.657
Zambia	Lower Middle Income	SSA	2998.888
Zimbabwe	Low Income	SSA	2963.168
Morocco	Lower Middle Income	S. America & MENA	2940.361
Rwanda	Low Income	SSA	2397.115
Djibouti	Lower Middle Income	SSA	2270.267
Lesotho	Lower Middle Income	SSA	2112.668
Botswana	Upper Middle Income	SSA	1995.732
Algeria	Upper Middle Income	S. America & MENA	1894.78
Madagascar	Low Income	SSA	1784.697
Niger	Low Income	SSA	1679.791
Romania	Upper Middle Income	European Union	1502.296
Fiji	Upper Middle Income	S. Asia & Oceania	1501.622
Nicaragua	Lower Middle Income	Central America	1466.673
Laos	Lower Middle Income	S. Asia & Oceania	1364.15
Bulgaria	Upper Middle Income	European Union	1341.589
Seychelles	Upper Middle Income	SSA	1336.242
Ethiopia, former	Low Income	SSA	1334.78
Burkina Faso	Low Income	SSA	1328.298
Swaziland	Lower Middle Income	SSA	1262.037
Mauritius	Upper Middle Income	SSA	1260.259
Ghana	Lower Middle Income	SSA	1202.68
Iraq	Upper Middle Income	S. America & MENA	1192.552
Liberia	Low Income	SSA	1177.308
Afghanistan	Low Income	S. Asia & Oceania	1164.808
Paraguay	Lower Middle Income	S. America & MENA	1139.393
Libya	Upper Middle Income	S. America & MENA	1131.748
Chad	Low Income	SSA	1094.68

Note: Table 3.9 only includes 36 countries with the highest SSD's. Regional grouping is based on Fuglie (2011).

Table 3.10. Sum of Squared Differences between Estimated Annual TFP Changes: SFA by Region Group - Smoothed Data vs. Unsmoothed Data

Country	Income Group	Regional Group	SSD
Sao Tome and Principe	Lower Middle Income	SSA	3784.504
Cambodia	Low Income	S. Asia & Oceania	3619.782
Djibouti	Lower Middle Income	SSA	3464.842
Botswana	Upper Middle Income	SSA	2778.925
Lesotho	Lower Middle Income	SSA	2373.117
Senegal	Lower Middle Income	SSA	2303.787
Seychelles	Upper Middle Income	SSA	2168.701
Cape Verde	Lower Middle Income	SSA	2072.487
Niger	Low Income	SSA	1864.997
Malawi	Low Income	SSA	1797.513
Zimbabwe	Low Income	SSA	1705.686
Ethiopia, former	Low Income	SSA	1663.743
Mozambique	Low Income	SSA	1348.503
Gambia	Low Income	SSA	1334.278
Namibia	Upper Middle Income	SSA	1297.82
Rwanda	Low Income	SSA	1177.329
Burkina Faso	Low Income	SSA	1105.437
Chad	Low Income	SSA	1000.885
Zambia	Lower Middle Income	SSA	914.877
Swaziland	Lower Middle Income	SSA	880.365
Angola	Upper Middle Income	SSA	692.604
Liberia	Low Income	SSA	687.734
Mauritius	Upper Middle Income	SSA	642.006
Tanzania	Low Income	SSA	609.769
Mali	Low Income	SSA	609.07
Madagascar	Low Income	SSA	594.121
Sudan	Lower Middle Income	SSA	531.794
Nigeria	Lower Middle Income	SSA	504.3
Sierra Leone	Low Income	SSA	485.693
Burundi	Low Income	SSA	478.428
Somalia	Low Income	SSA	454.423
Afghanistan	Low Income	S. Asia & Oceania	449.305
Laos	Lower Middle Income	S. Asia & Oceania	422.747
Togo	Low Income	SSA	370.34
Vanuatu	Lower Middle Income	S. Asia & Oceania	347.335
Ghana	Lower Middle Income	SSA	298.389

Note: Table 3.10 only includes 36 countries with the highest SSD's. Regional grouping is based on Fuglie (2011).

Table 3.11. Sum of Squared Differences between Estimated Annual TFP Changes: Fuglie Smoothed Data vs. Unsmoothed Data

Country	Income Group	Regional Group	SSD
Senegal	Lower Middle Income	SSA	17133.56
Tunisia	Upper Middle Income	S. America & MENA	15693.98
Jordan	Upper Middle Income	S. America & MENA	15355.63
Gambia	Low Income	SSA	12597.99
Cambodia	Low Income	S. Asia & Oceania	10086.83
Syria	Lower Middle Income	S. America & MENA	10017.55
Morocco	Lower Middle Income	S. America & MENA	8788.06
Zimbabwe	Low Income	SSA	8199.767
Mauritius	Upper Middle Income	SSA	8147.082
Libya	Upper Middle Income	S. America & MENA	6667.853
Namibia	Upper Middle Income	SSA	6259.975
Fiji	Upper Middle Income	S. Asia & Oceania	6047.592
Rwanda	Low Income	SSA	5596.122
Algeria	Upper Middle Income	S. America & MENA	5218.589
Cuba	Upper Middle Income	Central America	5122.672
Niger	Low Income	SSA	5044.839
Iraq	Upper Middle Income	S. America & MENA	4910.844
Cape Verde	Lower Middle Income	SSA	4772.419
Lesotho	Lower Middle Income	SSA	4684.695
Vanuatu	Lower Middle Income	S. Asia & Oceania	4353.976
Seychelles	Upper Middle Income	SSA	4235.577
Malawi	Low Income	SSA	4200.276
Bulgaria	Upper Middle Income	European Union	4177.974
Romania	Upper Middle Income	European Union	3612.235
Zambia	Lower Middle Income	SSA	3592.399
Burkina Faso	Low Income	SSA	3490.934
Botswana	Upper Middle Income	SSA	3344.768
Ghana	Lower Middle Income	SSA	3248.574
Lebanon	Upper Middle Income	S. America & MENA	3022.188
Hungary	Upper Middle Income	European Union	3018.588
Laos	Lower Middle Income	S. Asia & Oceania	2977.339
Nicaragua	Lower Middle Income	Central America	2866.7
Belize	Upper Middle Income	Central America	2762.131
Liberia	Low Income	SSA	2670.137
Sao Tome and Principe	Lower Middle Income	SSA	2662.106
South Africa	Upper Middle Income	Africa	2522.638

Note: Table 3.11 only includes 36 countries with the highest SSD’s. Regional grouping is based on Fuglie (2011).

Table 3.12. Summary of Tables 3.5 to 3.11

Data	Comparison	No. of Low Income	No. of Lower Middle Income	No. of Upper Middle Income	No. of SSA	No. of S. Asia & Oceania	No. of S. America & MENA
Smooth	Fuglie vs. SFA by Income Group	14	10	12	21	5	4
	Fuglie Vs SFA by Region	13	13	10	24	1	11
Unsmooth	Fuglie vs. SFA by Income Group	11	13	12	19	4	8
	Fuglie vs. SFA by Region	11	14	11	19	4	13
Smoothed vs. Unsmoothed	SFA by Income Group	12	14	10	22	4	6
	SFA by Region	19	12	5	32	4	0
	Fuglie	8	11	17	17	4	8

From table 3.5, comparing Fuglie to SFA by Income group using smoothed data, it is clear that most of the countries with highest SSD's belong to low income group. In table 3.6, comparing Fuglie to SFA by Region using smoothed data, it can be inferred that more number of countries with highest SSD's belong to low and lower middle income group. The tables 3.7 and 3.8, comparison Fuglie to SFA by Income group and Fuglie to SFA by Region using unsmoothed data show that more middle income countries are present in the list of top 36 countries with highest SSD's. Table 3.9 shows that in the comparison of SFA by Income group for smoothed and unsmoothed data, 14 out of 36 countries with highest SSD's are found to be from middle income group. Table 3.10 shows countries with highest SSDs from comparing estimates from SFA by Region for smoothed and unsmoothed data. It shows 19 out of 36 countries with highest SSD's are among low income group. More upper middle income countries are found in the list comparing Fuglie's estimates for smoothed and unsmoothed output. In all of these cases, the highest numbers of countries that are found to be most affected by the choice of TFP estimation method belong to SSA region.

3.6. Summary and Conclusions

We used agricultural output and input data for 108 countries over the period 1961-2009 and applied three widely used techniques, i.e. growth accounting approach, Data Envelopment Analysis, and Stochastic Frontier Analysis approach to calculate TFP growth for each country over time. We further divided the countries into sub-samples based on their income level and based on geographical regions as found in Fuglie (2011). In addition, we use both smoothed and unsmoothed output data and quality adjusted land data.

Overall, estimation from Pooled SFA and SFA by income group give different annual growth rates for the most countries. Smoothing outputs doesn't seem to affect the estimated mean growth rates; however they result in different annual estimated growth rates. Fuglie's growth accounting method is more affected if output is not smoothed as compared to SFA. SFA is less sensitive in that case as it involves econometric estimation. When SFA is estimated for the similar regional groupings as Fuglie (2011) did, the resulting TFP growth rates are found to be very different from Fuglie's TFP growth rates. In spite of the adjustment in outputs and some inputs that account for any inefficiency, DEA based results show high differences in annual TFP growth rates when compared with growth accounting based TFP growth rates. The mean TFP growth rates for different income groups don't show much difference when estimated in pooled SFA, whereas SFA by Income group yields different mean TFP growth rates for different income group. However, analysis of differences in the annual TFP growth rate reveals that more variation in annual TFP growth rates is observed for countries when SFA is estimated by grouping them.

We conclude that DEA and SFA methods give different TFP growth rates for the same country when estimated for the pooled sample and sub-samples. DEA is highly affected by groups and results are unrealistic. Smoothing of output has little effect on mean TFP growth rates for income groups as well as for regional group. They do affect annual TFP changes. SFA by Region gives estimates that are closer to Fuglie’s estimates as compared to estimates obtained from SFA by Income group.

CHAPTER 4

LINK BETWEEN AGRICULTURAL PRODUCTIVITY AND POVERTY IN DEVELOPING COUNTRIES

4.1. Background and Literature Review

There is a broad consensus that economic growth is associated with sustained poverty reduction. The early literature based on the "trickle down" theory of economic development argues that the benefits from rapid economic growth rate diffuse automatically among all segments of the economy. During the process of development, the rich gets the benefits first. The poor start getting benefits when rich spend their gains. It was believed that faster economic growth would reduce poverty faster. The main focus of economists during 1950s and 1960s was thus to stimulate economic growth through increasing savings and investments. However, in the 1970s and later, economists casted doubt on "trickle down theory" when evidences of high poverty rates were found in some countries despite rapid growth rates. Debate continues over the extent to which economic growth has benefited poor people in developing countries.

Over time, the concept of "pro-poor growth" received increased emphasis in trying to understand the relationship between growth and poverty. Economists argue that growth alone is not sufficient for poverty reduction unless reflected in the distribution of income as well. This argument is mainly driven by the Kuznets curve hypothesis proposed by Simon Kuznets in 1955. It implies that as incomes grow in the early stages of development, income distribution at first worsens and then improves as a larger share of the population participate in the rising national income. If income distribution becomes dramatically unequal with economic growth, however, poverty may not decline or it may take longer to decline. The conclusions drawn by Kuznets, however, were based on cross-country data on selected developed countries. Later studies by Ravallion (1995), Deininger and Squire (1996), and Schultz (1998) examined the relationship between GDP per capita and inequality for a panel of developing countries and rejected the Kuznet hypothesis. These studies suggest that growth does not increase or decrease inequality. Moreover, they conclude that economic growth can be expected to reduce poverty more if inequality falls, than if it does not. Barrow (2000, 2008) estimating the relation with panel data for both developed and developing countries shows that the Kuznets curve is a clearly empirical phenomenon. His findings show that inequality initially rises with increase in income.

Many studies examined the impact of growth on poverty reduction in different countries and confirmed that growth is associated with poverty reduction. However, there was substantial variation in the magnitude of poverty reduction. Mellor (1999) points out that these variations were due to the structure of growth, he emphasizes the importance of sectoral growth on poverty reduction. In the early development literature, agriculture was considered as a backward and subsistence sector. As a consequence, resources were to be diverted from the agricultural sector to support non-agricultural sector. This was done mostly by means of taxing agricultural sector leading to an urban bias strategy in developing countries. The majority of the world's poor lives in rural areas and depends to a large extent on agriculture. It is often argued that agricultural sector growth has a higher impact on poverty reduction than that of growth in non-agriculture. Mellor argues that agricultural growth is very effective in reducing poverty because in addition to generating income for the poor farmers, it also creates demand for goods that can easily be produced by the poor. His argument also highlights the contribution of the agricultural sector growth to growth in the non-agricultural sectors, implying that investments and policy reforms in agriculture might actually lead to faster overall economic growth.

Several authors have found significant multiplier effects from agriculture to non-agriculture in developing countries. The Green Revolution in Asia led to rapid transformation of the traditional agriculture sector into a fast growing modern sector through the adoption of new technology (Christiaensen et al., 2006). Structural transformation of the economy is possible through agricultural sector development. As agriculture grows, it provides food, increases employment and thereby wages and income. Demand for goods in the non-farm sector increases, which stimulates overall production and growth. This strategy was termed as “Agriculture Demand Led Industrialization” by Adleman (1984). Mellor and Johnson (1984) argue for a rural development strategy to promote extension and research aimed primarily at rural smallholders to improve income, nutrition, and income distribution, while promoting overall growth.

Vogel (1994) demonstrated such a strategy by examining the forward and backward linkages between the agricultural and non-agricultural sectors. The forward multiplier indicates increase the demand for agricultural inputs from the non-agricultural sector. The backward multiplier implies increased expenditures of agricultural households on non-agricultural products, and hence increased incomes for non-agricultural households, and further expenditures on non-agricultural goods. Vogel finds that the backward multipliers of agriculture are much larger than the forward multipliers.

Empirical evidence suggests that sectoral composition of growth matters substantially for poverty reduction. Ravallion & Datt (1996) showed that 84.5% of the poverty reduction in India was due to agricultural growth. Rural growth significantly reduced poverty in both rural and urban areas and thereby national poverty declined. But urban growth did not contribute to rural poverty reduction in India. Studies by Woden (1999) in Bangladesh and by Thorbecke and Jung (1996) in Indonesia concluded that agricultural growth is important for rural as well as urban areas in developing countries. Various studies show that non-agricultural sector growth does reduce poverty from the direct effect of income increase, but it has an unfavorable effect on the distribution of income, thereby reducing the effect on poverty. On the other hand, agricultural growth does not seem to have any unfavorable distributional effect (Ravallion & Datt, 1996; Timmer, 1997).

Literature identifies both direct and indirect impacts of agricultural growth on poverty reduction. It can directly reduce poverty by increasing income in rural areas and indirectly through labor market and food prices. The poverty-reducing effect of increasing farm incomes depends on the participation of poor smallholders in the growth. Agricultural growth also reduces poverty by creating employment opportunities for the poor. Many countries with high agricultural growth rate have shown dramatic decrease in poverty rate. For example, China's rapid growth in agriculture was responsible for the rapid decline in rural poverty from 53% in 1981 to 8% in 2001. India's and Ghana's strong agricultural performances resulted in rapid decline in poverty over the past years. However, in Bolivia and Brazil, where agricultural growth has been concentrated in a dynamic export-oriented sector of large capital-intensive farms, agricultural employment declined with little poverty reduction effects. Since many Latin American countries (LAC) fall into Middle income category, agriculture seems to have a diminished role there. Also, in contrast to Asia and Africa, poverty in Latin American countries in not primarily a rural phenomenon (Fan, 2008). One might suspect that agriculture may not play any significant role in LAC countries. However, a recent study by De Janvry & Sadoulet (2000) shows that although agricultural growth is effective for reducing poverty in Latin

America, it is unfavorable for overall equality. Agricultural growth leads to poverty reduction through an increase in farmers' income, increase in wages, etc. On the other hand, it can, however, affect inequality that could increase poverty. If the benefits from higher agricultural growth go to those on the high end of the income scale, it would lead to greater inequality. So, the direct benefits of agricultural growth on poverty reduction are outweighed by its effect of increasing overall inequality, resulting in greater poverty. It seems from the findings De Janvry & Sadoulet (2000) and other country studies that the role of overall income growth in poverty reduction depends on the distribution of income in the economy, and the role of agriculture in reducing poverty depends on the country context.

The profiles of the poor differ considerably in different countries and regions. For example, a majority of the poor in South-East Asia are rural smallholders, whose main source of income is agriculture. However, there are many landless who rely primarily on farm and non-farm labor income. The poor in Sub-Saharan Africa are mainly rural, with the major portion of their incomes from agriculture. In Latin America, on the other hand, a larger part of the poor are urban, depending on informal enterprise activity and non-farm labor. In addition to differences in characteristics of the poor, the agro-ecological condition and farming system too differ across regions (FAO, 2000). In such a heterogeneous scenario, it is shown that benefits from agricultural growth will differ across countries and regions.

Increased productivity of inputs is an important potential driver of growth in agricultural income (Sarris, 2001). Agricultural productivity growth can increase agricultural output and agricultural income and can drive a rural growth process that can be fundamentally pro-poor. It can increase real income and reduce poverty by benefiting poor farmers directly by increasing agricultural production, providing small farmers and landless laborers greater employment, lowering food prices for all consumers, increasing migration opportunities, benefiting the rural and urban poor through growth in the rural and urban non-farm economy, and leading to access to crops that are high in nutrients, etc. (Thirtle, 2001).

Agricultural Productivity –Poverty Relationship

Datt and Ravallion (1998) examine the effects of yield growth on poverty, the relative price of food and real wages in rural India, from 1958-94. They examine both direct and indirect gains from increased land productivity in their econometric model. The direct gains are analyzed in an equation that relates poverty to wages, relative prices of food, and land productivity. The indirect gains are analyzed from the impact of yields on wages and relative food prices in the model. The authors use standard absolute poverty measures (headcount, poverty gap, squared poverty gap) as well as relative poverty measures. However, due to data unavailability, they had only 24 observations in their model. They find that higher land productivity and higher wages reduce absolute poverty. The authors compare short-term and long-term elasticities of poverty to farm yields. In the short run, the direct effect of higher yields on poverty is greater than the indirect effect through wages and prices. But in the long run, the indirect effects dominate the direct effect on poverty. Their result suggests that the full effect of higher agricultural productivity takes time, considering the indirect effect through wages and prices.

Hanmer & Nashchold (2000) study the impact of agricultural productivity relative to modern sector productivity in a cross country analysis. They use a ratio of value added per worker in agriculture to value added per worker in modern sector as their main independent variable. They estimate their model by taking sub-samples based on regions and for the whole sample. They find that the relative productivity measure has a significant impact in Sub-Saharan and South-Asian countries sub-samples, but not in the whole sample. They conclude that higher productivity growth is critical for poverty reduction in these regions. However, when they group their countries based on regions, the sub-samples size is significantly reduced.

Studies have shown that whether agricultural growth could be best for poverty reduction in developing countries is conditional on initial level of land and income distribution. Highly skewed land and income distribution leads consumption patterns of farmers skewed towards capital-intensive consumer goods instead of labor-intensive manufacturing goods. De Janvry & Sadoulet (1996) find that due to high land inequality in Latin American countries, agricultural growth led to an increase in overall income inequality and hence poverty worsened there between 1970 and 1994.

Irz et al. (2001) examine the direct impact of agricultural land and labor productivity growth on poverty reduction in a cross country study of developing countries. They use agricultural value added per unit of land and labor for productivity measures. Their results show that increases in both land and labor productivity significantly decreases poverty, and growth in labor productivity is more poverty reducing than land productivity.

Thirtle et al. (2003) found significant positive impacts of research-led agricultural productivity growth on reducing poverty in developing countries. Using Three Stage Least Squares estimation technique for a system of equations and cross section data, they estimate the impact of land and labor productivity on GDP per capita and Gini index and evaluate how those contribute to poverty reduction. They divide the whole sample in to three sub-samples based on regions and estimate their model for both sub-samples and whole sample with regional dummies. Both land and labor productivities have significant impact on GDP per capita.The impact is higher for African countries than for Latin America countries. For Asia and Africa, labor productivity is inequality reducing, but in Latin America it has the opposite effect. Increased

GDP per capita is found to be inequality reducing in Latin America, but for Asia and Africa, it is inequality increasing. The elasticity of poverty with respect to agricultural productivity appears to be higher in Africa than in Asia and Latin America.

Much of the early literature uses partial factor productivity measures to study their impact on poverty. Recently, total factor productivity (TFP) is gaining its focus in poverty literature.

Fan et al. (2000) examine the relationship between TFP growth in agriculture and poverty reduction in India. Using state level panel data from 1970-93, they estimate a simultaneous equation system, where they study the impact of TFP and different types of government expenditure on poverty reduction. The TFP growth indices they use in their model are calculated using a growth accounting approach. Their results indicate that an increase in agricultural TFP reduces rural poverty by increasing income and reducing agricultural prices. Their results show that government expenditures on R&D, education, roads, and irrigation significantly contribute to poverty reduction.

In a cross country study, Self and Grabowski (2007) find that agricultural TFP plays crucial role in originating growth and improving well being. They use a DEA based TFP index from Ludena et al. (2007) and regress it on growth in real GDP per capita income and Human Development Index (HDI). They also show that institutional quality is important for growth as well. Ajao et al. (2013) also use a DEA based TFP index and examine its impact on poverty in African countries where they use HDI as a proxy for poverty reduction. The elasticity of TFP index to HDI is found to be 0.69, suggesting that a 1% increase in the TFP growth will likely lead to 0.69% increase in the HDI.

In a recent study, Hassine et al. (2009) examined the impact of TFP growth on poverty reduction in a panel of Mediterranean countries and show that TFP growth significantly increased income, decreased inequality, and reduced poverty. They used a Latent Class Stochastic Frontier Analysis (LCSFA) technique to estimate TFP, which is a special case of Stochastic Frontier Analysis. In standard SFA technique, all producers are assumed to use the same technology. They argue that farmers belong to different regions and operate under various agro-climatic conditions with different resource endowments. In such a situation, they might not share the same production possibilities. Ignoring the technological differences in the stochastic frontier model may result in biased efficiency estimates. Using data for 14 Mediterranean countries in a dynamic panel model, they show that the poverty reducing impact of agricultural TFP growth can be determined by taking into account its impact on income growth and inequality change. Their results show that short run poverty elasticity of TFP growth varies from -0.51 to a high of -1.27 among countries. Further analysis of their results indicates that several pro-growth policies, such as agricultural trade, agricultural productivity growth, greater human capital and more equitable land distribution would reduce inequality and are, therefore, pro-poor. These support the previous theoretical and empirical findings of growth and inequality determinants. On the other hand, agricultural R&D expenditures possibly increase inequality and, thus, present a trade-off between their growth and inequality outcomes. They conclude that policies that support both higher growth and lower inequality would contribute to poverty reduction. However, pro-growth policies worsening income distribution may have ambiguous poverty outcomes, since the poverty-reducing effects of growth may be outweighed by the poverty-raising effects of inequality.

Even though empirical evidence shows agricultural growth could significantly be poverty reducing, a broad consensus about it has not been developed yet because there are few studies on this subject. Moreover, the methodologies used to estimate productivity, especially to estimate

TFP, has been subject to debate. The above studies that have dealt with the impact of TFP on poverty reduction use frontier based TFP measures or are based on single country studies. We use TFP measures based on frontier as well as non-frontier methods, to examine their impact on poverty in a panel of developing countries. We also use single factor productivity in our model to examine the poverty reducing impact of various productivity measures.

4.2. Theoretical Framework: Productivity-Poverty Link

Lopez (2004) argues that the depth of poverty in a country depends on the per capita income level of the country and the extent of income inequality and can be expressed as:

$$P = P(Y, L(p)) \qquad (4.1)$$

where P is a poverty measure, Y is per capita income and L(p) is measure of income distribution (Lopez, 2004). Changes in poverty can be decomposed into a growth component that accounts for changes in Y to P and an inequality component that relates changes in inequality to P. This can be expressed as

$$\frac{dP}{P} = \eta \frac{dY}{\mathrm{Y}} + \varphi \frac{dG}{\mathrm{G}} \qquad (4.2)$$

where $\eta = \frac{\partial \mathrm{P}}{\partial \mathrm{Y}} \frac{Y}{P}$ is the growth elasticity of poverty and $\varphi = \frac{\partial \mathrm{P}}{\partial \mathrm{G}} \frac{\mathrm{G}}{\mathrm{P}}$ is the elasticity of poverty w.r.t. inequality. G represents the income Gini index and is used as a measure of inequality. Based on the two components, the impact of agricultural productivity growth on poverty can be expressed as:

$$\frac{\partial \ln \mathrm{P}}{\partial \mathrm{PG}} = \eta \frac{\partial \ln \mathrm{Y}}{\partial \ \mathrm{PG}} + \varphi \frac{\partial \ln \mathrm{G}}{\partial \ \mathrm{PG}}$$

$$= \left(\frac{\partial \mathrm{P}}{\partial \mathrm{Y}} \frac{Y}{P}\right) \frac{\partial \ln \mathrm{Y}}{\partial \mathrm{PG}} + \left(\frac{\partial \mathrm{P}}{\partial \mathrm{G}} \frac{\mathrm{G}}{\mathrm{P}}\right) \frac{\partial \ln \mathrm{G}}{\partial \mathrm{PG}} \qquad (4.3)$$

where PG refers to agricultural productivity growth. Equation (4.3) indicates that the productivity growth impact on poverty depends on: the impact of agricultural productivity growth on per capita income growth and how growth is rendered into poverty reduction; the impact of productivity growth on inequality and how that contributes to poverty reduction.

4.3. Empirical model

Economic growth literature is much larger and more developed than literature on inequality. Numerous empirical models show effects of a particular policy or other variable on economic growth. Most of the studies on inequality estimate inequality levels instead of inequality change as the dependent variable. This makes the poverty analysis more complicated. Our empirical model follows the framework originally established by Lopez (2004) and developed by Hassine et al. (2009). Productivity's impact on poverty is determined by estimating its impact on income growth and income distribution in a dynamic panel setting as follows:

$$\ln Y_{it} - \ln Y_{it-1} = \alpha \ln Y_{it-1} + \beta K_{it} + \rho_i + \tau_t + u_{it} \qquad (4.4)$$

$$\ln G_{it} - \ln G_{it-1} = \lambda \ln G_{it-1} + \theta K_{it} + \xi_i + \vartheta_t + v_{it} \qquad (4.5)$$

where Y is per capita income of a country, G is the income Gini index, K is a set of explanatory variables including agricultural productivity growth, ρ & ξ are unobserved country specific effects, τ & ϑ are time specific effects, and u and v are the error terms, i represents country, and t represents time. Subscripts t and t-1 correspond to observations 4 years apart; K_{it} represents average values of the explanatory variables measured over the 4 year period ending in *t*. The dependent variables in equation (4.4) and (4.5) represent average changes in Y and G over a 4 year period (e.g. for 2005-2008 period, $\ln Y_{it} - \ln Y_{it-1}$ represents $(\ln Y_{2008} - \ln Y_{2004})/4$, which is equivalent to average of growth rate in 2005, 2006, 2007, 2008. The explanatory variables are averaged over 2005-2008. This is the way typically used while averaging data in growth models.).

The above equations implicitly assume that the change in income and inequality are due to productivity growth and other variables. It ignores any effect of growth on inequality or inequality on growth. Following Alesina & Rodrik (1994), Barro (2000), and Forbes (2000), we consider the possibility of potential interactions between growth and inequality and our model becomes:

$$\ln Y_{it} - \ln Y_{it-1} = \alpha \ln Y_{it-1} + \beta K_{it} + \gamma \ln G_{it} + \rho_i + \tau_t + u_{it} \quad (4.6)$$

$$\ln G_{it} - \ln G_{it-1} = \lambda \ln G_{it-1} + \theta K_{it} + \mu \ln Y_{it-1} + \xi_i + \vartheta_t + v_{it} \quad (4.7)$$

The impact of agricultural productivity growth on growth and inequality and hence on poverty can be calculated as:

$$\frac{\partial \ln P}{\partial PG} = (\beta_1 + \gamma\theta_1)\,\eta + \varphi\,\theta_1 \quad (4.8)$$

where PG is agricultural productivity growth. β_1 and θ_1 are coefficients associated with it in the per capita income growth and change in Gini equations respectively, η is the growth elasticity of poverty and φ is the elasticity of poverty w.r.t. inequality.

4.4. Estimation and Data Issues

4.4.1. Growth and Inequality Elasticity of Poverty

In order to assess the impact of productivity growth on poverty, we first need to compute the income growth and inequality elasticities of poverty. Increases in average per capita income and the equality of income distribution are both expected to decrease poverty rates, ceteris paribus. If productivity growth increases incomes of high income people more than low income people, however, the expected decrease in poverty from higher average income may be offset by an incease in poverty associated with the increase in the inequality of income distribution. In order to capture the poverty impact of inequality changes, Lopez and Serven (2006) suggest assuming log normal distribution for income. However, Fosu (2010) argues that such specification may be too constraining given the specific nature of income distribution. He suggests a simpler model to calculate elasticities as follows:

$$lnP_{it} = e0 + e1lnY_{it} + e2lnG_{it} + e12lnY_{it}*lnG_{it} \quad (4.9)$$

where, P is the poverty headcount ratio, Y and G represent per capita income and the Gini index. The income growth elasticity of poverty can be calculated as $e1 + e12\ lnG_{it}$ and inequality elasticity of poverty can be calculated as $e2 + e12\ lnY_{it.}$ Even though the model looks simpler than a more complicated model based on a log normal distribution, Fosu (2009, 2010, 2011) finds no appreciable differences in the elasticities estimated in both ways. We estimate equation (4.9) using a fixed-effects model. The income growth and inequality elasticities are found to be -1.144 and 1.861 respectively.

4.4.2. Growth and Inequality Model Estimation

Equations 4.6 and 4.7 were estimated to examine the impact of agricultural growth on growth and inequality change. These equations are dynamic in nature in the sense that both income growth and change in inequality depend on past income and inequality levels respectively. Hence, lagged dependent variables are included in the model as regressors. The dynamic estimation of the equations above might lead to biased estimators as there is possibility of endogeneity between the explanatory variables and unobserved country specific effects. The immediate problem in applying OLS to this model is that the lagged dependent variable is correlated with the fixed effects in the error term, which leads to dynamic panel bias (Nickel, 1981). The Generalized Method of Moments (GMM) technique is widely used to overcome this type of problem. One way to eliminate the endogeneity arising out of country specific effect is to difference the data. However, this procedure does not eliminate dynamic panel bias where the lagged dependent variable is a regressor. The differencing results in another bias as the new error term (u_{it} - u_{it-1}) are correlated with the lagged dependent variable. Two different GMM techniques are used to estimate dynamic panel models. One is Difference GMM and another is System GMM. The Difference GMM estimator takes the first difference of the data and then uses lagged values of the endogenous variables as instruments. However, Arellano and Bover (1995) point out that lagged levels are poor instruments for first differences. Besides, Blundell and Bond (1998) argue that Difference GMM has poor finite sample properties and it is downward biased, especially when data are averaged over a period making T smaller. We apply a two-step System GMM procedure as suggested in Blundell & Bond (2000) to estimate the above equations. In the absence of exogenous variables that can provide external instruments, a GMM estimator based only on internal instruments can be constructed following Blundell and Bond (1998), who propose a system estimator combining the regressions in differences and levels. To compute the system estimator, pre-determined and endogenous variables in first differences are instrumented with suitable lags of their own levels, while variables in levels are instrumented with suitable lags of their own first differences. In multivariate dynamic panel models, the System GMM estimator is shown to perform better than the Difference GMM when series are persistent, and there is a dramatic reduction in the finite sample bias due to the exploitation of additional moment conditions (Blundell et al. 2000). Hayakawa (2007) provides theoretical evidence of smaller bias in System GMM than in Difference GMM. Moreover, the consistency of the System GMM can be checked by testing for autocorrelation using Arenello-Bond autocorrelation test, validity of the instruments using Hansen test of overidentifying restrictions, and exogeneity of instruments using Difference-in-Hansen test (Roodman, 2006).

4.4.3. Data

Our data set is comprised of four year averaged country level data for a panel of developing countries over the period 1961-2008. We have two endogenous variables in our model, per capita GDP growth and the change in inequality. We use Gini index data from the World Bank to represent inequality in income distribution. However, data on Gini index are unbalanced and irregular. We approximated missing values of the Gini index using linear interpolation. Our main explanatory variable is agricultural productivity growth. We use single (land and labor) and frontier and non-frontier multi-factor productivity measures in our model. The non-frontier TFP estimates are taken from Fuglie (2011). All other multi-factor productivity measures are obtained by estimating SFA using data from Fuglie (2011). We use four measures of TFP growth. The first set of productivity growth estimates comes from Fuglie's productivity estimates (Fuglie's TFP growth). The second set of TFP growth estimates are from our Stochastic Frontier estimation of a pooled sample of 108 countries. The third set of estimates of productivity growth (TFP growth-by income group) is taken from our Stochastic Frontier estimation of productivity change for three different income groups. The final set of data on productivity growth (TFP growth-by region) is calculated using Stochastic Frontier estimation of productivity for different geographical regions. We also calculate all of these productivity measures using smoothed and unsmoothed output and use them in our poverty model.

The other explanatory variables in the poverty models are a set of variables that are expected to affect growth and inequality, and hence poverty, and are commonly found in the growth and inequality literature. They include initial GDP per capita, human capital, government expenditure, infrastructure development, trade openness, inflation, and institutional quality, etc. Initial GDP per capita is used to account for conditional convergence as found in the literature. Gross secondary school enrollment rate is used to approximate human capital. Exports plus imports as a share of GDP is used as a proxy for trade openness. Telecommunication capacity (phones per capita) is used to proxy for infrastructure development. Inflation is used as a proxy for monetary policy. All these data are obtained from WDI-2010 (World Bank). The ICRG indicator (Political Risk Group's IRIS III dataset), measured as an average of corruption in government, bureaucratic quality and rule of law (law and order) indicators, is used to account for institutional quality of a country. In our model specification, we consider all explanatory variables as predetermined.

It is well known that a number of variables are associated with GDP growth and inequality change. Omitted variable bias could be problematic if there is strong correlation between the dependent variable, agricultural productivity, and any other omitted variable. However, given the large potential number of variables that could be included in a growth model, it is not possible to infer how omitted variables could affect the estimates of our analysis. We cannot do much about it other than relying on a control set that has been extensively used in the literature (Acosta, 2008). The selected explanatory variables are expected to affect both growth and inequality, as found in Barro 2000, 2008; Acosta, 2008; Forbes, 2000; Levine, 2004)

The number of four year observations available for the growth equation is 274 for 69 countries when land and labor productivities and Fuglie's TFP growth variables are used. It is reduced to 261 observations for 63 countries when SFA based TFPs obtained for whole sample and income groups are used. The income growth equation using TFP growth variables from SFA by region has 186 observations for 48 countries. The inequality change equation is estimated for a sample of 178 observations for 63 countries when land, labor, and Fuglie's TFP growth variables are used. 170 observations for 57 countries are included in the inequality change model using SFA based TFPs for whole sample and income groups. We have 121 observations for 42 countries when using TFP growth variables obtained from SFA-by region estimation. The number of countries and number of observations can be found at the end of the results tables. The number of countries and total number of observations used in both growth and inequality equation is based on the availability of data on all the variables included in the model.

4.5. Results and Discussion

The following regression results use the following productivity measures:

1. land productivity growth (Smoothed and Unsmoothed output)
2. labor productivity growth (Smoothed and Unsmoothed output)
3. Fuglie's TFP growth (Smoothed and Unsmoothed output)
4. TFP growth from SFA Pooled (Smoothed and Unsmoothed output)
5. TFP growth from SFA by Income Group (Smoothed and Unsmoothed output)
6. TFP growth from SFA by Region (Smoothed and Unsmoothed output).

All the explanatory variables are in logs except institutional quality. All the regressions are performed using period dummies. Table 4.1 presents the results for the income growth equations and table 4.2 reports results for the inequality equations. The consistency of the System GMM estimator is checked using three specification tests. The first test is the Arenello-Bond autocorrelation test for serial correlation; the second test is for instrument validity using the Hansen test of overidentifying restrictions; and the third test is for exogeneity of instruments using the difference-in-Hansen test. On the basis of the results of these tests, the assumption of no second-order serial correlation, validity and exogeneity of the instruments is not rejected.

Table-4.1: Impact of Productivity Growth on Income Growth: Two-step System GMM Estimation (Dependent Variable:GDP per capita Growth)

	Smoothed Data					
	Labor Productivity Growth	Land Productivity Growth	Fuglie's TFP Growth	TFP Growth-Pooled	TFP Growth-By Income Group	TFP Growth-By Region
Initial GDP per capita	-0.0323***	-0.0397***	-0.0481***	-0.0411***	-0.0386***	-0.0187
	0.0111	0.0148	0.0141	0.0116	0.0143	0.0154
Productivity Growth	**0.370*** **	**0.126** **	**0.0978** **	**-0.0331**	**0.0215**	**-0.0583**
	0.0485	0.0596	0.0481	0.0682	0.0529	0.0576
Inequality	-0.0625***	-0.0523**	-0.0605***	-0.00527	-0.0223	-.0502***
	0.019	0.0222	0.0212	0.0148	0.0218	0.0186
Human Capital	0.0258**	0.0222**	0.0286***	0.0313***	0.0362***	0.0245**
	0.0103	0.011	0.0102	0.00867	0.0116	0.0102
Government Expenditure	-0.0260***	-0.0215**	-0.0246***	-0.0374***	-0.0364***	-0.00293
	0.00801	0.00976	0.00722	0.00566	0.00641	0.011
Infrastructure Development	0.00557	0.00115	0.0072	-0.000151	-0.00149	0.00471
	0.00659	0.0083	0.0077	0.00488	0.00664	0.00875
Trade Openness	0.0209*	0.0132	0.00242	-0.0105	0.000261	0.0551***
	0.0111	0.0132	0.0112	0.00795	0.00934	0.00961
Inflation	-0.0320***	-0.0356***	-0.0348***	-0.0372***	-0.0358***	- 0.0287***
	0.0076	0.00642	0.00583	0.00512	0.00635	0.00344
Institutional Quality	0.00598	0.0201***	0.0159***	0.0225***	0.0186***	-0.00204
	0.00444	0.00519	0.00331	0.0027	0.00464	0.00695
Constant	0.555***	0.591***	0.745***	0.532***	0.504***	0.204
	0.144	0.154	0.133	0.111	0.157	0.162
Arellano-Bond test for AR(1) in first differences	0.004	0.004	0.006	0.011	0.009	0.003
Arellano-Bond test for AR(2) in first differences	0.86	0.67	0.57	0.86	0.67	0.61
Hansen Instrumental validity test (p-value)	0.51	0.49	0.77	0.54	0.86	0.24
Difference-in-Hansen tests of exogeneity of instrument (p-value)	0.79	0.8	0.87	0.65	0.9	0.29
Instruments	48	48	56	56	48	40
Number of id	69	69	69	63	63	48
Observations	274	274	274	261	261	186

Note: *** p<0.01, ** p<0.05, * p<0.1

Table-4.1(cont'd): Impact of Productivity Growth on Income Growth: Two-step System GMM Estimation (Dependent Variable:GDP per capita Growth)

	Unsmoothed Data					
	Labor Productivity Growth	Land Productivity Growth	Fuglie's TFP Growth	TFP Growth-Pooled	TFP Growth-By Income Group	TFP Growth-By Region
Initial GDP per capita	-0.0304**	-0.0345**	-0.0445***	-0.0382***	-0.0360**	-0.0238
	0.0123	0.0141	0.0166	0.0143	0.0177	0.0159
Productivity Growth	**0.177*** **	**0.104** **	**0.0764* **	**0.0816**	**0.0823* **	**-0.062**
	0.0368	0.0498	0.0412	0.0791	0.0474	0.0556
Inequality	-0.0669***	-0.0478**	-0.0501**	-0.0194	-0.0365	-0.0390*
	0.0181	0.022	0.0222	0.0216	0.024	0.0202
Human Capital	0.0224**	0.0251**	0.0282**	0.0253**	0.0365***	0.0259**
	0.0105	0.0116	0.0123	0.00994	0.012	0.0105
Government Expenditure	-0.0289***	-0.0267***	-0.0308***	-0.0368***	-0.0360***	-0.00388
	0.00962	0.0102	0.0103	0.00559	0.0131	0.011
Infrastructure Development	0.00235	0.000403	0.00671	-0.00122	-0.00335	0.0122
	0.00702	0.00835	0.00952	0.00677	0.00981	0.00875
Trade Openness	0.0119	0.00761	0.00126	-0.00772	-0.00106	0.0599***
	0.0117	0.0132	0.0126	0.00966	0.0132	0.009
Inflation	-0.0303***	-0.0327***	-0.0344***	-0.0410***	-0.0409***	-.0295***
	0.00817	0.00678	0.00816	0.00613	0.0083	0.00343
Institutional Quality	0.00936**	0.0185***	0.0141***	0.0241***	0.0186***	-0.00816
	0.00445	0.00505	0.0048	0.00362	0.00661	0.00663
Constant	0.598***	0.547***	0.701***	0.579***	0.553***	0.222
	0.15	0.168	0.181	0.139	0.19	0.156
Arellano-Bond test for AR(1) in first differences	0.002	0.004	0.006	0.008	0.008	0.004
Arellano-Bond test for AR(2) in first differences	0.97	0.88	0.69	0.96	0.86	0.68
Hansen Instrumental validity test (p-value)	0.6	0.67	0.78	0.75	0.82	0.25
Difference-in-Hansen tests of exogeneity of instrument (p-value)	0.96	0.96	0.9	0.89	0.95	0.42
Instruments	48	48	48	48	40	40
Number of id	69	69	69	63	63	48
Observations	274	274	274	261	261	186

Note: *** p<0.01, ** p<0.05, * p<0.1

Table-4.2: Impact of Productivity Growth on Inequality: Two-step System GMM estimation (Dependent Variable: Change in Income Gini)

	Smoothed Data					
	Labor Productivity Growth	Land Productivity Growth	Fuglie's TFP Growth	TFP Growth-Pooled	TFP Growth-By Income Group	TFP Growth-By Region
Initial GDP per capita	0.0665***	0.0426***	0.0544***	0.0277**	0.0435***	0.0176
	0.0147	0.0103	0.0173	0.0115	0.0158	0.0352
Productivity Growth	**-0.165*****	**-0.0661****	**-0.245*****	**-0.0588**	**0.146**	**0.748**
	0.0475	0.032	0.083	0.146	0.101	0.534
Initial Inequality	-0.173***	-0.179***	-0.167***	-0.138***	-0.0999***	-0.0126
	0.0252	0.016	0.0259	0.0241	0.0254	0.0493
Human Capital	-0.0537***	-0.0238**	-0.0262	-0.0220*	-0.0251**	0.0316
	0.0186	0.00997	0.0199	0.0132	0.0126	0.02
Government Expenditure	-0.0245	-0.0200***	-0.0229	-0.0132	-0.00801	-0.00175
	0.0196	0.00667	0.0198	0.00843	0.0135	0.0345
Infrastructure Development	-0.0061	-0.0015	-0.00648	0.00654	-0.00614	-0.0296**
	0.00847	0.00388	0.00913	0.00525	0.00784	0.014
Trade Openness	-4.80E-05	0.0126**	0.0147	0.00692	0.00217	0.0433*
	0.0123	0.00547	0.011	0.00738	0.00723	0.0252
Inflation	-0.0210*	-0.0160***	-0.0185*	-0.00760***	-0.0153*	0.0199
	0.0109	0.00351	0.0112	0.00258	0.00782	0.0132
Institutional Quality	-0.0103*	-0.0114***	-0.0102	-0.00827**	-0.00783*	0.00815
	0.00602	0.00262	0.00732	0.00397	0.00425	0.0057
Constant	0.492***	0.533***	0.385**	0.475***	0.204	-0.610*
	0.185	0.0708	0.186	0.104	0.149	0.367
Arellano-Bond test for AR(1) in first differences	0.1	0.1	0.08	0.07	0.05	0.08
Arellano-Bond test for AR(2) in first differences	0.76	0.92	0.67	0.64	0.62	0.68
Hansen Instrumental validity test (p-value)	0.8	0.91	0.91	0.61	0.4	0.39
Difference-in-Hansen tests of exogeneity of instrument (p-value)	0.78	0.58	0.9	0.6	0.55	0.39
Instruments	31	47	31	39	31	23
Number of id	63	63	63	57	57	42
Observations	178	178	178	170	170	121

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table-4.2 (cont'd.): Impact of Productivity Growth on Inequality: Two-step System GMM estimation (Dependent Variable: Change in Income Gini)

	Unsmoothed Data					
	Labor Productivity Growth	Land Productivity Growth	Fuglie's TFP Growth	TFP Growth-Pooled	TFP Growth-By Income Group	TFP Growth-By Region
Initial GDP per capita	0.0527***	0.0521***	0.0474***	0.0350***	0.0552***	-0.0193
	0.0125	0.0137	0.0129	0.012	0.0168	0.0253
Productivity Growth	**-0.0805****	**-0.0979****	**-0.118*****	**-0.281****	**-0.0289**	**0.408**
	0.0315	0.0451	0.0443	0.124	0.0774	0.324
Initial Inequality	-0.144***	-0.150***	-0.133***	-0.149***	-0.138***	-0.0682*
	0.0249	0.0232	0.0236	0.0244	0.0294	0.0399
Human Capital	-0.0532***	-0.0423***	-0.0375**	-0.0191	-0.0214	0.0086
	0.0159	0.0151	0.0159	0.0146	0.019	0.0118
Government Expenditure	-0.00135	-0.0153	-0.00168	-0.0117	-0.00148	0.015
	0.017	0.0118	0.0157	0.00927	0.0125	0.0265
Infrastructure Development	-0.00878	-0.0107	-0.0121*	0.000754	-0.0145	0.00538
	0.00705	0.00751	0.00725	0.00607	0.00908	0.0123
Trade Openness	0.0079	0.0122	0.0173	0.0118	0.0128	-0.0305*
	0.0109	0.0126	0.0124	0.00767	0.00888	0.0163
Inflation	-0.00859*	-0.0112***	-0.00683	- 0.00765***	-0.00494	-0.0128
	0.00445	0.00338	0.00419	0.00268	0.00397	0.00979
Institutional Quality	-0.00860*	-0.0101*	-0.00900*	-0.00653	-0.00883	0.00902*
	0.00441	0.00533	0.00541	0.00467	0.00576	0.00481
Constant	0.328**	0.341***	0.213	0.397***	0.0976	0.494**
	0.14	0.131	0.132	0.126	0.174	0.25
Arellano-Bond test for AR(1) in first differences	0.06	0.07	0.05	0.05	0.1	0.1
Arellano-Bond test for AR(2) in first differences	0.32	0.74	0.61	0.46	0.6	0.73
Hansen Instrumental validity test (p-value)	0.72	0.56	0.77	0.76	0.65	12
Difference-in-Hansen tests of exogeneity of instrument (p-value)	0.58	0.57	0.74	0.75	0.45	12
Instruments	31	31	31	39	31	23
Number of id	63	63	63	57	57	42
Observations	178	178	178	170	170	121

Note: *** p<0.01, ** p<0.05, * p<0.1

From table 4.1, it is clear that land productivity, labor productivity, and Fuglie's TFP variables are positively related to growth, whether or not output is smoothed. However, higher coefficients are seen for the smoothed output case. The marginal impact of labor productivity growth on per capita income growth is higher than that for the land and multifactor productivity measures, the coefficient of Fuglie's TFP being the lowest among these three. Among the SFA based TFP measures, only TFP from SFA by Income Group (for unsmoothed output) is found to be significant in the growth equation. Among the other explanatory variables, the expected signs for some of the coefficients have roots in the traditional growth theory. Our results indicate that an open economy, according to the trade openness indicator, a high number for the ICRG index, higher level of education are all associated with higher growth. On the other hand, initial per capita income, inequality, and inflation are negatively associated with growth. The negative sign of the initial GDP per capita in growth equation confirms conditional convergence. Results show that higher inequality is associated with lower growth. Human capital is positively related with growth. This result is in accordance with those of Datt and Ravallion (2002) and Lundberg and Squire (2003). They show that poor basic education is an obstacle to the ability of the poor to participate in opportunities for economic growth. Government expenditure is found to be negatively and significantly correlated with income growth. This result is consistent with the findings of Li and Zou (2002) and Lopez (2004), who also find that government spending is negatively associated with income growth, though this could be due to governments with lower income growth increasing government spending rather than government spending having a negative impact on income growth. Trade openness is found to be positively associated with growth, though not significant in all cases. High inflation adversely affects growth. Better institutional quality seems to be positively correlated with higher growth.

Results from the inequality regressions show that Fuglie's TFP growth has higher impact on inequality change as compared to land and labor productivities. Among the SFA based TFP measures, only TFP estimates from SFA Pooled (for unsmoothed output) is significant in the inequality equation. The positive and significant sign of initial GDP per capita in the inequality equation supports Barro's studies (2000, 2008) on Kuznets hypothesis. Higher initial inequality seems to be associated with increased inequality. Human capital is negatively related with inequality. This result is in accordance with those of Lundberg and Squire (2003). They find that education is likely to be correlated with lower income inequality. Results indicate that higher government expenditure can lead to lower inequality. The coefficient of trade openness in the inequality equations shows of having contradictory signs, positive in some cases and negative in some others. Even in the literature, the available results for trade openness point toward less than unanimous conclusions. Dollar and Kraay (2002) find that trade openness positively affects income distribution. However, Sanchez and Schady (2003) find the opposite result, where trade volumes would negatively affect inequality. Barro (2000) also finds that trade openness is associated with higher inequality, whereas Lundberg and Squire (2003) conclude that there is a positive correlation between the trade openness and the Gini coefficient. Infrastructure development can alleviate inequality. Better institutional quality is found to be positively correlated with lower inequality.

Based on the results, we calculate the elasticity of poverty with respect to agricultural productivity growth. It is presented in table 4.4 below.

Table 4.3: Elasticity of Poverty w.r.t. Agricultural Productivity Found in Selected Literature

Study	Country Coverage	Land Productivity	Labor Productivity	TFP
Datt & Ravallion, 1998	India	0.17		
Irz et al., 2001	Developing countries	0.37, 0.29	0.83, 0.62	
Thirtle et el., 2003	Developing countries	0.27		
Hassine et al., 2009	Mediterranean countries			0.51-1.27
Alene et al., 2009	SSA countries	0.58		

Table 4.4: Elasticity of Poverty w.r.t. Agricultural Productivity - Our Findings

	Elasticity	
Productivity measure	Smoothed Data	Unsmoothed Data
Labor productivity Growth	0.74	0.36
Land productivity Growth	0.27	0.31
Fuglie's TFP Growth	0.59	0.31
TFP Growth (SFA Pooled)	insignificant	0.52
TFP Growth (SFA By Income Group)	insignificant	0.09
TFP Growth (SFA Region)	insignificant	insignificant

Land and labor productivity elasticities of poverty do not differ much when estimated with unsmoothed output, but labor productivity shows a higher impact on reducing poverty than land productivity when smoothed data is used. In the literature, labor productivity is usually more poverty reducing than land productivity. The impact of labor productivity for smoothed output is almost double the impact estimated using unsmoothed output. The impact on poverty reduction of growth accounting based TFP is higher than the impact land of productivity, but lower than the effect of labor productivity.

We also found poverty elasticities of agricultural productivity growth for all the income groups and regional groups. These results are presented in tables 4.5 and 4.6.

Table 4.5: Elasticity of Poverty w.r.t. Agricultural Productivity for Income Groups

	Low Income		Lower Middle Income		Upper Middle Income	
	Smoothed Data	Unsmoothed Data	Smoothed Data	Unsmoothed Data	Smoothed Data	Unsmoothed Data
Labor productivity Growth	0.13	0.06	0.62	0.30	1.09	0.53
Land productivity Growth	0.05	0.04	0.23	0.28	0.40	0.47
Fuglie's TFP Growth	0.04	0.03	0.59	0.06	0.93	0.12
TFP Growth (SFA Pooled)	insignificant	insignificant	insignificant	0.59	insignificant	0.87
TFP Growth (SFA By Income Group)	insignificant	0.03	insignificant	0.06	insignificant	0.13
TFP Growth (SFA Region)	insignificant	insignificant	insignificant	insignificant	insignificant	insignificant

Table 4.6: Elasticity of Poverty w.r.t. Agricultural Productivity for Regional Groups

	S. Asia & Oceania		SSA		S. America & MENA	
	Smoothed Data	Unsmoothed Data	Smoothed Data	Unsmoothed Data	Smoothed Data	Unsmoothed Data
Labor productivity Growth	0.90	0.44	0.41	0.20	1.19	0.58
Land productivity Growth	0.32	0.34	0.15	0.18	0.44	0.54
Fuglie's TFP Growth	0.59	0.13	0.36	0.04	1.11	0.11
TFP Growth (SFA Pooled)	insignificant	0.46	insignificant	0.34	insignificant	1.09
TFP Growth (SFA By Income Group)	insignificant	0.14	insignificant	0.05	insignificant	0.12
TFP Growth (SFA Region)	insignificant	insignificant	insignificant	insignificant	insignificant	insignificant

From table 4.5, it is clear that the elasticity of poverty to the within country estimates of agricultural productivity is lowest for low income countries, slightly higher for lower middle income group, and highest for upper middle income group. Table 4.6 reveals that the elasticity of poverty to the within country estimates of agricultural productivity is lowest for SSA countries, higher for S. Asia & Oceania Countries, and highest for S. America & MENA countries. Smoothing of output results in substantially higher poverty elasticities for labor productivity and Fuglie's TFP estimates.

4.6. Conclusions

Even though theories imply that agricultural productivity growth could significantly be poverty reducing, a broad consensus about it has not been developed yet because there are few studies directly testing on this subject. Moreover, the methodologies and data used to estimate productivity have been subject to debate, especially in the case of measuring multi factor productivity. In chapter 3, we found that TFP estimates measured using different techniques can be significantly different. Moreover, frontier based TFP estimates are found to be sensitive to selection of sample. On the other hand, non frontier growth accounting yields productivity growth within a country over time. So, we started with a notion that based on how one measures productivity, its impact on poverty will be different. We used partial productivity measures, and TFP measures based on frontier as well as non-frontier methods to examine their impacts on poverty in a panel of developing countries. We find that single productivity measures as well as TFP measures based on a growth accounting approach are significantly poverty reducing. The magnitude of the estimated impact is different for different productivity measures. Point estimate of the impact of growth accounting TFP growth is found to be higher than the impact of increased land productivity, but lower than the effects of increased labor productivity on poverty reduction. Some of the frontier based TFP measures are found to be both ambiguous in sign and weaker in the sense that they are not significant. Results from our study suggest that the poverty reducing impact of total factor productivity is sensitive to the methodologies used to measure it.

CHAPTER 5

SUMMARY AND POLICY IMPLICATIONS

5.1. Summary and Conclusions

Improvements in agricultural productivity are important for development objectives such as poverty reduction in developing countries. Whereas on the one hand, theory suggests that agricultural productivity has special powers to enhance agricultural growth and poverty alleviation, on the other hand, the appropriate methodology for measuring agricultural productivity and especially for measuring agricultural total factor productivity has always been the subject of debate among researchers. The literature reveals quite varied measurement and analytical approaches for measuring total factor productivity. Given that productivity embodies many different components and varied methodologies are available to measure it, it is essential to use the appropriate indicator, method, and measure of agricultural productivity to investigate whether it reduces poverty. Variability in the methods used sometimes makes it difficult for the policy makers to compare and evaluate the results of productivity studies. The measures used to estimate productivity growth affect the magnitude of the estimates, and furthermore, the magnitude of effects on poverty. So, it is important and quite useful to study and understand the impact of productivity on poverty when productivity is measured in various ways.

Earlier studies mainly used partial productivity measures in poverty studies, whereas recently frontier based TFP measures have been used. The frontier based TFP measures are obtained relative to the most efficient country in the sample, and hence these are sensitive to the selection of countries in the sample. However, theory emphasizes the impact of productivity growth within a country over time on poverty in that country. This in turn warrants the need of non-frontier method of measuring TFP growth for each individual country over time relative to its own past TFP measures.

This study compares the impact of single factor productivity growth as well as frontier and non-frontier TFP growth on poverty reduction in developing countries. We use two frontier based techniques namely Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to obtain TFP growth rates for 108 developing countries. We estimate frontier TFP measures using observed output and output that is smoothed after adjusted for short run fluctuations. We then make alternative groupings of countries based on their income level and based on geographical region to allow the frontiers to vary across income groups and regional groups. We compare these TFP estimates with the TFP estimates developed by Fuglie (2011), where he uses a non-frontier growth accounting approach to find TFP growth rates. We then use all these TFP estimates in a poverty model to examine any differences in the magnitude of their impacts on poverty rate in developing countries.

The results obtained from productivity estimation in chapter 3 provide a practical understanding of the sensitivity of TFP estimates to methodologies used to estimate them. We empirically show that frontier based TFP measures are sensitive to the selection of countries. The findings provide strong indications that frontier based TFP growth rates for a country could be dramatically different if the country is included in different samples for study. Each of the methodologies yields different TFP measures for a country, and hence their impact on poverty is found to be of different magnitude. The empirical poverty literature that has used frontier based TFP is therefore greatly challenged for whether these TFP measures are better suited for poverty study within country context. This study contributes to the limited literature on the agricultural productivity and poverty relationship. Existing studies primarily focus on partial productivity and frontier based multi factor productivity. This study contributes by adding non-frontier TFP growth rates that enables us to understand evolution of TFP within a country over time and its impact on poverty in that country.

5.2. Policy Implications

Productivity growth in agriculture is very important and has significant policy implications for poverty reduction. The measures used to estimate productivity growth affect the magnitude of the estimates. Annual TFP change indices as well as cumulative TFP indices for all countries are found to be different when estimated using different methodologies. The choice of methodologies may also affect the direction of estimated productivity growth, which could lead to contradictory policy implications. Hence, the methodology and assumptions used in measuring productivity growth should be chosen with caution.

Our results indicate that both SFA and DEA are sensitive to the selection of countries for study and DEA is more sensitive among the two. Moreover, DEA results based on pooled sample and sub-sample show greater differences in estimated annual growth rates for countries even after smoothing outputs data and adjusting land data for quality. It is clear that DEA is greatly influenced by measurement error, production shocks, etc. Policy makers, especially those who might rely on applying DEA for agricultural data, therefore need to be cautious about doing so.

As far as the sensitivity of the sample selection is concerned, SFA is found to be better performing than DEA. However, in SFA pooled model we did not find much difference in the average TFP growth rate between different income groups. SFA estimated by Income group, on the other hand, results in substantial differences in average growth rates between income groups.

This is supported by the arguments in favor of the recent Latent Class SFA model that estimate TFP by grouping countries facing similar technologies.

The growth accounting method yields quite different TFP growth rates for countries when smoothed and unsmoothed output data are used. It is very important to adjust output data for noise and adjust inputs based on quality before employing growth accounting approach as this method, like DEA, doesn’t involve econometric estimation.

While the concept and measurement of TFP is still controversial, economists agree on the importance of productivity growth for poverty reduction. This ensures strong interest in the measurement and explanation of productivity changes over time. Even with the development of new and better theoretical models and estimation techniques, more accurate data are important to obtain reliable estimates of productivity change.

It is also very important to recognize the importance of using the appropriate approach to measure productivity. Each of the techniques produces different TFP estimates for countries and they tell a different story on the evolution of productivity over time. Hence, their impact on poverty would be different. We found that land and labor productivities, as well as TFP based on growth accounting, are significantly growth enhancing and inequality reducing and hence poverty alleviating. Thus, policies designed to increase agricultural productivity in developing countries are warranted.

To sum up, this study provides strong evidence that developing countries should be more actively taking measures to increase agricultural productivity for poverty reduction. The inferences drawn from this study also call for extra caution on the choice of methodology and handling of data while measuring productivity to use them in a policy related development model.

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APPENDIX A: GRAPHS FROM SFA AND FUGLIE'S ESTIMATION

Cumulative TFP indices for each country and Annual TFP change index for selected countries are presented in the graphs below. Cumulative TFP indices are calculated from annual TFP change index with base 1961 =1. The countries for graphs showing annual TFP change index are countries with largest Sum of Squared Differences in Annual TFP growth rates obtained while comparing annual TFP growth rates from two different methods.

A1. Graphs from SFA and Fuglie's Estimation: Smoothed Data

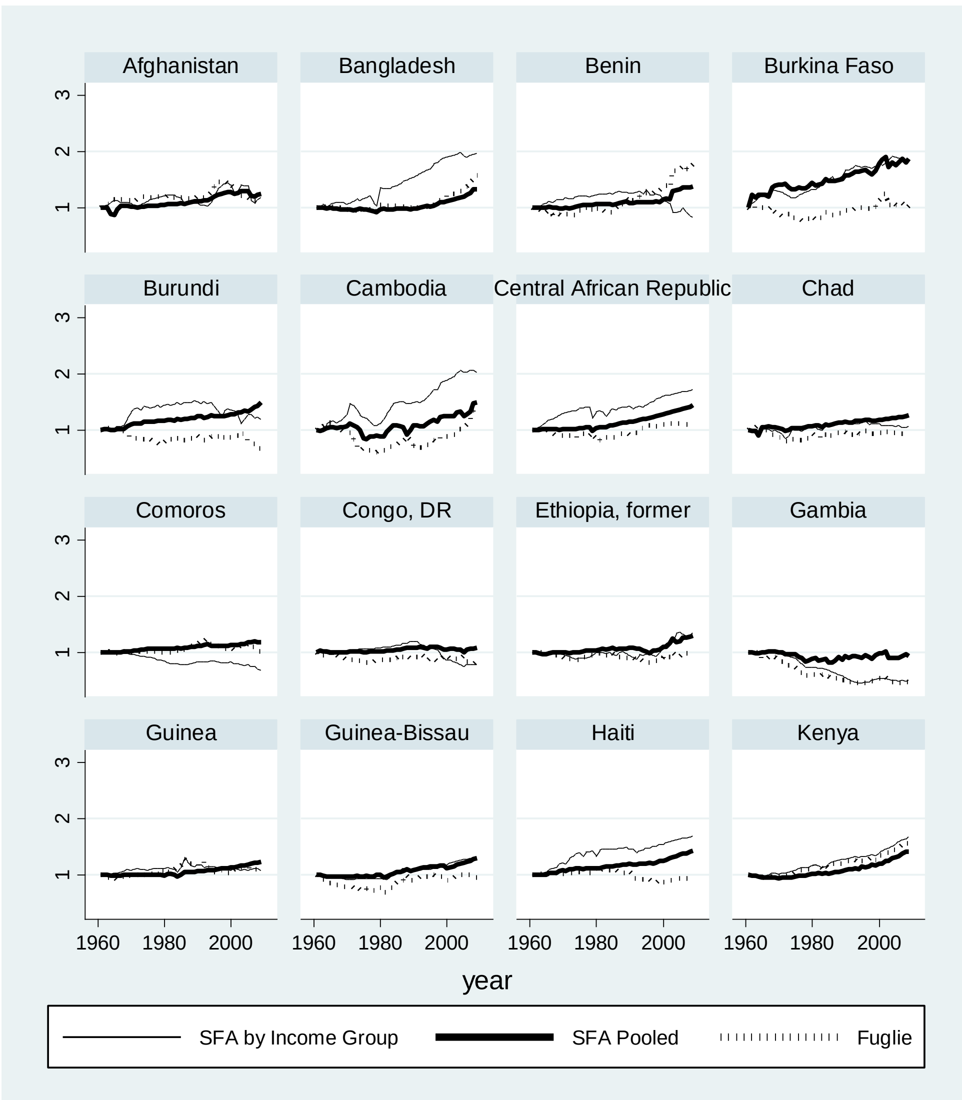

Figure A1.1. Cumulative TFP Index (1961=1) for Low Income Countries: Fuglie vs. SFA Pooled vs. SFA by Income Group - Smoothed Data

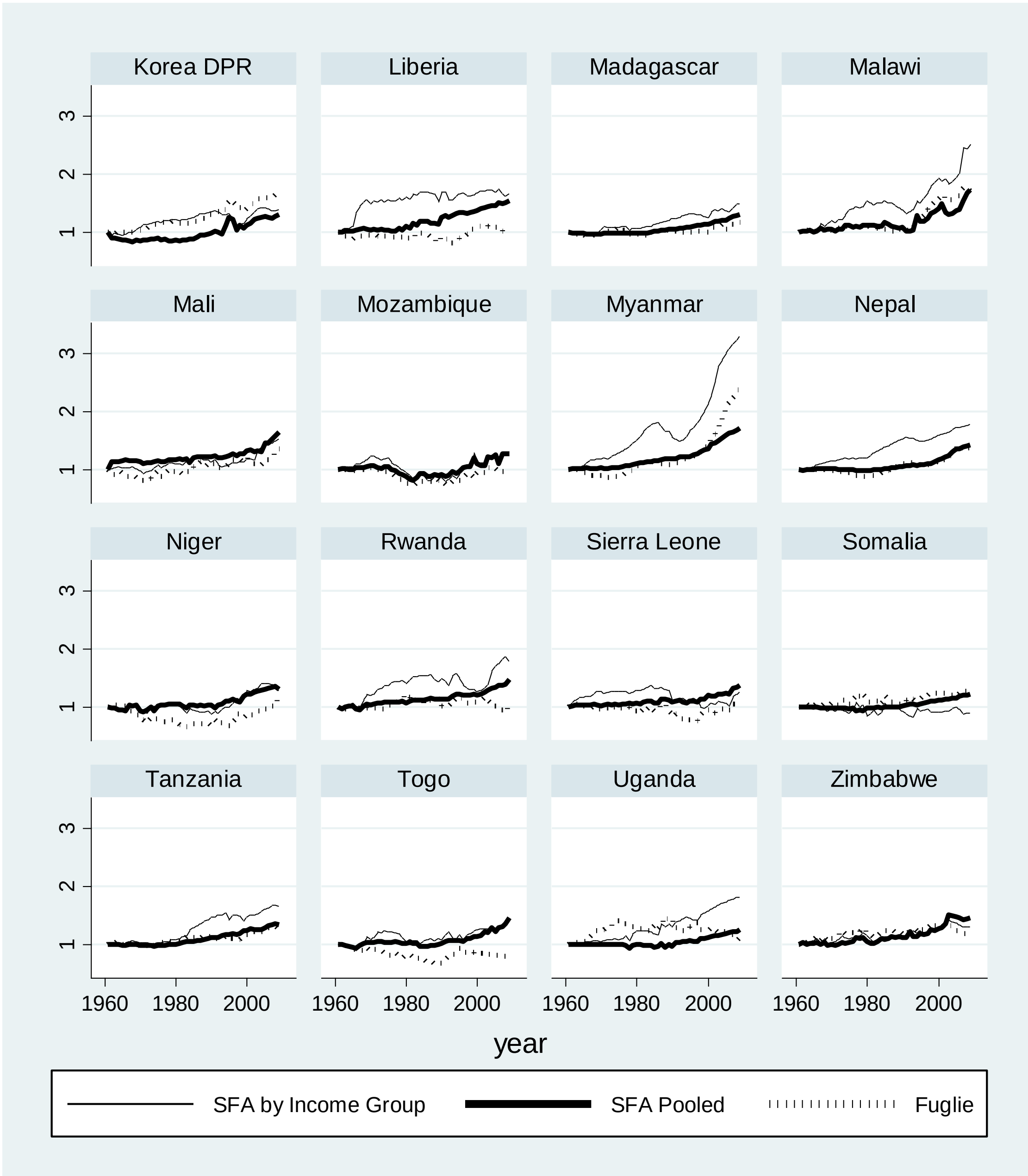

Figure A1.1 (cont'd). Cumulative TFP Index (1961=1) for Low Income Countries: Fuglie vs. SFA Pooled vs. SFA by Income Group - Smoothed Data

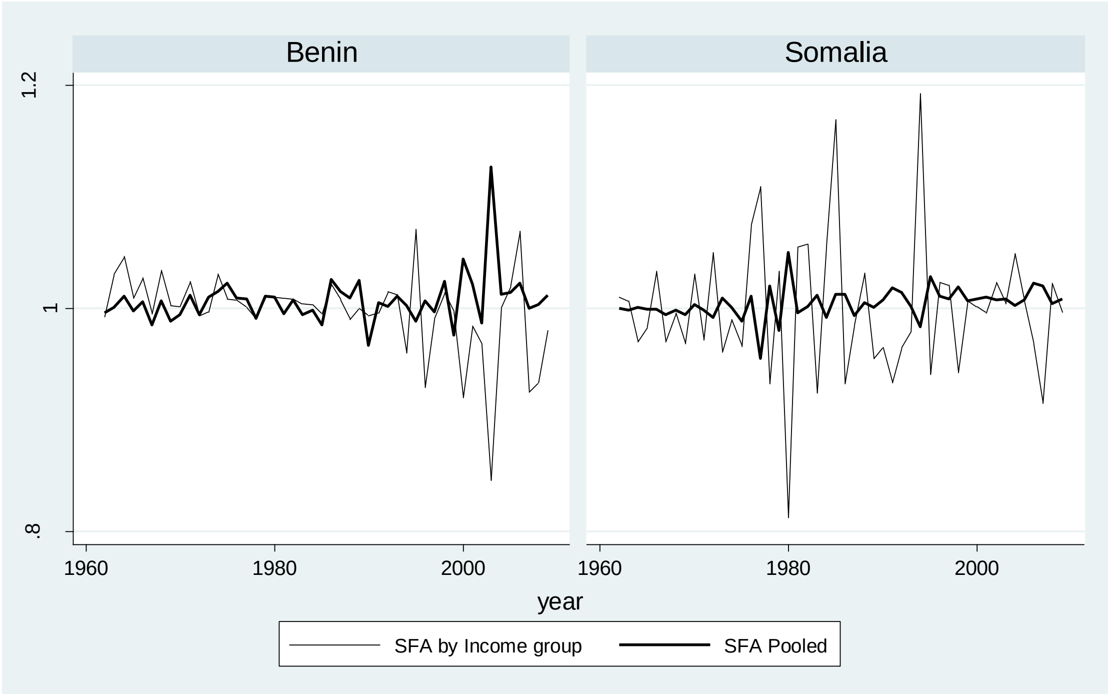

Figure A1.1a. Annual TFP Change Index for Selected Low Income Countries: SFA Pooled vs. SFA by Income Group - Smoothed Data

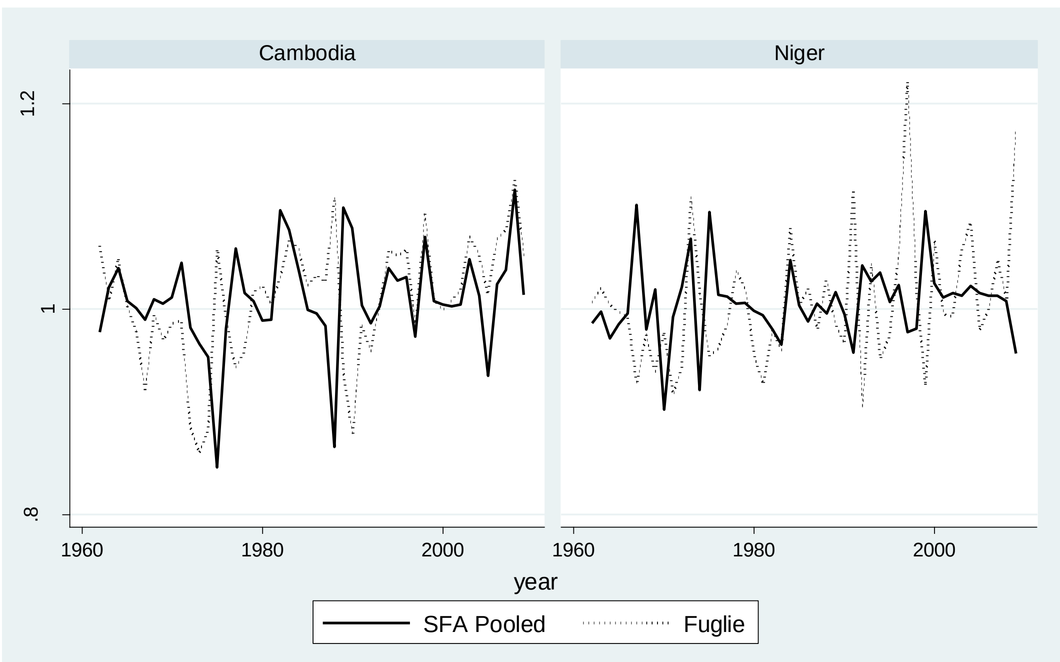

Figure A1.1b. Annual TFP Change Index for Selected Low Income Countries: SFA Pooled vs. Fuglie - Smoothed Data

Figure A1.c Annual TFP Change Index for Selected Low Income Countries: SFA by Income Group vs. Fuglie - Smoothed Data

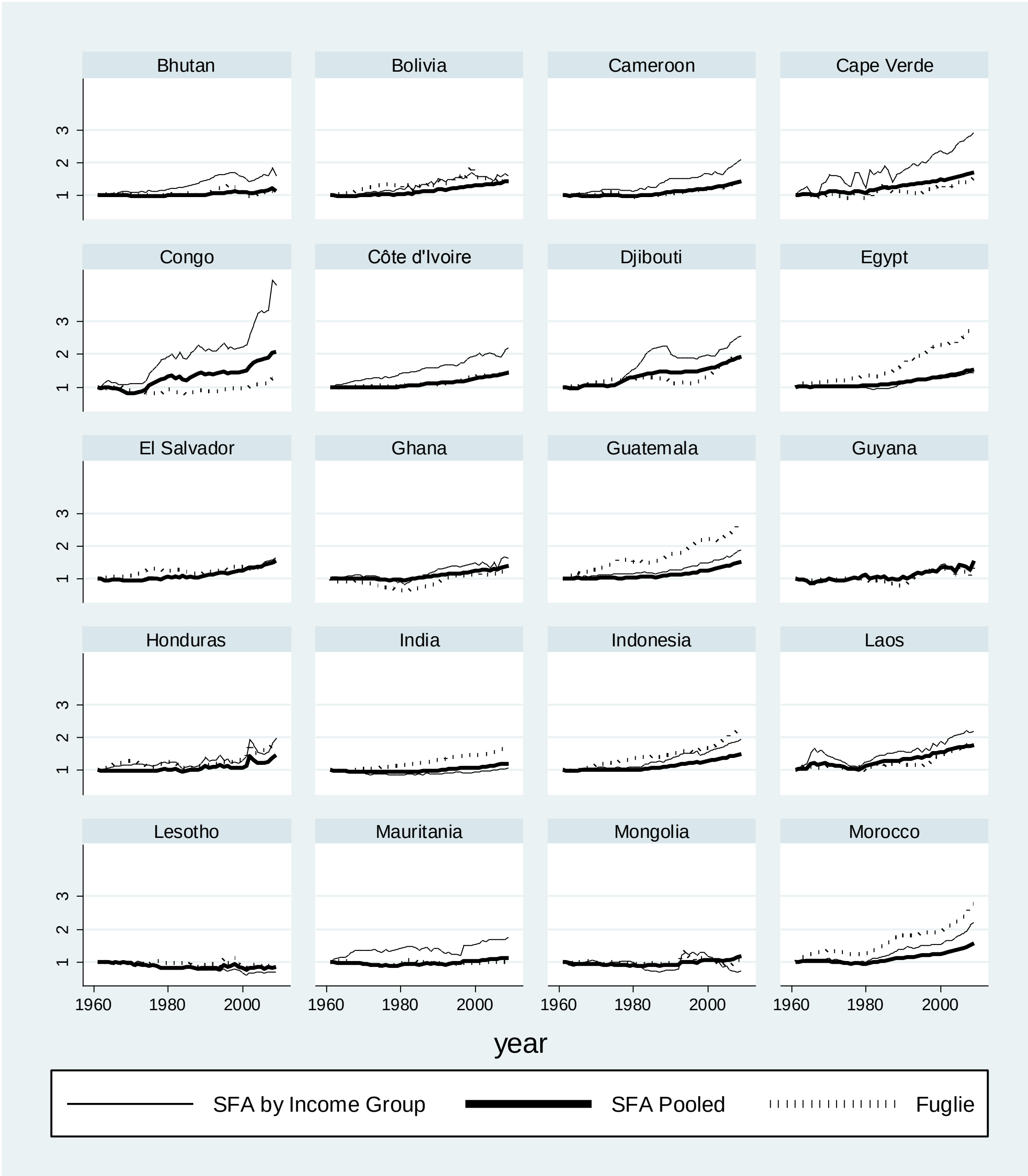

Figure A1.2. Cumulative TFP Index (1961=1) for Lower Middle Income Countries: Fuglie vs. SFA Pooled vs. SFA by Income Group - Smoothed Data

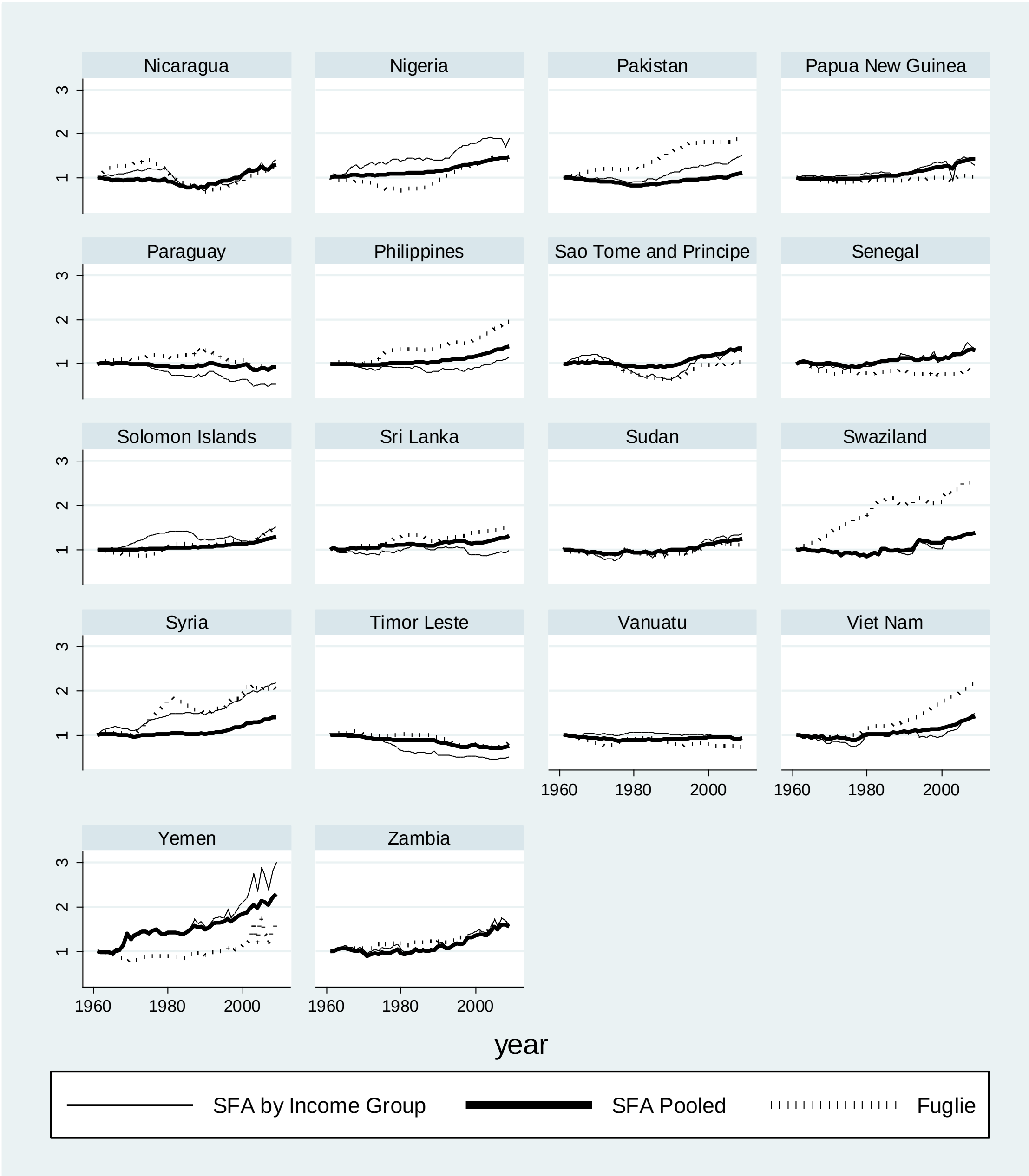

Figure A1.2 (cont'd). Cumulative TFP Index (1961=1) for Lower Middle Income Countries: Fuglie vs. SFA Pooled vs. SFA by Income Group - Smoothed Data

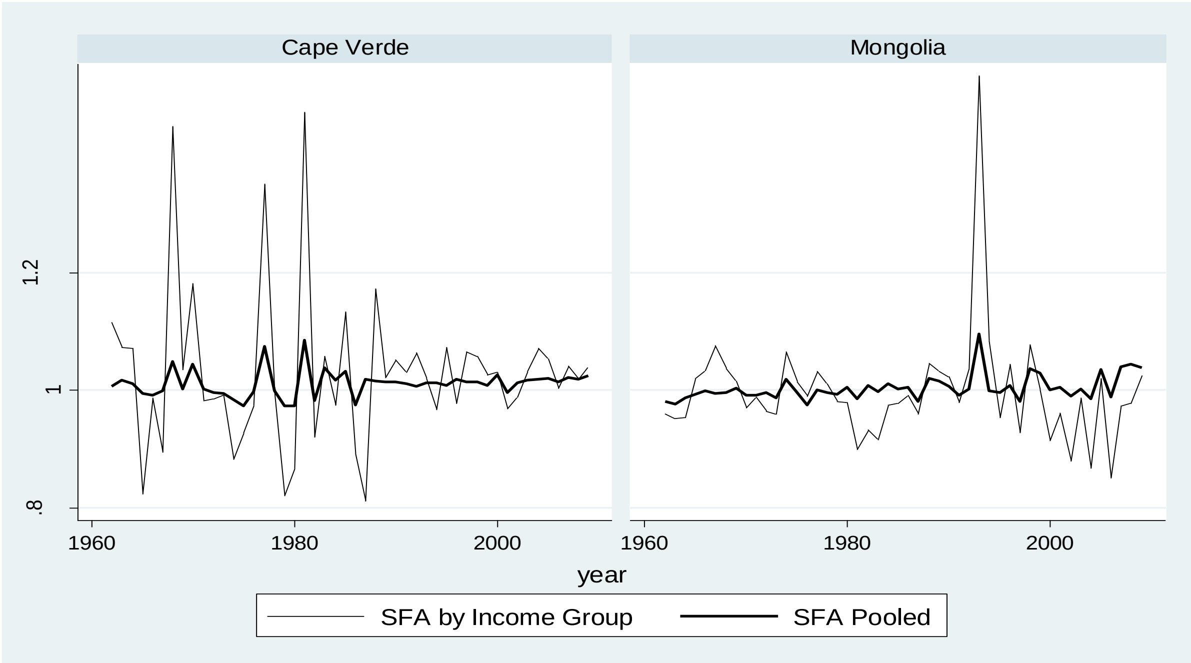

Figure A1.2a. Annual TFP Change Index for Selected Lower Middle Income Countries: SFA Pooled vs. SFA by Income Group - Smoothed Data

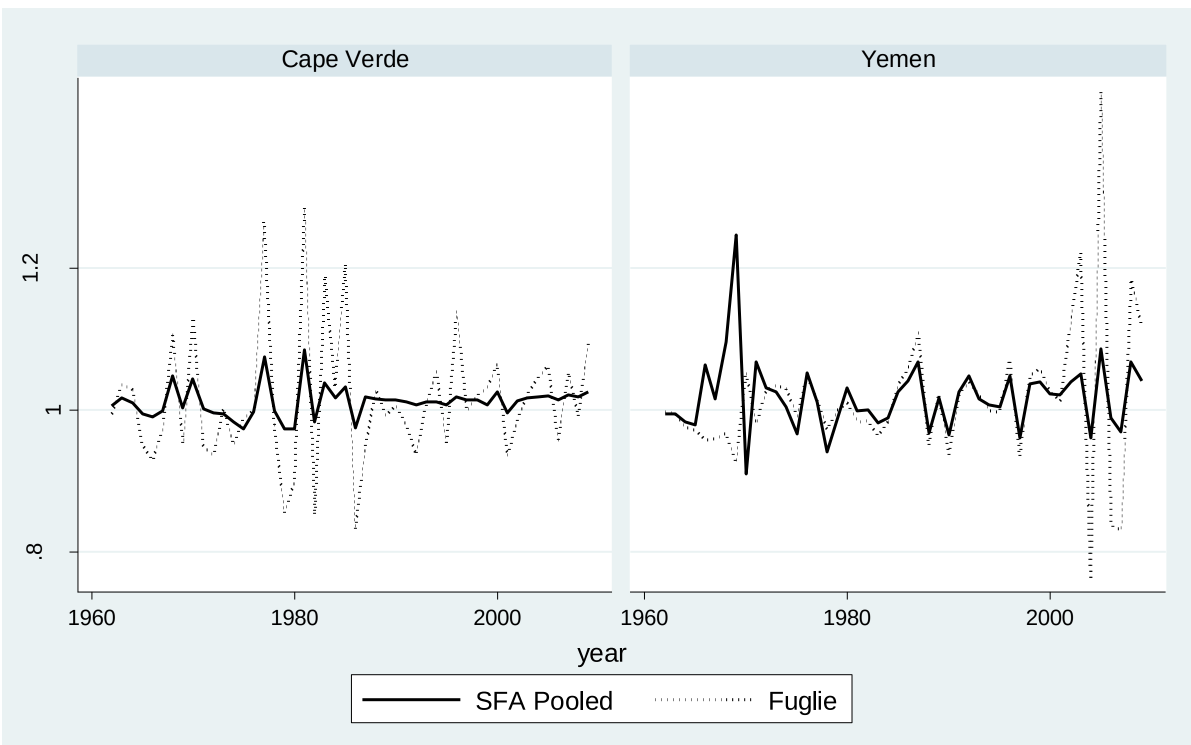

Figure A1.2.b. Annual TFP Change Index for Selected Lower Middle Income Countries: SFA Pooled vs. Fuglie - Smoothed Data

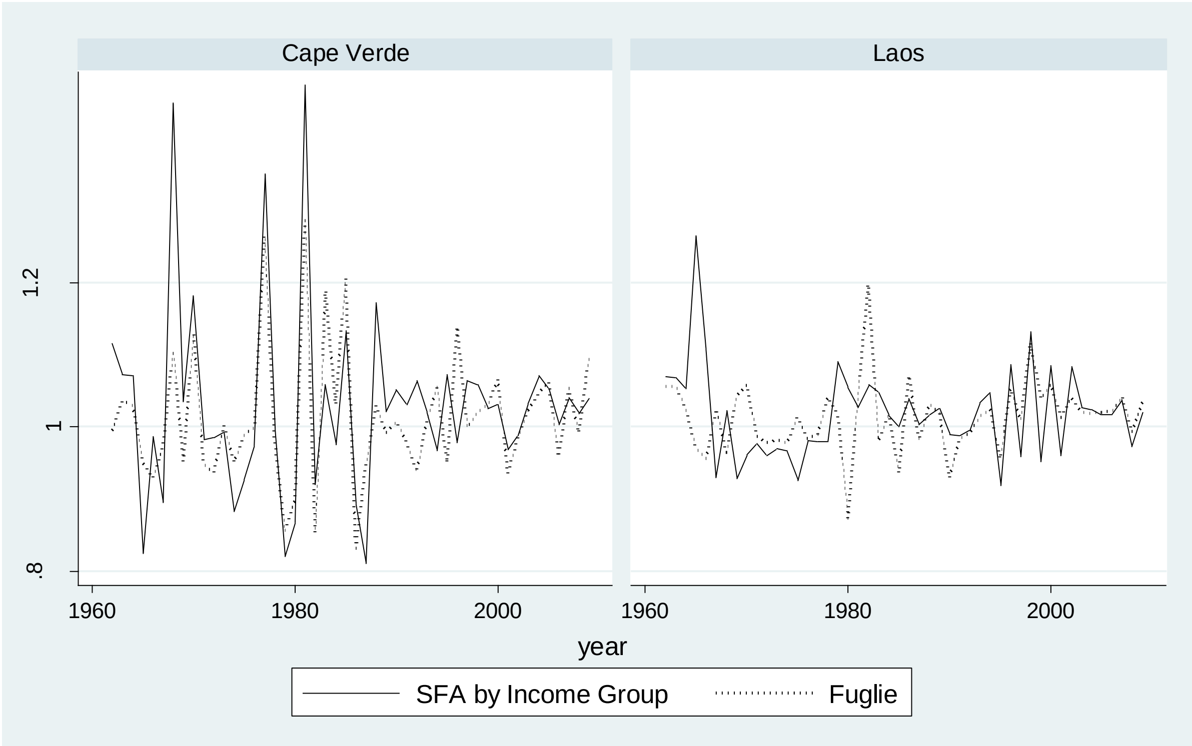

Figure A1.2a. Annual TFP Change Index for Selected Lower Middle Income Countries: SFA by Income Group vs. Fuglie - Smoothed Data

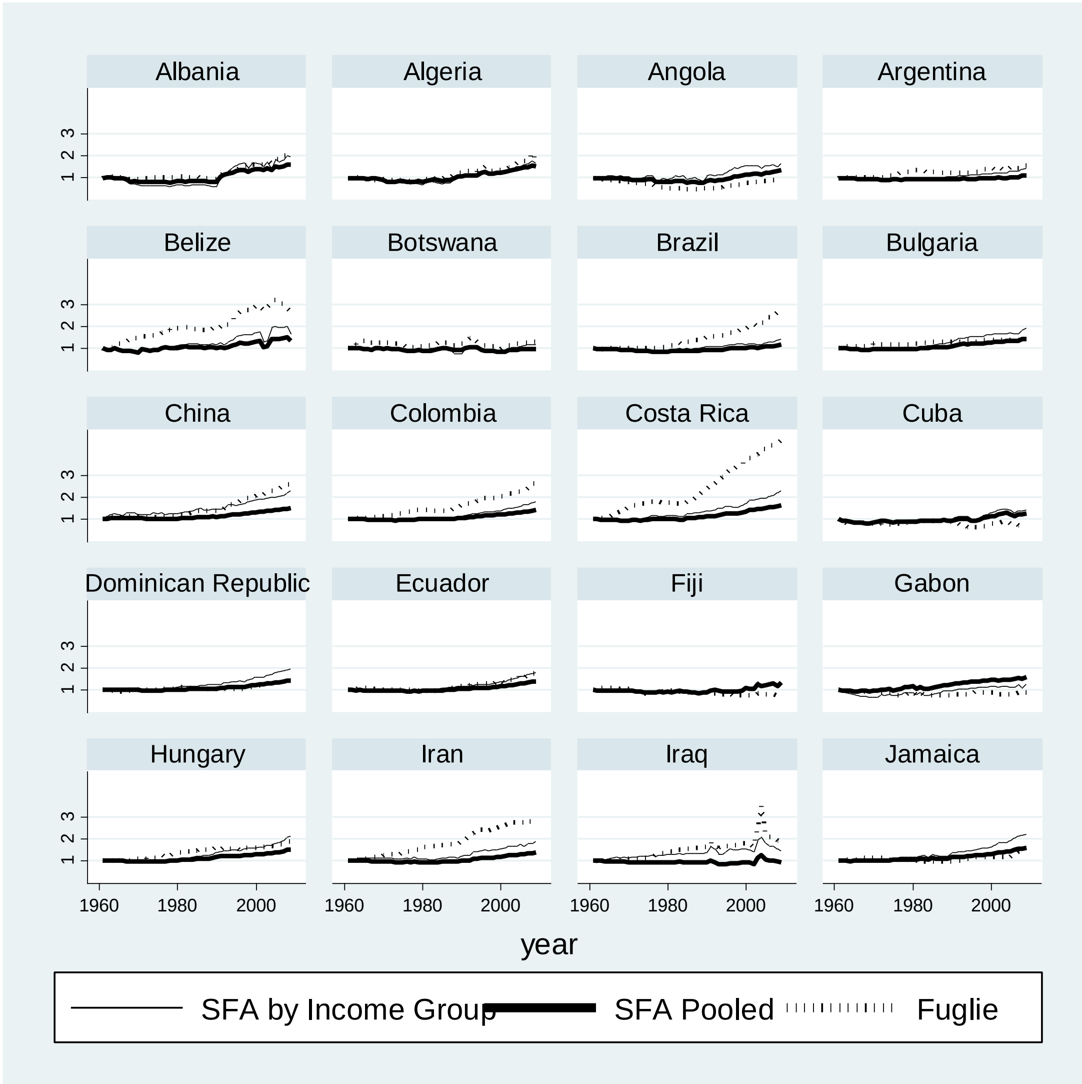

Figure A1.3. Cumulative TFP Index (1961=1) for Upper Middle Income Countries: Fuglie vs. SFA Pooled vs. SFA by Income Group - Smoothed Data

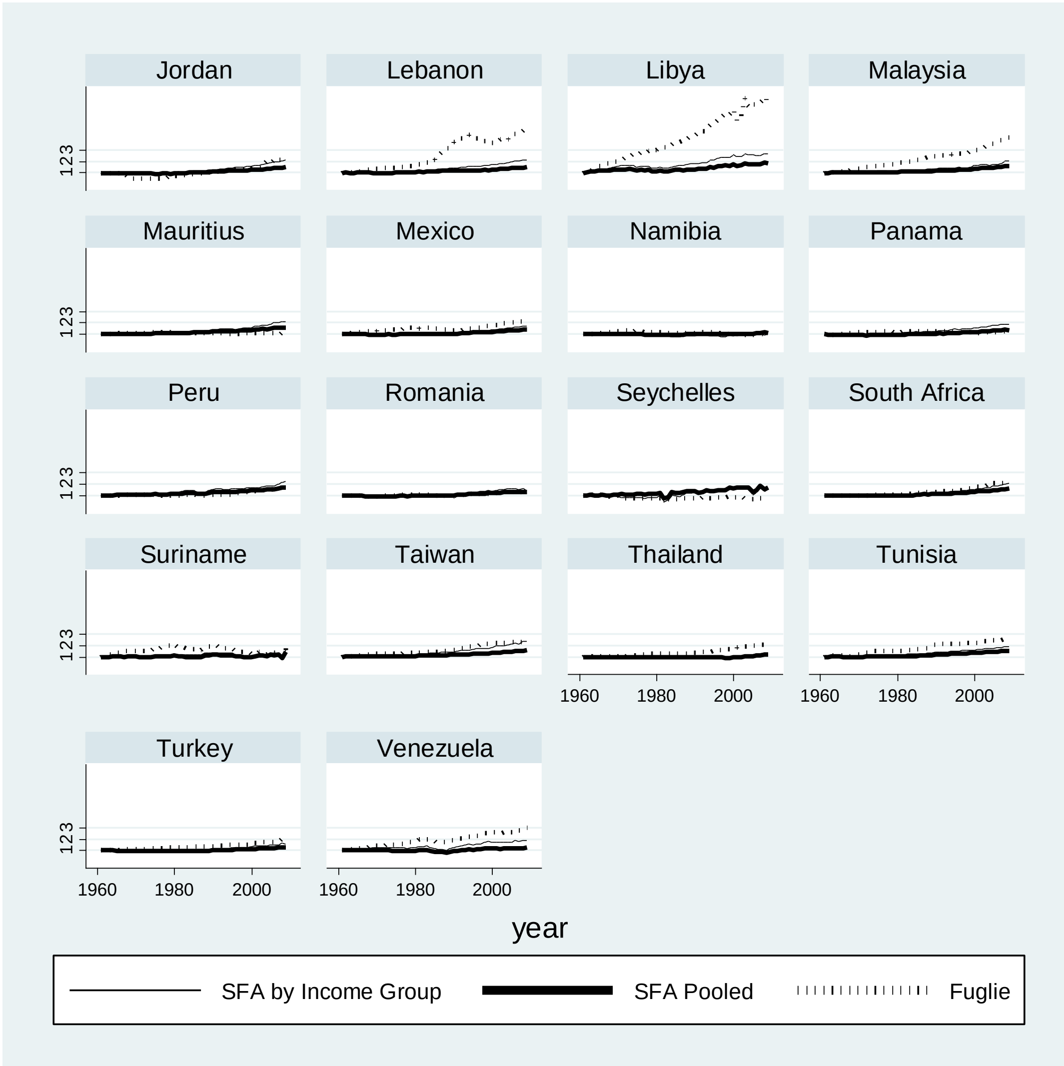

Figure A1.3 (cont'd). Cumulative TFP Index (1961=1) for Upper Middle Income Countries: Fuglie vs. SFA Pooled vs. SFA by Income Group - Smoothed Data

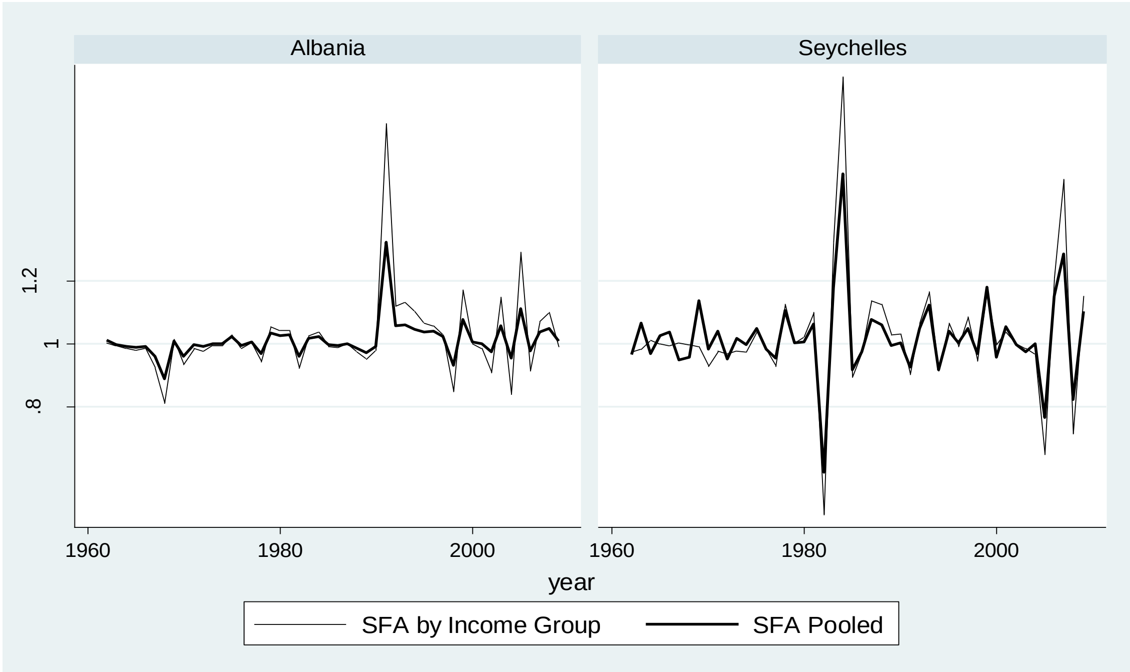

Figure A1.3a. Annual TFP Change Index for Selected Upper Middle Income Countries: SFA Pooled vs. SFA by Income Group - Smoothed Data

Figure A1.3b. Annual TFP Change Index for Selected Upper Middle Income Countries: SFA Pooled vs. Fuglie - Smoothed Data

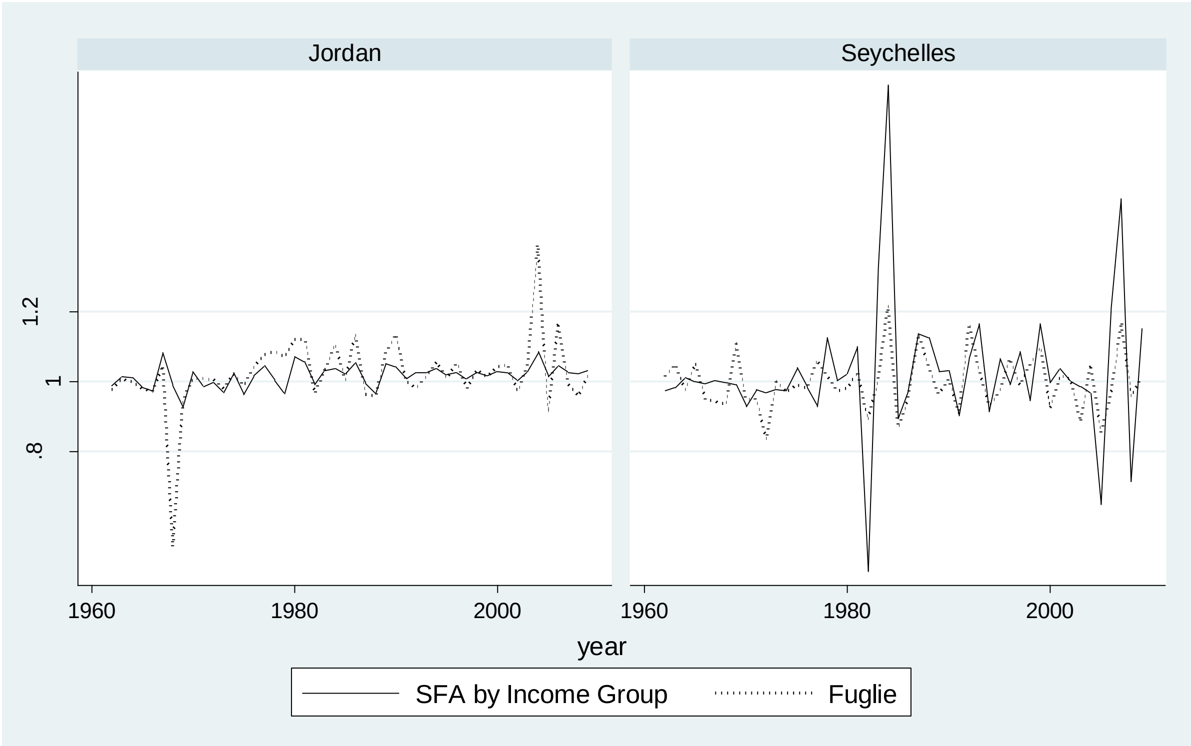

Figure A1.3c. Annual TFP Change Index for Selected Upper Middle Income Countries: SFA by Income Group vs. Fuglie - Smoothed Data

A.2. Graphs from SFA and Fuglie's Estimation: Unsmoothed Data

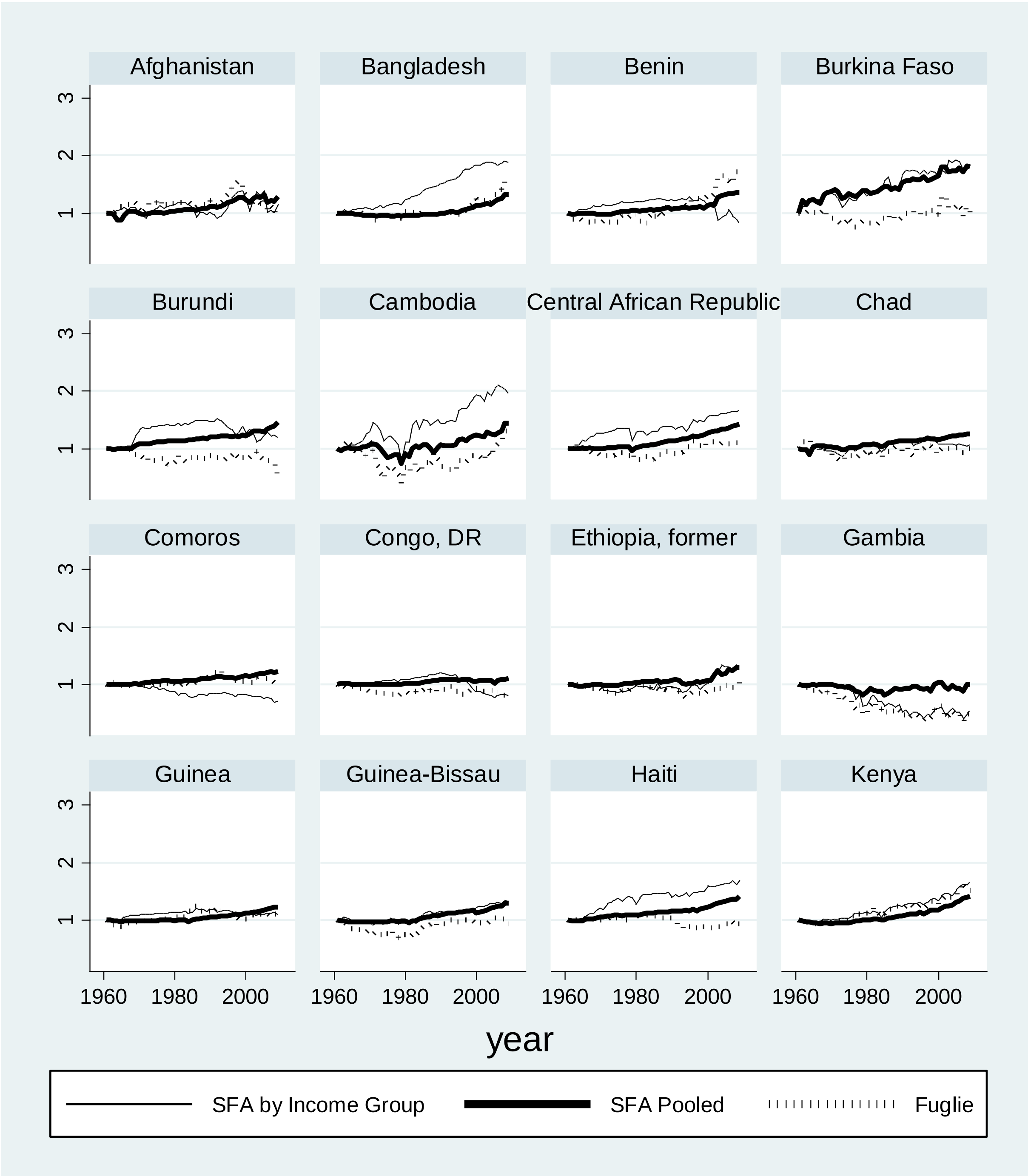

Figure A2.1. Cumulative TFP Index (1961=1) for Low Income Countries: Fuglie vs. SFA Pooled vs. SFA by Income Group - Unsmoothed Data

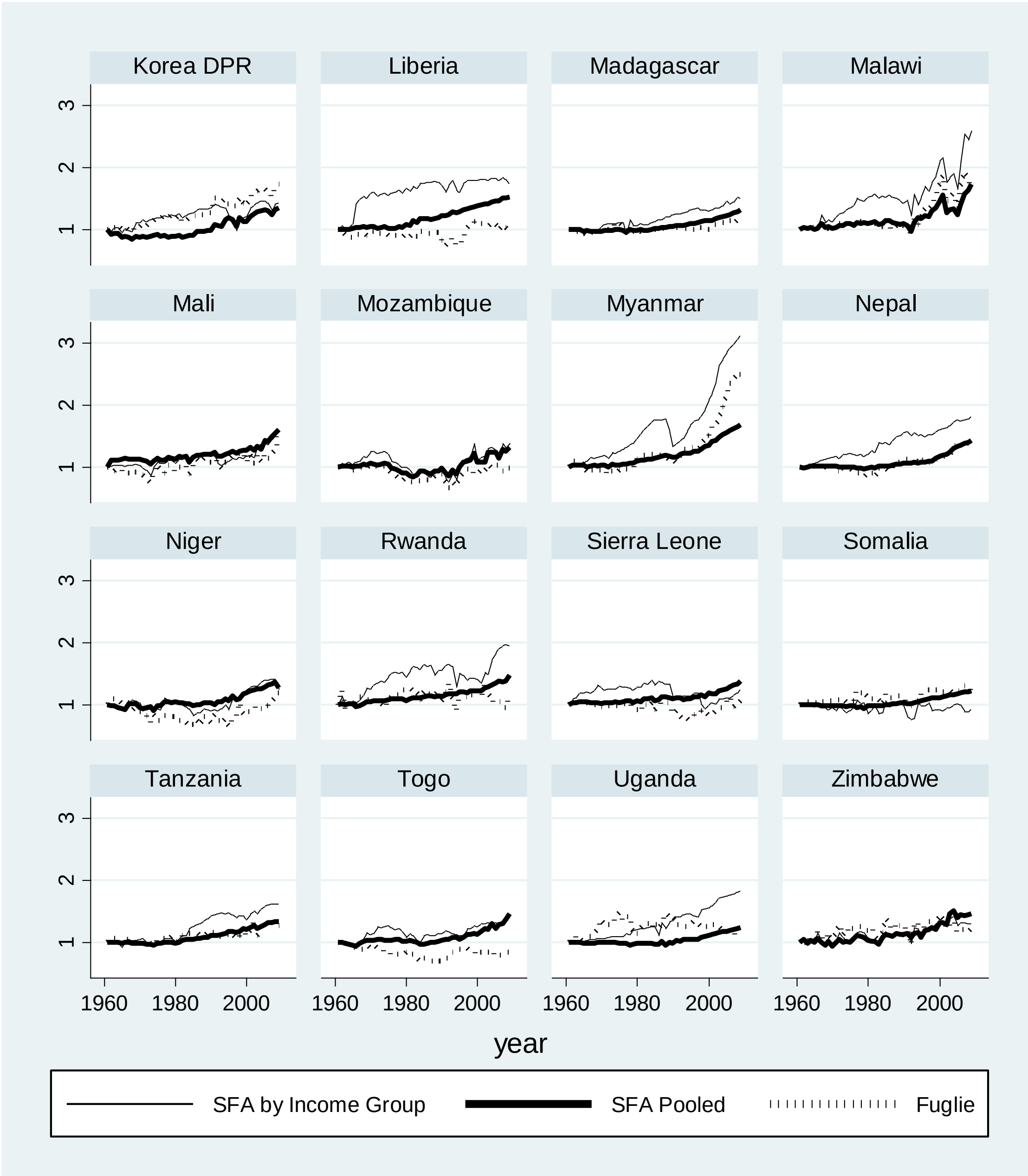

Figure A2.1 (cont'd). Cumulative TFP Index (1961=1) for Low Income Countries: Fuglie vs. SFA Pooled vs. SFA by Income Group - Unsmoothed Data

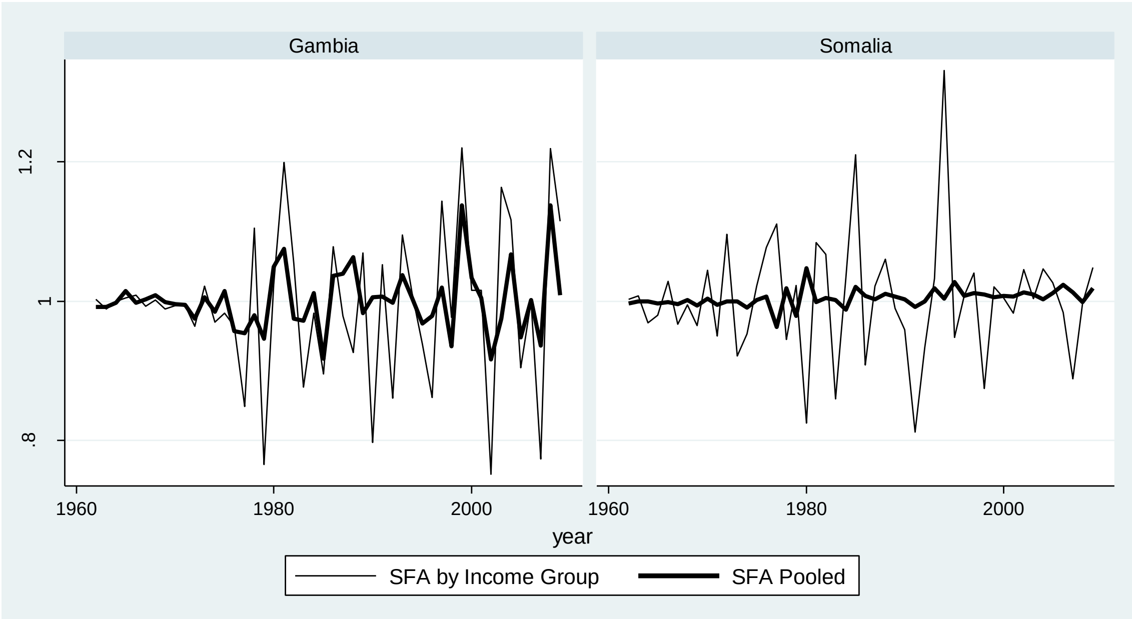

Figure A2.1a. Annual TFP Change Index for Selected Low Income Countries: SFA by Income Group vs. SFA Pooled - Unsmoothed Data

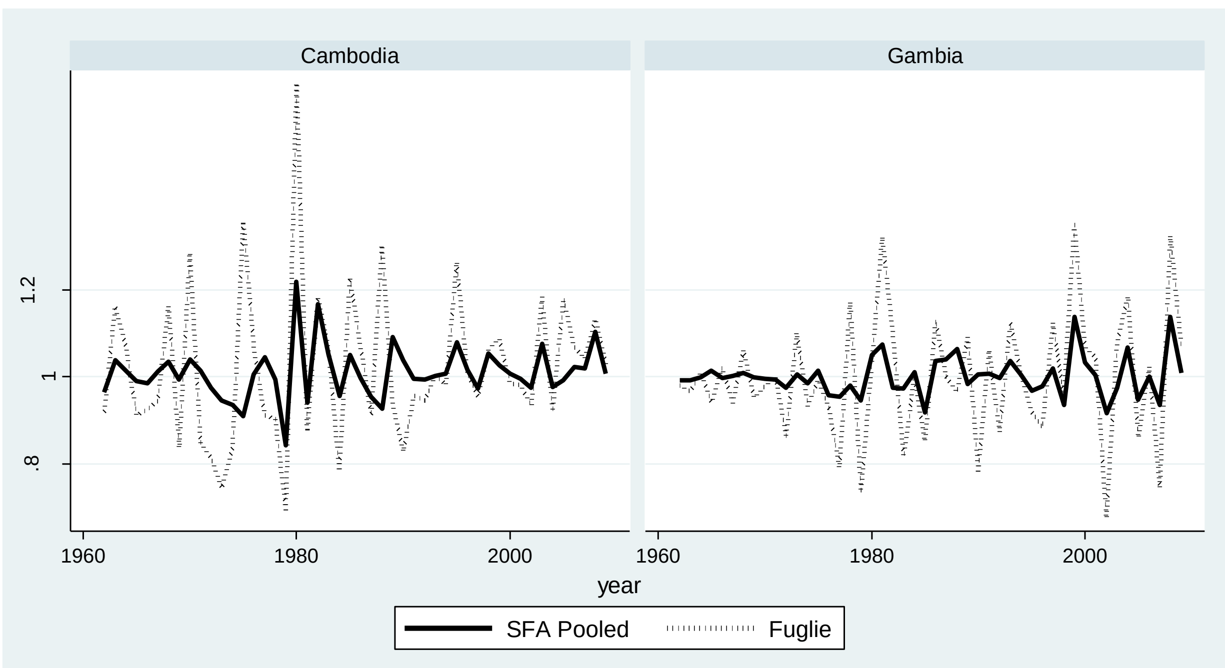

Figure A2.1b. Annual TFP Change Index for Selected Low Income Countries: SFA Pooled vs. Fuglie - Unsmoothed Data

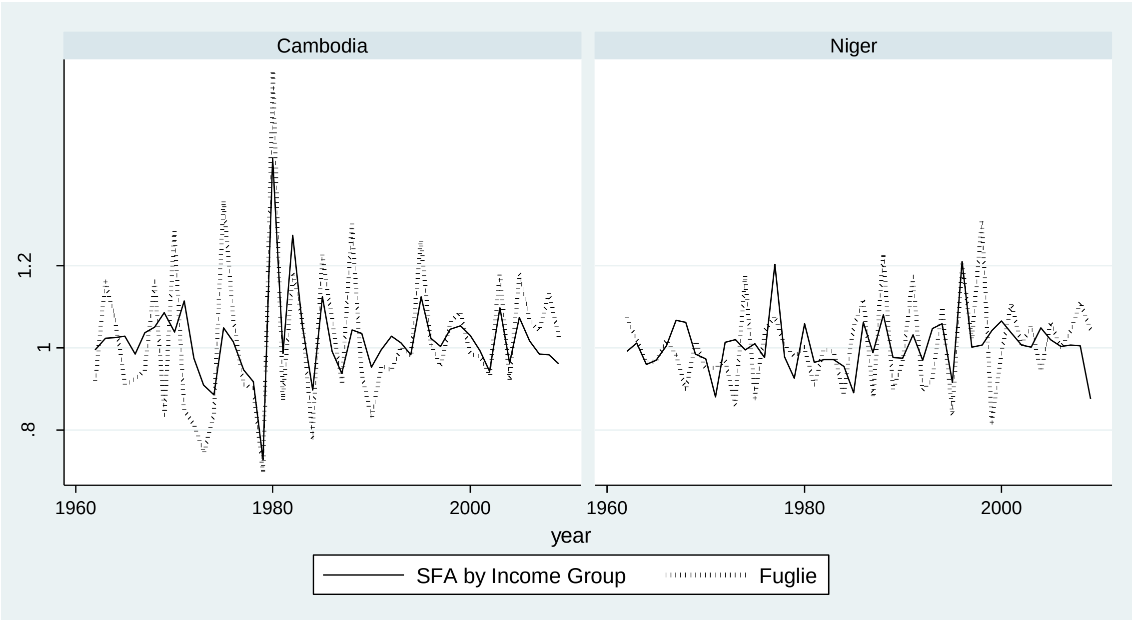

Figure A2.1c. Annual TFP Change Index for Selected Low Income Countries: SFA Pooled vs. Fuglie - Unsmoothed Data

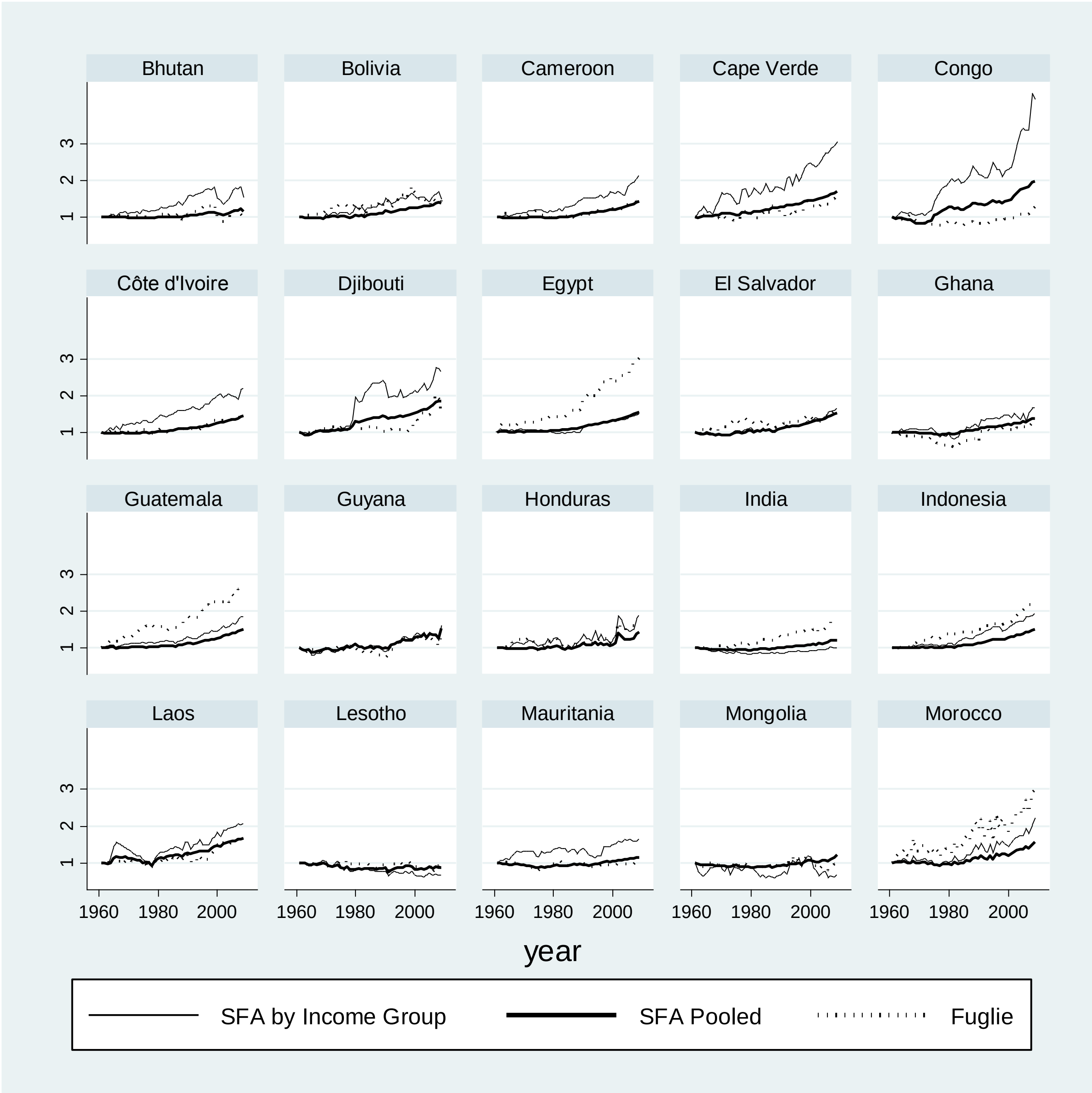

Figure A2.2. Cumulative TFP Index (1961=1) for Lower Middle Income Countries: Fuglie vs. SFA Pooled vs. SFA by Income Group - Unsmoothed Data

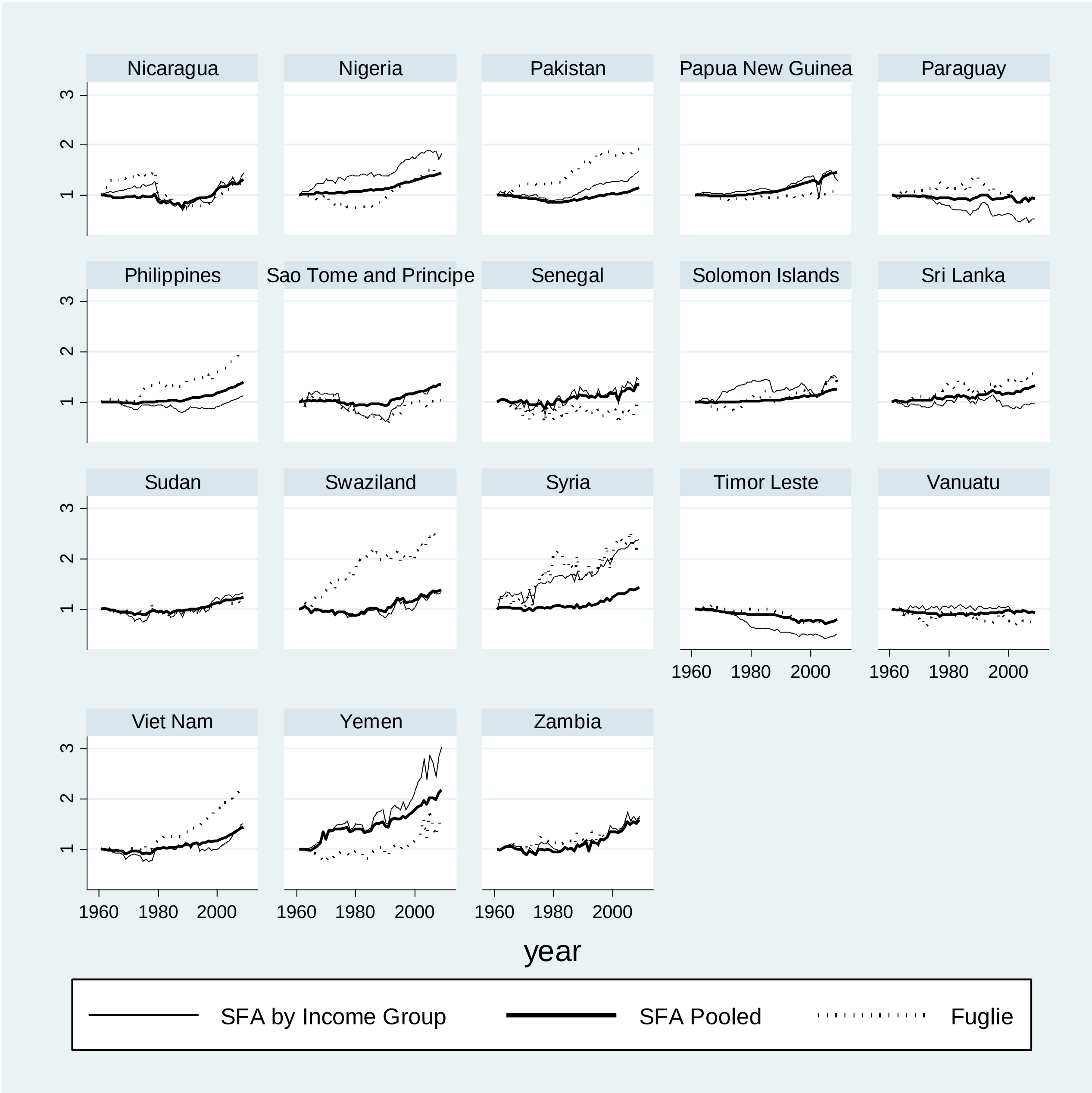

Figure A2.2 (cont'd). Cumulative TFP Index (1961=1) for Lower Middle Income Countries: Fuglie vs. SFA Pooled vs. SFA by Income Group - Unsmoothed Data

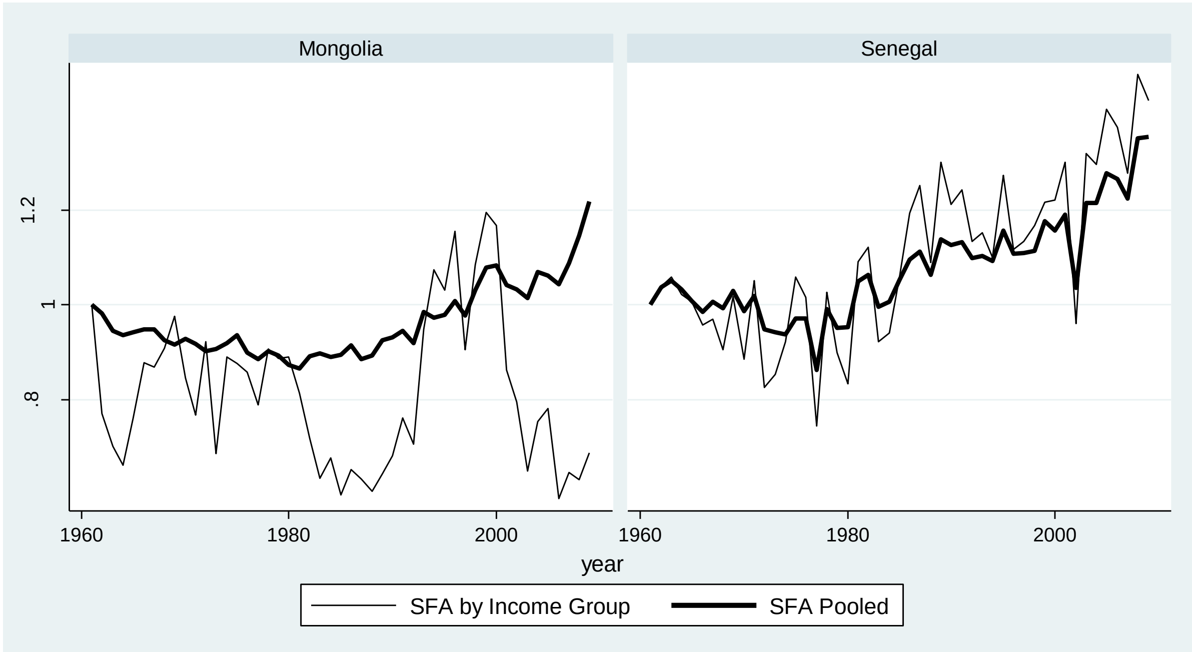

Figure A2.2a. Annual TFP Change Index for Selected Lower Middle Income Countries: SFA by Income Group vs. SFA Pooled - Unsmoothed Data

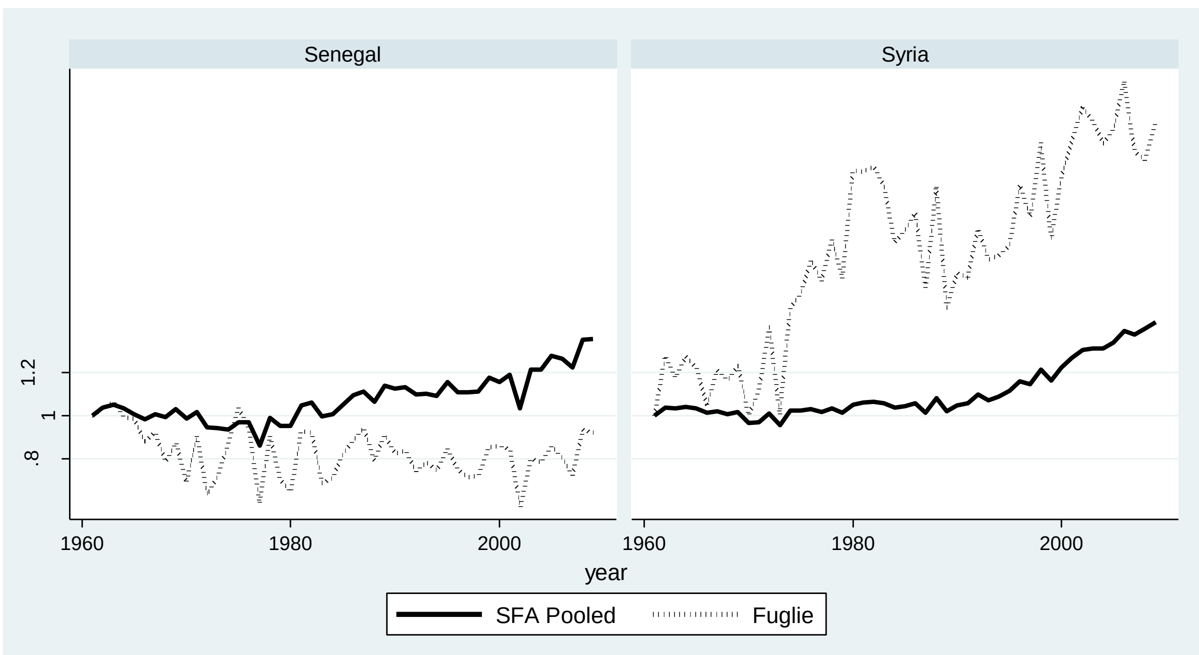

Figure A2.2b. Annual TFP Change Index for Selected Lower Middle Income Countries: SFA Pooled vs. Fuglie - Unsmoothed Data

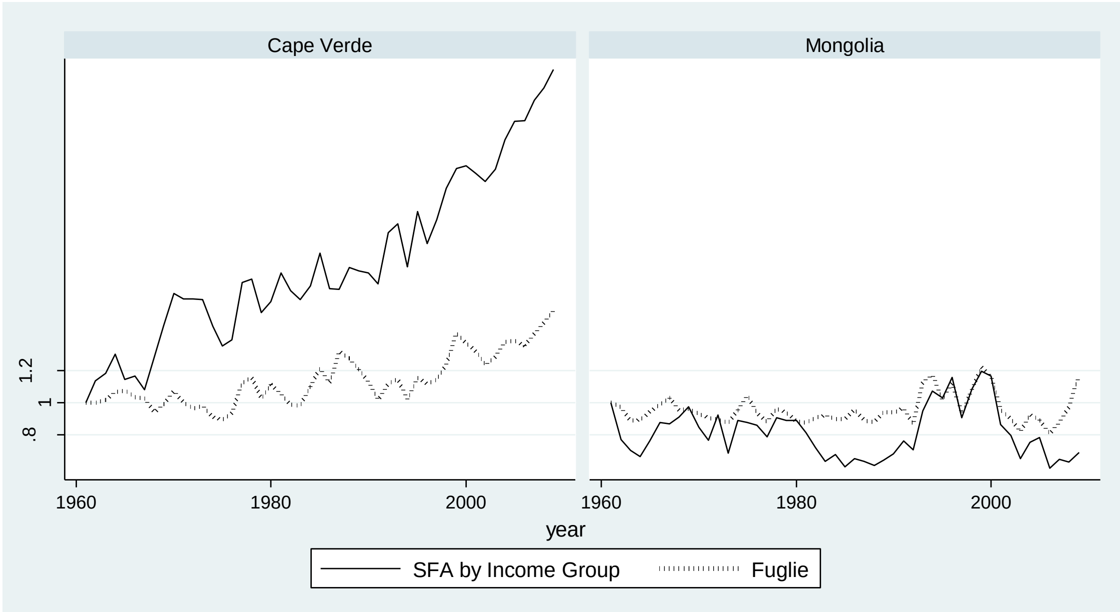

Figure A2.2c. Annual TFP Change Index for Selected Lower Middle Income Countries: SFA by Income Group vs. Fuglie - Unsmoothed Data

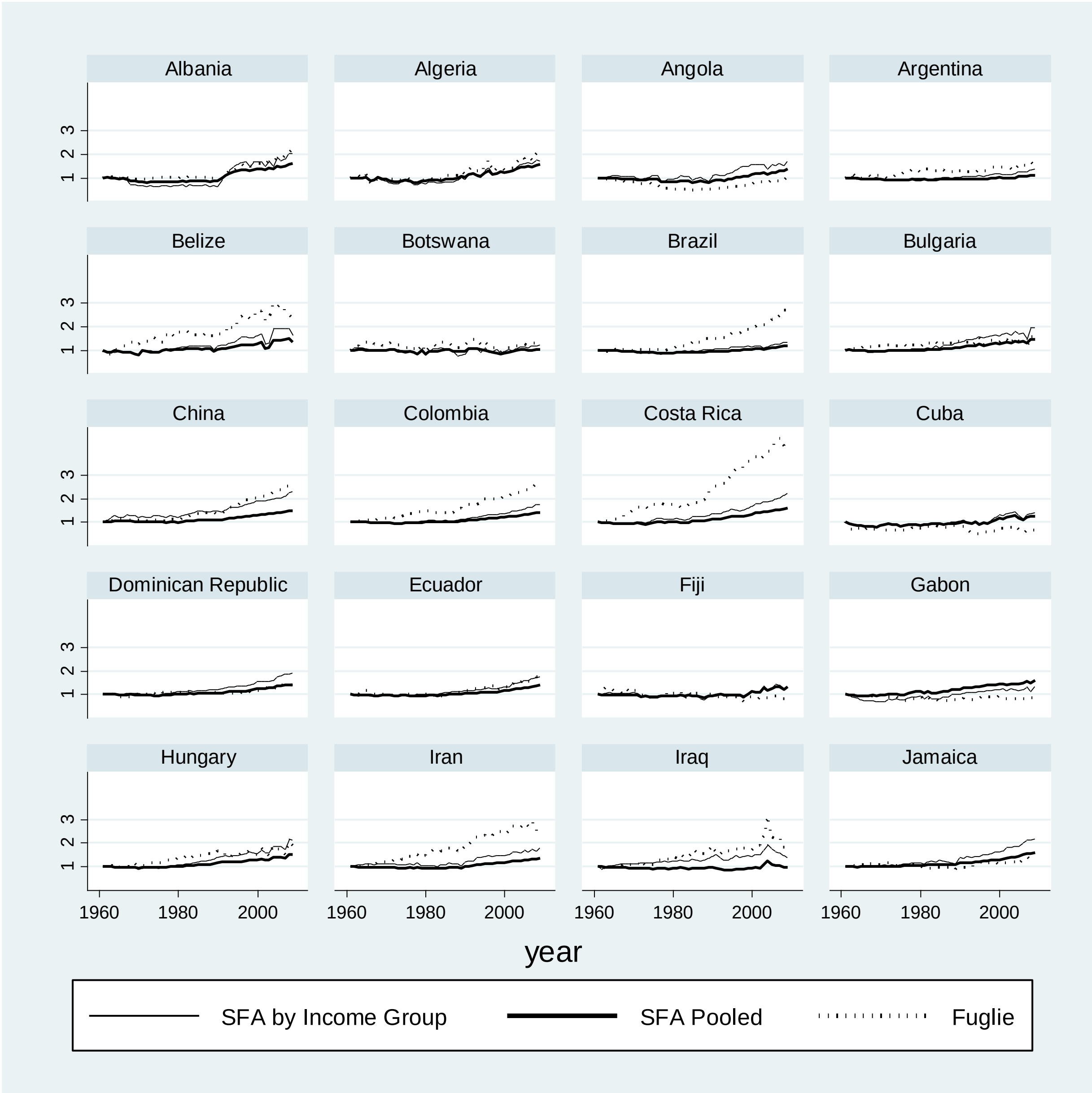

Figure A2.3. Cumulative TFP Index (1961=1) for Upper Middle Income Countries: Fuglie vs. SFA Pooled vs. SFA by Income Group - Unsmoothed Data

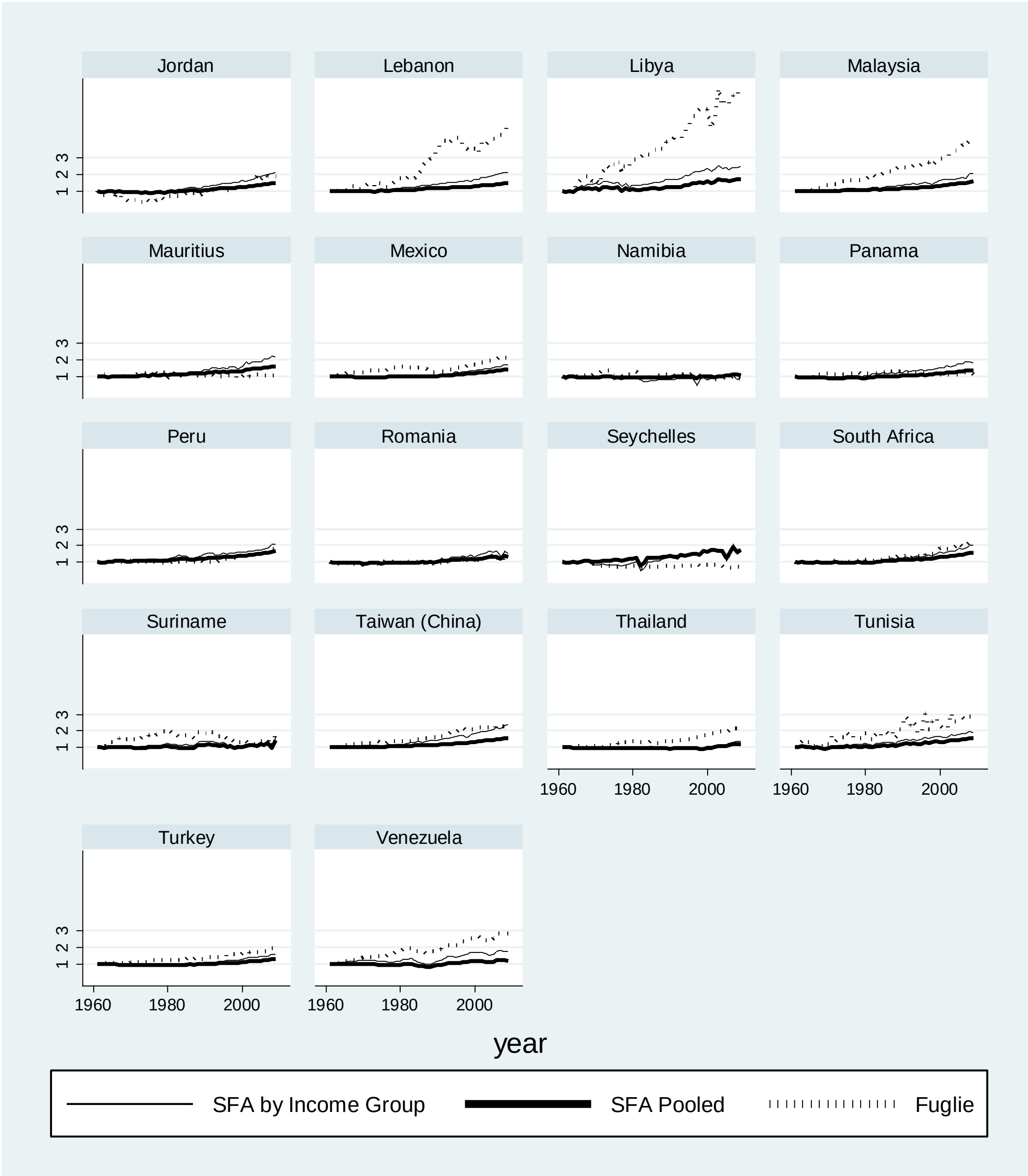

Figure A2.3 (cont'd). Cumulative TFP Index (1961=1) for Upper Middle Income Countries: Fuglie vs. SFA Pooled vs. SFA by Income Group - Unsmoothed Data

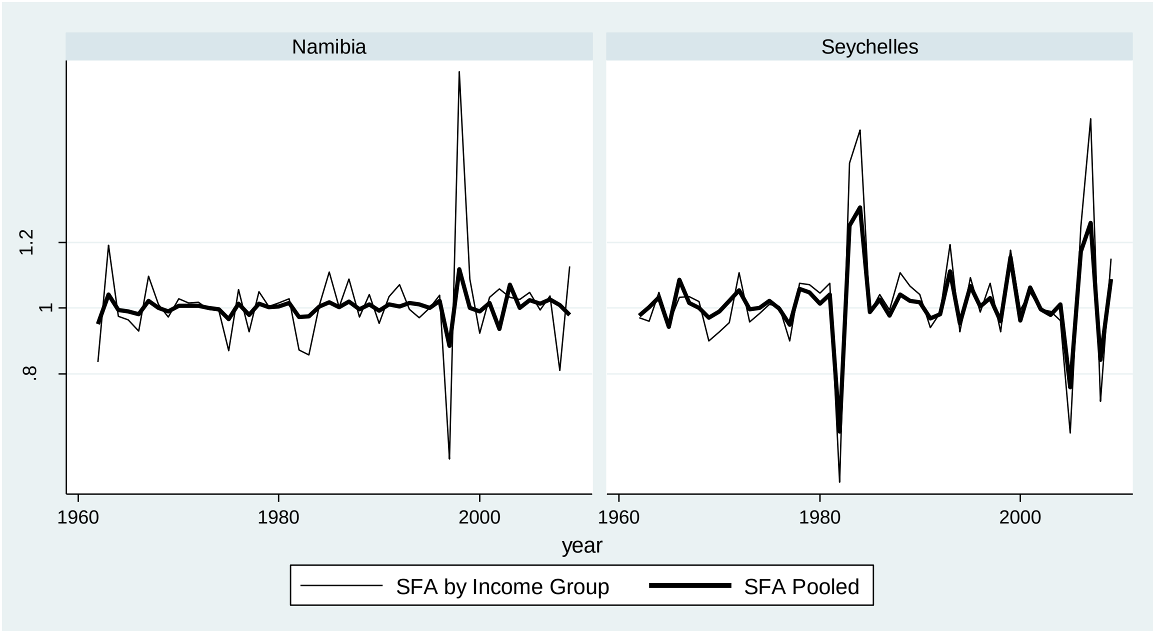

Figure A2.3a. Annual TFP Change Index for Selected Upper Middle Income Countries: SFA by Income Group vs. SFA Pooled - Unsmoothed Data

Figure A2.3b. Annual TFP Change Index for Selected Upper Middle Income Countries: SFA Pooled vs. Fuglie - Unsmoothed Data

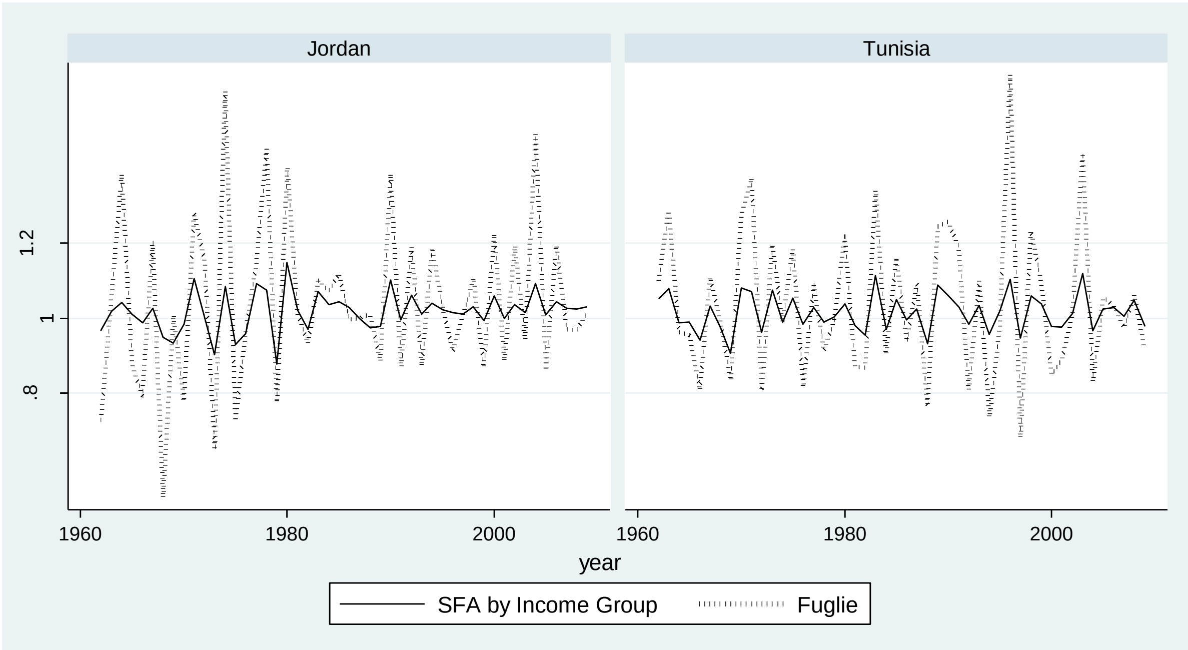

Figure A2.3c. Annual TFP Change Index for Selected Upper Middle Income Countries: SFA by Income Group vs. Fuglie - Unsmoothed Data

A3. Graphs from SFA & Fuglie's Estimation: Smoothed Data vs. Unsmoothed Data

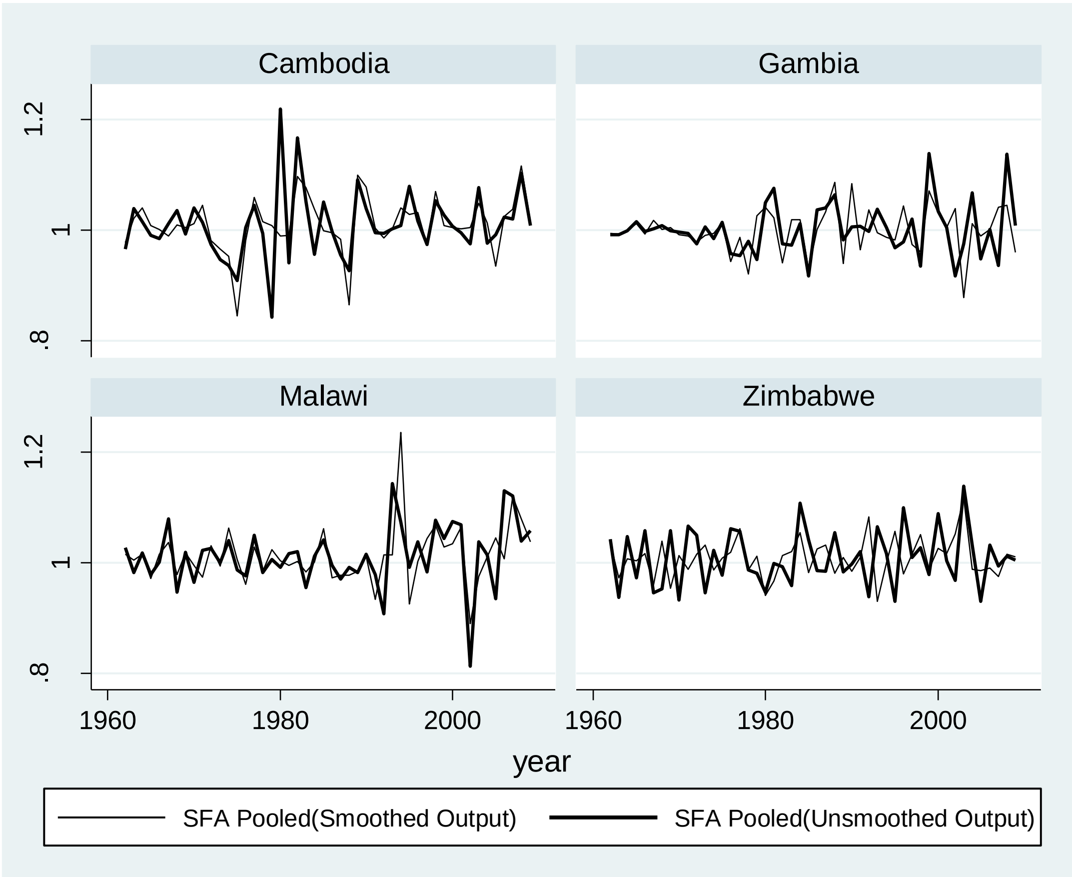

Figure A3.1a. Annual TFP Change Index for Selected Low Income Countries: SFA Pooled - Smoothed Data vs. Unsmoothed Data

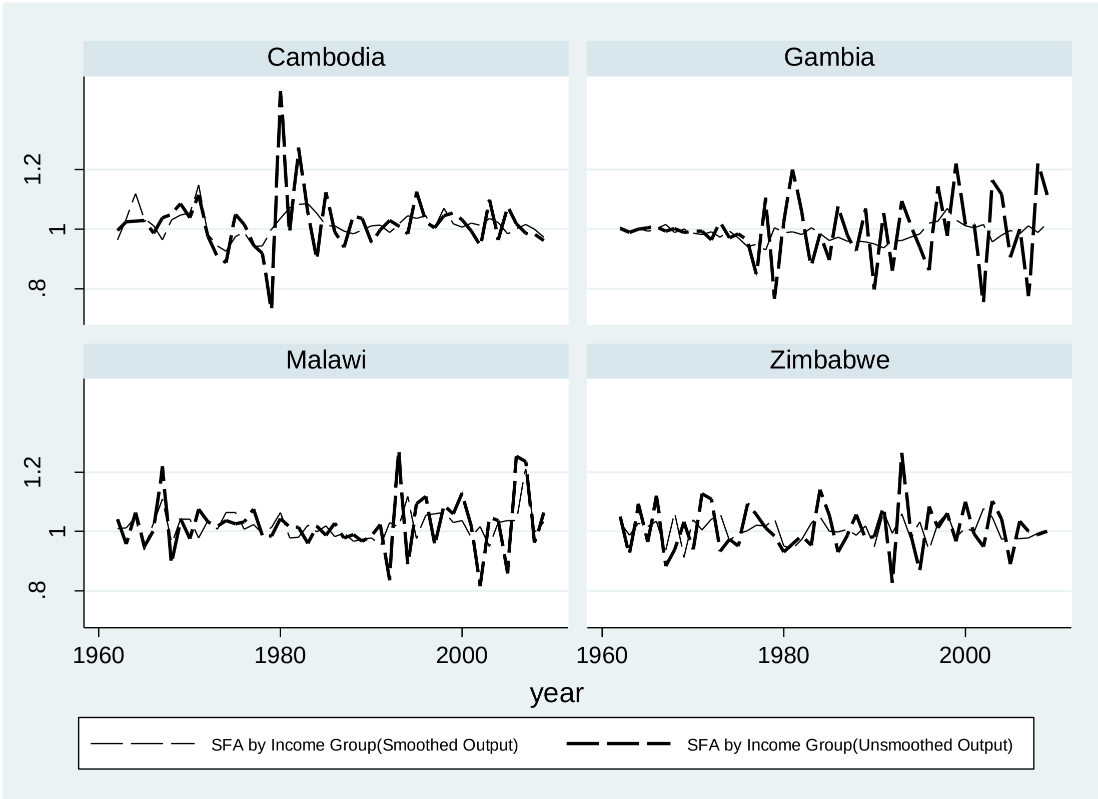

Figure A3.1b. Annual TFP Change Index for Selected Low Income Countries: SFA by Income Group - Smoothed Data vs. Unsmoothed Data

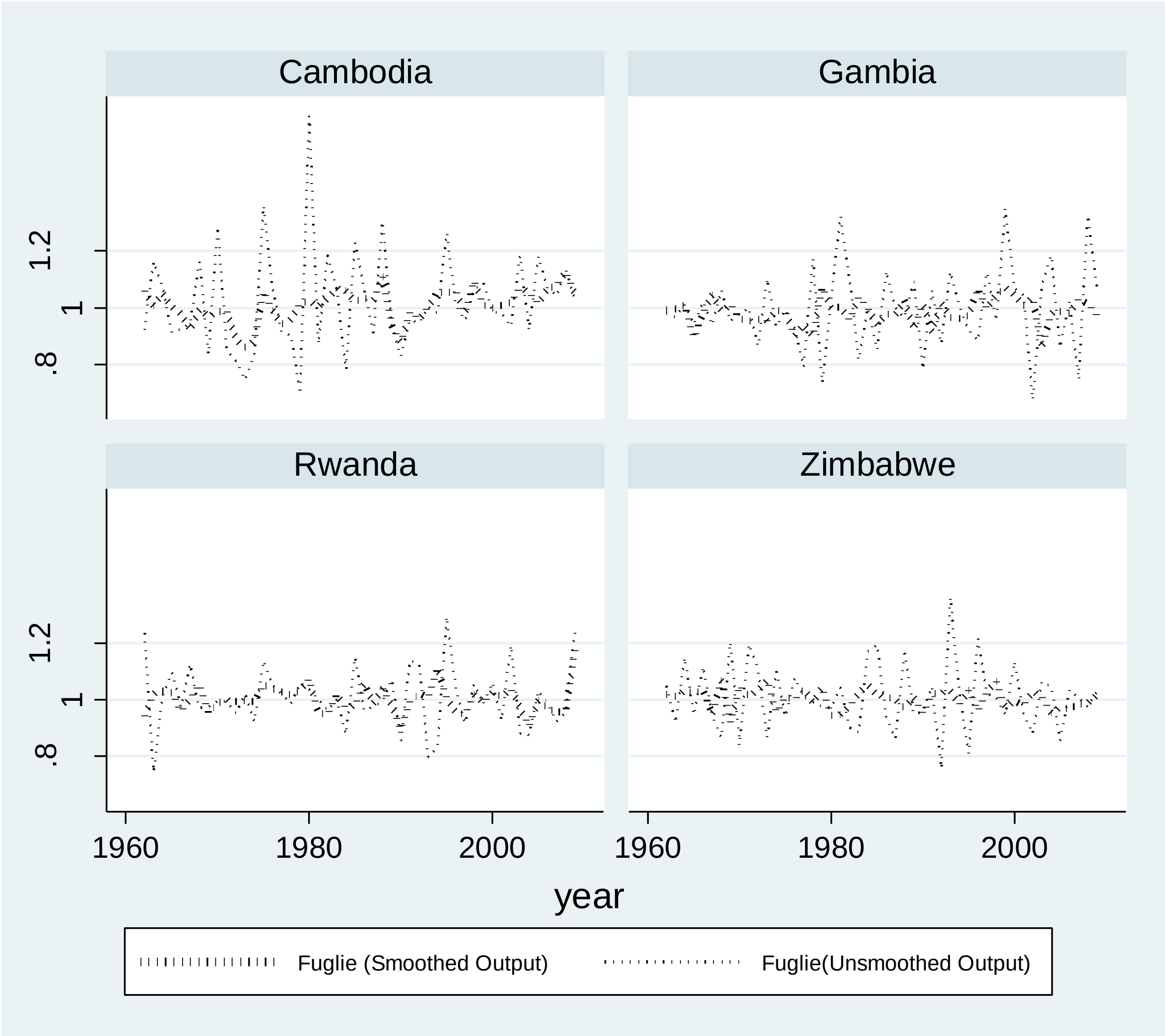

Figure A3.1c. Annual TFP Change Index for Selected Low Income Countries: Fuglie - Smoothed Data vs. Unsmoothed Data

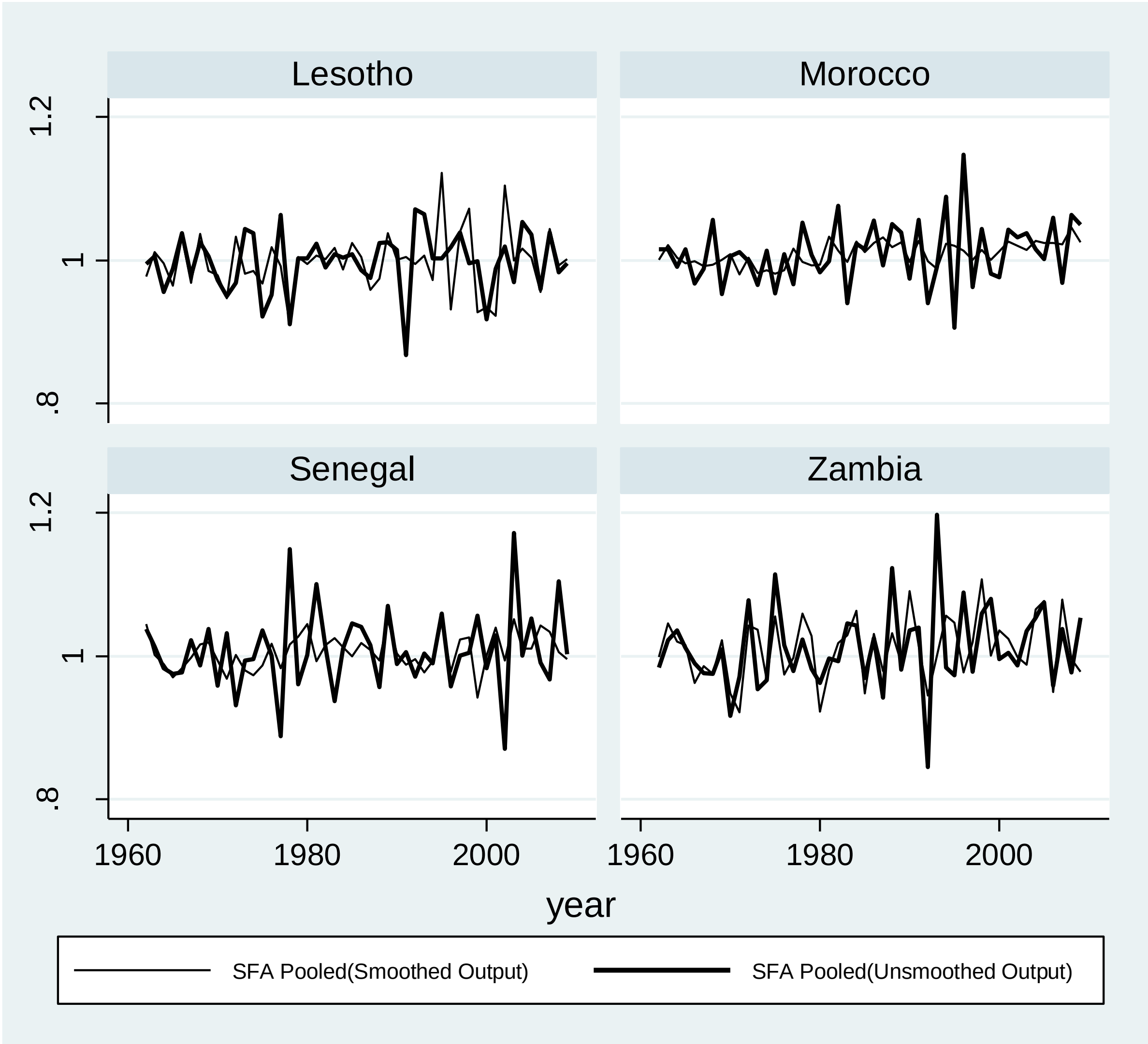

Figure A3.2a. Annual TFP Change Index for Selected Lower Middle Income Countries: SFA Pooled - Smoothed Data vs. Unsmoothed Data

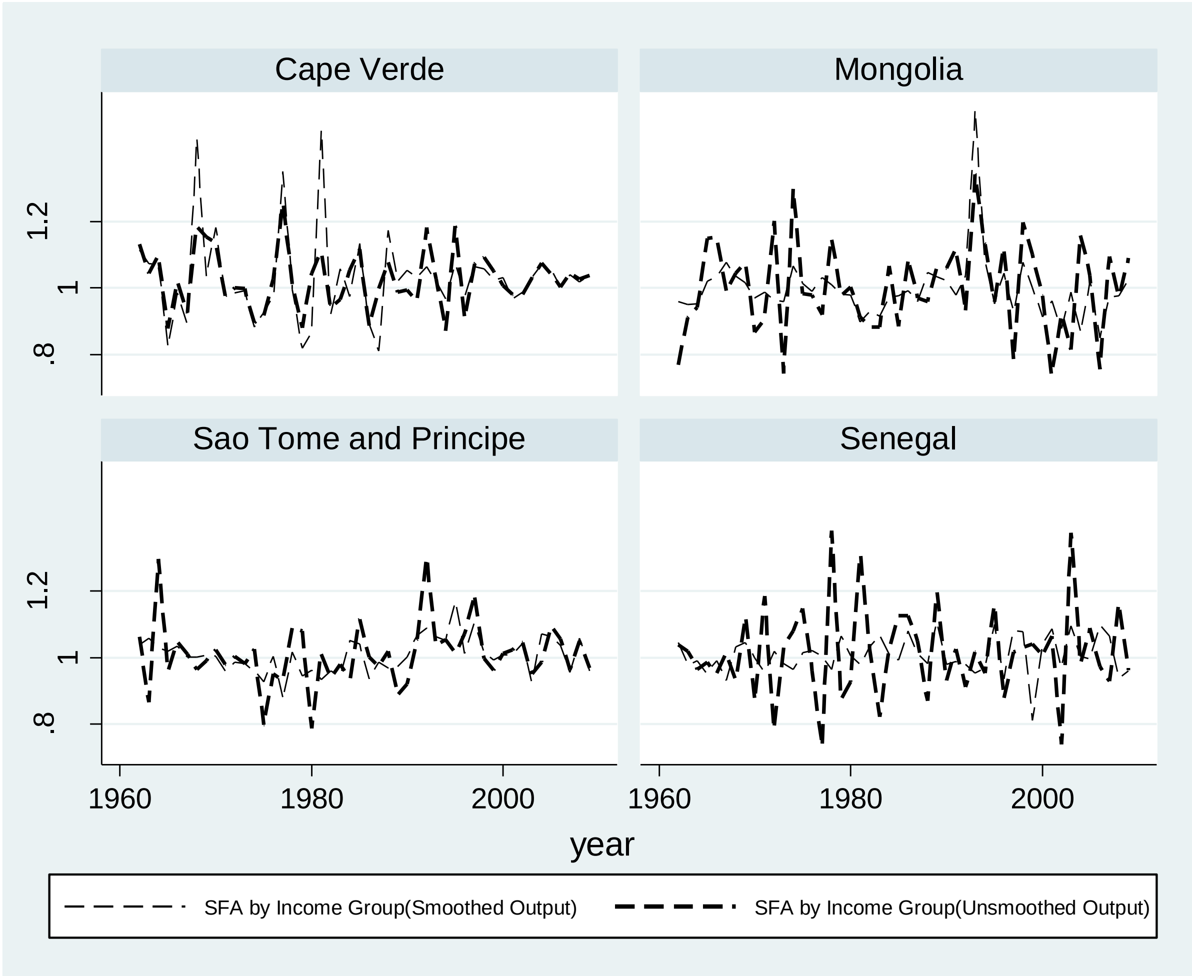

Figure A3.2b. Annual TFP Change Index for Selected Lower Middle Income Countries: SFA by Income Group - Smoothed Data vs. Unsmoothed Data

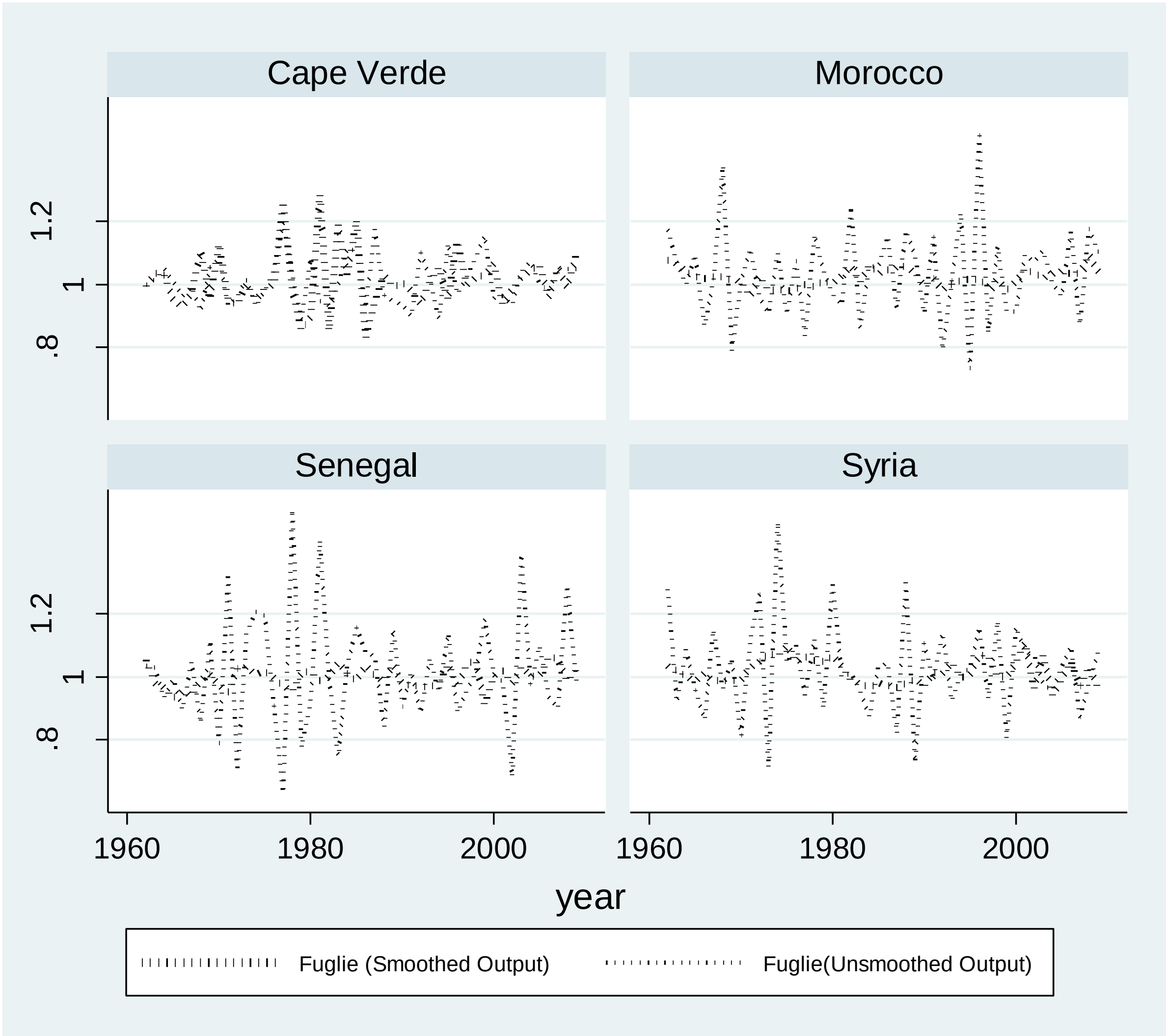

Figure A3.2c. Annual TFP Change Index for Selected Lower Middle Income Countries: Fuglie - Smoothed Data vs. Unsmoothed Data

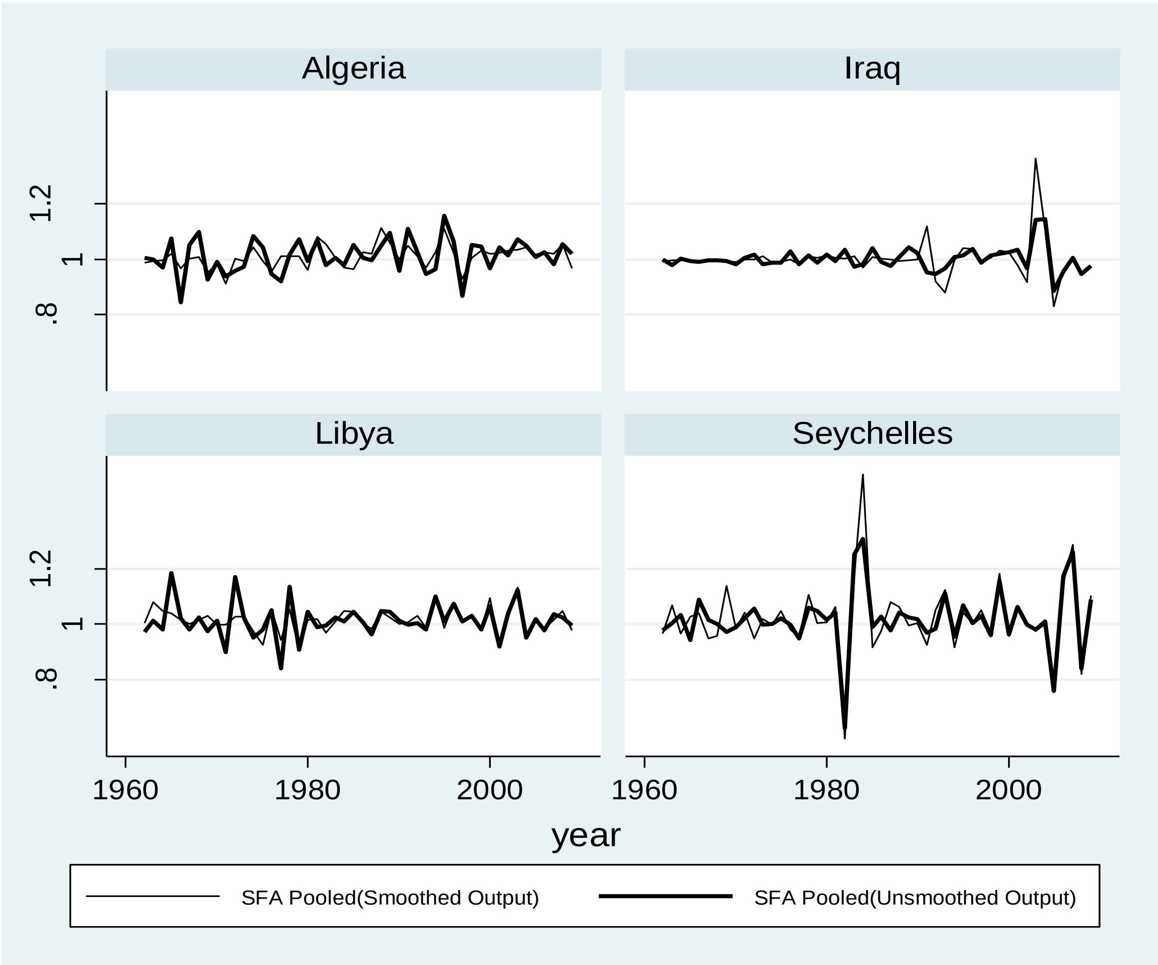

Figure A3.3a. Annual TFP Change Index for Selected Upper Middle Income Countries: SFA Pooled - Smoothed Data vs. Unsmoothed Data

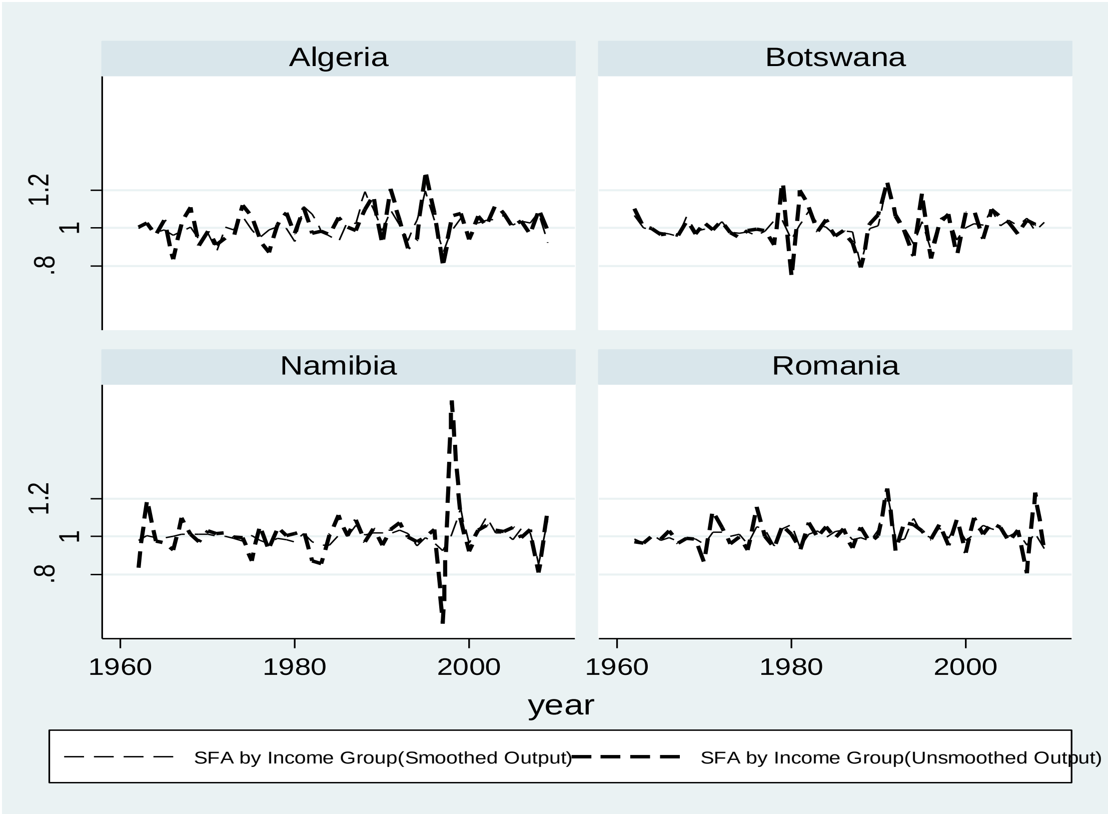

Figure A3.3b. Annual TFP Change Index for Selected Upper Middle Income Countries: SFA by Income Group - Smoothed Data vs. Unsmoothed Data

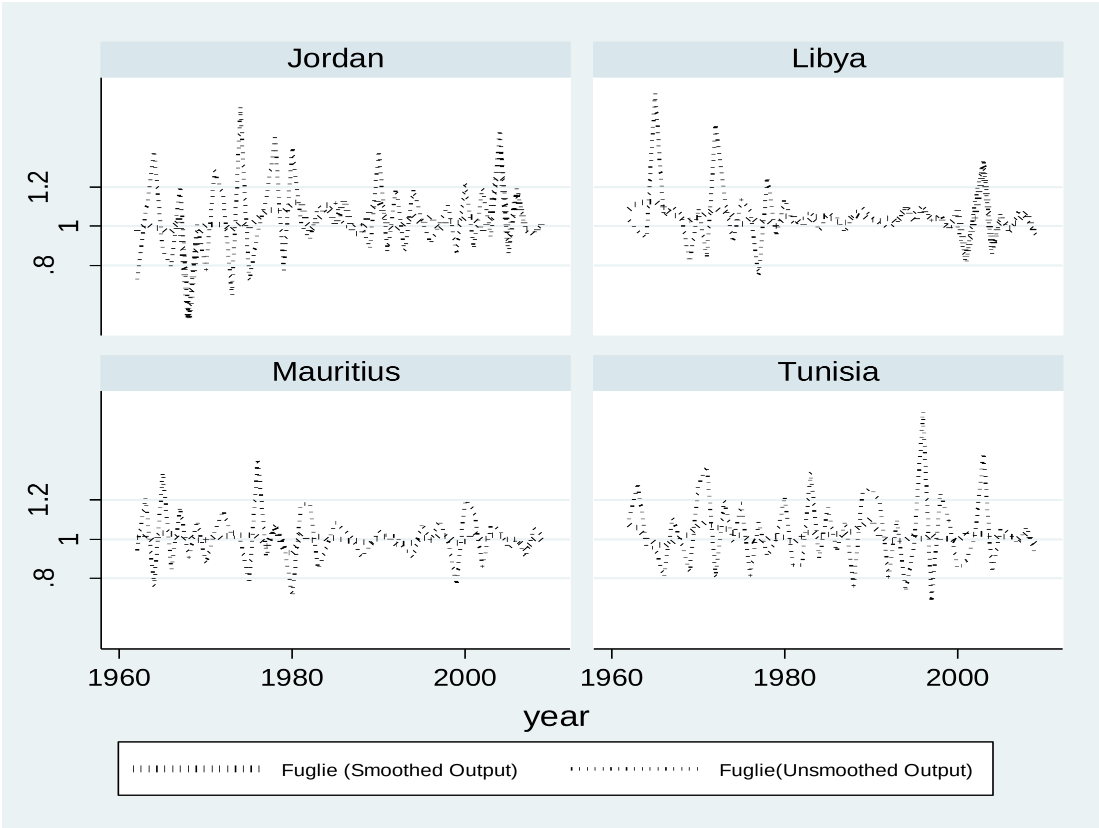

Figure A3.3c. Annual TFP Change Index for Selected Upper Middle Income Countries: Fuglie - Smoothed Data vs. Unsmoothed Data

A4. Graphs from SFA & Fuglie's Estimation for Regions

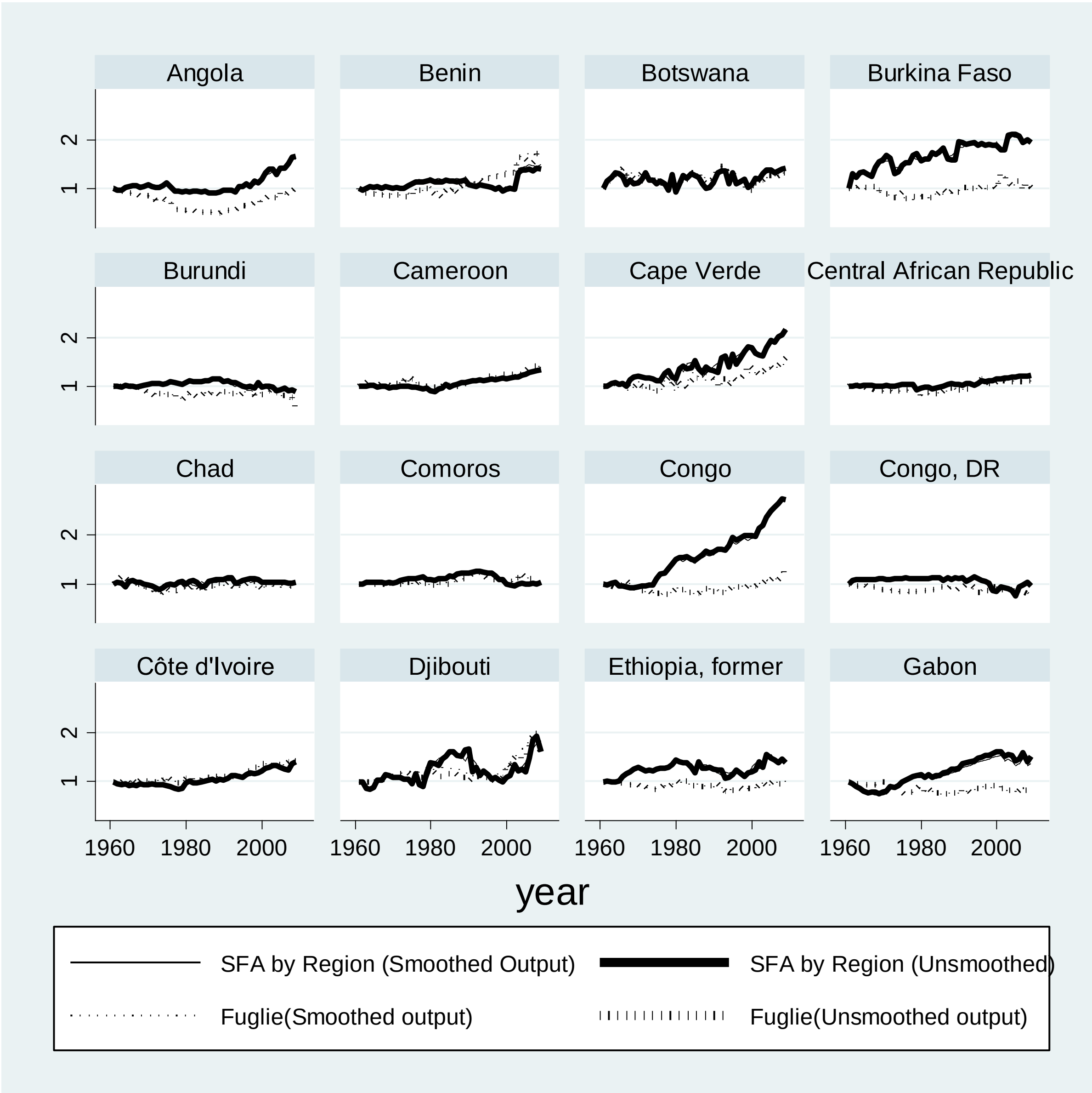

Figure A4.1. Cumulative TFP Index (1961=1) for SSA Countries: Fuglie vs. SFA by Region – Smoothed Data vs. Unsmoothed Data

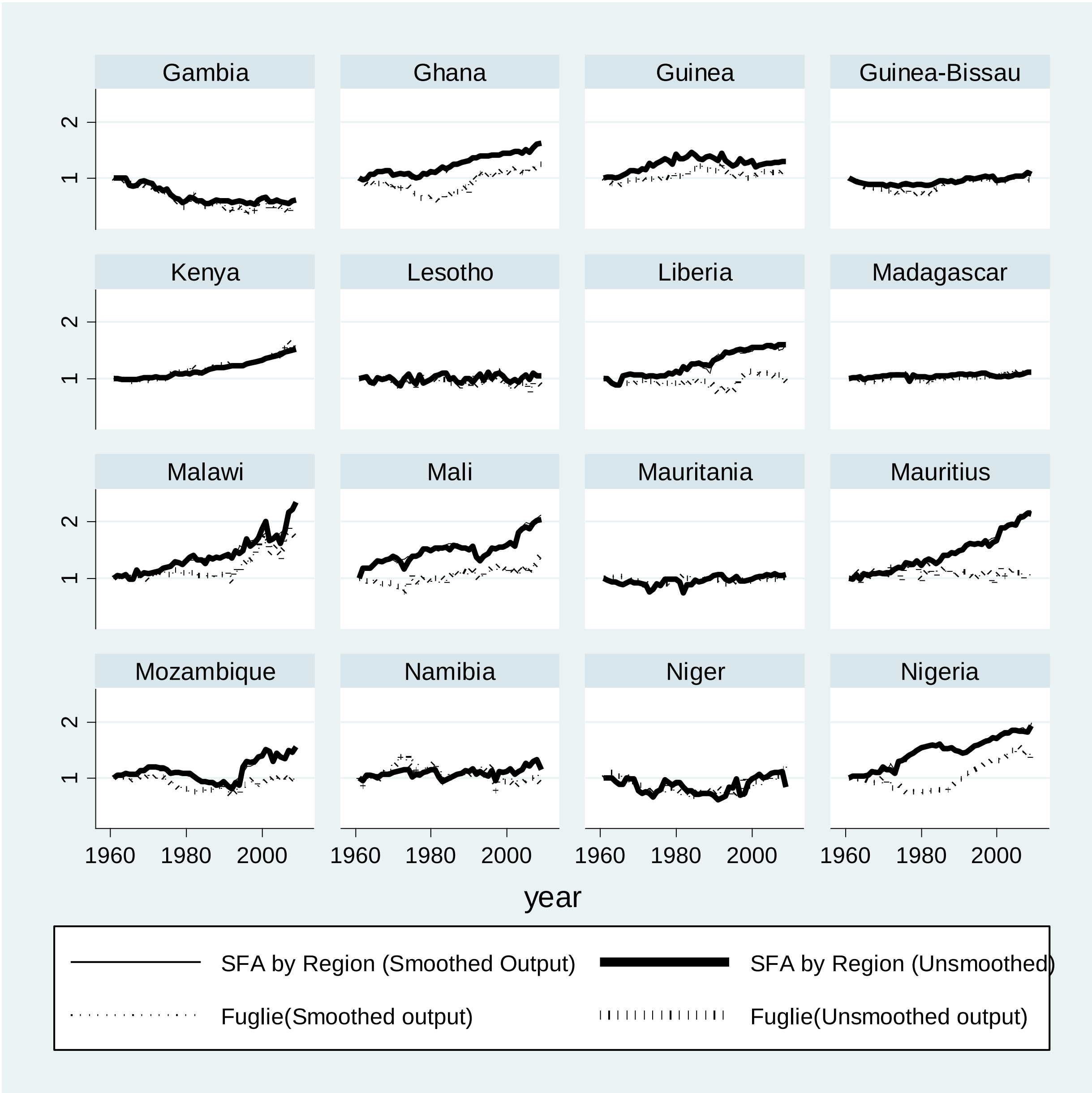

Figure A4.1 (cont'd). Cumulative TFP Index (1961=1) for SSA Countries: Fuglie vs. SFA by Region - Smoothed Data vs. Unsmoothed Data

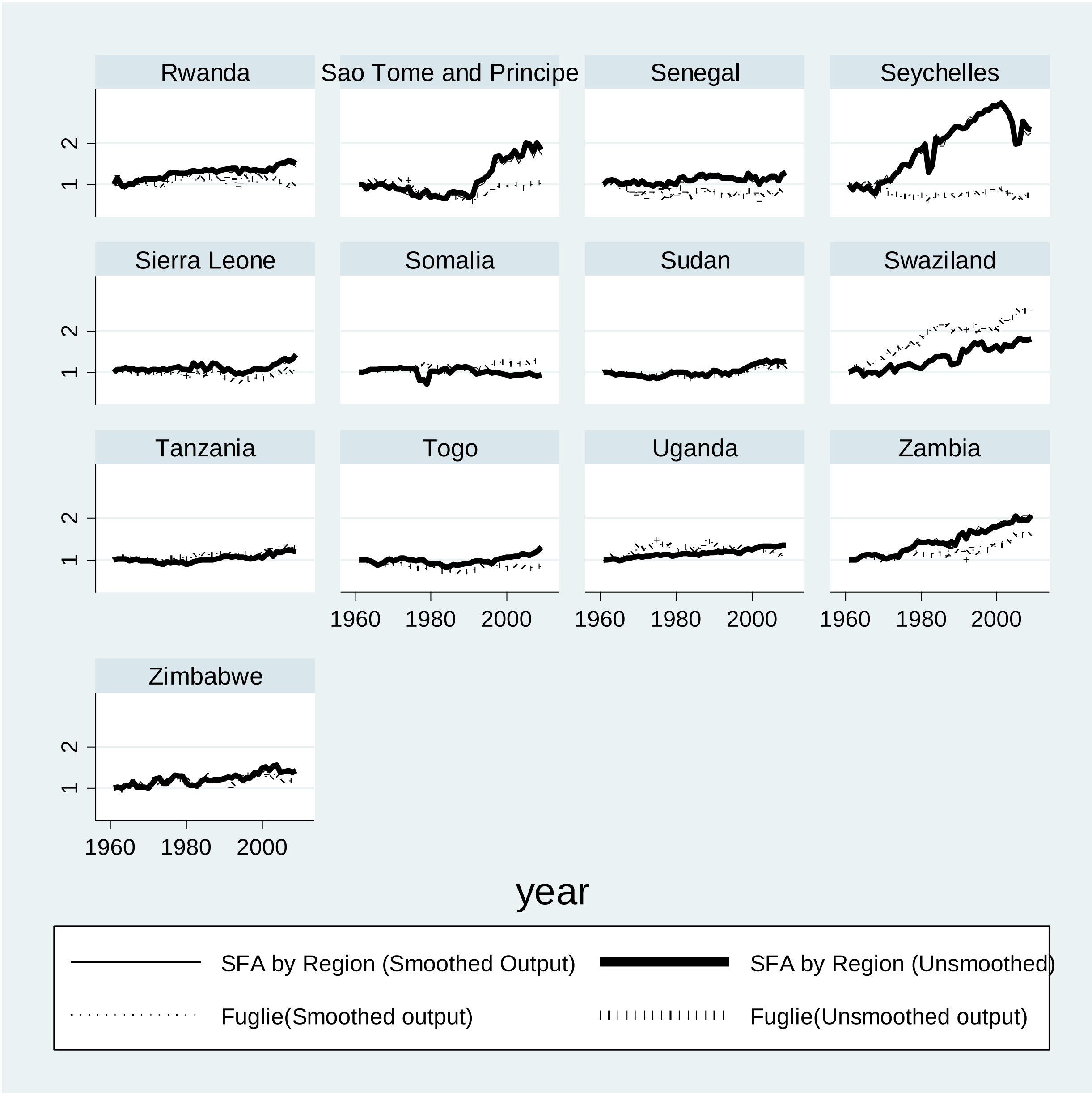

Figure A4.1 (cont'd). Cumulative TFP Index (1961=1) for SSA Countries: Fuglie vs. SFA by Region SSA - Smoothed Data vs. Unsmoothed Data

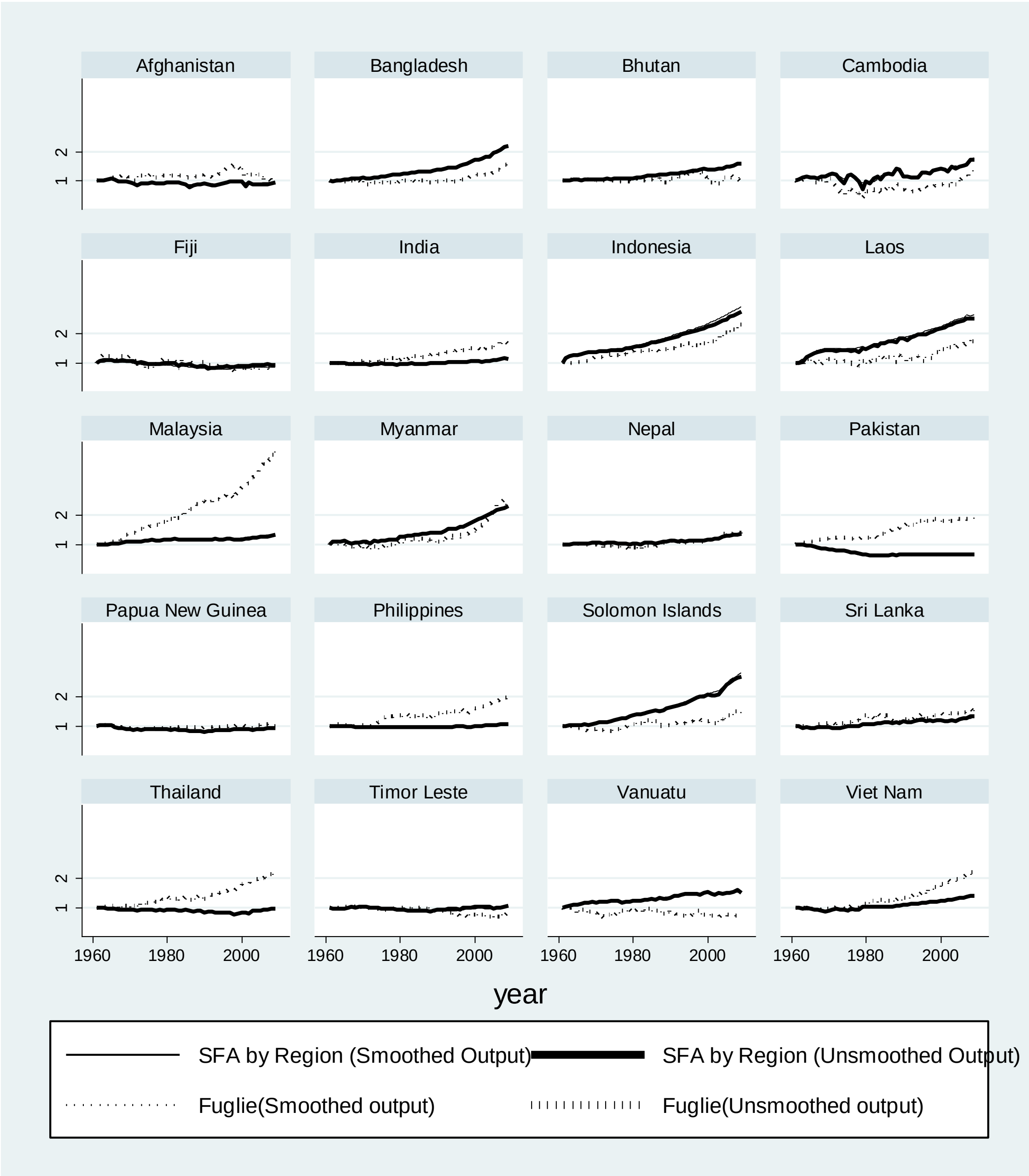

Figure A4.2. Cumulative TFP Index (1961=1) for S. Asia and Oceania Countries: Fuglie vs. SFA by Region - Smoothed Data vs. Unsmoothed Data

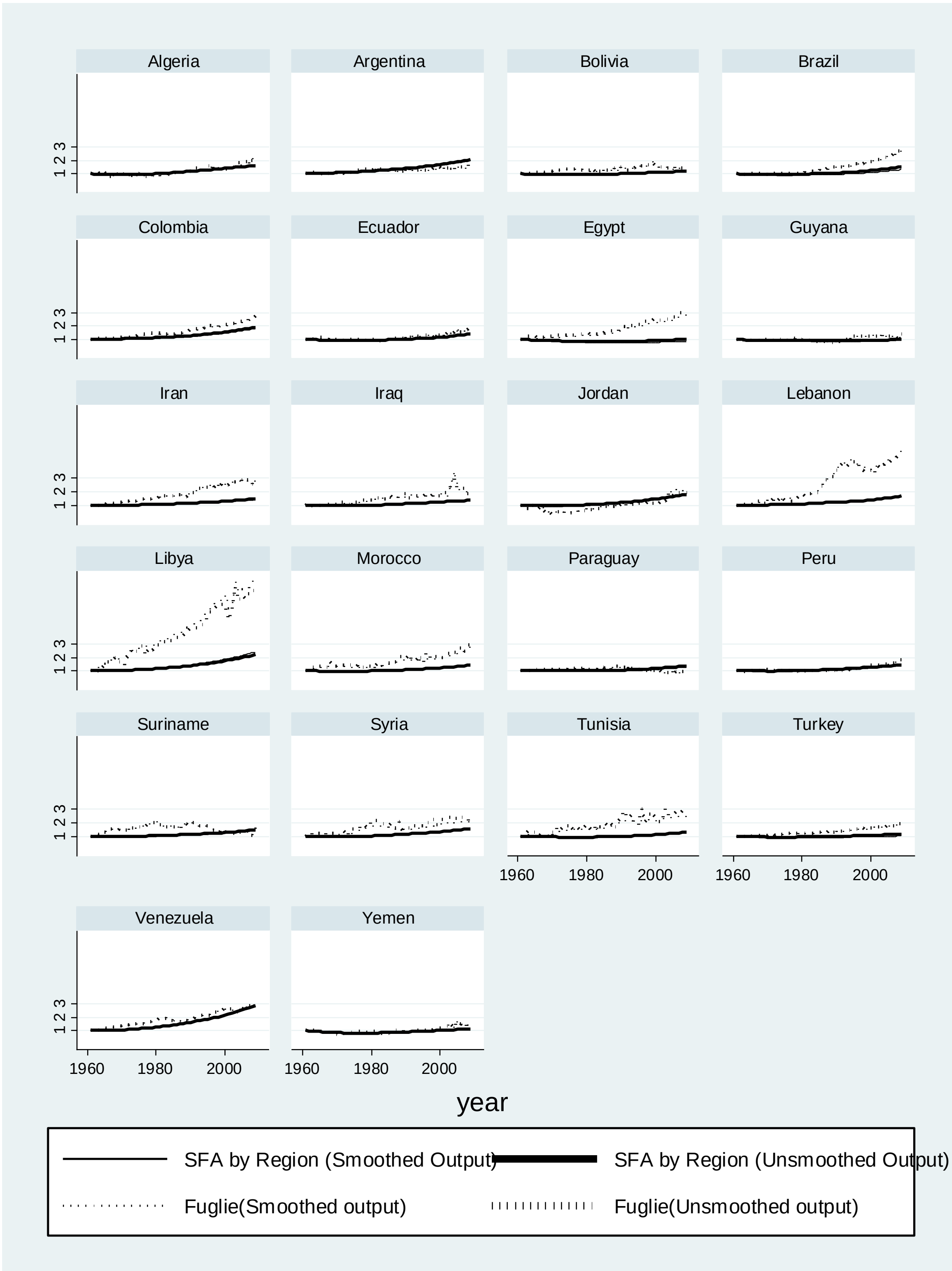

Figure A4.3. Cumulative TFP Index (1961=1) for S. America & MENA Countries: Fuglie vs. SFA by Region - Smoothed Data vs. Unsmoothed Data

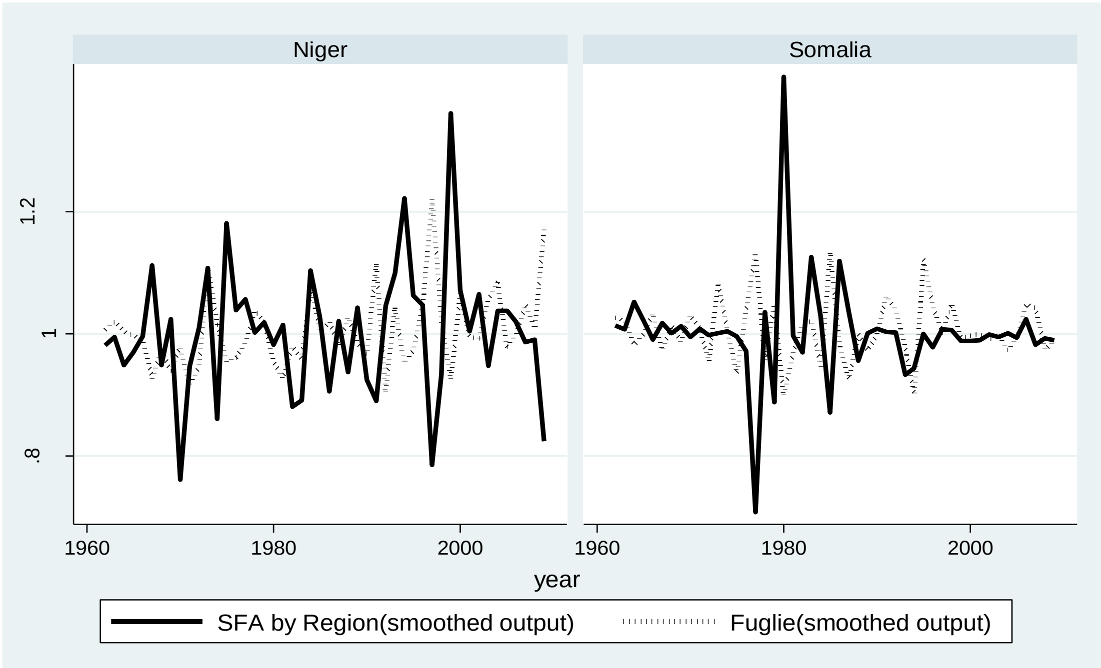

Figure A4.1a. Annual TFP Change Index for Selected SSA Countries: SFA by Region vs. Fuglie - Smoothed Data

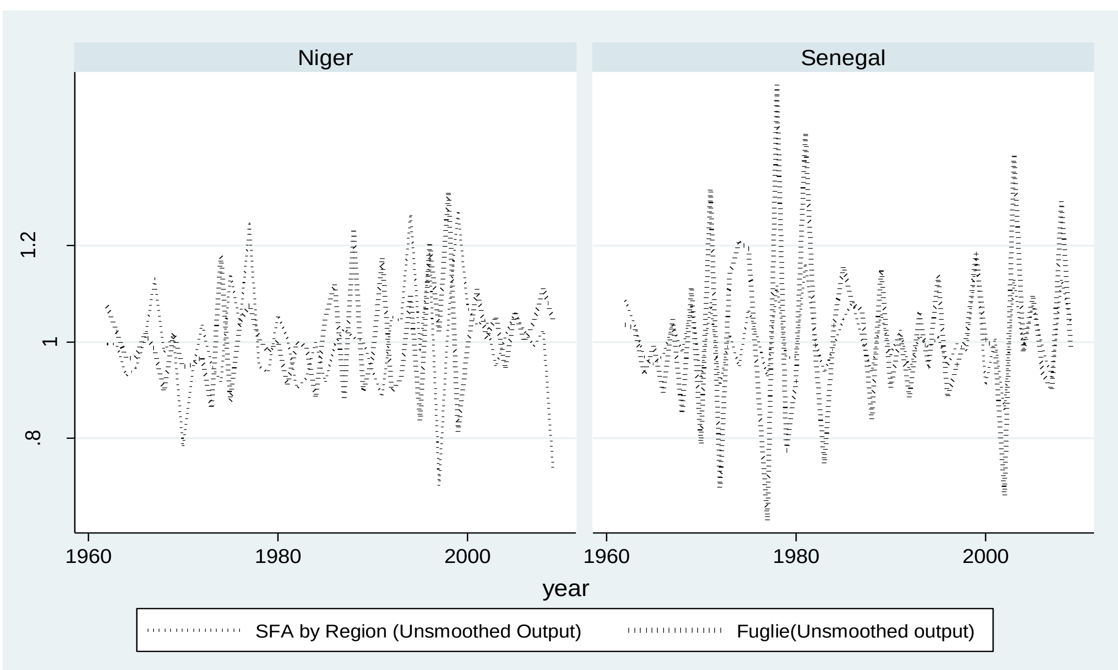

Figure A4.1b. Annual TFP Change Index for Selected SSA Countries: SFA by Region vs. Fuglie - Unsmoothed Data

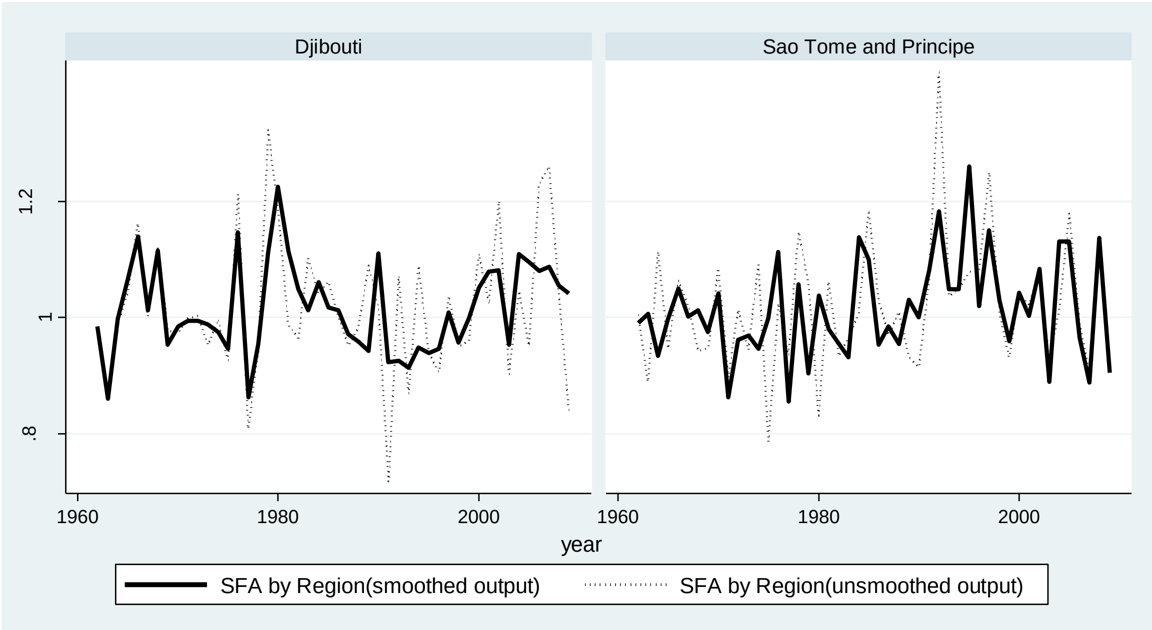

Figure A4.1c. Annual TFP Change Index for Selected SSA Countries: SFA by Region - Smoothed Data vs. Unsmoothed Data

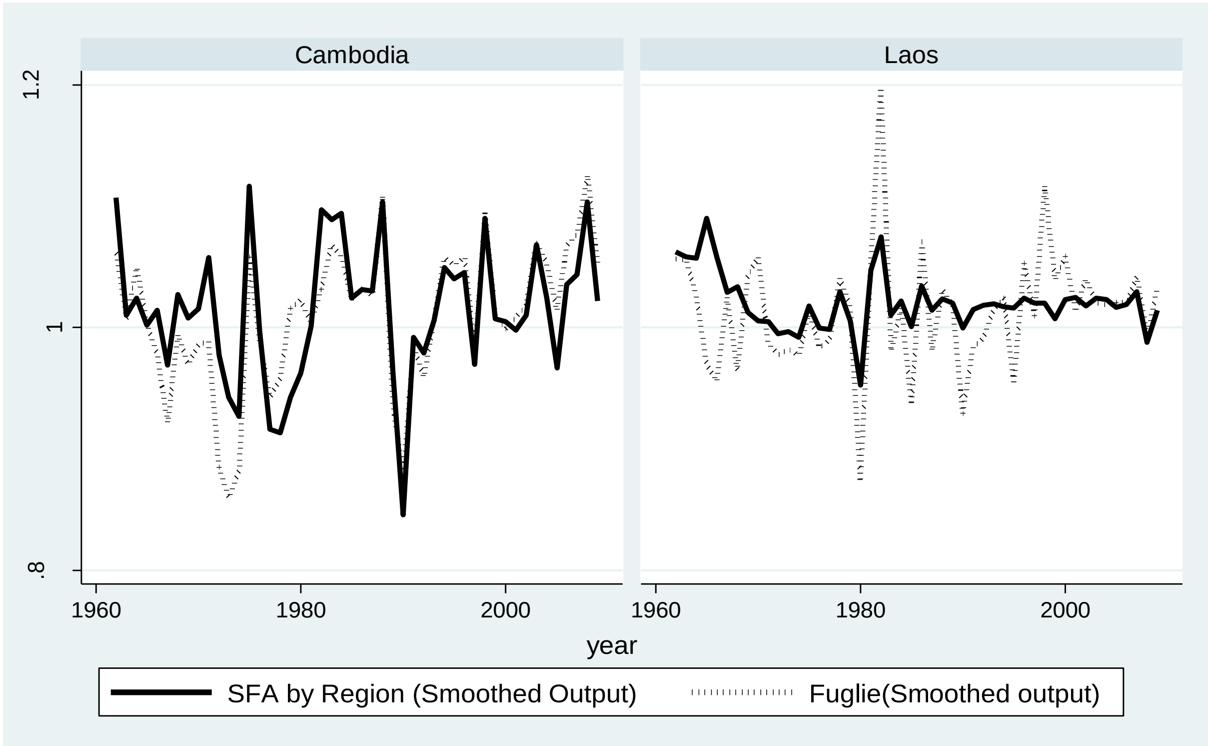

Figure A4.2a. Annual TFP Change Index for Selected S. Asia & Oceania Countries: SFA by Region vs. Fuglie - Smoothed Data

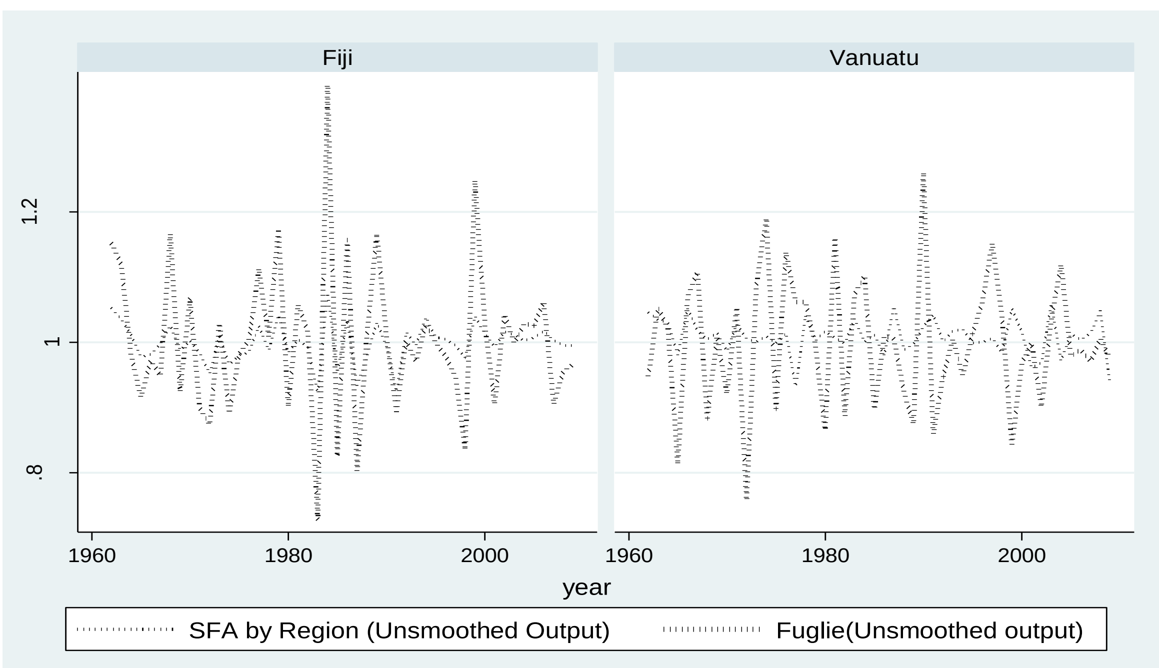

Figure A4.2b. Annual TFP Change Index for Selected S. Asia & Oceania Countries: SFA by Region vs. Fuglie - Unsmoothed Data

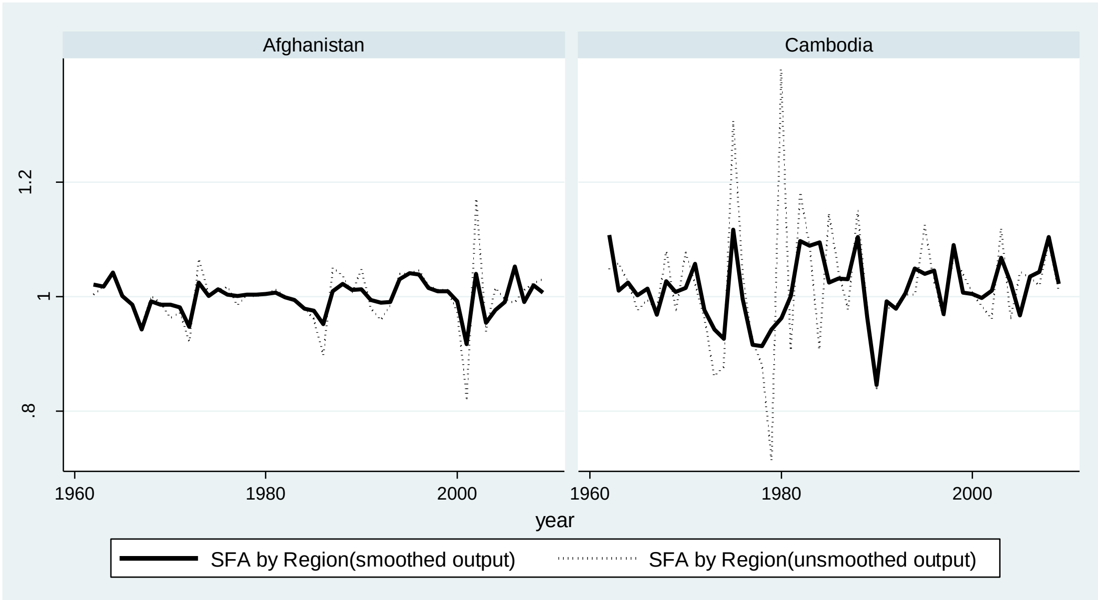

Figure A4.2c. Annual TFP Change Index for Selected S. Asia & Oceania Countries: SFA by Region - Smoothed Data vs. Unsmoothed Data

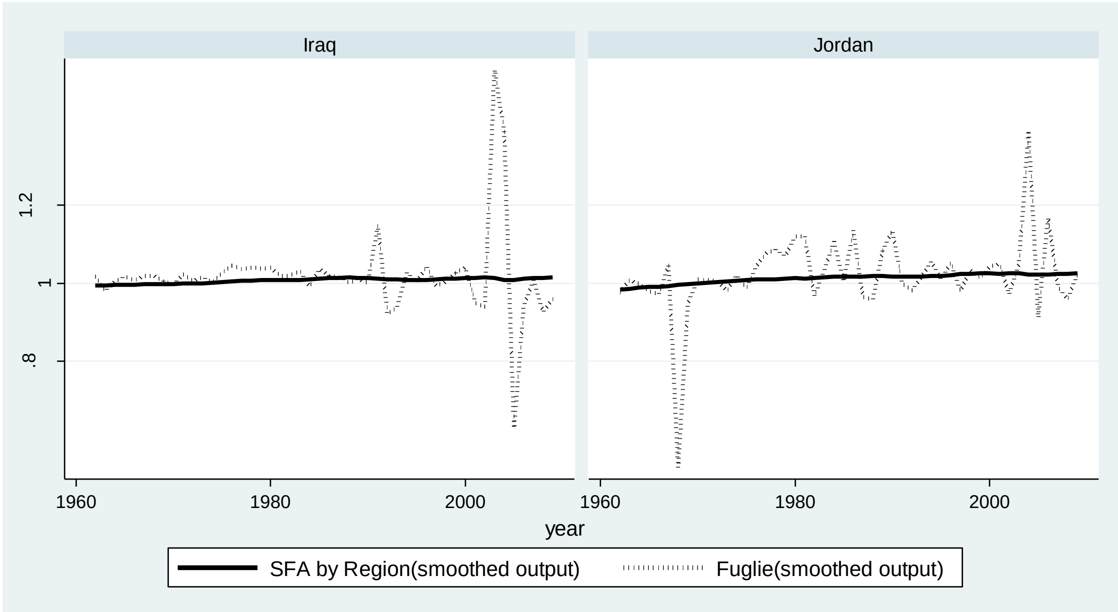

Figure A4.3a. Annual TFP Change Index for Selected S. America & MENA Countries: SFA by Region vs. Fuglie - Smoothed Data

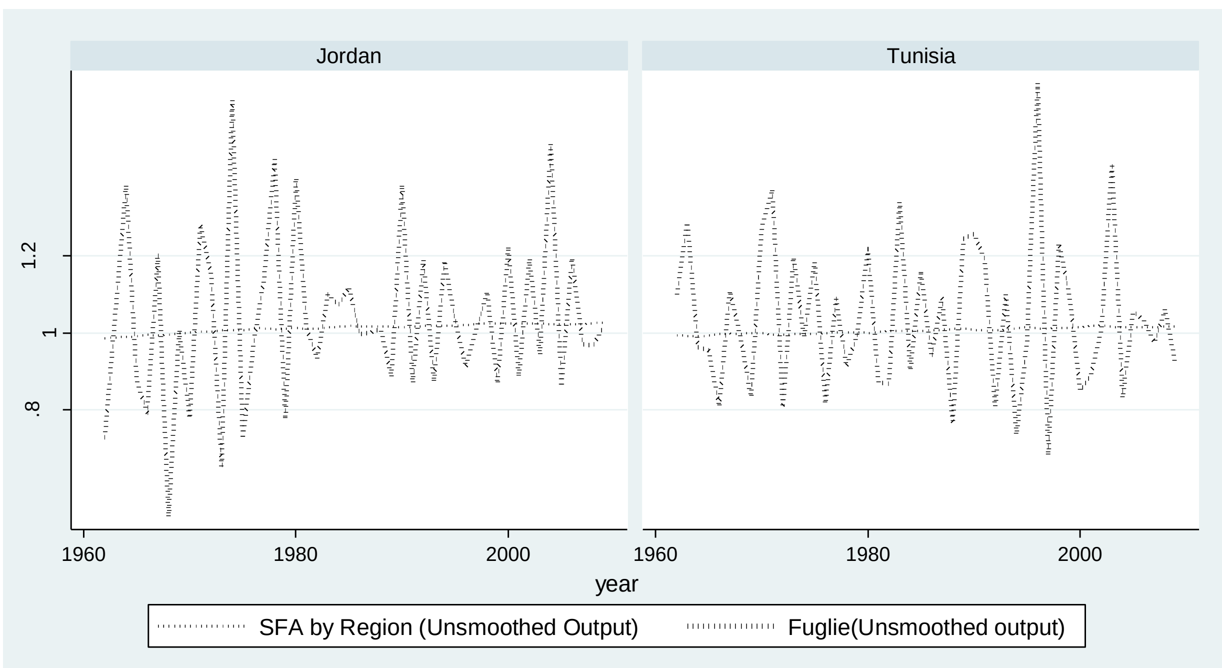

Figure A4.3b. Annual TFP Change Index for Selected S. America & MENA Countries: SFA by Region vs. Fuglie - Unsmoothed Data

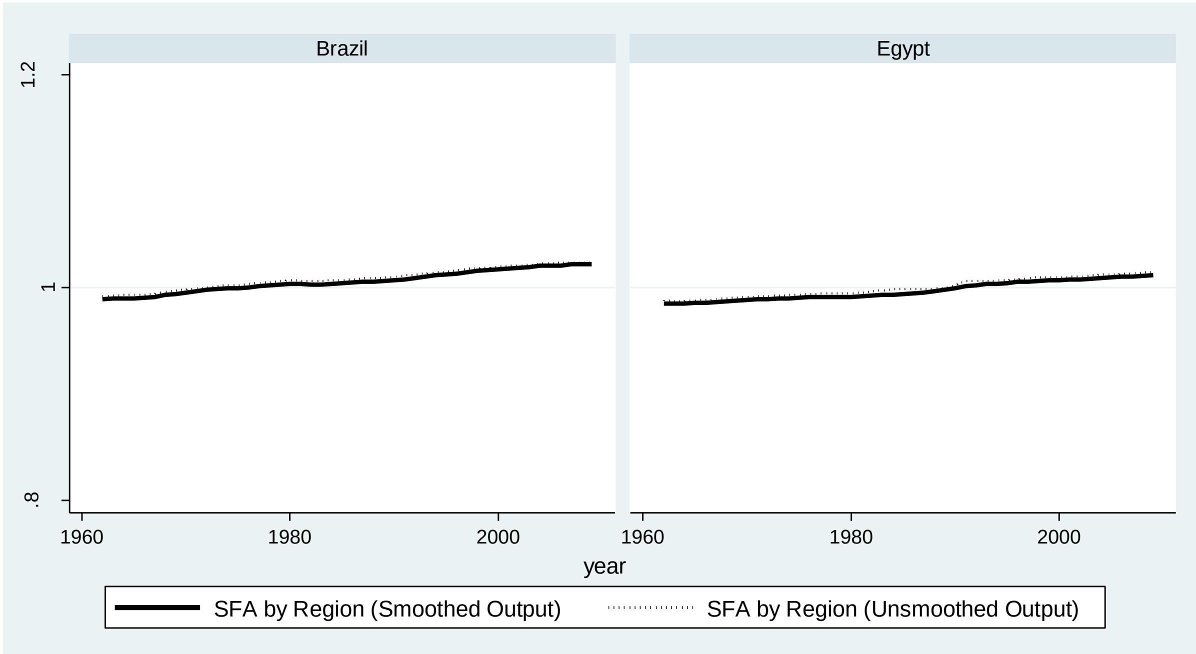

Figure A4.3c. Annual TFP Change Index for Selected S. America & MENA Countries: SFA by Region – Smoothed Data vs. Unsmoothed Data

APPENDIX B

Table B1. Maximum Likelihood Estimation for Income Groups (Smoothed Data)

	Low Income		Lower Middle Income		Upper Middle Income	
Variables	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	-0.1677***	0.0154	-0.1378***	0.0198	-0.0723***	0.0206
Livestock output	0.5499***	0.0174	0.4684***	0.0152	0.5845***	0.0164
(Livestock output)^2	-0.3689***	0.04	0.0781***	0.023	-0.1259**	0.0411
Land	-0.2894***	0.0204	-0.4848***	0.0197	-0.0840***	0.0173
Labor	-0.3127***	0.0163	-0.2435***	0.0118	-0.1282***	0.0126
Live animals	-0.3290***	0.0169	-0.0967***	0.015	-0.3241***	0.0124
Machineries	-0.0272***	0.0058	-0.0360***	0.0075	-0.1212***	0.012
Fertilizers	-0.0013	0.0051	-0.1215***	0.0056	-0.2900***	0.0074
(Land)^2	-0.3666***	0.0483	-0.2389***	0.0409	0.3570***	0.0552
Land*Labor	0.1126**	0.0544	0.0001	0.0222	-0.2530***	0.0233
Land*Live animals	0.3045***	0.0361	0.1247***	0.0424	-0.1917***	0.0369
Land*Machineries	-0.0300**	0.0115	0.1099***	0.0157	-0.0166	0.0276
Land*Fertilizers	-0.0215**	0.0079	0.0175**	0.0087	0.0800***	0.0163
(Labor)^2	-0.4695***	0.0849	-0.3057***	0.019	-0.0798***	0.0177
Labor*Live animals	0.4906***	0.0444	0.4219***	0.0169	0.4262***	0.0188
Labor*Machineries	0.0272*	0.0156	-0.0213**	0.0093	0.0374**	0.0165
Labor*Fertilizers	0.0081	0.0121	-0.0104**	0.0043	-0.1009***	0.0085
(Live animals)^2	-0.8965***	0.051	-0.5532***	0.0421	-0.4348***	0.0423
Live animals * Machineries	-0.0275**	0.0123	-0.0500***	0.0138	0.0861***	0.0188
Live animals * Fertilizers	0.0501***	0.0108	0.0266***	0.0081	0.1121***	0.0128
(Machineries)^2	0.0153**	0.0053	-0.0339***	0.0076	-0.0396**	0.0186
Machineries* Fertilizers	-0.0177***	0.0032	-0.0119**	0.0043	-0.0075	0.0107
(Fertilizers)^2	-0.0079*	0.0043	-0.0354***	0.0042	-0.1143***	0.0073
Land *Livestock output	0.0372	0.032	-0.0286	0.0259	-0.0554	0.0384
Labor *Livestock output	-0.4565***	0.0466	-0.1999***	0.0133	-0.1833***	0.0207
Live animals *Livestock output	0.5939***	0.0417	0.2843***	0.0276	0.4301***	0.0365
Machineries *Livestock output	0.0044	0.0126	0.0312**	0.0127	-0.1272***	0.023
Fertilizers *Livestock output	-0.0550***	0.0092	-0.0353***	0.0068	-0.0833***	0.0127
Livestock output * Time	0.0026**	0.0008	-0.0001	0.0006	-0.0002	0.001
Land * Time	-0.0001	0.0011	-0.0046***	0.001	0.002	0.0013
Labor* Time	-0.0005	0.0012	0.0024***	0.0007	0.0005	0.0008
Live animals * Time	-0.0033***	0.0009	0.0027***	0.0008	0.0011	0.001
Machineries * Time	-0.0006	0.0004	0.0033***	0.0005	-0.0006	0.0008
Fertilizers * Time	0.0007**	0.0003	-0.0027***	0.0002	-0.0021***	0.0004
Time	-0.0075***	0.0004	-0.0076***	0.0004	-0.0123***	0.0005
(Time)^2	-0.0001**	0.0001	-0.0004***	0.0001	-0.0006***	0.0001
GAMMA	0.9668***	0.0101	0.9380***	0.0104	0.7585***	0.034
S2	0.1124***	0.0062	0.1911***	0.0089	0.1150***	0.007

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B1(cont'd). Maximum Likelihood Estimation for Income Groups (Smoothed Data)

	Pooled	
Variables	Estimate	SE
Intercept	0.0612**	0.0255
Livestock output	0.5060***	0.0103
(Livestock output)^2	-0.0888***	0.0149
Land	-0.2850***	0.0105
Labor	-0.1576***	0.0086
Live animals	-0.2713***	0.0103
Machineries	-0.0761***	0.0046
Fertilizers	-0.1754***	0.0037
(Land)^2	0.017	0.0236
Land*Labor	-0.2338***	0.0131
Land*Live animals	0.1822***	0.0206
Land*Machineries	-0.0321***	0.0062
Land*Fertilizers	0.0348***	0.006
(Labor)^2	-0.1470***	0.0132
Labor*Live animals	0.3561***	0.0123
Labor*Machineries	0.0250***	0.0058
Labor*Fertilizers	0.0099**	0.0038
(Live animals)^2	-0.5697***	0.024
Live animals * Machineries	0.0130**	0.0059
Live animals * Fertilizers	0.0413***	0.0049
(Machineries)^2	-0.0024	0.0035
Machineries* Fertilizers	-0.0075**	0.0025
(Fertilizers)^2	-0.0665***	0.0024
Land *Livestock output	-0.0612***	0.0124
Labor *Livestock output	-0.2087***	0.0106
Live animals *Livestock output	0.3149***	0.0158
Machineries *Livestock output	-0.0435***	0.0051
Fertilizers *Livestock output	-0.0256***	0.0042
Livestock output * Time	-0.0005	0.0005
Land * Time	0.0002	0.0006
Labor* Time	-0.0003	0.0005
Live animals * Time	0.0011*	0.0006
Machineries * Time	0.0002	0.0002
Fertilizers * Time	-0.0008***	0.0002
Time	-0.0066***	0.0003
(Time)^2	-0.0005***	0
GAMMA	0.6038***	0.0704
S2	0.1544***	0.0123

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B2. Maximum Likelihood Estimation for Income Groups (Unsmoothed Data)

	Low Income		Lower Middle Income		Upper Middle Income	
Variables	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	-0.1550***	0.017	-0.1242***	0.0199	-0.7741***	0.0212
Livestock output	0.5690***	0.0178	0.4730***	0.0152	0.5911***	0.0163
$(\text{Livestock output})^2$	-0.3369***	0.0419	0.0422**	0.0214	-0.1334***	0.0399
Land	-0.3024***	0.0217	-0.4881***	0.02	-0.0796***	0.0178
Labor	-0.2895***	0.0172	-0.2399***	0.012	-0.1287***	0.0127
Live animals	-0.3436***	0.018	-0.0998***	0.0152	-0.3256***	0.0126
Machineries	-0.0237***	0.006	-0.0329***	0.0075	-0.1231***	0.0123
Fertilizers	-0.0033	0.0054	-0.1251***	0.0058	-0.2941***	0.0075
$(\text{Land})^2$	-0.3844***	0.0511	-0.2560***	0.0411	0.3941***	0.056
Land*Labor	0.08	0.0543	-0.0164	0.0223	-0.2557***	0.0237
Land*Live animals	0.3704***	0.0369	0.1664***	0.0417	-0.2269***	0.0373
Land*Machineries	-0.0333**	0.0118	0.1062***	0.0159	-0.0227	0.0281
Land*Fertilizers	-0.0213**	0.0085	0.0161*	0.0092	0.0889***	0.0166
$(\text{Labor})^2$	-0.4036***	0.0843	-0.2971***	0.0192	-0.0856***	0.018
Labor*Live animals	0.4441***	0.0449	0.4238***	0.0172	0.4275***	0.0193
Labor*Machineries	0.0233	0.0157	-0.0225**	0.0093	0.0444**	0.0168
Labor*Fertilizers	0.0112	0.0127	-0.0079*	0.0045	-0.0999***	0.0087
$(\text{Live animals})^2$	-0.9032***	0.0513	-0.5960***	0.0414	-0.3883***	0.043
Live animals * Machineries	-0.0290**	0.0123	-0.0491***	0.014	0.0870***	0.0191
Live animals * Fertilizers	0.0494***	0.0111	0.0281***	0.0084	0.0986***	0.013
$(\text{Machineries})^2$	0.0191***	0.0055	-0.0345***	0.0078	-0.0409**	0.019
Machineries* Fertilizers	-0.0180***	0.0033	-0.0102**	0.0044	-0.0071	0.0108
$(\text{Fertilizers})^2$	-0.0107**	0.0047	-0.0383***	0.0043	-0.1127***	0.0074
Land *Livestock output	-0.0061	0.0316	-0.0528**	0.0249	-0.0306	0.0379
Labor *Livestock output	-0.4009***	0.0473	-0.2076**	0.0133	-0.1878***	0.0208
Live animals *Livestock output	0.5612***	0.0423	0.3173***	0.0264	0.3992***	0.0361
Machineries *Livestock output	0.0057	0.0127	0.0286**	0.0127	-0.1227***	0.023
Fertilizers *Livestock output	-0.0552***	0.0091	-0.0369***	0.0072	-0.0788***	0.0127
Livestock output * Time	0.0023**	0.0009	0	0.0006	-0.0008	0.001
Land * Time	-0.0001	0.0011	-0.0045***	0.001	0.0016	0.0014
Labor* Time	-0.0009	0.0013	0.0024***	0.0007	0.0001	0.0008
Live animals * Time	-0.0027**	0.0009	0.0028***	0.0008	0.0019	0.001
Machineries * Time	-0.0007*	0.0004	0.0035***	0.0005	-0.0005	0.0008
Fertilizers * Time	0.0008**	0.0003	-0.0027***	0.0003	-0.0022***	0.0004
Time	-0.0076***	0.0004	-0.0076***	0.0005	-0.0122***	0.0005
$(\text{Time})^2$	-0.0001**	0.0001	-0.0005***	0.0001	-0.0006***	0.0001
GAMMA	0.9579***	0.0143	0.9307***	0.0121	0.7504***	0.0359
S2	0.1136***	0.0071	0.1939***	0.0094	0.1190***	0.0074

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B2 (cont'd). Maximum Likelihood Estimation for Income Groups (Unsmoothed Data)

	Pooled	
Variables	Estimate	SE
Intercept	0.0729**	0.028
Livestock output	0.5134***	0.0103
$(\text{Livestock output})^2$	-0.0877***	0.0146
Land	-0.2854***	0.0106
Labor	-0.1529***	0.0087
Live animals	-0.2772***	0.0104
Machineries	-0.0752***	0.0046
Fertilizers	-0.1756***	0.0037
$(\text{Land })^2$	0.0205	0.0239
Land*Labor	-0.2342***	0.0131
Land*Live animals	0.1795***	0.0207
Land*Machineries	-0.0313***	0.0062
Land*Fertilizers	0.0342***	0.0061
$(\text{Labor})^2$	-0.1452***	0.0133
Labor*Live animals	0.3549***	0.0123
Labor*Machineries	0.0239***	0.0058
Labor*Fertilizers	0.0111**	0.0039
$(\text{Live animals})^2$	-0.5655***	0.024
Live animals * Machineries	0.0133**	0.006
Live animals * Fertilizers	0.0400***	0.005
$(\text{Machineries})^2$	-0.0028	0.0036
Machineries* Fertilizers	-0.0074**	0.0025
$(\text{Fertilizers})^2$	-0.0662***	0.0024
Land *Livestock output	-0.0609***	0.0123
Labor *Livestock output	-0.2061***	0.0106
Live animals *Livestock output	0.3108***	0.0157
Machineries *Livestock output	-0.0427***	0.0051
Fertilizers *Livestock output	-0.0244***	0.0042
Livestock output * Time	-0.0006	0.0005
Land * Time	0.0002	0.0006
Labor* Time	-0.0003	0.0005
Live animals * Time	0.0012**	0.0006
Machineries * Time	0.0002	0.0002
Fertilizers * Time	-0.0008***	0.0002
Time	-0.0066***	0.0003
$(\text{Time})^2$	-0.0005***	0.0001
GAMMA	0.5642***	0.0802
S2	0.1508***	0.0129

Note: *** p<0.01, ** p<0.05, * p<0.1

Table B3. Maximum Likelihood Estimation for Regional Groups (Smoothed Data)

	S. Asia & Oceania		SSA		S. America & MENA	
Variables	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	0.0998**	0.0422	-0.1994***	0.0173	0.0288	0.1242
Livestock output	0.2594***	0.0195	0.6199***	0.0133	0.7017***	0.0320
(Livestock output)^2	-0.0427	0.0528	0.1202***	0.0189	1.0613***	0.1325
Land	-0.5913***	0.0227	-0.3851***	0.0160	0.2186***	0.0311
Labor	-0.3022***	0.0179	-0.2244***	0.0136	-0.1121***	0.0219
Live animals	0.1004***	0.0237	-0.2897***	0.0131	-0.5764***	0.0179
Machineries	-0.0249***	0.0059	-0.0667***	0.0045	-0.3366***	0.0239
Fertilizers	-0.0975***	0.0064	-0.0237***	0.0042	-0.1721***	0.0131
(Land)^2	0.0686	0.0727	-0.3726***	0.0455	-0.4599***	0.0725
Land*Labor	0.2377***	0.0504	0.1808***	0.0342	0.0336	0.0454
Land*Live animals	-0.1380**	0.0567	0.2889***	0.0320	-0.0441	0.0541
Land*Machineries	0.0064	0.0101	-0.1280***	0.0083	0.4786***	0.0547
Land*Fertilizers	-0.0673***	0.0103	0.0324***	0.0099	-0.0499*	0.0302
(Labor)^2	-0.5185***	0.0534	-0.2255***	0.0470	0.0760	0.0488
Labor*Live animals	0.1994***	0.0491	-0.0877***	0.0265	0.0583	0.0472
Labor*Machineries	0.1347***	0.0136	0.0244**	0.0085	-0.0469	0.0360
Labor*Fertilizers	-0.0277***	0.0081	0.0818***	0.0082	-0.0387*	0.0206
(Live animals)^2	-0.1851**	0.0778	-0.2764***	0.0311	0.0101	0.0685
Live animals * Machineries	-0.0531***	0.0138	0.0993***	0.0070	-0.1343***	0.0341
Live animals * Fertilizers	0.0796***	0.0096	-0.0491***	0.0078	0.0896***	0.0190
(Machineries)^2	-0.0526***	0.0065	0.0314***	0.0044	-0.4082***	0.0450
Machineries* Fertilizers	-0.0261***	0.0040	-0.0209***	0.0025	0.1267***	0.0210
(Fertilizers)^2	0.0145**	0.0051	-0.0119***	0.0034	-0.0801***	0.0113
Land *Livestock output	0.2799***	0.0342	-0.0524**	0.0216	0.1861**	0.0745
Labor *Livestock output	-0.5744***	0.0354	0.0134	0.0209	-0.0471	0.0452
Live animals *Livestock output	0.3892***	0.0345	0.0557**	0.0215	-0.2632***	0.0707
Machineries *Livestock output	-0.0768***	0.0129	-0.0908***	0.0054	-0.0833	0.0535
Fertilizers *Livestock output	-0.0086	0.0095	0.0792***	0.0055	0.0638**	0.0325
Livestock output * Time	0.0108***	0.0009	0.0014**	0.0006	-0.0152***	0.0023
Land * Time	0.0019	0.0014	0.0021**	0.0009	-0.0030	0.0023
Labor* Time	-0.0020***	0.0008	0.0014*	0.0007	0.0032**	0.0013
Live animals * Time	-0.0028**	0.0011	-0.0003	0.0008	0.0035**	0.0017
Machineries * Time	0.0023***	0.0005	-0.0017***	0.0002	0.0019	0.0015
Fertilizers * Time	0.0004	0.0003	-0.0003	0.0002	-0.0036***	0.0008
Time	-0.0064***	0.0006	-0.0080***	0.0004	-0.0081***	0.0009
(Time)^2	-0.0006***	0.0001	-0.0003***	0.0001	-0.0003***	0.0001
GAMMA	0.6059***	0.1294	0.9560***	0.0104	0.0000	0.0034
S2	0.0360***	0.0054	0.1583***	0.0076	0.0455***	0.0020

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B4. Maximum Likelihood Estimation for Regional Groups (Unsmoothed Data)

	S. Asia & Oceania		SSA		S. America & MENA	
Variables	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	0.1137**	0.0395	-0.1816***	0.0179	0.0314	0.1523
Livestock output	0.2810***	0.0194	0.6243***	0.0140	0.7127***	0.0299
$(\text{Livestock output})^2$	-0.0872*	0.0503	0.1045***	0.0194	0.7919***	0.1077
Land	-0.5766***	0.0221	-0.4016***	0.0162	0.2027***	0.0309
Labor	-0.3011***	0.0187	-0.2071***	0.0144	-0.1009***	0.0219
Live animals	0.0822***	0.0236	-0.2929***	0.0138	-0.5879***	0.0178
Machineries	-0.0265***	0.0061	-0.0617***	0.0045	-0.3254***	0.0238
Fertilizers	-0.0984***	0.0065	-0.0269***	0.0042	-0.1716***	0.0132
$(\text{Land })^2$	0.0827	0.0751	-0.3951***	0.0466	-0.4216***	0.0727
Land*Labor	0.2169***	0.0521	0.1848***	0.0349	0.0184	0.0447
Land*Live animals	-0.1287**	0.0576	0.3088***	0.0332	-0.0438	0.0528
Land*Machineries	0.0043	0.0105	-0.1319***	0.0084	0.4355***	0.0537
Land*Fertilizers	-0.0693***	0.0107	0.0366***	0.0102	-0.0457	0.0296
$(\text{Labor})^2$	-0.5511***	0.0546	-0.2356***	0.0466	0.1067***	0.0480
Labor*Live animals	0.2473***	0.0479	-0.0819**	0.0269	0.0399	0.0470
Labor*Machineries	0.1295***	0.0139	0.0251**	0.0085	-0.0328	0.0360
Labor*Fertilizers	-0.0216**	0.0079	0.0816***	0.0084	-0.0409***	0.0204
$(\text{Live animals})^2$	-0.2395**	0.0768	-0.3047***	0.0322	0.0117	0.0664
Live animals * Machineries	-0.0481**	0.0143	0.1002***	0.0072	-0.1297***	0.0335
Live animals * Fertilizers	0.0775***	0.0099	-0.0495***	0.0080	0.0906***	0.0186
$(\text{Machineries})^2$	-0.0507***	0.0068	0.0321***	0.0045	-0.3838***	0.0448
Machineries* Fertilizers	-0.0256***	0.0042	-0.0210***	0.0026	0.1293***	0.0208
$(\text{Fertilizers})^2$	0.0125*	0.0050	-0.0136***	0.0035	-0.0827***	0.0114
Land *Livestock output	0.2585***	0.0351	-0.0606**	0.0223	0.1499**	0.0652
Labor *Livestock output	-0.5884***	0.0334	0.0115	0.0208	-0.0573	0.0423
Live animals *Livestock output	0.4105***	0.0338	0.0724***	0.0223	-0.1701**	0.0596
Machineries *Livestock output	-0.0676***	0.0128	-0.0918***	0.0054	-0.0684	0.0493
Fertilizers *Livestock output	-0.0087	0.0094	0.0770***	0.0056	0.0579*	0.0310
Livestock output * Time	0.0103***	0.0009	0.0008	0.0006	-0.0128***	0.0022
Land * Time	0.0026*	0.0014	0.0014	0.0009	-0.0009	0.0023
Labor* Time	-0.0021**	0.0008	0.0012	0.0007	0.0030**	0.0013
Live animals * Time	-0.0031**	0.0011	0.0005	0.0008	0.0020	0.0017
Machineries * Time	0.0020***	0.0005	-0.0016***	0.0002	0.0008	0.0015
Fertilizers * Time	0.0004	0.0003	-0.0002	0.0002	-0.0033***	0.0008
Time	-0.0063***	0.0006	-0.0079***	0.0004	-0.0084***	0.0008
$(\text{time})^2$	-0.0005***	0.0001	-0.0003***	0.0001	-0.0003**	0.0001
GAMMA	0.6039	0.1146	0.9410***	0.0141	0.0000	0.0049
S2	0.0397	0.0054	0.1542***	0.0081	0.0475***	0.0021

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$