ANNUAL HARD FROSTS AND ECONOMIC GROWTH

The members of the Committee approve
the doctoral dissertation of Xinjuan Zuo

Supervising Professor	Prof. Dr. Michael Funke
Committee Member	Prof. Dr. Richard Tol
Dean of Graduate School	Prof. Dr. Christian Scheer

Universität Hamburg

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To my parents

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TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

LIST OF TABLES

CHAPTER 1

INTRODUCTION

The state of the whole commercial world can seldom be much affected by the improvement of any particular country; and the market for such commodities may remain the same or very nearly the same after such improvements as before. It should, however, in the natural course of things rather upon the whole be somewhat extended in consequence of them. If the manufactures, especially, of which those commodities are the materials should ever come to flourish in the country, the market, though it might not be much enlarged, would at least be brought much nearer to the place of growth than before; and the price of those materials might at least be increased by what had usually been the expense of transporting them to distant countries. Though it might not rise therefore in the same proportion as that of butcher's meat, it ought naturally to rise somewhat, and it ought certainly not to fall.

Adam Smith (1776)

Economists have sought to understand the processes and frameworks of economic growth across countries since Adam Smith developed the modern concept of economic growth in 1776. Two centuries later, Robert Solow observed some additional advantages of economic concepts and developed the standard neoclassical model of economic growth. The neoclassical perspective led some to argue that some countries achieve large increases in output over extended periods of time that in turn dramatically changes the general economic, political, and institutional landscape. The link between economic growth and a wider concept of “determinants” is, however, controversial.

In the 1980s, many economists argue against the assumption in the Solow model that the permanent changes in conventional government policies have no permanent effects on an economy's long-term growth. Paul Romer (1986) presents a profound finding that the long-term growth is clearly endogenous. The key determinants of long-term growth, rather than by some exogenously growing variables such as unexplained technological change, are the reason for the name endogenous growth.

Despite the vast literature on empirical growth studies following the papers of Sachs and Warner (1995), and Hall and Jones (1999), the empirical work attempted that has tried explain the dynamics of growth has identified a number of variables that only partially directly correlate with economic growth. The major problem is the lack of an explicit theory about the exact true causality of growth model.

Why are some so rich and some so poor? Gallup et al. (1999) focus on the significant impacts of geography on economic development. They found that geography directly impacts growth, controlling economic policies and institutions, and the effects of geography on policy choices and institutions. The geography variables used in the model are the geographical proportion of land in the tropics, the proportion of land in the ecological tropics, the prevalence of malaria, hydrocarbon deposits, and regional dummy variables. Following the natural resources research, Jeffrey Sachs has emphasized the impact of human health on economic development, particularly, malaria in Africa.

An empirical study, by Acemoglu et al. (2001), argues that the geography mechanism works entirely through institutions. Acemoglu et al. (2001) present the evidence on the significant role geography plays in explaining the establishment of early institutions. On the contrary, Rodrik (2002) claims that geography plays both direct and indirect roles in the growth model.

A solution to the reasonable question of how to "go further" is proposed by Masters and McMillan (2001), who introduce a new climate variable labeled "annual hard frosts" that directly impacts economic growth. They note, however, as Masters and McMillan (2001) paraphrase above, that their aggregate measures choose a climate threshold that may perhaps be arbitrary. There are also various initially more substantial obstacles that can contribute to an incomplete picture and thus lead to possibly wrong conclusions since not all assumptions of the model uncertainty then hold.

This study contributes to the debate on growth empirics by empirically identifying robust determinants of per capita growth rates across the world. The study is organized as follows: Chapter 2 starts with a short retrospective regarding climate impact on economic growth rate along with a few remarks on robustness in econometrics. Subsequently, I present an introduction to several extensions and empirical applications of robust estimation techniques which are both addressed and discussed.

The following Chapter 3 applies the quantile regression procedure to the analysis of the economic growth model. The impact of climate factor on the conditional distribution of per capita income growth is considered. The obtained results vary significantly for different economic development. In next section, Chapter 4, the climate proxy "annual hard frosts" needs to be robustly linked to technical efficiency in agriculture. Finally, a brief summary is offered in Chapter 5.

CHAPTER 2

ANNUAL HARD FROSTS AND ECONOMIC DEVELOPMENT

2.1 Introduction

Many empirical studies of the growth of countries have tried to investigate which factors matter most for economic growth. For many years economists has emphasized the importance of factor endowments, good economic policy (openness to trade, exchange rate system, inflation, and investment climate) and institutions (political stability, property rights, and legal systems) that are conducive to growth. Other economists have put a greater weight on climate and geography (which affects the incidence of disease, agricultural opportunities, as well as the applicability of some technologies) as well as access to the sea (which affects the scope for trade).[1]

Climate is an important factor that influences human health and agricultural productivity. Tropical areas are consistently poorer than temperate zone areas, because of the intrinsic effects of tropical ecology on human health and agricultural productivity. Tropical infectious diseases impose very high burdens on human health, which may lead to shortfalls in economic performance.

The influential paper by Masters and McMillan (2001) tests the importance of these alternative hypotheses, looking at a sample of about 90 rich and poor countries. They apply different data sources measuring climate, frostdays, as proxy for climate factors. The studies find a correlation between climate and economic growth using frostdays. The growth regression shows that countries with more frostdays in winter time had dramatically higher economic growth in the subsequent years, after controlling for other factors that likely influenced growth, like initial income level, initial human capital formation, and ethnolingustic heterogeneity. Their main conclusion is that one factor differentiating wealthy

[1] Geographic isolation can be costly because it lowers international integration. This helps to explain, for example, why U.S. economic development is concentrated at its ocean and Great Lakes coasts [see Rappaport and Sachs (2003)].

countries from poor includes winter frosts, which reduces insect borne disease. Annual hard frosts can also improve agricultural success by allowing a buildup of organic matter that leads to rich, fertile topsoil, and by ensuring moist soils in the spring. In other words, hard frosts boost economic development.

This explanatory factor, however, is not mutually exclusive. The recent paper by Easterly and Levine (2003) has also tested the relative importance of geography versus institutions and policy. The results are intriguing. Institutions turn out to matter most for growth, while geography and policy don't matter at all. The general conclusion is that countries with good institutions tend to do all right with policies. In the same way, countries with bad institutions tend to do badly regardless. Other studies have found that geography affects institutions. Favorable geography promotes good institutions; good institutions then promote development.[2] The occurrence of conflicting studies evokes a legitimate quest for an assessment of the robustness of research findings. This paper therefore re-examines the cross-sectional link between annual hard frosts and economic growth.[3] One believes that by outlining existing methodological difficulties and by suggesting methods to solve some of these problems, the paper constitutes a further step towards developing a framework for the frost-growth nexus.

The paper is organized as follows. Section 2.2 reviews the discussion on the robustness of empirical economic growth studies and revisits the frost-growth nexus. Where there are differences in results, I identify and discuss the source of the differences and explain

[2] For a critical view, see Sachs (2003). Recently a few other papers have carried out somewhat similar analyses. Acemoglu et al. (2001) investigate a variety of seventeenth- to nineteenth-century European colonial strategies. Where settler mortality was low, because geography and climate were conducive to good health, Europeans moved in and planted good institutions (examples include the United States, Australia and New Zealand). Where settler mortality was high, because of bad geography and diseases, they stayed away and planted bad institutions (examples include much of sub-Saharan Africa and Latin America). These institutions, good and bad, put down roots explaining the pattern of modern world income distribution. The paper focuses in particular on institutional developments among former colonies of European countries; it is therefore not directly applicable to many other countries that were not subject to colonization.

[3] Cross-sectional growth empirics has come under attack by those who advocate panel data studies because the cross-sectional framework permits a very limited treatment of problems of estimation resulting from parameter heterogeneity [among them are Islam (1995) and Caselli et al. (1996)]. Panel data methods, however, have their own problems because they may introduce unwanted business cycle effects and are also not immune from methodological issues because the popular Generalised Method of Moments (GMM) estimator has been found to have large finite sample bias.

why one believes this approach is superior on conceptual or empirical grounds. Conclusions and topics for further research are presented in Section 2.3.

2.2 The Robustness of the Frost-Growth Nexus

The existing empirical growth literature using "Barro-regressions" has been criticized for its lack of robustness. With competing guidance as to the precise nature of the hypothesized relationships, a plethora of specifications exist. In this sub-field, there is much debate over such questions as, "what variables should be included?" and "how should those variables be measured?". There is also a corresponding debate over the "right" or "best" statistical methodology to employ.

Durlauf and Quah (1999) and Temple (1998, 2000) stress that applied macroeconomists are inclined to follow theory rather loosely and simply try variables to establish factors determining economic growth. In these empirical specification searches, econometric problems such as robustness are often ignored [Durlauf (2001)]. Because the literature also reveals more than 50 variables significantly correlated with growth, the question arises as to how sensitive the results of cross-country growth regressions are to slight alterations in the setup.[4]

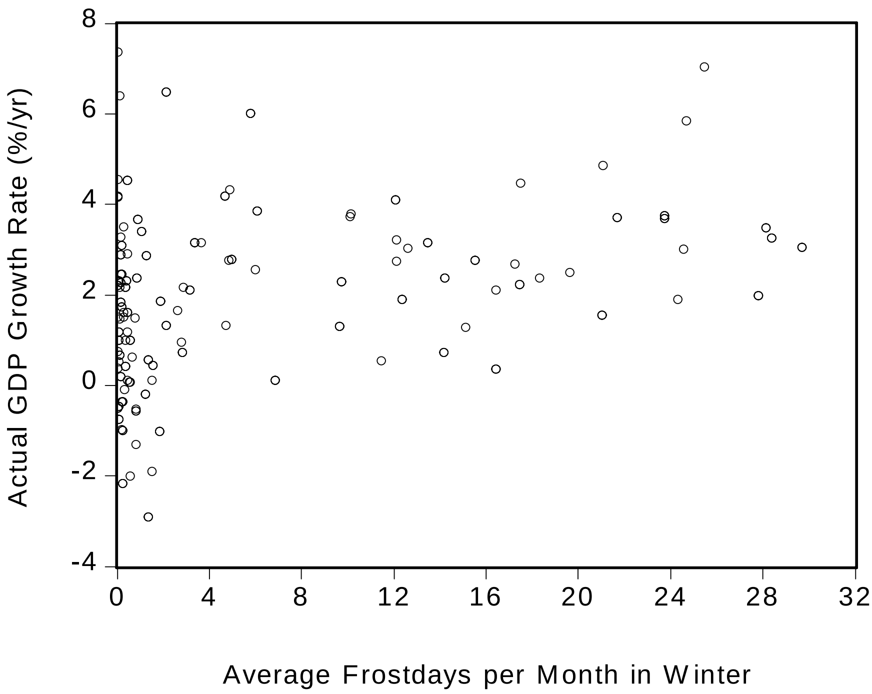
Dollar and Kraay (2002) claim that the model is too weakly identified to be able to sharply estimate any of the parameters of interest if institutions to be endogenous. They are at least able to uncover a significant partial association between trade and growth which survives the inclusion of a variety of proxies for institutional quality if institution is treated as exogenous.

Following the analysis in Masters and McMillan (2001), this section considers to re-examine the relative importance of climate and geography, the cross-sectional econometric framework presented in Masters and McMillan (2001) is used. Fig. 2.1 presents the frequency of frost against the average real GDP growth rate over the sample period. The broad

[4] Excellent surveys of the literature are provided by Durlauf and Quah (1999) and Temple (1999). An extensive treatment of robustness issues is provided in McAleer et al. (1985).

feature is that poor countries are located in the geographic tropics with little frost, and most of the wealthy countries are in temperate regions with hard frosts. The intuition is that frost kills pests and pathogens, so that agricultural productivity is higher in temperate climates.

Figure 2.1 Frost Frequency and Average GDP Growth, 1960 - 1990



Note: Frostdays are defined as the average number of such days per month in winter (December – February in the Northern hemisphere and June – August in the Southern hemisphere) where the estimated temperature falls below 0ºC. Values are averages for 1961 – 1990.

It now turns to the question of how significant average frostdays may be for long-term growth prospects. This analysis starts with the function for country's per capita growth rate in period t, Δy_t, as $\Delta y_t = F(y_0, h_0, \cdots)$, where y_0 is initial per capita GDP, h_0 is initial human capital formation, and other variables comprise an array of control and environmental influences. Table 2.1 replicates the *OLS* estimates originally presented in Masters and McMillan (2001). It uses the following Barro and Sala-i-Martin (1991) cross-country growth framework, in which the average annual income growth in country *i* is regressed on initial incomes, annual hard frosts, domestic population size, total trade as a fraction of GDP, linguistic heterogeneity, as well as all other variables used in previous studies.

$$(2.1)\ Y_i = \alpha + \beta InitialIncome + \gamma_1(Population, Trade, Schooling) + \gamma_2 Frostdays + \gamma_3(others) + \mu_i$$

where Y_i is the average per capita growth rate and μ_i is the error term. The model regresses the average per capita growth rate for 89 countries over the period 1960 to 1990 on measures of its endowments, macroeconomic policy, institutional development, and frost variables.

Table 2.1 Baseline Empirical Growth Model

(Dependent Variable: Average Annual Growth in Real GDP, 1960 – 1990)

Variable	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics
Constant	6.308	3.360	6.210	3.337
ln(Pop) 1960-62	0.845	2.724	0.853	2.757
X+M/GDP 1960-62	0.025	5.042	0.026	5.276
Language heterogeneity	-0.030	-3.963	-0.029	-3.869
ln(GDP) 1960-62	-1.811	-3.177	-1.902	-3.357
Area-weighted frostdays	0.087	3.619	0.390	2.367
Frost-days squared			-0.027	-1.682
Frost-days cubed			0.001	1.503
Observations	89		89	
Adjusted R-squared	0.371		0.384	
Jarque-Bera	5.204	p = 0.074	2.467	p = 0.291
Ramsey RESET F-statistic	0.159	p = 0.691	0.451	p = 0.504

Notes: The data definitions and sources are explained in Masters and McMillan (2001), p. 177. The Jarque-Bera diagnostic is one for normality of the residuals. Ramsey's RESET test for incorrect functional form and nonlinearities is also reported.

Table 2.1 shows regressions for annual average growth rates of per capita real GDP. Most of the data apply from Master and McMillan (2001). It characterizes worldwide growth in terms of convergence, scale impacts and climate effects. The frost variable is highly significant and thus ignoring the growth effects of hard frosts leads to an overestimate of growth in the tropics. The second row also suggests the possibility of a nonlinear climate effect: as the number of frost days increases, the impact on growth becomes larger.[5] The regressions shows that, as one of the few variables found to do so, the frostdays robustly matter for economic growth. Moreover, it seems likely that more frostdays indeed cause higher growth and not the other way around. The results in Table 2.1 set the stage for the remainder of the paper, where one asks: how robust are these results?

2.2.1 Threshold Estimation

A first problem with the work of Masters and McMillan (2001) is their assumption that a "natural" breakpoint of five days of frost per month is apparent in the data [Masters and McMillan (2001), p. 176]. This assumption is not borne out by any estimation technique and therefore the cut-off for hard frosts (≥ 5) is inevitably arbitrary. A better solution here is to use Hansen's (2000) threshold estimation technique which provides an intuitive and simple setting for sample-splitting. The approach is based on a very simple idea. The model with a single threshold takes the form

$$(2.2)\qquad y_i = \alpha_i + \beta'_1 x_i I(q_i \le \gamma) + \beta'_2 x_i I(q_i > \gamma) + e_i$$

where the dependent variable y_i is a scalar, x_i is a vector of regressors, $I(\cdot)$ is an indicator function, the threshold variable q_i is a scalar, and e_i is an i.i.d. $N(0, \sigma^2)$. The subscript indexes the regions $\{1 \le i \le n\}$. Equation (2.2) can be re-written as

$$(2.3)\qquad y_i = \begin{cases} \alpha_i + \beta'_1 x_i + e_i & if \quad q_i \le \gamma \\ \alpha_i + \beta'_2 x_i + e_i & if \quad q_i > \gamma \end{cases}$$

[5] If investment in physical and human capital creates new knowledge, then there will be a spillover from each agent's investments to knowledge useful for other agents in the economy. Economies that already have high per capita incomes will have the highest returns for new investments. If these spillover effects are strong enough, then virtuous and vicious circles will form in the long run [see Azariadis (1996), Azariadis and Drazen (1990) and Murphy et al. (1989)]. In a similar vein, Gallup et al. (1999) have argued that vector-borne diseases, particularly malaria, have such a large effect on labour productivity that some countries, particularly in Sub-Saharan Africa, are trapped in a vicious poverty-disease trap.

The threshold model therefore allows the regression parameters to differ depending on the value of q_i. The specification collapses to the traditional linear one if $\beta'_1 = \beta'_2$. This implies that the procedure allows formal verification of the number of convergence clubs in the cross-section. Hansen (2000) has suggested a practical and straightforward method to estimate γ using least squares techniques and to construct asymptotically valid confidence intervals for γ.[6] *F*-tests can then be used to test for threshold effects ($\beta'_1 \neq \beta'_2$), and likelihood ratio tests LR(γ) can be constructed to test the hypothesis H_0: $\gamma = \gamma_0$. In other words, the major innovation of the elegant technique is to treat the number and the size of the thresholds as unknown. Furthermore, the procedure allows to test whether the identified threshold effect is statistically significant.

An additional problem is the possibility of multiple thresholds. Bai (1997a, 1997b, 1999) shows that (mechanically) proceeding sequentially in testing for thresholds, i.e. test first for one threshold against no threshold; then conditional on the results of the first test, test for the existence of a threshold in each of the two subsamples and so on, produces consistent estimates of the number and the location of the thresholds. However, when there are multiple thresholds, and one tests for the presence of one threshold only, the estimated break point is consistent for any of the existing break points and its location depends upon which of the breaks is "stronger". If this is the case, Bai (1997a, 1997b, 1999) has suggested to refine the estimate of the thresholds. That is, if two thresholds are identified at n_1 and n_2, one should re-estimate n_1 over the interval $[1, n_2]$ and n_2 over $[n_1, n]$. Each refined estimator of the location of the threshold has then the same properties as the estimator obtained in the case the sample has a single break point.

Following this computationally convenient sequential procedure this analysis allows the number of thresholds to be unknown and endogenously determined by the data.[7] The frost variable (area weighted frostdays) as the threshold variable has been used in this study. Fig.

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[6] The computationally easy procedure determines γ as that value that minimizes the concentrated sum of squared errors function.

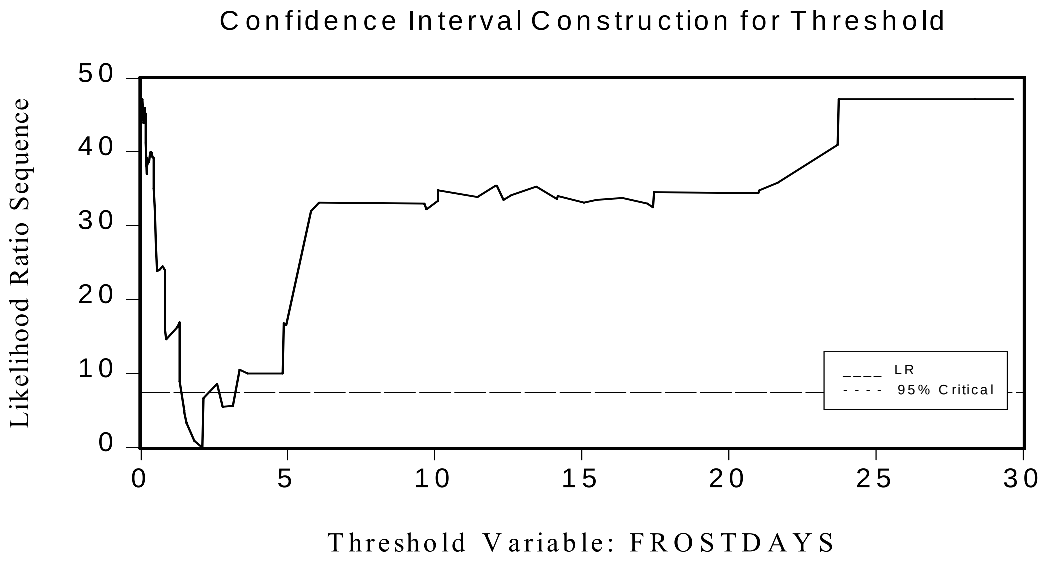
[7] The estimation and test procedures made use of a *GAUSS* procedure, which is available on Bruce Hansen's homepage http://www.ssc.wisc.edu/~bhansen.

2.2 displays a graph of the normalized likelihood ratio sequence LR(γ) when estimating a single-threshold model. The least squares estimate of γ is the value that minimizes this graph, which occurs at γ_1 = 2.11049. The asymptotic 95% critical value of 7.35 is also plotted (dotted line). The result shows that there is reasonable evidence for a two-regime specification and therefore geography matters.[8]

Finally, following the procedure suggested by Bai (1997a, 1997b, 1999), this analysis has searched for a double threshold. This sequential procedure using subsamples leads to no further significant thresholds. Thus one concludes that there exists a single threshold effect which is less than half as large as the assumed breakpoint in Masters and McMillan (2001). The implication is that temperate regions have tended to forge ahead of the sub-tropical and tropical countries and frost may be viewed, statistically speaking, as an important component of the rich/poor distinction among the countries of the world. This frost-produces-growth hypothesis potentially supports the finding of Hansen (2000) and Quah (1996) that the world income distribution is polarising into two groups, i.e. both subgroups are growing apart.

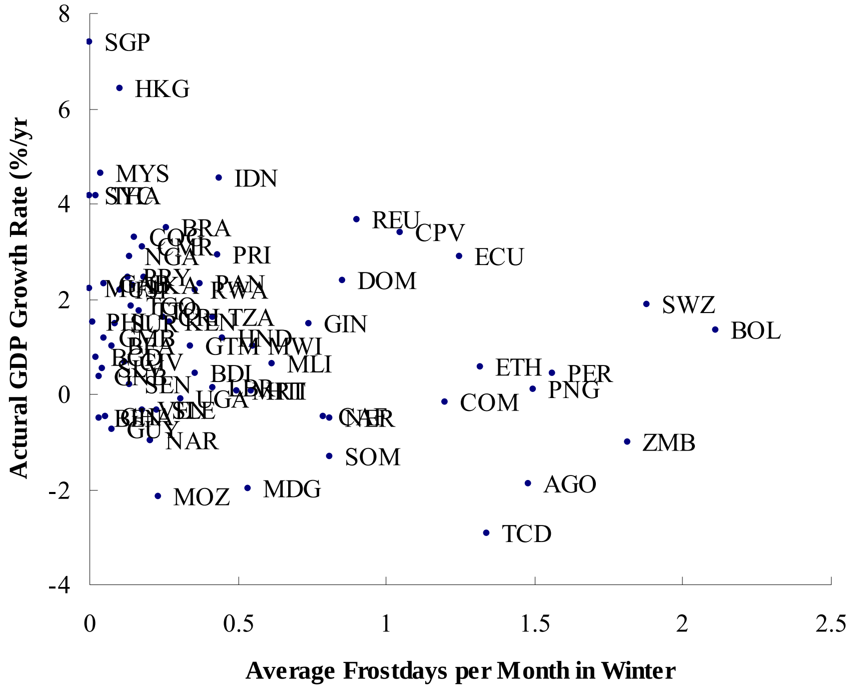
[8] While one finds evidence of multiple equilibria, it has nothing to say about how countries can make the transition from one equilibrium to the other. To do this requires a more structural, dynamic model with various stages of development.

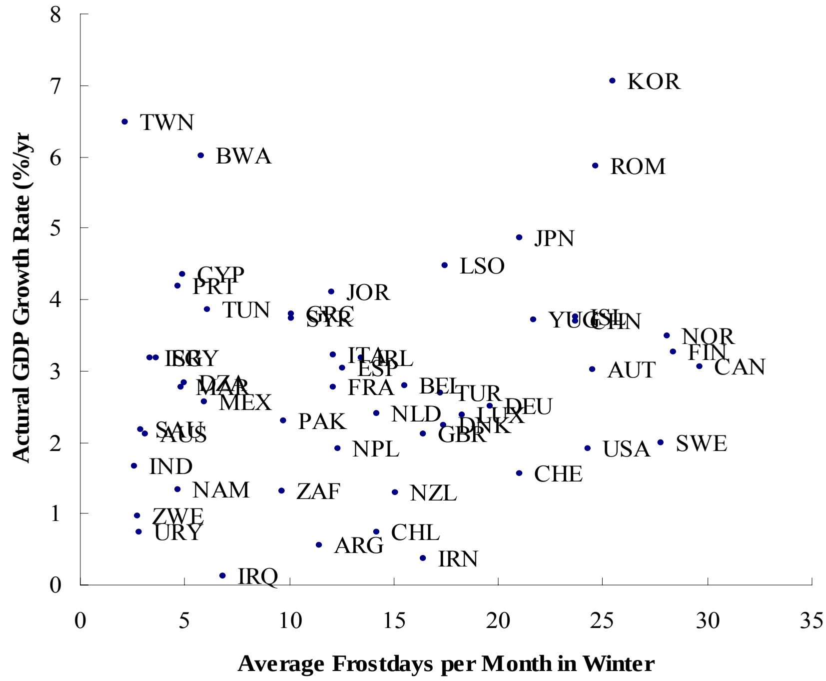
Figure 2.2 Likelihood Ratio Sequence in the Single Threshold Model



Having obtained an estimated threshold for the frost variable, it can use that criterion to subdivide the sample and test for parameter heterogeneity across the temperate-tropical divide. Fig. 2.3 presents the frequency of frost against the average real GDP growth rate over the sample period in two subsamples. It shows that frost is negatively correlated with growth in the tropical subsample, but it is positively correlated with growth in the temperate subsample.

Figure 2.3 Frost Frequency and Average GDP Growth of Subsamples, 1960 – 1990





2.2.2 Outliers

Equation (2.1) and (2.2) provide a feasible method of estimation, however, the question of outliers is another problem. A valid concern with cross-country work is that the equations will fit some observations particularly badly, and it is possible that these observations will act as influential outliers. Take for instance Fig. 2.4(a). In that Figure point *A* is clearly an outlier; it lies outside the typical relationship between *x* and *y*. Especially such outliers in the dependent variable, i.e. in the *y*-direction, have received quite some attention in the literature. Such vertical outliers often possess large positive or large negative residuals, which are easy to identify when plotting the residuals. Note, however, that if x_i is near the center of the set of explanatory variables, as is the case in Fig. 2.4(a), it will mainly affect the constant and hardly alter the slope. Alternatively, outliers can occur in the *x*-direction. As Fig. 2.4(b) shows, even one unusual observation in the *x*-direction (point *B*) can actually tilt the *OLS* regression line. It does not fit the main sequence (in fact, it does slope downwards) because it attempts to fit all the data points and is pulled away by point *B*. In such a case it calls the outlier a bad leverage point, in analogy to the notion of leverage in mechanics. In general one calls an observation a leverage point whenever it lies far away from the bulk of the observed *x* in the sample. Note that this does not take *y* into account, so a leverage point does not necessarily have to be an outlier. For instance in Fig. 2.4(c), the leverage point *C* lies exactly on the regression line determined by the majority of the data, and hence is not an outlier. It is considered to be a good leverage point. Therefore, saying that an observation is a leverage point refers only to its potential for strongly affecting the regression coefficients. Obviously, the most worrisome outliers, i.e. bad leverage points often cannot be discovered by looking at the *OLS* residuals. As in Fig. 2.4(b), if the regression line is tilted by the bad leverage point, deleting the points with the largest *OLS* residuals implies that some "good" observations would be deleted instead of the bad leverage point. Hence, outliers pose a serious threat to standard least squares analysis.[9]

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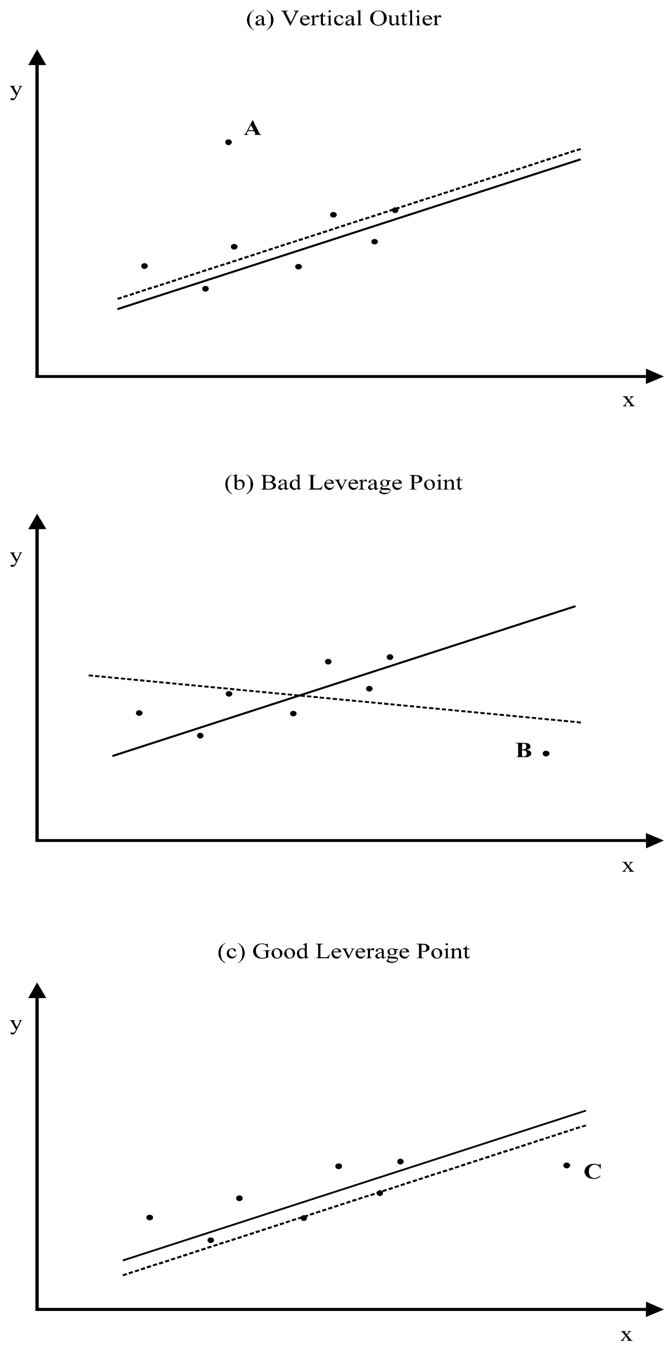
[9] For example, in the recent empirical growth literature, the link between equipment investment and economic growth has been analyzed for a broad cross section of countries. DeLong and Summers (1991, 1992) have initially argued that equipment investment yields high externalities. Auerbach et al. (1994) have, however,

Figure 2.4 Outlying Observations and Leverage Points



Note: The dashed lines represent the *OLS* estimates including the unusual observation. The solid lines represent the *OLS* estimates without the outlying observations.

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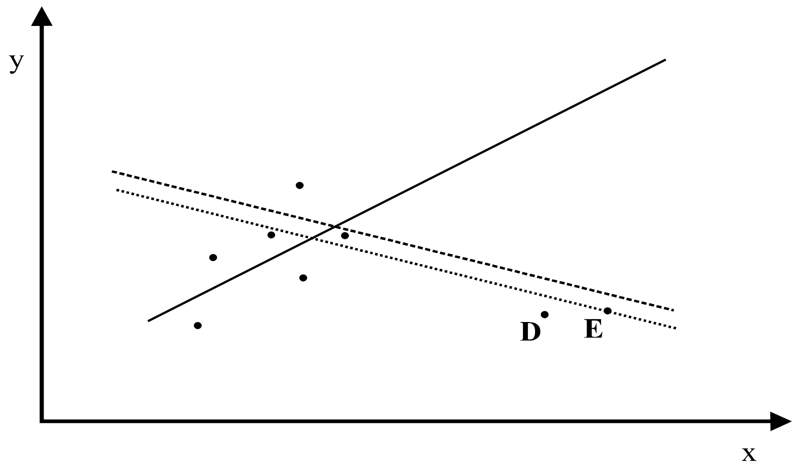
demonstrated that this result is very fragile and essentially driven by *one* outlier in the cross-section dataset (Botswana).

Basically, there are two solutions to this problem: regression diagnostics and robust estimation. Regression diagnostics are certain statistics mostly computed from the *OLS* regression estimates with the purpose of pinpointing outliers and leverage points.[10] Often the outliers are then removed from the dataset. When there is only one outlier, then some of these methods work quite well. It is, however, much more difficult to identify outliers when there are several of them. Take for instance Fig. 2.5. Deleting either of the two observations *D* and *E* will have little effect on the regression outcome and will therefore not be spotted by single-case diagnostics. The potential effect of one outlying observation is actually masked by the presence of the other. This so-called masking-effect can only be solved when observations are considered to be jointly outliers and/or leverage points.[11]

Figure 2.5 The Masking Effect



Note: The dotted line represents the *OLS* estimates including both outlying observations *D* and *E*. The dashed line represents the *OLS* estimates without the first unusual observations *D*. The solid line represents the *OLS* estimate without both unusual observations *D* and *E*.

[10] Of course, in simple regression this is not a big problem since one should first look at a scatter plot of the (x_i, y_i) data. But in multiple regression, this is no longer possible, i.e. the real challenge is multiple regression. Chatterjee and Hardi (1988) and Rousseeuw and Leroy (1987) discuss regression diagnostics.

[11] Such joint tests, however, pose serious computational problems. For the single-case diagnostic measure I need to compute n diagnostics, one for each observation. In the multiple observations case, for each subset of variables of size m, there are $n!/[m!(n-m)!]$ possible subsets for which diagnostic test statistics can be computed. For n=90 and m=10 this results in $5.72 \cdot 10^{12}$ diagnostics. Masters and McMillan (2001) have addressed the outlier problem with the *DFITS* diagnostic. These statistics, however, may fail to pick up “unrepresentative” outliers due to the masking effect explained above.

This study turns to the second approach, called robust regression. It tries to devise estimators which are not so strongly affected by outliers. When using as a diagnostic tool, robust techniques first fit a regression to the majority of the data and then determine outliers as those points which possess large residuals from that robust solution.
The most well-known estimator is the *OLS* method. The basic idea behind this estimator is to optimize the fit by minimizing the sum of squared residuals (e_i):

$$(2.4) \qquad \min_{\hat{\beta}} \sum_{i=1}^{n} e_i^2$$

For *OLS* one knows that one outlier can be sufficient to cause the estimator to take on values for $\hat{\beta}$ arbitrarily far from β. As shown in Fig. 2.4(a), one observation like point *B* is sufficient to throw the *OLS* line indefinitely far off target. This is independent of the total number of observations *n* available. The *OLS* breakdown point equals 1/*n* which tends to zero for increasing sample size, which reflects the extreme sensitivity of the *OLS* method to outliers. A robust alternative adopted in this paper is the least trimmed squares (*LTS*) estimator of Rousseeuw and Leroy (1987).[12] The *LTS* estimator can formally be written as

$$(2.5) \qquad \min_{\hat{\beta}} \sum_{i=1}^{h} \left(e^2\right)_{i:n}$$

where$(e^2)_{1:n} \leq (e^2)_{2:n} \leq \ldots \leq (e^2)_{n:n}$ are the ordered squared residuals (note that the residuals are first squared and than ordered). Formula (2.5) is very similar to *OLS*, the only difference being that the largest squared residuals are not used in the summation, thereby allowing the fit to stay away from the outliers. The *LTS* estimator is consistent and asymptotically normal. In order to determine the *LTS* location estimate one has to consider the *n*-*h*+1 subsamples $\{y_{1:n}, \ldots, y_{h:n}\}, \{y_{2:n}, \ldots, y_{h+1:n}\}, \ldots, \{y_{n-h+1:n}, \ldots, y_{n:n}\}$. With *k* unknown parameters the *LTS* method attains the highest possible breakdown value, namely $\{[(n-k)/2]+1\}/n$ which asymptotically equals 50

[12] Temple (1998) has also used the *LTS* estimator when re-examining the augmented Solow with human capital.

percent, i.e. it can withstand a lot of bad leverage points occurring anywhere in the data. Equation (2.3) resembles that of *OLS* but does not count the largest squared residuals, thereby allowing the *LTS* fit to steer clear of outliers. The default setting for h suggested in the literature is $h \approx n/2$.[13] The *LTS* regression and scale estimates can then be used to identify outlying observations, defined to be those observations whose studentised residual is larger than the rule-of-thumb cut-off value $|2.5|$.[14]

Therefore, this study uses the least trimmed squares (*LTS*) estimator of Rousseeuw and Leroy (1987) which can withstand a lot of bad leverage points occurring anywhere in the data.[15] The corresponding estimation results for both subsamples are given in Table 2.2 and Table 2.3. To account for cross-country growth differences, the same array of right-hand-side variables as Master and McMillan (2001) is used. Looking at the results of both tables it is clear that in some ways the "frost model" stands up rather well. The estimated coefficient of the frost variable is significant in the tropical subsample, but has the "wrong" sign. While negative growth impacts seem to prevail for little frost, the effect of frost disappears when the level of frost is higher. The Sachs-Warner measure of openness and initial income turn out significant in both subsamples and trump all other variables in the temperate subsample. On the contrary, the so-called Gastil index of institutional quality and the ethnolinguistic diversity measure turn out insignificant. In particular, as shown in Table 2.3, the inclusion of geographical variables seems to reduce the role of frost variable. Most variables lose their significance except the investment rate and the secondary school enrollment rate in temperate subsample. The geography has the insignificantly positive correlation with economic growth in temperate subsample, but insignificantly negative correlation in tropical subsample.

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[13] For larger h the breakpoint value is approximately given by $(n\text{-}h)/n$.

[14] Various resampling algorithms have been suggested to obtain the *LTS* regression and scale estimates. The resampling approach is required because the *LTS* criterion function is not at all smooth; it typically contains many local minima and therefore cannot be minimized by conventional methods. Rousseeuw and Leroy (1987) propose drawing a large number of subsamples, each of size k (the number of regression coefficients, including the constant term) and evaluate the objective function (2). This is repeated often, and the solution with lowest objective function is kept. Both authors show that, if the number of subsamples is large, at least one of them is virtually certain to be uncontaminated by outliers. The *LTS* regression is based on these "clean" subsamples. In this paper 3000 subsamples have been drawn.

[15] Temple (1998) has also used the *LTS* estimator when re-examining the augmented Solow with human capital.

Table 2.2 *LTS* Estimates for Both Sub-Samples

(Dependent Variable: Average Annual Growth in Real GDP, 1960 – 1990)

Variable	Frostdays ≤ 2.11049		Frostdays > 2.11049	
	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics
Constant	20.331	8.517	17.061	6.517
ln(Pop) 1960-62	0.338	1.120	-0.388	-1.429
X+M/GDP 1960-62	-0.027	-3.785	-0.007	-0.875
Language heterogeneity	0.008	1.425	-0.011	-1.519
ln(GDP) 1960-62	-3.539	-5.540	-3.488	-4.234
Area-weighted frostdays	-0.959	-4.574	0.017	0.861
ln(I/GDP)	3.596	4.780	1.653	1.436
ln(SCHOOL)	3.207	6.247	1.617	1.477
Openness(Sachs-Warner)	1.366	2.555	1.744	3.372
Institutional quality (*GADP*)	0.934	0.753	0.778	0.418
Observation	37		33	
Adjusted R-squared	0.862		0.592	
Jarque-Bera	5.637	p = 0.060	0.008	p = 0.996
Ramsey RESET F-statistic	0.216	p = 0.646	0.464	p = 0.503
Outliers	Ghana Hong Kong Nicaragua Philippines Rwanda Singapore Trinidad Zaire		Botswana Chile Lesotho	

Notes: The data definitions and sources are explained in Masters and McMillan (2001), p.177. The Jarque-Bera diagnostic is one for normality of the residuals. Ramsey's RESET test for incorrect functional form and nonlinearities is also reported.

Table 2.3 *LTS* Estimates for Both Subsamples

(Dependent Variable: Average Annual Growth in Real GDP, 1960 – 1990)

Variable	Frostdays ≤ 2.11049		Frostdays > 2.11049	
	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics
Constant	16.823	4.486	19.127	8.496
ln(Pop) 1960-62	0.563	1.221	-0.073	-0.333
X+M/GDP 1960-62	-0.019	-1.807	0.000	-0.014
Language heterogeneity	-0.001	-0.151	-0.003	-0.554
ln(GDP) 1960-62	-3.238	-3.254	-3.853	-6.322
Area-weighted frostdays	-0.857	-2.611	0.007	0.326
ln(I/GDP)	3.704	3.281	2.283	2.404
ln(SCHOOL)	1.341	1.816	2.365	3.006
Openness(Sachs-Warner)	2.263	2.623	1.499	3.603
Institutional quality (*GADP*)	0.122	0.065	0.741	0.572
Absolute latitude	-0.029	-0.908	0.001	0.059
Observation	40		32	
Adjusted R-squared	0.657		0.733	
Jarque-Bera	0.230	p = 0.891	2.598	p = 0.273
Ramsey *RESET* F-statistic	0.704	p = 0.409	7.238	p = 0.014
Outliers	Hongkong Singapore Trinidad and Tobago Zaire		Botswana Chile India Zimbabwe	

Notes: The data definitions and sources are explained in Masters and McMillan (2001), p. 177. The Jarque-Bera diagnostic is one for normality of the residuals. Ramsey's RESET test for incorrect functional form and nonlinearities is also reported.

The outlying countries Hongkong and Singapore reveal that rich, non-agricultural tropical countries do not suffer a geographical deficit of this kind. Air conditioning is probably the great equalizer in labour productivity in manufacturing and services. If a country can escape to high incomes via non-agricultural sectors, the burdens of the tropics and sub-tropics can be lifted.

2.2.3 Model Uncertainty

In order to test for the robustness of these results, it has turned to other "usual suspects" which have been used as explanatory variables in the literature before.[16] Hundreds of variables have been estimated to be significantly correlated with growth in the literature, unfortunately, there seems to be no agreement on which other variables should always be accounted for in growth regressions. Some variables are used systematically in most studies. Which variable should one select in this note?

Trade openness is used to indicate the degree of goods market integration. It is measured as the fraction of years that the country does not interfere with foreign trade, as compiled by Sachs and Warner (1995). The index, measured on a (0, 1) scale, have been widely used in cross-sectional on growth. A country is considered open if it satisfies all the following criteria: (a) non-tariff barriers cover less than 40 percent of trade; (b) average tariff rates are less than 40 percent; (c) the black market premium was less than 20 percent in the 1970s and 1980s; (d) the economy is not socialist; and (e) the government does not control major exports. This openness index covers 79 countries during the 1950-1994 time period. The shortcomings of the Sachs-Warner index as a measure of trade policy are discussed at length in Rodriguez and Rodrik (2000). They argue not all countries have data for each of the five index components in the original sample. They stress Sachs-Warner index's strength derives mainly from the combination of the black market premium and the government monopoly of exports, but little action directly measure from tariff and non-tariff barriers. The African economics are closed to (e) because of their state monopolies of exports and Latin American economics are closed to (c) because of their high levels of black market premium.

The Gastil index of institutional quality, also named Government Anti-Diversion Policies (*GADP*) index, is constructed by Knack and Keefer (1995) with data from the International Country Risk Guide. The index is measured on a (0, 1) scale, though it is the best

[16] In order to keep the specification simple one limited oneself to a relatively small number of additional explanatory variables. However, other variables may be included in an extended model and are certainly worth monitoring in an extended model: alternative measures of fractionalization and legal origins. Alesina et al. (2003) have shown that fractionalization creates destructive rent-seeking and conflicts and has detrimental effects upon growth. The impact of alternative legal institutions has also received substantial attention in the literature, notably the impact of systems stemming from different colonial influences [see La Porta et al. (1999)].

measure of institutional indicators one could construct, is admittedly crude. The index is an equal-weighted average of the following criteria: (a) rule of law; (b) quality of bureaucracy; (c) corruption in government; (d) risk of expropriation; and (e) government repudiation of contracts. The *GADP* index covers 130 countries measured around 1985. Knack and Keefer's bureaucracy and corruption variables, which are computed for 1985 only; corruption and bad bureaucracy could very well by the endogenous response to a poor economic performance between 1960 and 1985. This study has also developed an alternative measure of institution indicators, which although it is also crude, is derived from completely different data sources, and covers a different time period. The alternative institution indicator used qualitative assessments of the civil liberties from Freedom House.[17] The earliest description of civil liberties in these advisories data from 1965, and are drawn from the Heritage Foundation's Index of Economic Freedom. Each country is rated on a scale of 1 to 5, with a higher score indicating fewer liberties. The external war index is set equal to one from countries in which an external war effects the whole countries or the while country except for major cities, and zero otherwise.[18]

Empirical research on economic growth has used a number of data sets related to geography and economic policies and institutions of countries after neglecting geography over the past decade. Though most results point out the strong correlation of geographical variables and economic development, economists argue the physical geography is an extremely dubious explanatory variable in growth model. Favorable geography plays a role in promoting institutions and inducing growth.

Table 2.4 replaces the Sachs-Warner openness variables and the institutional variable *GADP* by the black market premium on foreign exchange, civil liberties and the occurrence of an external war, and drop out geographical variable from model.

[17] The civil liberty measure indicates the degree of freedom. In general, the Freedom House indicators are widely recognized (and used) as a high-quality measure of political freedom and democratic rights. For further details, see www.heritage.org/research/features/index.

[18] The external war index measures the dummy variable for countries that participated at least one external war over period 1960 – 1985. For further details, see www.worldbank.org

Table 2.4 *LTS* Estimates for Both Subsamples

(Dependent Variable: Average Annual Growth in Real GDP, 1960 – 1990)

Variable	Frostdays ≤ 2.11049		Frostdays > 2.11049	
	Coefficient	*t*-Statistics	Coefficient	*t*-Statistics
Constant	17.085	6.892	18.828	5.314
ln(Pop) 1960-62	2.025	6.885	-0.102	-0.301
X+M/GDP 1960-62	0.025	8.572	-0.001	-0.071
Language heterogeneity	-0.027	-5.158	-0.012	-1.278
ln(GDP) 1960-62	-4.058	-6.260	-3.207	-4.578
Area-weighted frostdays	-0.067	-0.297	0.024	1.081
ln(I/GDP)	1.446	1.657	1.687	1.319
ln(SCHOOL)	1.013	2.327	3.209	2.709
Black market premium	-0.657	-3.265	-2.006	-2.706
Civil liberties	-0.334	-2.907	0.152	0.814
External war	-1.102	-4.263	-0.469	-1.068
Observation	41		34	
Adjusted R-squared	0.884		0.480	
Jarque-Bera	0.536	p = 0.765	0.046	p = 0.977
Ramsey RESET F-statistic	1.415	p = 0.244	0.536	p = 0.472
Outliers	Guatemala Indonesia Madagascar Paraguay Zambia		Botswana Algeria	

Notes: Jarque-Bera diagnostic is one for normality of the residuals. Ramsey's *RESET* test for incorrect functional form and nonlinearities is also reported.

Using data on economic growth from 1960 to 1990 and corresponding data on covariates in Table 2.4, the area-weighted frostdays variable is no longer significant for the tropical subsample but the civil liberty variable is correctly signed and highly significant for the developing countries. The external war indicator shows a significant negative correlation with subsequent growth. The Black Market Premium has a high and apparently robust coefficient when inserted in growth regressions. Therefore, institutions and economic policies are indeed crucial in economic development. First, market distortions as measured by the black market exchange rate premium are found to harm growth. Second, the rule of law delivers growth. Third, human capital has a significant explanatory power. These results are encouraging because they are not indulging in economic determinism.

Growth empirics in practice involve consideration of a number of possible combinations of explanatory variables, justify a set of assumptions for inclusion/exclusion of variables, and then settle on a final model to report. The comparison of Table 2.2 and 2.3 with a diverse set of explanatory variables illustrates that the significance of explanatory variables depends to some extent on which other variables are included in the regressions, which questions the robustness of the correlation between growth rates and the explanatory variables used. Hence, Extreme Bounds Analysis (*EBA*) to deal with this subtle difficulty is additionally used.

In the work below it will call an explanatory variable "robust" in case changes in the list of explanatory variables do not alter its estimated coefficient too much. It assembled a cross-sectional data set with a large number of potential regressors and subjected to a variety of Edward Leamer's (1983, 1985) "extreme bounds analysis". The central idea in Leamer's analysis is that a coefficient of interest is robust only to the degree that it displays a small variation to the presence or absence of other regressors. The *EBA* approach estimates the following cross-section regression:

(2.6) $$G = \alpha + \beta X + \gamma Y + \delta Z_i + \mu$$

where G is the rates of per capita GDP growth, and X is a set of variables should be included in every regression on assumption, Y is a set of up to three variables drawn from the possible additional explanatory variables by past studies, Z_i is the variable of interest, and μ is the error term. The extreme upper bound is defined by the maximum value of δ plus two standard deviations, and the extreme lower bound is defined by the minimum value of δ minus two standard deviations. Levine and Renelt (1992) have initially pursued the *EBA* approach to investigate this type of "robustness" of explanatory variables in cross-section growth regressions. The *EBA* approach boils down to an assessment of the sign and significance of a variable's estimated coefficient under permutations of the set of conditioning variables. Levine and Renelt (1992) conclude that almost all results are fragile, except for the correlations between the investment share and growth, and between international trade to output.

The *EBA* technique can be applied to our dataset, and that is the task of the remainder of this section. The complete dataset for the Extreme Bounds Analysis comprises of 13 variables. Following earlier sensitivity analyses, the set of "fixed" conditioning variables is restricted to three [ln(GDP) 1960-62, ln(I/GDP) and ln(SCHOOL)] because they have been widely used and have been found reasonably robust. Table 2.5 gives the estimation results, containing the number of models being estimated, the mean, the standard deviation, the percentage of regressions in which the variable of interest has a significant positive or negative sign, and the strong and weak *EBA* test. The results indicate that almost all of the variables except initial income and openness are fragile. In other words, the openness variable measuring market integration and impediments thereof is the clear winner of the "horse race" and seems to play a starring role in fostering economic convergence across countries.

Table 2.5 Extreme Bounds Analysis

Variable	No. of Models	Mean Value	Standard Dev.	No. of Signif. Positive Coeff.	No. of Signif. Negative Coeff.	Strong Extreme Bounds Test	Weak Extreme Bounds Test
Frostdays > 2.11049							
ln(Pop) 1960-62	256	-0.384	0.142	0	2	-	-
X+M/GDP 1960-62	256	-0.005	0.00572	0	0	-	-
Language heterogeneity	256	-0.009	0.00476	0	0	-	-
ln(GDP) 1960-62	512	-3.710	0.328	0	512	+	+
Area-weighted frostdays	256	0.014	0.0112	0	0	-	-
ln(I/GDP)	512	1.920	0.488	32	0	-	-
ln(SCHOOL)	512	2.290	0.558	276	0	-	-
Openness(Sachs-Warner)	256	1.930	0.154	256	0	+	+
Institutional quality (*GADP*)	256	1.240	2.14	17	0	-	-
Black market premium	256	-0.817	0.424	0	46	-	-
Civil liberties	256	-0.043	0.111	0	12	-	-
External war	256	-0.965	0.123	0	221	-	-
Frostdays ≤ 2.11049							
ln(Pop) 1960-62	256	0.984	0.373	122	0	-	-
X+M/GDP 1960-62	256	0.013	0.005	162	0	-	-
Language heterogeneity	256	-0.010	0.005	0	31	-	-
ln(GDP) 1960-62	512	-3.410	0.713	0	494	-	+
Area-weighted frostdays	256	-0.874	0.160	0	186	-	-
ln(I/GDP)	512	2.860	0.913	293	0	-	-
ln(SCHOOL)	512	1.630	0.639	271	0	-	-
Openness(Sachs-Warner)	256	2.560	0.478	251	0	-	+
Institutional quality (*GADP*)	256	4.090	1.710	127	0	-	-
Black market premium	256	-0.828	0.109	0	239	-	-
Civil liberties	256	-0.332	0.108	0	77	-	-
External war	256	-0.312	0.246	0	1	-	-

Notes: The weak extreme bounds test indicates whether 95% of the coefficients are significant and have equal signs. The "+" indicates pass, and the "-" fail. The results for the constant are not reported.

One problem of the *EBA* approach is that it may be too mechanical and may overstate the degree of uncertainty about parameters because it ignores the information that some models are poor and should therefore be dismissed. This intuitive idea can easily be formalized. Sala-i-Martin (1997) has refuted *EBA* and Levine and Renelt's (1992) "kiss of death" for the empirical growth literature because the test is "too" strong. Alternatively, he suggests to investigate the distribution of coefficient estimates and suggests that a variable that is significant in 95 percent of the cases provides sufficient evidence for a variable to be robustly correlated with growth. What this suggests is to use a weighted extreme bounds test. The weights are defined as the value of the likelihood of the regression equation, giving more weight to regressions that are more likely to represent the true model. Hence, weighting is based on model adequacy.[19] Analogous conclusions are reached by Doppelhofer et al. (2000), Ley and Steel (1999) and Fernandez et al. (2001), who base their tests of robustness on the Bayesian Moving Average (*BMA*). The relaxation of the robustness criterion leads to a more optimistic conclusion since for a larger number of variables the relation to economic growth turns out to be robust.[20] The following table also reports the fraction of estimates that fall within the Cumulative Density Function (*CDF*) of the weighted average of the estimated coefficients.

[19] The output of alternative models is weighted with the log likelihood measure of goodness-of-fit (ln likelihood). Granger and Uhlig (1990, 1992) have also suggested to ignore any bounds generated by poor models.

[20] In fact, the problem is not limited to growth analysis. Faust and Irons (1999), for instance, show that empirical tests of business cycle models are often based on too small macroeconomic information set and this casts serious doubts on the reliability of results.

Table 2.6 Weighted Extreme Bounds Tests

Variable	No. of Models	Weighted Mean Value	Weighted Standard Dev.	Weighted Extreme Bounds Test	Weighted CDF
Frostdays > 2.11049					
ln(Pop) 1960-62	256	-0.388	0.290	+	0.090
X+M/GDP 1960-62	256	-0.004	0.008	-	0.297
Language heterogeneity	256	-0.009	0.009	+	0.169
ln(GDP) 1960-62	512	-3.700	0.728	+	0.000
Area-weighted frostdays	256	0.015	0.024	+	0.725
ln(I/GDP)	512	1.920	1.370	+	0.918
ln(SCHOOL)	512	2.290	1.130	+	0.979
Openness(Sachs-Warner)	256	1.930	0.617	+	0.999
Institutional quality (*GADP*)	256	1.400	2.460	+	0.715
Black market premium	256	-0.833	0.663	+	0.105
Civil liberties	256	-0.048	0.186	-	0.397
External war	256	-0.964	0.394	+	0.007
Frostdays ≤ 2.11049					
ln(Pop) 1960-62	256	0.975	0.488	+	0.977
X+M/GDP 1960-62	256	0.012	0.005	+	0.992
Language heterogeneity	256	-0.010	0.008	+	0.112
ln(GDP) 1960-62	512	-3.410	1.090	+	0.001
Area-weighted frostdays	256	-0.873	0.369	+	0.009
ln(I/GDP)	512	2.890	1.320	+	0.986
ln(SCHOOL)	512	1.660	0.759	+	0.986
Openness(Sachs-Warner)	256	2.570	0.808	+	0.999
Institutional quality (*GADP*)	256	4.170	2.040	+	0.980
Black market premium	256	-0.831	0.334	+	0.006
Civil liberties	256	-0.332	0.201	+	0.050
External war	256	-0.311	0.448	+	0.244

Notes: The results are weighted with the log likelihood of the regressions. The column CDF gives the fraction that lies at the right side of zero. The weighted weak extreme bounds test indicates whether 95% of the weighted coefficients are significant and have equal signs. The "+" indicates pass, and the "-" fail. The results for the constant are not reported.

The results of this less strict definition of robustness in Table 2.6 clearly replicate the divergence between the Levine and Renelt (1992) and Sala-i-Martin (1997) using a different dataset. The estimates lead to a much more optimistic conclusion regarding the robustness of the coefficients. The number of robust variables increases substantially and the frost variable turns out significant for both subsamples. The robustness results for the frost variable in Table

2.6 are consistent with the hypothesis in Masters and McMillan (2001). On the other hand their "core hypothesis" (p.171) that the scale variables population size, total trade as a fraction of GDP, and linguistic heterogeneity are insignificant for the temperate regions is clearly rejected and therefore the main message of their paper is fragile.

2.2.4 Endogeneity

Many recent researches have reflected on the impact of institutions on economic performance. Good institutions guarantee property rights and minimize transaction costs, creating an environment conducive to economic growth; Countries may be able to afford efficient institutions because they are rich. This section follows the previous literature by using Instrumental Variable (*IV*) methods to address the issue of endogeneity.

The instrumental variable is a variable that is uncorrelated with the error term but correlated with the explanatory variables in the equation. I am looking for a "good" variable which is highly correlated with explanatory variables, however, a lot of recent theoretical pay attention to the "weak instruments" problem. If the correlation between the instrument and the variable it instruments for is insufficient, it is called a weak instrument. Unfortunately, there is no benchmark to estimate that how low the correlation must be before it becomes a weak instrument. Dollar and Kraay (2003) argue that existing attempts to isolate the partial effects of institutions and trade on growth in the long run suffer from serious identification problems. They point out that existing historical and geographical instruments in the literature tend to have strong predictive power for both institutions and trade. Many specifications are weakly identified although instruments have apparently good performance in the first stage regressions. Shea (1997) provides a computationally simple measure of instrument relevance for multivariate models. In these models, instrumental variable works poorly even when the R^2 is high if instruments are highly collinear. It therefore follows previous papers in regressing the average GDP growth on measures of institutional quality by using the following Two-stage Least-square procedure:

(2.7) Second Stage: $Y = \alpha InstitutionalQuality + \beta X + \mu$, (2.8) First Stage: $Institutional Quality = \delta Instruments + \gamma X + w$

where Y is average GDP growth, X is a set of included exogenous variables, μ and w are the error terms of the second stage and the first stage regressions, respectively.

Recently a few seminal publications have carried out somewhat similar analyses and deserve discussion. The subsequent study focuses on those instruments variables that have been shown to be the key determinants in the following three previous papers [Hall and Jones (1999), Gallup et al. (1999), and Acemoglu et al. (2001)].

Starting at the 15th century, Western Europeans were likely to settle regions of the rest of the world and were likely to settle in the similar climate as Western Europe. Hall and Jones (1999) use two language variables as instruments for social infrastructure because they argue that the languages of Western Europe are spoken as a mother tongue is correlated with "Western influence", which are the fraction of a country's population speaking one of the five primary Western European languages (English, French, German, Portuguese, and Spanish) as a mother tongue and the fraction speaking English as a mother tongue. The data set covers 134 countries and comes from the work of Barbara Hunter (1992).

Gallup, Sachs, and Mellinger (1999) examine that regions linked to coasts or ocean-navigable waterways, are strongly favored in development relative to the hinterlands. The instrument variable is the proportion of the region's population within 100 kilometers of the coastline or within 100 kilometers of the coastline or ocean-navigable river. The data set comes from geographical information system data.

Acemoglu, Johnson and Robinson (2001) introduce the settler mortality rate as a plausible instrument for institutional development. Many European settlers influenced the colonization strategy and tried to replicate the European institutions in most colonies. They hypothesize that settler mortality rate is the major determinants of settlements which correlated with early institutions and institutions today. The higher settler mortality European faced the worse institutions today the country has. They find that there is no evidence that settler mortality has a direct effect on economic performance. Data compiled by Acemoglu *et al.* (2001) covers 64 ex-colonies, mostly followed Curtin (1989, 1998), using the earliest available number for each country. They produce remarkably similar results as Curtin by alternative methods.

Table 2.7 reports the results from instrumental variable estimation of the effect of a change in institutional quality on the average per capita growth rate. Four instruments are used: settler mortality, the fractions of the population speaking English and a European language, as well as the proportion of land area within 100 kilometers of the coast, respectively.

Table 2.7 Instrumental Variable Estimates for Both Sub-Samples

(Dependent Variable: Average Annual Growth in Real GDP, 1960 – 1990)

Variable	**Frostdays ≤ 2.11049**		**Frostdays > 2.11049**		**Frostdays ≤ 2.11049**		**Frostdays > 2.11049**	
	Coefficient	***t*-Stat.**	**Coefficient**	***t*-Stat.**	**Coefficient**	***t*-Stat.**	**Coefficient**	***t*-Stat.**
Constant	19.875	7.270	17.999	2.480	19.950	7.904	17.831	2.480
ln(Pop) 1960-62	0.197	0.515	-0.345	-0.467	0.231	0.674	-0.325	-0.445
X+M/GDP 1960-62	-0.026	-2.640	0.016	0.856	-0.028	-3.089	-0.016	-0.852
Language heterogeneity	0.008	1.037	-0.020	-1.002	0.009	1.329	-0.021	-1.117
ln(GDP) 1960-62	-3.794	-3.082	-4.393	-2.975	-3.564	-3.593	-4.452	-3.094
Area-weighted frostdays	-1.052	-3.826	0.044	1.454	-1.064	-4.207	0.045	1.523
ln(I/GDP)	3.335	1.973	3.427	1.657	3.663	2.725	3.484	1.706
ln(SCHOOL)	3.081	4.905	-0.259	-0.080	3.042	5.303	-0.456	-0.150
Openness(Sachs-Warner)	1.763	2.035	2.636	3.070	1.660	2.179	2.609	3.089
Institutional quality (*GADP*)	2.866	0.585	0.700	0.195	1.768	0.483	0.949	0.287
Observations	31		12		31		12	
Instruments:								
Settler mortality	Yes		Yes		Yes		Yes	
English fraction					Yes		Yes	
European fraction					Yes		Yes	
Land100km					Yes		Yes	

As shown in Table 2.7, the corresponding *2SLS* estimate of the impact of institutions on income per capita is much higher that the *OLS* estimates reported in Table 2.3. This suggests that measurement error in the institutions variables that creates attenuation bias is likely to be more important than reverse causality and omitted variables biases. However, institutions are all insignificant in *OLS* and *2SLS*. Furthermore, The estimated coefficients of X+M/GDP and ln(SCHOOL) in Column 2 and the coefficient of ln(SCHOOL) in Column 4 have "wrong" sign. This result suggests that the historical and geographical instruments have insufficient explanatory power for institutions in the temperate countries. How does one move forward from such a negative result? One possibility is regarding the strength of the instrument. When includes the settler mortality as the instrument in Table 2.7, the sample of countries is drastically cut from 81 to 43. Especially, it is 64.7% missing data in the temperate countries. The instruments in the temperate countries are less weak than in the tropical countries.

2.3 Conclusions

This chapter argues that the frost-growth nexus in a systematic way in order to assess what the "bottom line" of previous studies is when appropriate econometric estimators and test procedures are used to draw inferences. Master and McMillan (2001, p.179) claim that scale effects (total trade as a fraction of GDP, population size, and linguistic heterogeneity) are significant for the tropical but not the temperate climatic-zones is the main result of their paper. The upshot of these conflicting results is that this claim is fragile and seems too strong.

Several kinds of evidence suggest that trade policy and human capital formation seems to be a sufficient statistic for accounting for economic development in a large cross-section of countries. There is a clear positive relation between changes in policy openness and changes in institutional policy in tropical countries. Tropical countries produce high levels of output per capita in the long run because they achieve high rates of investment in physical capital and human capital and because they implement efficient institutions and government policies. According to this line of research, geography matters for many poor developing countries because they are far from markets and thus less likely to realize benefits from trade. Economic development in tropical regions will benefit from a concerted international effort to develop human capital formation, therefore agricultural technologies specific to the needs of the tropical economies.

CHAPTER 3

A QUANTILE REGRESSION ANALYSIS OF THE FROST－GROWTH NEXUS

3.1 Introduction

Most of the empirical literatures adopt the ordinary least squares approach to long-term growth study, which is based on the analysis of the mean of linear regression. Several researches argue that the classical linear regression model provides an incomplete analysis of the distribution dynamics of economic development. Koenker and Bassett (1978) firstly suggested that the quantile regression approach is one of the ways to analyze development distribution dynamics, providing a more complete view of possible causal relationships between variables in the growth model. The quantile regression model gives a richer description of functional changes than other regression models. Afterward, Quah (1993, 1997) and Magrini (1996) give alternative frameworks.[21]

In this chapter, a quantile regression approach is used to estimate and to test for the average rate of growth of income per capita. The research revisits the pervious study in Chapter 2 and seeks to address evidence that the effect of climate variables on growth rates varies across the quantiles. This chapter consists of five sections: Section 3.2 introduces the basic principles of the quantile regression approach; Section 3.3 applies the quantile regression procedure to the analysis of economic growth; and the findings of this study are summarized in Section 3.4.

3.2 Methodology

Koenker and Bassett (1978) introduced the quantile regression approach to investigate the functional relations between variables for all portions of a probability distribution. Quantile

[21] Quah (1993, 1997) and Magrini (1996) provide alternative frameworks to consider the distribution dynamics of economic growth, which based on non-parametric analysis and the application of Markov chains.

regression has been used in a broad range of application settings, such as ecological applications [Kaiser et al. (1994), Terrell et al. (1996), Thomson et al. (1996), as well as Huston (2002)]; investigations of wage structures [Buchinsky and Leslie (1997)]; earnings mobility [Eide and Showalter (1999), Buchinsky and Hunt (1996)]; and educational attainment [Eide and Showalter (1998)]. Several publications have used quantile regression approach for the analysis of growth and welfare. Engle and Manganelli (1999) and Morillo (2000) have used it for financial applications to assess the problems of value at risk and option pricing respectively. Growth applications include Mello and Novo (2002), Cunningham (2003), Mello and Perreli (2003), Barreto and Hughes (2004), and Canarella and Pollard (2004).

In an unpublished paper, Mello and Novo (2002) illustrate how traditional conditional mean estimation methods fail to explain complex explanatory variables on the conditional distribution of GDP growth rates. They introduce a quantile regression technique on the growth equation. They employ Barro-Lee's database, which covers 98 countries between 1960 and 1985, on both the Barro and Mankiw-Romer-Weil growth models.[22] In the Barro model, initial income is positive for the lower quantiles and turns negative at the 65th quantile. In the MRW model, the coefficient of initial income increases in the quantiles. They find that the effect of policy variables depends on the position on the conditional distribution of GDP growth rates, which suggests that the quantile regression provides a more complete analysis of the growth experiences witnessed in these countries.

The above work is further explored in Mello and Perrelli (2003), who estimate the convergence growth equation with MRW variables using quantile regression. Mello and Perrelli (2003) use both MRW and the Bernanke-Gurkaynak database, which includes 104 countries covering two periods, 1960-1985 and 1960-1995, in models of different sample sizes. The work displays different results on initial income, which has a negative effect on the average growth rate, displays a concave pattern at all quantiles. Investment share and

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[22] The Barro model calculates the correlation between the real per capita GDP in the initial year and the average rate of growth of real GDP for the period.
The MRW model is given by $\ln(Y_{85}/Y_{60}) = \beta_0 + \beta_1 \ln Y_{60} + \beta_2 \ln(I/GDP) + \beta_3 \ln(n + g + \delta) + \beta_4 \ln(h) + \varepsilon_i$, where the explanatory variables include the initial GDP per capita, the average share of real investment to real GDP over the period, the average rate of growth in the working-age (between 15 and 64 years) population, the rate of technological growth and depreciation, as well as human capital.

population growth are highly significant and relatively stable around their *OLS* estimates. Their results provide evidence that OECD countries are indeed capturing the strong convergence forces among many countries but that there is no convergence tendency among all 104 countries.

Further evidence of conditional convergence in the neoclassical growth model is developed by Canarella and Pollard (2004). They estimate the same MRW growth model covering 86 countries over the period 1960-2000. Their findings support the contention that the growth dynamics of rich and poor countries are different. Their evidence suggests that countries residing the lower quantiles have no conditional convergence and can not catch up with countries at the higher quantiles. Conditional convergence is a characteristic only of those countries at the higher quantiles.

Two additional publications of quantile regression are relevant to the estimation of the neoclassical growth model. Cunningham (2003) presents a comprehensive analysis of the effects of social and political variables on economic growth from both international cross-sectional and panel data. He provides evidence that the impact of initial GDP, financial system performance, social factors, and trade distortions are insignificant in long-run economic growth. To estimate the significance of institutional realities on growth across countries, Barreto and Hughes (2004) develop further the sensitivity analysis of Levine and Renelt (1992) on quantile regression estimation.[23] They assume that institutions are a significant determinant of rapid national growth and conditional convergence of per capita income. Their study covers 119 countries between 1960 and 1989. It indicates that the population growth is not an important determinant of growth, especially at higher quantiles. Initial income is insignificant in the extreme lower tail, while it is negative and significant at the lower quantiles. Moreover, their results show that investment to facilitate growth exists at the highest quantiles and institutional inadequacies exist at the lowest quantiles.

The methodology used in the above papers has been developed by Koenker and Bassett's (1978) is a heteroscedastic linear location scale model. Koenker and Bassett (1982) develop a new robust approach to the problems of testing homoscedasticity, based on regression quantiles, which emphasized the robustness of their previous work. They describe the general quantile regression model, which can be written as:

(3.1) $y_i = x_i^{'}\beta_0 + u_i$, $i = 1,...,n$

where β_0 is an unknown $K \times 1$ vector of coefficients, x_i' is a $K \times 1$ vector of independent variables, y_i is the i^{th} observation of the dependent variable, and u_i is the i.i.d. error term.[24] Based on the equation in (3.1), the conditional quantile of y given x is

(3.2) $Quant(y_i | x_i) = x_i^{'}\beta_0$ or $Q_\tau (y_i | x_i) = x_i^{'}\beta_0$

where $\tau \in (0,1)$ is a fixed and known quantile of interest. As the τ increases from 0 to 1, it can be traced through the entire conditional distribution of y given x. One can obtain the quantile regression estimator by solving the minimization problem,

(3.3) $\hat{Q}_\tau = \min_{x_i\beta_0 \in \Re} \left\{ \sum_{i \in \{i | y_i \geq x_i\beta_0\}} \tau | y_i - x_i\beta_0 | + \sum_{i \in \{i | y_i < x_i\beta_0\}} (1-\tau) | y_i - x_i\beta_o | \right\}$

Equation 3.3 can be reformulated as a single expression:

(3.4) $\hat{Q}_\tau = \min_{\beta \in R} \sum_i \rho_\tau (y_i - x_i\beta_0)$

[23] Levine and Renelt (1992) find that investment share and trade share are the two significant and positive explanatory variables of growth.
[24] Rogers (1992) points out that in the presence of heteroscedastic errors Koenker and Bassett's (1982) method understates the standard errors. He suggests the bootstrapped estimator of standard errors.

where $\rho_\tau(u)$ is the "check function" defined as $\rho_\tau(u) = \tau u$ if $u \geq 0$ *or* $\rho_\tau(u) = (\tau - 1)u$ if $u < 0$. The estimator $\hat{\beta}_0$ is the specific case of the generalized method of moment framework. Buchinsky (1998) points out that the form and construction of $\hat{\beta}_0$ can be written as:

$$(3.5)\ \sqrt{n}\left(\hat{\beta}_0 - \beta_0\right) \xrightarrow{d} N\left(0, \Omega_0\right)$$

where the matrix Ω_0 is estimated by the application of a non-parametric bootstrap.

The quantile function is a weighted sum of the absolute value of the residuals. Koenker and Bassett's conventional quantile regression methods complement the established mean regression methods, which occur when $\tau = 0.5$. They provide a more flexible role for the covariate effects, allowing them to influence the location, scale and shape of the response distribution. The quantile regression approach allows for a full characterization of the conditional distribution of the dependent variable, which describes the tail characteristics of the conditional distribution.[25]

The quantile regression approach also addresses the problems of parameter heterogeneity and sample selection. One important characteristic of quantile regression is the robustness of the quantile regression estimator. Quantile regression is robust to outliers, with the added benefit that it gives us a better insight into the behavior of unusual observations.[26]

Since Koenker and Bassett's (1978, 1982) seminal papers, the theoretical framework of quantile regression has been furthered in many publications. Newey and Powell (1990) as well as Koenker and Zhao (1994) present a weighting scheme that creates opportunities for improved efficiency of estimation.[27] In order to enable the estimation of all conditional

[25] Friedman (1992), Quah (1993), and Bernard and Durlauf (1994) begin to estimate the relationship between per capita growth rates and investment in physical and human capital, population growth rates, and the initial level of per capita income.

[26] Adrover et al. (2004) provide evidence that Koenker and Bassett's Quantile Regression is not robust when the predictors contain leverage points. Rousseeuw and Hubert (1999) introduce a "deepest regression" approach with which to address this leverage points problem. However, He et al. (1998) points out that the approach is more computationally demanding and less efficient than quantile regression.

[27] Newey and Powell (1990) argue that their estimator is not efficient under the conditional quantile restriction. Therefore they propose an efficient quantile regression estimator which requires a sample splitting device to estimate the efficient score and optimal weight.

quantiles, censored quantile regression was proposed by Powell (1994), Fitzenberger (1997), Buchinsky and Hahn (1998), Khan and Powell (1999), as well as Portnoy (2003).[28] For endogenous explanatory variables, Chernozhukov and Hansen (2001, 2002), Powell (1983), Blundell and Powell (2003), as well as Ma and Koener (2004) propose a two-stage estimation procedure. Several publications extended the focus of the linear-in-parameters quantile regression model onto the application of the nonlinear quantile regression model, see Weiss (1991), Welsh, Carroll, and Ruppert (1994), Koenker and Park (1996), and Fitzenberger (1997).

In Chapter 2 are presented several pieces of evidence supporting the proposition that there is a clear, positive relationship between changes in policy openness and changes in institutional policy in tropical countries. This chapter proposes to revisit Masters and McMillan's (2001) empirical study. Given the same set of explanatory variables used in Chapter 2, quantile regression estimates the dependent variable conditional on the selected quantile. The dataset covers 89 countries.

3.3 Empirical Results

This section examines the relationship between annual frostdays and economic growth. Koenker and Xiao (2002) suggest testing the hypothesis on the entire conditional distribution of GDP growth rates. Next, the impact of annual frostdays on both the mean and the dispersion of the conditional distribution of GDP growth rates are tested.

The section begins with the same base model used in Chapter 2, which includes regressing the average real per capita growth rate covering 89 countries for the period of 1960-1990 on initial GDP per capita, initial population size, total trade expressed as a percentage of GDP, language heterogeneity, the annual frostdays, the investment share of GDP, human

[28] One drawback of Powell (1994, 1996) and Fitzenberger (1997) is that the estimation problem no longer has a strict linear programming representation.

capital, the black market premium on foreign exchange, civil liberties, as well as the occurrence of an external war, which are listed in Table 3.1.[29]

Table 3.1 Raw Statistics for the Main Variables

Variable	Ob.	Mean	SD	Min	Max
Growth Rate	89	1.992	2.002	-2.910	7.380
ln(Pop) 1960-62	89	0.828	0.631	-0.745	2.822
X+M/GDP 1960-62	89	49.618	39.370	8.000	309.000
Language Heterogeneity	89	35.371	27.129	0.000	84.000
ln(GDP) 1960-62	89	3.200	0.394	2.417	4.003
Area-weighted frostdays	89	6.691	8.700	0.000	29.684
ln(I/GDP)	82	17.996	8.085	5.400	36.900
ln(SCHOOL)	82	5.498	3.466	0.400	11.900
Black Market Premium	82	0.324	0.519	0.000	3.275
Civil Liberties	82	3.838	1.841	1.000	6.778
External War	82	0.439	0.499	0.000	1.000

This chapter proceeds to estimate generalized quantile regression, which is similar to median regression, the difference being that one estimates an equation describing a quantile other than the 0.50 quantile.[30] This approach provides a more complete and systematic analysis of the growth experiences witnessed in the countries under consideration.

[29] All variables are defined in Chapter 2.
[30] This chapter use the computer program STATA.

Table 3.2 OLS and Quantile Regression Estimates for the Base Model

Variable	Regression Coefficients									
	OLS	**Q10**	**Q20**	**Q30**	**Q40**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
Constant	6.308 (3.36)	1.451 (0.49)	4.569 (1.70)	4.553 (1.37)	7.420 (3.44)	6.292 (2.86)	7.426 (3.77)	7.338 (3.87)	8.482 (3.85)	10.524 (1.80)
ln(Pop) 1960-62	0.845 (2.72)	1.340 (3.27)	0.700 (1.69)	0.715 (1.42)	0.646 (1.91)	0.722 (2.14)	0.944 (2.72)	0.809 (2.24)	0.787 (1.18)	0.228 (0.14)
X+M/GDP 60-62	0.025 (5.04)	0.035 (4.34)	0.024 (3.88)	0.029 (4.66)	0.027 (6.93)	0.025 (6.45)	0.025 (6.24)	0.023 (5.70)	0.021 (2.81)	0.020 (1.96)
Language Heterogeneity	-0.030 (-3.96)	-0.023 (-1.29)	-0.028 (-2.08)	-0.025 (-1.69)	-0.029 (-3.36)	-0.029 (-3.39)	-0.033 (-4.05)	-0.036 (-4.72)	-0.038 (-3.69)	-0.028 (-1.46)
ln(GDP) 1960-62	-1.811 (-3.18)	-1.334 (-1.91)	-1.679 (-2.40)	-1.585 (-1.64)	-2.223 (-3.41)	-1.741 (-2.59)	-1.995 (-3.31)	-1.783 (-3.13)	-1.950 (-2.81)	-2.248 (-1.22)
Area-weighted frostdays	0.087 (3.62)	0.114 (3.61)	0.109 (3.46)	0.091 (2.04)	0.086 (3.10)	0.088 (3.26)	0.080 (3.11)	0.065 (2.54)	0.059 (1.59)	0.038 (0.48)
Observations	89	89	89	89	89	89	89	89	89	89
(Pseudo[31]) R^2	0.407	0.292	0.274	0.265	0.265	0.266	0.269	0.257	0.251	0.269

Notes: The calculation of standard errors is based on the "delta method", an approximation appropriate in large samples.[32] The t-statistics values are given in brackets.

Table 3.2 presents the results from *OLS* and a selection of ten quantiles. As a benchmark, the results obtained using the traditional *OLS* method are presented firstly. The *OLS* regression indicates that five explanatory variables are significant at the five percent level. Table 3.3 presents the results of a selection of ten quantiles from three models, which are estimated in Chapter 2. Models 1 and 2 suggest the possibility of a nonlinear climate effect.

[31] Pseudo R^2 is calculated as $1-\frac{\textit{sum of weighted deviations about estimated quantile}}{\textit{sum of weighted deviations about raw quantile}}$. This is based on the likelihood for a double exponential distribution $e^{h_i|r_i|}$.

[32] Delta Method is a straightforward and well structured approach for computing confidence interval and maximum likelihood estimate.

Total trade is individually significant beyond the 90th percentile, and language heterogeneity is individually insignificant under the 10th percentile. The quantile process for the variable initial income exhibits a non-linear increasing trend. It lies below the zero line for all quantiles. For countries in the bottom 10 percent of the conditional growth distribution the estimated coefficient on initial income is minus 1.334. It decreases to minus 2.223 for countries in the bottom 40 percent of the distribution, increases to minus 1.995 for countries in the top 40 percent of the distribution, and then decreases again to minus 2.248 in the top 10 percent of the distribution. The coefficients on the trade and language variables are extraordinarily stable across the quantiles, and are not statistically different from its least squares estimate. The coefficient on area-weighted frostdays decreases as one moves down the distribution. On average, each extra percent of frostdays improves growth by approximately 11.4% at 0.10 quantiles, declining to a 3.8% increase in growth for the 0.90 quantiles. Where there are differences across the quantiles, frostdays is more effective in increasing income in countries with lower values of growth.

In the base model the quantile process for the frostdays variable lies above the zero line and exhibits a slight downwards trend. It would seem that what one observes at the highest quantiles is uncorrelated to initial population and annual frostdays, albeit not identified in the *OLS* model, which shows more frostdays toward growth. More interestingly, the Model 1 estimate for the bottom 10 percent of countries experiencing slow growth is highly significant for all explanatory variables. As the number of frostdays increases, the impact on growth becomes greater. This suggests that the positive and significant effects of frostdays on GDP growth rates tend to apply to countries in the lower tail of conditional growth distribution. The results in Table 3.3 support the proposition that more frostdays do indeed cause a higher rate of economic growth in those countries which were previously experiencing slow growth.

Table 3.3 Quantile Regression Estimates for Selected Models

Variable	τ	Base Model		Model 1		Model 2	
		Coef.	T-stat.	Coef.	T-stat.	Coef.	T-stat.
Constant	0.10	1.451	0.44	-0.512	-3.66	2.127	0.54
	0.20	4.569	1.70	3.740	1.46	3.000	1.18
	0.30	4.553	1.37	5.785	1.94	3.776	1.31
	0.40	7.420	3.44	6.315	2.04	6.626	2.09
	0.50	6.292	3.47	6.178	3.08	6.768	4.74
	0.60	7.426	3.77	5.655	4.20	6.599	4.43
	0.70	7.338	3.87	6.969	3.18	7.129	2.79
	0.80	8.482	3.85	8.476	3.24	8.455	3.05
	0.90	10.524	2.79	10.338	1.68	14.286	2.27
ln(Pop) 1960-62	0.10	1.340	2.40	1.483	67.95	1.862	3.77
	0.20	0.700	1.69	0.672	1.76	0.957	2.57
	0.30	0.715	1.42	0.820	1.76	1.052	2.63
	0.40	0.646	1.91	0.627	1.31	0.441	0.89
	0.50	0.722	1.55	0.712	2.23	0.542	2.37
	0.60	0.944	2.72	0.663	2.75	0.571	2.12
	0.70	0.809	2.24	0.642	1.46	0.920	1.79
	0.80	0.787	1.18	0.777	0.94	0.779	0.87
	0.90	0.228	0.39	0.210	0.11	0.116	0.07
X+M/GDP 60-62	0.10	0.035	3.73	0.041	162.38	0.035	2.99
	0.20	0.024	3.88	0.025	3.75	0.025	3.74
	0.30	0.029	4.66	0.030	5.51	0.031	5.71
	0.40	0.027	6.93	0.027	4.83	0.027	4.47
	0.50	0.025	3.18	0.026	6.81	0.026	9.65
	0.60	0.025	6.24	0.024	9.12	0.025	8.16
	0.70	0.023	5.70	0.023	4.84	0.024	4.25
	0.80	0.021	2.81	0.022	2.31	0.022	2.19
	0.90	0.020	1.85	0.020	1.84	0.020	2.04
Language Heterogeneity	0.10	-0.023	-1.63	-0.022	-37.47	-0.034	-1.47
	0.20	-0.028	-2.08	-0.020	-1.51	-0.021	-1.63
	0.30	-0.025	-1.69	-0.024	-1.91	-0.028	-2.34
	0.40	-0.029	-3.36	-0.030	-2.37	-0.030	-2.23
	0.50	-0.029	-3.85	-0.031	-3.69	-0.030	-4.94
	0.60	-0.033	-4.05	-0.029	-5.13	-0.031	-4.86
	0.70	-0.036	-4.72	-0.036	-4.05	-0.034	-3.28
	0.80	-0.038	-3.69	-0.038	-2.88	-0.038	-2.64
	0.90	-0.028	-2.10	-0.028	-1.28	-0.035	-1.87

Variable	τ	Base Model		Model 1		Model 2	
		Coef.	T-stat.	Coef.	T-stat.	Coef.	T-stat.
ln(GDP) 1960-62	0.10	-1.334	-1.33	-1.254	-30.03	-1.579	-1.74
	0.20	-1.679	-2.40	-1.618	-2.38	-1.455	-2.10
	0.30	-1.585	-1.64	-2.105	-2.38	-1.534	-1.75
	0.40	-2.224	-3.41	-1.890	-2.03	-1.997	-2.09
	0.50	-1.741	-3.08	-1.735	-2.87	-1.967	-4.49
	0.60	-1.995	-3.31	-1.474	-3.60	-1.827	-4.01
	0.70	-1.783	-3.13	-1.666	-2.49	-1.866	-2.38
	0.80	-1.950	-2.81	-1.956	-2.31	-1.951	-2.20
	0.90	-2.248	-2.20	-2.169	-1.10	-3.354	-1.67
Frostdays	0.10	0.114	3.61	0.202	38.31	0.552	1.90
	0.20	0.109	3.46	0.237	2.29	0.464	2.18
	0.30	0.091	2.04	0.183	1.64	0.424	1.73
	0.40	0.086	3.10	0.136	1.18	0.384	1.40
	0.50	0.088	3.26	0.186	2.44	0.437	3.30
	0.60	0.080	3.11	0.133	2.50	0.366	2.56
	0.70	0.065	2.54	0.094	1.12	0.222	0.90
	0.80	0.059	1.59	0.086	0.66	0.078	0.20
	0.90	0.038	0.48	0.031	0.12	0.161	0.19
Frostdays Square	0.10			-0.001	-7.59	-0.046	-1.85
	0.20			-0.005	-1.21	-0.031	-1.54
	0.30			-0.003	-0.67	-0.028	-1.28
	0.40			-0.002	-0.55	-0.026	-1.02
	0.50			-0.005	-1.59	-0.031	-2.47
	0.60			-0.002	-0.96	-0.025	-1.81
	0.70			-0.001	-0.28	-0.012	-0.53
	0.80			-0.001	-0.24	-0.000	-0.01
	0.90			0.000	0.01	-0.009	-0.12
Frostdays Cubic	0.10					0.001	1.85
	0.20					0.001	1.35
	0.30					0.001	1.10
	0.40					0.001	0.94
	0.50					0.001	2.25
	0.60					0.001	1.62
	0.70					0.000	0.46
	0.80					-0.000	-0.02
	0.90					0.000	0.11

Robust regression is another attempt to correct the outlier-sensitivity deficiency in ordinary regression. Robust regression estimation yields similar results to describe the central tendency but generates different standard errors. Rogers (1992) points out that in the presence of heteroscedastic errors this method understates the standard errors and suggests using bootstrapped standard errors. Provided the error terms are homoscedastic, Koenker and Bassett (1982) and Rogers' (1992) methods would be adequate to calculate the variance-covariance matrix. With STATA, generalized quantile regression and simultaneous quantile regression provides an estimate of the entire variance-covariance matrix of the estimators. Simultaneous quantile regression estimates the equations simultaneously and obtains estimators by bootstrapping, which empirical research has shown to be better than generalized quantile regression.[33] Bootstrapping entails random re-sampling to obtain the desired empirical distribution, which provides more appropriate standard errors and confidence intervals. Bootstrapped estimator of standard errors is therefore used in the following estimations in Table 3.4.

[33] Rogers (1992) provides evidence that, in the case of quantile regression, the bootstrap standard errors are better than the convention asymptotic distribution approaches.

Table 3.4 *OLS* and Simultaneous Quantile Regression Estimates for the Base Model

Variable	Regression Coefficients									
	OLS	**Q10**	**Q20**	**Q30**	**Q40**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
Constant	6.308 (3.36)	1.451 (0.32)	4.569 (1.64)	4.553 (1.85)	7.420 (3.88)	6.292 (3.29)	7.426 (3.94)	7.338 (3.15)	8.482 (3.02)	10.524 (2.23)
ln(Pop) 1960-62	0.845 (2.72)	1.340 (2.32)	0.700 (1.27)	0.715 (1.47)	0.646 (1.43)	0.722 (1.57)	0.944 (1.79)	0.809 (1.42)	0.787 (1.49)	0.228 (0.36)
X+M/GDP 60-62	0.025 (5.04)	0.035 (4.15)	0.024 (2.58)	0.029 (3.32)	0.027 (3.75)	0.025 (3.34)	0.025 (2.44)	0.023 (2.64)	0.021 (2.13)	0.020 (1.49)
Language Heterogeneity	-0.030 (-3.96)	-0.023 (-1.44)	-0.028 (-1.93)	-0.025 (-1.97)	-0.029 (-3.49)	-0.029 (-3.69)	-0.033 (-3.79)	-0.036 (-3.78)	-0.038 (-3.38)	-0.028 (-1.79)
ln(GDP) 1960-62	-1.811 (-3.18)	-1.334 (-1.04)	-1.679 (-2.24)	-1.585 (-2.90)	-2.223 (-3.69)	-1.741 (-2.88)	-1.995 (-3.81)	-1.783 (-2.59)	-1.950 (-2.32)	-2.248 (-1.73)
Area-weighted frostdays	0.087 (3.62)	0.114 (3.31)	0.109 (2.89)	0.091 (2.86)	0.086 (2.64)	0.088 (3.25)	0.080 (3.89)	0.065 (3.14)	0.059 (2.15)	0.038 (1.01)
Observations	89	89	89	89	89	89	89	89	89	89
(Pseudo) R^2	0.407	0.292	0.274	0.265	0.265	0.266	0.269	0.257	0.251	0.269
F tests	11.4	8.35	7.9	5.87	13.24	11.72	11.57	10.77	4.94	1.310
(*P*-value)	0	0	0	0	0	0	0	0	0.001	0.267

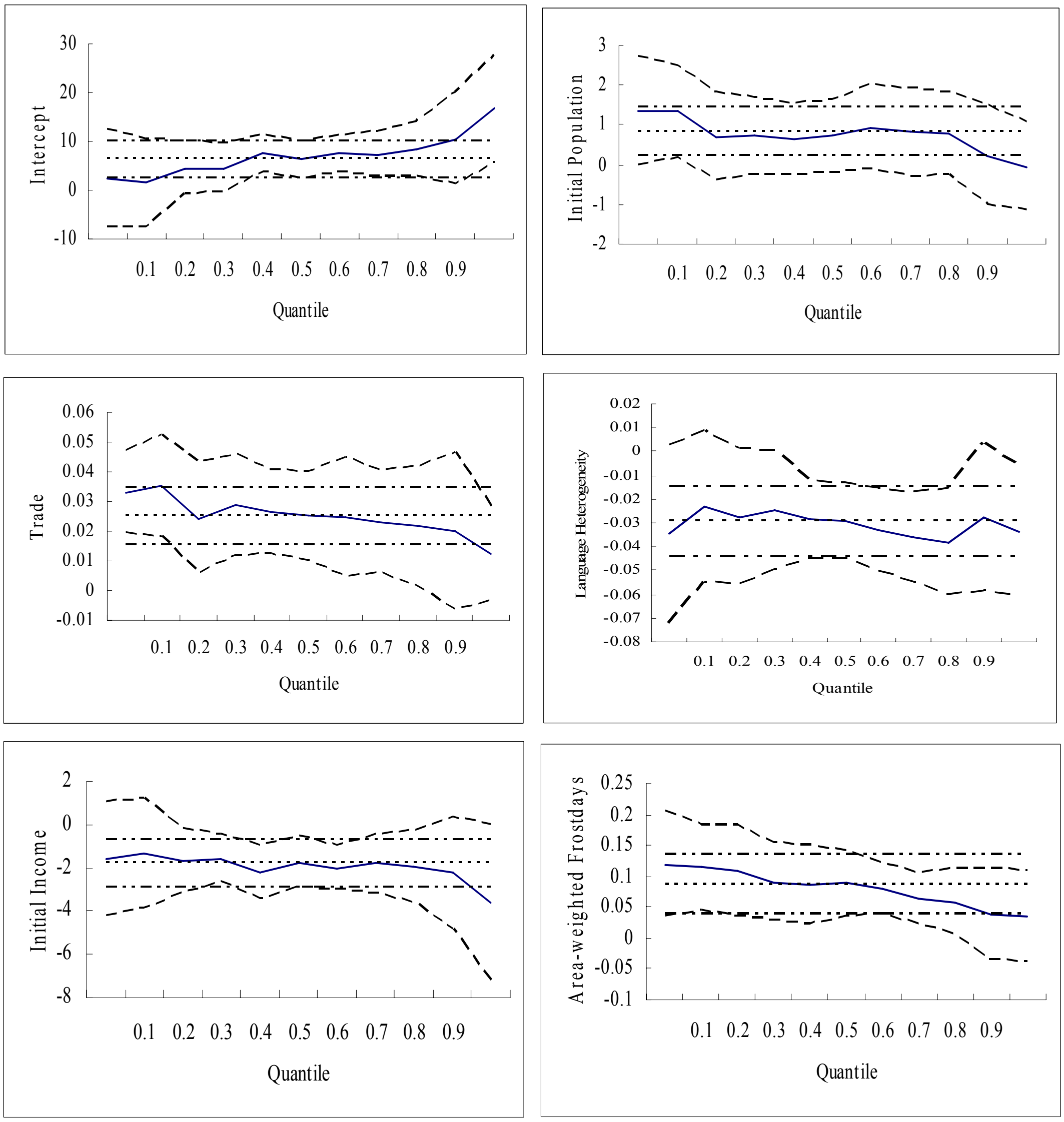
Notes: Standard errors are based on a bootstrapping procedure with 100 iterations. The t-statistics values are given in brackets.

The simultaneous quantile regression estimates in Table 3.4 yield the same coefficients as the estimates in Table 3.3. Due to the bootstrapping procedure presented by Efron (1983), the results of standard errors and confidence intervals are robust. The F-test suggests that the control variables are jointly highly significant for the ten quantiles considered. For this reason, Fig. 3.1 provides a summary of quantile regression results for the basic model in Table 3.4. For each of the six coefficients, the 10 distinct quantile regression estimates are plotted for τ ranging from 0.05 to 0.95 as the solid line, the 95% confidence interval for the quantile regression estimate as the dashed line, and the *OLS* estimate as the dotted line. The coefficient on total trade shares and initial income decreases as one moves down across quantiles. The coefficient of the language heterogeneity and initial income are close to the *OLS* coefficient when the regression moves down the quantiles. The initial GDP per capita is an insignificant determinant of growth in the lower quantile. These results are supported in the work by Cunningham (2004) and Barreto and Hughes (2004).[34]

In all the panels of Fig. 3.1, the quantile regression estimates lie outside the confidence intervals for the ordinary least squares regression at the lowest and highest tails. This is due largely to the fact that standard errors are much higher at these points than close to the median, suggesting that the *OLS* confidence interval performs well of representing this range of disparities in the base model.

[34] Cunningham (2004) reports his findings using quantile regression estimation on both cross-sectional and panel data. Barreto and Hughes (2004) consider the annual growth rate of real per capita GDP on initial GDP per capita and other variables covering 119 countries over 30 years. The initial GDP per capita and average rate of investment expressed as a percentage of GDP have the same effect across quantiles as the result of this study, albeit investment has an insignificant positive effect on growth at lower quantiles.

Figure 3.1 *OLS* and Simultaneous Quantile Regression Estimates for the Base Model



Annual frostdays is the only explanatory variable that displays a smooth decreasing curve when one begins to move further down the quantiles. In all the results above, one may conclude that annual frostdays boost economic growth across countries. In order to assess the robustness of the basic economic growth model, added policy and institution variables to the basing growth model, such as the investment share of GDP, human capital formation, the black market premium on foreign exchange, civil liberties, and the occurrence of an external war following the Barro and Sala-i-Martin (1991) cross-country growth model in Chapter 2.[35] Table 3.5 below exhibits the results from *OLS* and a selection of ten quantiles for the augmented growth model.

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[35] Barro and Sala-i-Martin (1991) cross-country growth framework is given as: $Y_i = \alpha + \beta InitialIncome + \gamma_1(Population, Trade, Schooling) + \gamma_2 Frostdays + \gamma_3(others) + \mu_i$.

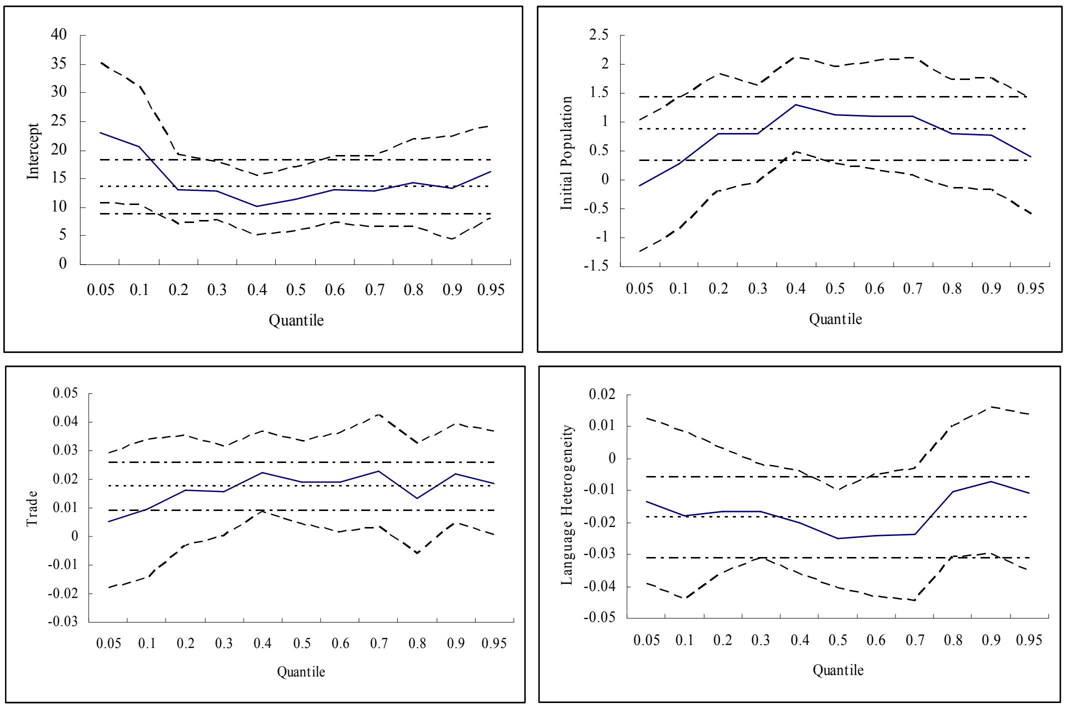
Table 3.5 *OLS* and Simultaneous Quantile Regression Estimates for the Augmented Growth Model

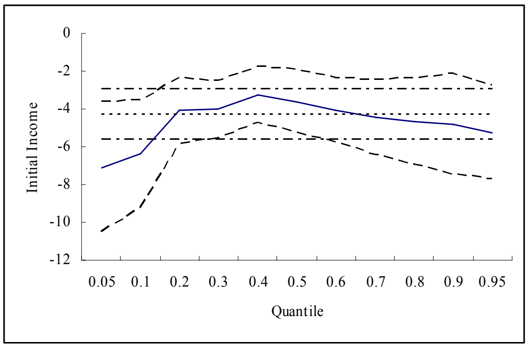
Variables	Regression Coefficients									
	OLS	**Q10**	**Q20**	**Q30**	**Q40**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
Constant	13.464 (5.66)	20.708 (4.03)	13.138 (4.32)	12.899 (5.07)	10.303 (3.99)	11.305 (4.06)	13.046 (4.49)	12.776 (4.08)	14.196 (3.76)	13.359 (2.98)
ln(Pop) 1960-62	0.876 (3.14)	0.263 (0.46)	0.802 (1.58)	0.789 (1.88)	1.297 (3.15)	1.123 (2.67)	1.103 (2.35)	1.088 (2.13)	0.788 (1.66)	0.778 (1.62)
X+M/GDP 1960-62	0.017 (4.11)	0.010 (0.79)	0.016 (1.64)	0.016 (2.00)	0.023 (3.23)	0.019 (2.59)	0.019 (2.18)	0.023 (2.35)	0.013 (1.37)	0.022 (2.52)
Language Heterogeneity	-0.018 (-2.91)	-0.018 (-1.36)	-0.016 (-1.70)	-0.017 (-2.23)	-0.020 (-2.49)	-0.025 (-3.27)	-0.024 (-2.48)	-0.024 (-2.29)	-0.010 (-1.01)	-0.007 (-0.61)
ln(GDP) 1960-62	-4.282 -6.360	-6.404 (-4.48)	-4.085 (-4.67)	-4.037 (-5.32)	-3.245 (-4.35)	-3.603 (-4.33)	-4.108 (-4.80)	-4.465 (-4.44)	-4.678 (-4.08)	-4.801 (-3.60)
Area-weighted Frostdays	0.038 (1.64)	0.094 (2.07)	0.049 (1.54)	0.048 (1.99)	0.034 (1.43)	0.022 (0.93)	0.040 (1.67)	0.039 (1.48)	0.008 (0.29)	0.016 (0.45)
ln(I/GDP)	0.066 (2.69)	0.037 (0.66)	0.044 (0.96)	0.043 (1.02)	0.038 (0.98)	0.074 (1.69)	0.076 (1.53)	0.115 (2.16)	0.137 (2.52)	0.129 (2.66)
ln(SCHOOL)	0.214 (3.05)	0.301 (2.44)	0.185 (2.25)	0.194 (2.63)	0.144 (1.58)	0.117 (1.15)	0.116 (0.97)	0.192 (1.54)	0.191 (1.52)	0.286 (2.52)
Black Market Premium	-0.731 (-2.51)	-0.294 (-0.41)	-0.363 (-0.56)	-0.428 (-0.82)	-0.564 (-1.16)	-0.604 (-1.28)	-0.636 (-1.32)	-0.722 (-1.50)	-0.899 (-1.92)	-1.312 (-2.61)
Civil Liberties	-0.272 (-1.99)	-0.620 (-2.28)	-0.415 (-2.13)	-0.355 (-1.97)	-0.272 (-1.49)	-0.150 (-0.72)	-0.189 (-0.83)	-0.065 (-0.28)	-0.140 (-0.52)	0.172 (0.68)
External War	-0.333 (-1.08)	-0.395 (-0.57)	-0.524 (-1.08)	-0.562 (-1.27)	-0.814 (-1.79)	-0.671 (-1.57)	-0.652 (-1.44)	-0.446 (-0.88)	-0.225 (-0.42)	-0.638 (-1.15)
Observations	82	82	82	82	82	82	82	82	82	82
(Pseudo) R^2	0.657	0.496	0.509	0.500	0.472	0.449	0425	0.405	0.408	0.479
F tests	13.63	5.43	13.85	22.84	10.99	12.04	7.77	9.24	4.07	15.78
(*P*-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000

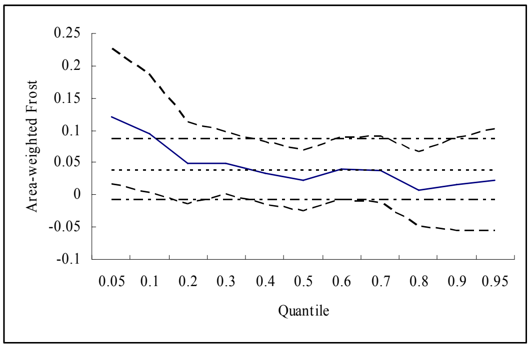
Notes: Standard errors are based on a bootstrapping procedure with 100 iterations. The t-statistics values are given in brackets.

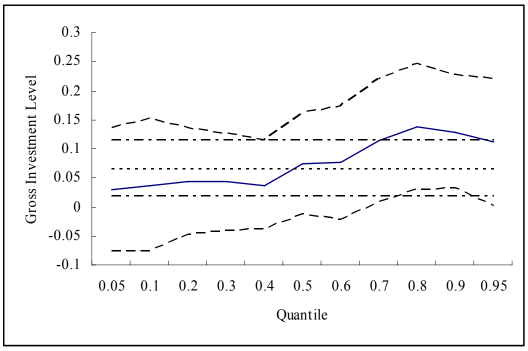
The initial income per capita is the only significant and most effective determinant of growth for all the quantiles. The result of variables used in the base model is similar to those used in Table 3.5. Initial population, language heterogeneity, and total trade are significant between the 30th and 70th quantiles. The results of the investment share and black market premium are insignificant at the lower quantiles. Conversely, human capital and civil liberties have insignificant effects at the higher quantiles. The coefficient on area-weighted frostdays decreases as one moves down the distribution a trend that is similar to that of the base model, albeit, having a statistically significant positive effect at the lower quantiles.

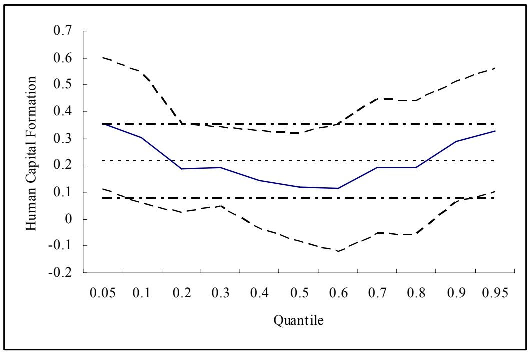
Figure 3.2 *OLS* and Simultaneous Quantile Regression Estimates for the Augmented Growth Model

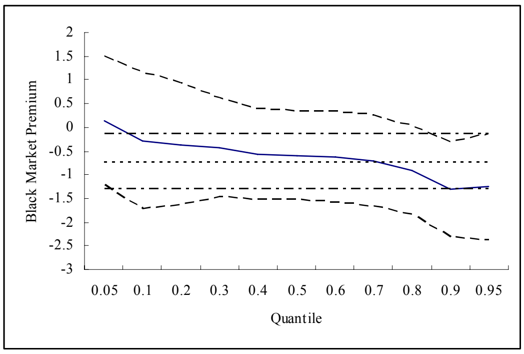


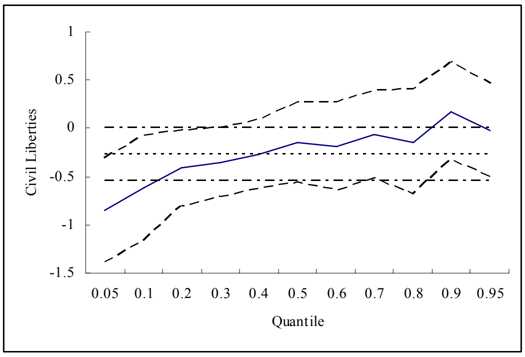

0
-2
-4
-6
-8
-10
-12
Initial Income
0.05 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 0.95
Quantile


0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
Area-weighted Frost
0.05 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 0.95
Quantile


0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
Gross Investment Level
0.05 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 0.95
Quantile


0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
Human Capital Formation
0.05 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 0.95
Quantile


2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
Black Market Premium
0.05 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 0.95
Quantile


1
0.5
0
-0.5
-1
-1.5
Civil Liberties
0.05 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 0.95
Quantile

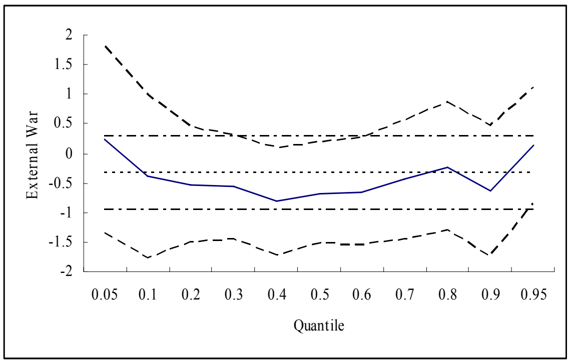

2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
External War
0.05 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 0.95
Quantile

Fig. 3.2 illustrates the regression results of ten variables across quantiles for the same selected quantiles by using simultaneous quantile regression estimation. For each of the eleven coefficients, the ten distinct simultaneous quantile regression estimates are plotted for τ and ranging from 0.05 to 0.95 as the solid line; the 95% confidence interval for the simultaneous quantile regression estimate as the dashed line; and the *OLS* estimate is represented by the dotted line. Again, the distribution of population size lies outside the 95% confidence interval. The coefficient of total trade as a fraction of GDP turns to a smooth increasing in Fig 3.2. Initial income is significantly negative in all quantiles, which is consistent with its least squares estimate. Similar results are obtained by Mello and Novo (2002), who use quantile regression to estimate the augmented Solow Growth Model by Mankiw-Romer-Weil. This finding is consistent with that of Canarella and Pollard (2004).[36] Interestingly, the quantile process for the initial income coefficient exhibits a convex shape, which is in opposition to the finding by Mello and Perrelli (2003).[37] The quantile process for the coefficient of investment share and civil liberties displays a slightly upward trend. The pattern of black market premium suggests that it has a stronger impact on countries in the upper tail of the conditional growth distribution. The results for the annual frostdays variable again largely mirrors those found for the *OLS* model. The coefficient has the same slightly downward trend as the base model, indicating that the positive effects of the annual frostdays growth on GDP growth rates tend to saddle the conditional growth distribution at the lower tail.

[36] Mello and Nevo (2003) estimate initial income and policy variables on the average GDP growth rate, covering 98 countries for the period of 1960-1985. However, their results show that the coefficient on the initial income per capita increases in the quantiles. Canerella and Pollard (2004) use a dataset, covering 86 countries between 1960 and 2000, and estimate the same model as Mankiw-Romer-Weil.

[37] Their result shows that the initial income coefficient lies below the zero line for all quantiles and exhibits a concave shape.

3.4 Conclusion

This chapter examines in general terms the effect of annual frostdays on economic growth using a quantile regression approach. *OLS* can only capture the effects of the frostdays variable on the mean of the conditional growth distribution but not on any other aspect of the conditional growth distribution. Quantile regression provides a more complete picture of the relationship between GDP growth rate and the frostdays variable. These findings imply that the quantile regression results are quite consistent with the ordinary least squares results.

This chapter supports the findings of Chapter 2, namely that tropical countries have low levels of output per capita and would benefit from a development of investment in physical capital, human capital, and civil liberties as these would facilitate the implementation of efficient institutions and sound government policies.

These findings provide evidence of conditional convergence, which is consistent with previous studies pointing to conditional convergence for fast-growing countries. Where there are differences across quantiles, annual frostdays have a larger impact in those countries which are located in primarily tropical regions and reside below the growth rate median.

CHAPTER 4

ANNUAL HARD FROSTS AND TECHNICAL EFFICIENCY IN AGRICULTURE

4.1 Introduction

Levels of agricultural productivity vary throughout the world. Empirical research has strived to determine the factors that are of greatest importance for agricultural production in different regions. Beginning with Jyoti Bhattacharjee's (1955) analysis of cross-country aggregate agricultural production, this applies economic literature has paid considerable attention to the widening gap in agricultural productivity between the developed and developing countries over the last three decades. This research was expanded on by Hayami and Ruttan (1970). They hypothesized that the higher level of agricultural productivity has been caused by the transmission by nonagricultural sectors of increased productivity to agriculture and by a continual succession of technical innovations in agriculture. Their results indicated that internal-resource endowments (land and livestock), modern technical inputs (machinery and fertilizer), and human capital (general and technical education) each accounted for about one-fourth of the difference in labor productivity between developed and developing countries.

Following the publication of Hayami and Ruttan's work, a number of empirical publications have studied agricultural productivity. Fulginiti and Perrin (1993, 1997, 1998, and 1999), Kudaligam and Yanagida (2000), Ball et al. (2001), Coelli and Rao (2003), as well as Trueblood and Coggins (2003) all identified an increase in agricultural productivity in developed countries while they find a decline in less developed countries.[38] However, Martin and Mitra (2001) and Nin et al. (2003) argue against these findings of declining agricultural

[38] They assume 10 developed countries in 1990, Germany, France, Italy, the Netherlands, Belgium, the United Kingdom, Ireland, Denmark, Greece, and the United States. The results show a positive relationship between capital accumulation and productivity growth.
Using a different approach, they estimate aggregated agricultural output among 18 less-developed countries over the period 1961 to 1985. The approach of Färe et al. (1992) is a nonparametric approach that provides only point estimates of productivity gains. It allows the partitioning of productivity changes into efficiency and technical-change components. The term of *less developed countries* is synonymous with the new IMF term *developing countries*.

productivity in developing countries and re-estimate the data under alternative technological assumptions.[39] They conclude that agricultural productivity in developing countries has increased, with technical change being the main source of the growth. The major limitations of all the approaches have been the lack of comparable data and the presence of inherent differences across countries.

Since the mid-1980s, a succession of studies has attempted to assess how strong a correlation there is between geography and climate variables and cross-country levels of agricultural productivity. Most tropical countries have low agricultural productivity because they have an inhospitable environment for agriculture. Gallup (1998) applies the aggregate production function approach to 101 countries from 1961 to 1996. Tropical agriculture is estimated to be only 6% as productive as temperate agriculture, even when using the same inputs. Geography variables have a large effect on agriculture, although they are not very helpful in identifying the set of obstacles to agriculture. Parry (1990) suggests that climate change has a negative annual impact on global agriculture (in the 2% to 4% range). Two recent seminal publications provide an important mechanism for linking agricultural productivity to climate. Wiebe et al. (2000) analyze agricultural productivity by incorporating spatially referenced soil and climate data combined with high-resolution land-cover data. They develop a measurement of annual rainfall by aggregating and overlaying monthly precipitation data for 110 countries over the period 1961- 1990. In most regions, better soils and climate are associated with increases of 20% or more in agricultural output per worker. Masters and Wiebe (2000) test the climate effect on agricultural productivity. They apply annual winter frostdays as the climate data which can improve agricultural success by allowing a buildup of organic matter that leads to rich, fertile topsoil, and by ensuring moist soils in the spring. Their main conclusion is that annual winter frostdays affects production both directly and indirectly through key inputs.[40]

[39] Nin et al. (2001) re-estimates a nonparametric *Malmquist* productivity index under alternative assumptions that allows negative productivity growth through the efficiency change component of the productivity index.

[40] The frostdays data represent about 12,500 individual $1^{\circ}\times 1^{\circ}$ cells covering almost the land surface of all over the world. Frostdays is defined as those temperature of ground-level grasses falls below 0°. Masters and Wiebe (2000) apply a set of simultaneous equations to estimate the net effect of the exogenous variables effect on aggregate productivity, using weighted *OLS* and *2SLS* instrumental variables regressions.

Methodologically, this chapter seeks to extend the work of Gallup (1998). It employs different frontier approaches to estimate the cross-sectional links between annual frostdays and technical efficiency in agriculture.

The remainder of the chapter is organized as followed: In section 4.2, the data used to estimate the production function are described. A comparison of different production function analyses is presented in section 4.3. Section 4.4 presents and interprets the results of the empirical estimation. Finally, section 4.5 summarizes the conclusions of this study.

4.2 Data

In order to estimate the agricultural production function, data are needed on output and inputs. Agricultural inputs are categorized as conventional and non-conventional. Conventional inputs consist of land, labor, livestock, tractors, and fertilizer. Non-conventional inputs are resource quality, physical infrastructure, research and development, and governmental policies. Most influential publications estimate the agricultural production function with five conventional inputs.[41] A recent paper by Coelli and Rao (2003) introduces irrigation as a new agricultural input variable.[42] These papers draw heavily from data published by the Food and Agriculture Organization (1997). The FAO provides an agricultural database by country and by year, with information on trade, land, economically active population in agricultural activity, and means of population. The data on means of production include details about agricultural tractors, harvesters and threshers, agricultural machinery, fertilizers and pesticides. As economic growth has occurred, agriculture has become more capital intensive for most countries. The capital of an agricultural origin has declined relative to capital from fixed investments in machinery, irrigation, and buildings. Different capital goods have different curvature parameters and different lengths of life. The FAO database does not include data on structures, hand tools, and value of improvements to land. Larson,

[41] See, e.g., Grilliches (1964), Kaneda (1968), Hayami and Ruttan (1985), Gallup (1998), Rao and Coelli (1998), as well as Lau and Yotpoulos (1989).

Crego, Butzer, and Mundlak (1997) construct a new agricultural fixed capital series for 57 countries during the period 1967-1992. They define capital stocks in agriculture consisting of fixed capital, livestock, and orchards. Agriculture has become more capital intensive, even though capital stocks have declined in about 30% of the countries. Agricultural capital components have changed in most countries in the sample period. Capital from fixed investments in machinery, irrigation, and buildings has become increasingly important while the capital of agricultural origin has declined.

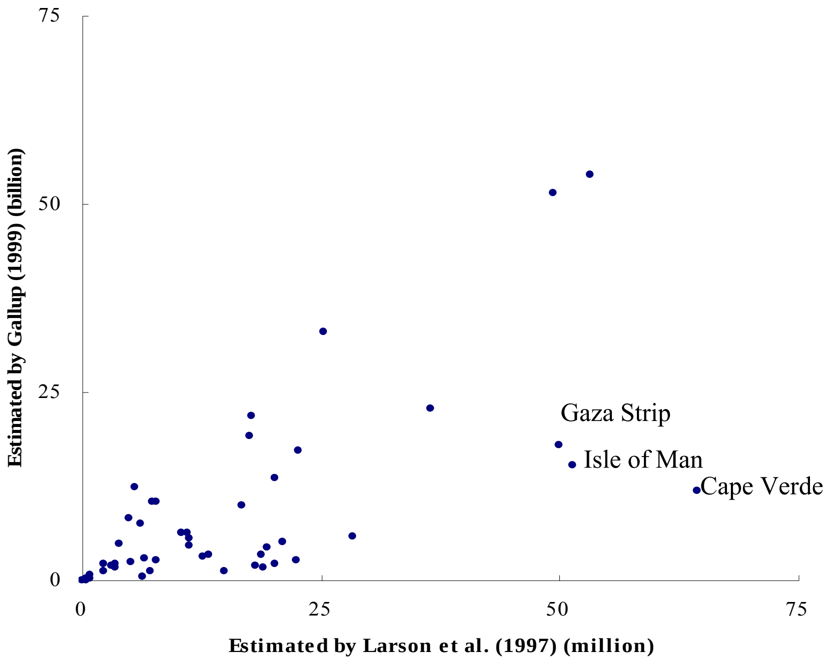
Alternatively, Gallup (1998), the pioneer of large-sample studies, applies the aggregate production function approach on 101 countries for the period 1961-1996. The countries in two studies are listed in Table 4.1.

Table 4.1 Agricultural Capital Stock Comparison

	Larson et al. (1997)	**Gallup (1998)**
Africa	15 countries	34 countries
North America	2 countries	2 countries
South and Central America	13 countries	20 countries
South and East Asia	11 countries	24 countries
Europe and Central Asia	16 countries	21 countries

[42] Coelli and Rao (2003) use the area under irrigation as a proxy for the capital infrastructure associated with the irrigation of farmlands.

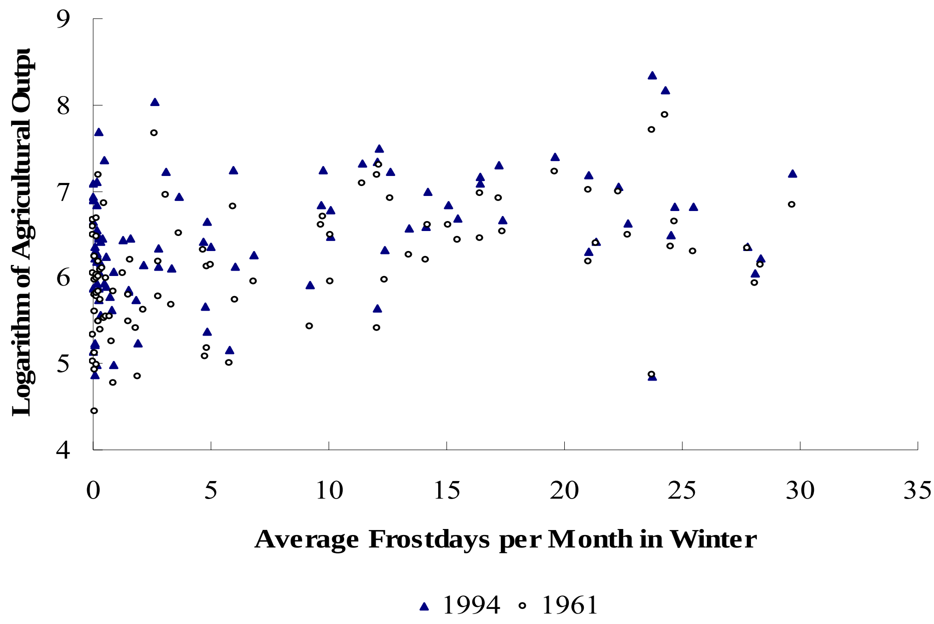
Figure 4.1 Agricultural Capital Stock Comparisons



The database of Crego et al. (1997) does not cover enough countries in Africa and the Americas to allow for accurate inferences about the role of geography in these regions. In the comparison scatter plots in Fig. 4.1, the majority of observations approximate to the 45° line, which imply that the two measurements are correlated. The data series used in this chapter are drawn primarily from a Gallup dataset developed at the World Bank. The dataset provides data for 101 countries from 1961 to 1994.

Masters and Wiebe (2000) use the prevalence of seasonal frost to test the effect of climate on agricultural productivity using panel data on 110 countries. They estimate the *OLS* regression, in which the climate variable is related to the agricultural productivity in developing countries when the relevant variables are covered. Fig. 4.2 illustrates the relationship between agricultural output and frost prevalence in 1961 and 1994. The following three figures, Fig. 4.3, Fig. 4.4, and Fig. 4.5, illustrate the relationship between soil quality and land quality by plotting them both against frost prevalence. The results indicate that regions with fewer frostdays have less soil quality and also less land quality.

Fig. 4.2 Agricultural Output and Frostdays Frequency, 1961 vs. 1994[43]



[43] Agricultural output is measured in constant 1995 U.S. dollars. See www.fao.org

Fig. 4.3 Soil Quality Index vs. Land Quality Index for the Entire Sample[44]

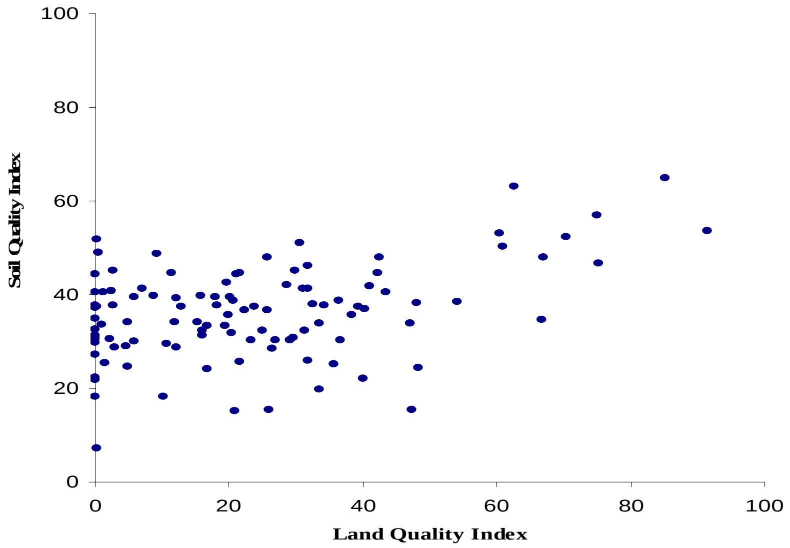
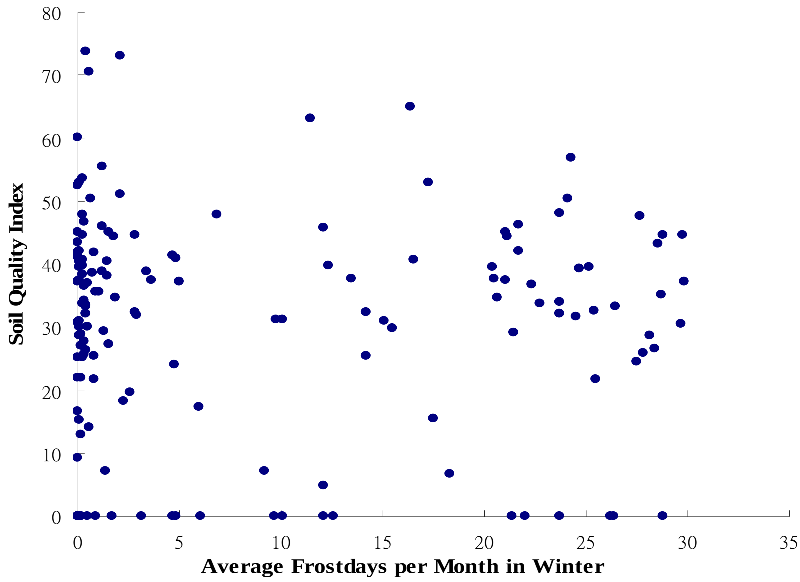
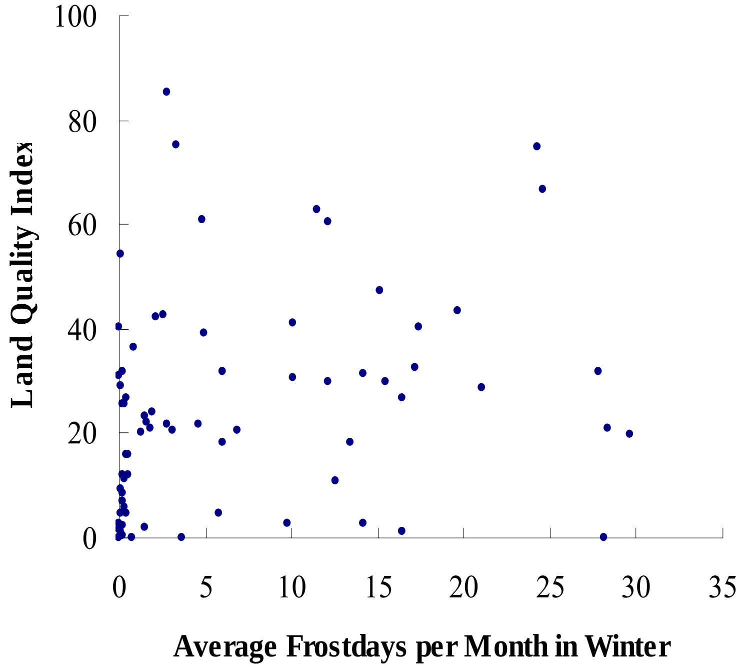


Fig. 4.4 Soil Quality Index vs. Frostdays Frequency



[44] The soil quality index is calculated the average of the suitability for different crops as indicators of overall suitability [Gallup, (1998)]. The land quality index is based on the share of each country's cropland [Wiebe et al., (2000)].

Fig. 4.5 Land Quality Index vs. Frostdays Frequency



Another perspective considers whether the gap between developed and developing countries is related to historical factors. If so, do these historical factors affect the agricultural sector? La Porta et al. (1998) find empirical support for the view that national commercial legal traditions influence the economic, political, and cultural theories of institutions.[45] In general, laws vary greatly across countries, in part because of differences in their origins. In order to help explain a country's laws on creditor right, shareholder right, and private property rights, they divide these traditions into British common law, French civil law, German civil law, Scandinavian law, and Soviet socialist law. These laws have spread all over the world through conquest, colonization, imitation, and voluntary adoption. The British government establishes common law, which is a mechanism for protecting subjects from the crown. Common law has acted as a powerful counterbalance that has promoted private property rights.

[45] La Porta et al. (1998) examine legal rules covering protection of corporate shareholders and creditors, the origin of these rules, and the quality of their enforcement in 49 countries.

Civil law gives investors weaker legal rights than common law, independent of the level of per capita income. Common law countries provide both shareholders and creditors the strongest protections, while French civil law countries provide the least protection. German civil law and Scandinavian countries generally fall between. This research comprises of 31 countries governed by British common law, 44 countries by French civil law, four countries by German civil law, and four countries by Scandinavian civil law.

Like Gallup's study, this paper is based on observational data, but it employs panel data. These data are mainly based on information from the FAO and World Bank. Table 4.2 summarizes the key variables used in the agricultural production function in this chapter.

Table 4.2 Database of Agricultural Variables

Definition of variables	Number of Countries	Time Period	Sources
Dependant Variables			
Agricultural GDP per capita refers to the gross domestic product divided in agriculture by midyear population, which used as an indicator of the general state of technology.	101	1961-1994	Gallup (1998)
	56 57	1967-1969 1970-1992	Larson et al. (1997)
	166	1960-2000	World Bank (2003) PWT6.1
Agricultural Output is measured in constant 1995 U.S. dollars.	101	1961-1994	Gallup (1998) FAO (1997)
Agricultural Productivity refers to the ratio of agricultural value added to the number of workers in agriculture.[46]	83	1961-1994	World Development Indicators (2003)
Conventional Inputs			
Agricultural fixed capital series in Larson et al. (1997) are based aggregate national accounts investment data.[47]	56 57	1967-1969 1970-1992	Larson et al. (1997)

[46] Agricultural value added is measured in constant 1995 U.S.

[47] Larson et al. (1997) point agricultural capital includes fixed capital stock, livestock, and orchards. Capital is equal to structures and equipment plus livestock and orchards. Gallup (1998) estimates agricultural capital, including fixed and working capital, which measures of the number of tractors, the number of livestock and the consumption of fertilizer.

Definition of variables	Number of Countries	Time Period	Sources
Livestock is measured by regional export unit values, based on FAO trade data. Livestock is measured in the quantities of livestock in a country. [48]	57 101	1967-1992 1961-1994	Larson et al. (1997) Gallup (1998)
Orchards are measured in the quantities of orchard or treestock in a country.	52	1967-1992	Larson et al. (1997)
Tractor refers to the total number of tractors used in agriculture.	101	1961-1994	Gallup (1998)
	163	1960-2000	World Bank (2003)
Fertilizer is measured as metric tons of nitrogenous, potash, and phosphate fertilizers.	101	1961-1994	Gallup (1998)
	163	1960-2000	World Bank (2003)
Agricultural land includes arable land, permanent cropland, and permanent pastures.	101	1961-1994	Gallup (1998), FAO database (1997)
Labor is taken to be the economically active population in agriculture.[49]	101	1961-1994	Gallup (1998) FAO
Non-conventional Inputs			
Labor quality, life expectancy and the rate of adult illiteracy (Wiebe et al. 2000)	101	1961-1994	Gallup (1998) World Bank

[48] Livestock of different kinds are aggregated using the weights from Hayami and Ruttan (1985).
[49] Original data is from FAO database. For some years and countries, labor force data is filled in by linear interpolation.

Definition of variables	Number of Countries	Time Period	Sources
Human capital is captured by mean years of schooling the population (Barro and Lee 1993).	101	1961-1994	Gallup (1998) World Bank
Population density is midyear population divided by land, which is in square kilometer.	83	1961-1994	World Bank (2003)
Frostdays is defined as the average number of such days per month in winter where the estimated temperature falls bellow 0℃.	97	1961-1990	Masters (2001)
Water indicator is calculated total water availability using Global Historical Climatology Network (GHCN 1997 data) which includes estimation of water from rivers and lakes, precipitation, and evaporation on a national basis.	101	1961-1994	Gallup (1998)
Land quality index is based on the share of each country's cropland.	110	1961-1997	Wiebe et al. (2000)
Soil quality is calculated the average of the suitability for different crops as the indicator of overall suitability. It is derived from the landmark FAO Digital Soil Map of the world (1995).	101	1961-1994	Gallup (1998)
Ecozones function is devised using four indicators: growing season length, growing season temperature, annual precipitation and a potential evapotranspiration ratio. They are aggregated from the more detailed Holdridge Life Zone Classification (Leemans, 1990)	101	1091-1994	Gallup (1998)

Definition of variables	**Number of Countries**	**Time Period**	**Sources**
The Gastil index of institutional quality is an indicator of a basic dimension of the quality of the institutional environment.[50]	97	1960-1996	Knack and Keefer (1995) World Bank
Trade openness is used to indicate the degree of goods market integration.[51]	83	1960-1996	Sachs & Warner (1995)
Civil Liberty is based on a (1 — 7) scale, with 1 representing the highest degree of freedom.[52]	83	1960-1996	Freedom House
Legal origin identifies the origin of the Company Law or Commercial Code in each country. There are five possible origins: British common law; French civil law; German civil law; Scandinavian civil law; and Socialist or Communist law.	212		World Bank[53]

[50] Also named Government Anti-Diversion Policies index, this variable is measured on a (0, 1) scale. The index is an equal-weighted average of five criteria: rule of law; quality of bureaucracy; corruption in government; risk of expropriation; and government repudiation of contracts.
[51] Sachs and Warner index is measured on the following criteria: (1) non-tariff barriers cover less than 40 percent of trade; (2) average tariff rates are less than 40 percent; (3) the black market premium was less than 20 percent in the 1970s and 1980s; (4) the economy is not socialist; and (5) the government does not control major exports.
[52] Freedom House has published the world country ratings from 1972 to 2003. See www.freedomhouse.org
[53] The legal origin factor is compiled by the *Doing Business* team using several sources, including La Porta et al. (1999) and the CIA Factbook (2002). See www.worldbank.org

4.3 Methodology

Various approaches can be used to estimate the technical efficiency of the production function with panel data. Battese and Coelli (1985) give a general overview of these methods. This section provides a description of the production function and the specification used in this chapter. The adopted methodology is based on a comparison of different production functions with respect to the estimated function parameters, estimated technical inefficiency scores, and the out-of-sample prediction errors.

Production functions for estimation of production frontiers have evolved within two parallel traditions: the parametric and the nonparametric approach. Stochastic Frontier Analysis (*SFA*) and Data Envelopment Analysis (*DEA*) are alternative methods for estimating frontier functions and thereby measuring efficiency of production. *SFA* involves the use of econometric methods, whereas *DEA* involves the use of linear programming. The parametric *SFA* [see, e.g., Aigner et al. (1977), Meeusen and Van den Broeck (1977), as well as Olson et al. (1980)] has focused on the development of stochastic frontier production functions on the basis of the parametric specification of functional forms for the frontier and the residuals involved. The nonparametric *DEA* has focused on the development of multiple-input and multiple-output configurations.[54] Both approaches have been applied to panel data. *SFA* is first applied to panel data by Pitt and Lee (1981), Schmidt and Sickles (1984), Craig et al. (1997), as well as Wiebe et al. (2000). *DEA* is developed for panel data by Charnes et al. (1985) and, in a much more informative way, by Färe et al. (1994), and in the recent studies of agricultural productivity by Trueblood and Coggins (2003), Rao and Coelli (1998), and further refined by Coelli and Rao (2003).

4.3.1 Parametric Stochastic Frontier Analysis

This section begins with a simple stochastic frontier production function. Aigner, Lovell, and Schmidt (1977) and Meeusen and Van den Broeck (1977) independently proposed

[54] See, e.g., Charnes et al. (1978, 1979); Banker et al. (1984); Färe, Grosskopf and Lovell (1985); Färe and Hunsaker (1986); Trueblood and Cogins (2003); as well as Coelli and Rao (2003).

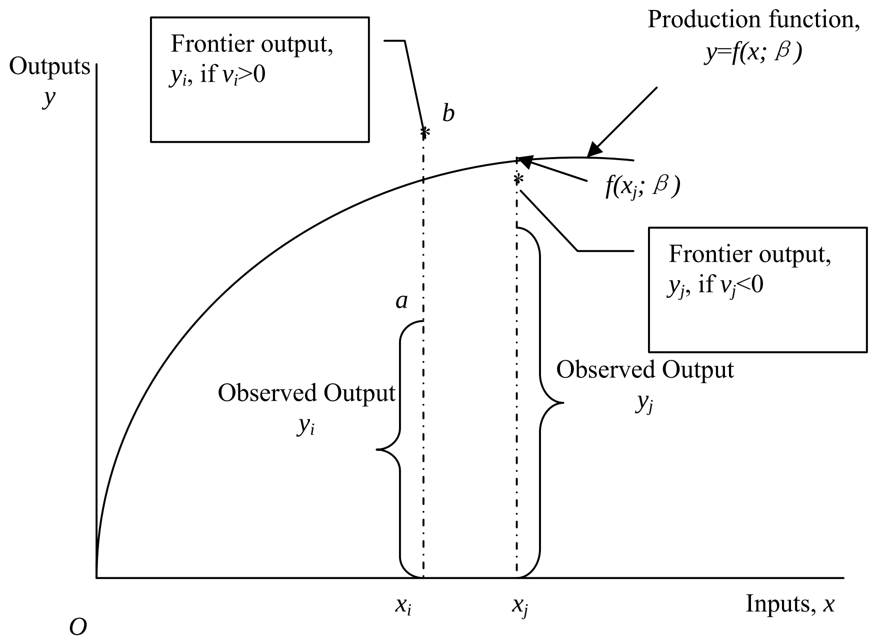
the stochastic frontier production function, in which an additional random error, v_i is added to the non-negative random variable, u_i, in the equation to present the following.

(4.1) $\ln(y_i) = x_i\beta + v_i - u_i$, i=1, 2, …, N.

The random error, v_i accounts for measurement errors and other random factors, such as the effects of weather and corruption on the value of the output variable, together with the combined effects of unspecified input variables in the production function. Aigner, Lovell, and Schmidt (1977) assume that each v_i was an independent and identically distributed normal random variables with mean zero and constant variance σ_v^2, independent of the instances of u_i, which is assumed to represent an independent and identically distributed, which is either exponential or half-normal random variables.

The basic features of the stochastic frontier production function are illustrated in two dimensions in Fig. 4.6. The inputs are represented on the horizontal axis, and the outputs on the vertical axis. The deterministic component of the frontier production function, $y = \exp(x\beta)$, is drawn assuming that diminishing returns to scale apply. The observed outputs and inputs for two firms, *i* and *j*, are presented on the graph. The *i-th* firm uses the level of inputs, x_i, to produce the output, y_i. The observed input-output value is indicated by the point marked with *a* above the value of x_i. The value of the stochastic frontier output, $y_i^* \equiv \exp(x_i\beta + v_i)$, is indicated by the point *b* above the production function, as the random error, v_i, is positive. Similarly, the *j-th* firm uses the level of inputs, x_j, and produces the output, y_i. However, the frontier output, $y_j^* \equiv \exp(x_j\beta + v_j)$, is below the production function, because the random error, v_j, is negative. Of course, the stochastic frontier production function lies between the stochastic frontier outputs. The observed output may be greater than the deterministic part of the frontier if the corresponding random errors are greater than the corresponding inefficiency effects (i.e., $y_i > \exp(x_i\beta)$ if $v_i > u_i$).

Fig. 4.6 The Stochastic Frontier Production Function



Transcendental Logarithm (Translog) and Cobb-Douglas functional forms have commonly been used in the empirical estimation of frontier production functions. The Translog function is the more flexible function for explaining the relationship between the output and input levels. The production technology is represented by the Translog function

$$(4.2) \qquad \ln y_{it} = \beta_0 + \sum_{j=1}^{n} \beta_j x_{jit} + \sum_{j\leq}^{n} \sum_{k=1}^{n} \beta_{jk} x_{jit} x_{kit} + v_{it} - u_{it}$$

where the subscripts *i* and *t* represent the *i*-th firm and the *t*-th year of observation, respectively. The log of agricultural output is represented by *y*, and *x* is the log of the agricultural inputs (agricultural land, fertilizer, livestock, tractors, and labor). It is assumed that v_{it} is independent and normally distributed $N(\mu, \sigma_u^2)$, truncated at zero from below. The non-negative, unobservable random variable u_{it} is associated with the technical inefficiency of production. The Cobb-Douglas production function is a special case of the Translog frontier, in which the coefficients of the second-order terms are zero, i.e., $\beta_{jk} = 0, j \le k = 1, 2$.

$$\text{(4.3)} \qquad \ln y_{it} = \beta_0 + \sum_{j=1}^{n} \beta_j x_{jit} + v_{it} - u_{it}$$

Many studies have focused on the technical efficiency of productivity, using mainly the Cobb-Douglas production function [e.g., Hayami and Ruttan (1970, 1985); Battese (1992)]. However, the Cobb-Douglas production has more restrictive assumptions [e.g., Greene (1980); Lau and Yotopolous (1989); Martin and Mitra (2001)]. Thiam et al. (2001) present their empirical result that studies using Cobb-Douglas production function, which yield a lower average technical efficiency than using the Translog production function.[55] While the Translog production function imposes no restrictions on returns to scale or substitution possibilities, it has the drawback of being susceptible to multicollinearity and degrees of freedom problems.

SFA production functions have three serious inherent deficiencies. First, the technical inefficiency of a particular observation can be estimated, but not consistently. Second, the estimation of the production function and the separation of technical inefficiency for statistical noise require specific assumptions about the distribution of technical inefficiency and statistical noise. Third, it may be incorrect to assume that inefficiency is independent of the regressors. All these problems are avoidable if one has panel data.[56] An important aspect of the SFA production function is the possibility it offers for a richer specification, particularly in the case of panel data. Here it considers two categories of the stochastic frontier analysis. The first is a panel data production function with time-varying technical inefficiency, as suggested by Cornwell, Schmidt and Sickles (1990) and Battese and Coelli (1992). The alternative

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[55] Ahmad and Bravo-Ureta (1996) argue that employing different functional forms do not affect the TE estimation.

[56] Schmidt and Sickles (1984) point out that all parameters in technical inefficiency model, without any distribution assumptions, can be obtained by simply using the traditional estimation procedures for panel data.

production function is a technical efficiency time-invariant production function, as pointed out by Schmidt and Sickles (1984), and Hjalmarsson et al. (1996).

4.3.1.1 Technical Efficiency Time-variant Production function

Cornwell et al. (1990) propose a production function that accounts for time-varying inefficiency effects within a stochastic panel data framework. They suggest that the production function can be specified as

$$(4.4) \quad Y_{it} = \beta_{0t} + \sum_{j=1}^{n} \beta_j x_{jit} + v_{it} - u_{it} = \beta_{it} + \sum_{j=1}^{n} \beta_j x_{jit} + v_{it}$$

where β_{0t} indicates the common production frontier intercept for all cross-sectional productive units in period *t* and $\beta_{it} = \beta_{0t} - u_{it}$ is the intercept of the unit *i* in period *t*, random variables are v_{it} and u_{it} are defined above.

Lee and Schmidt (1993) propose that the technical inefficiency effects for each productive unit at a different time period are defined by the product of individual technical inefficiency and time effects, $u_{it} = \delta_t u_i$, where each δ_t is a time effect represented by a time dummy, and the u_i can be either fixed or random producer-specific effects. Alternatively, Battese and Coelli (1992) propose technical inefficiency to be an exponential function of the time.

$$(4.5) \quad u_{it} = \exp\left(-\eta(t - T_i)\right) u_i \equiv \eta_{it} u_i$$

where η is a single unknown scalar parameter, and u_i is assumed to be normally distributed $N(\mu, \sigma_u^2)$ truncated at zero from below. The specification above allows technical inefficiency to change over time in a particular way. Technical inefficiency either increases ($\eta > 0$), decreases ($\eta < 0$), or remains constant ($\eta = 0$) over time. Thus, the temporal pattern is not only the same for all countries; it also either increases or decreases exponentially.

4.3.1.2 Technical efficiency time-invariant production function

Battese and Coelli (1995) propose specific technical inefficiency effects in the stochastic frontier production function that are assumed to be independently distributed non-negative random variables. The production function uses the z variables as determinants of technical efficiency:

(4.6) $u_{it} = \sum_s \delta_s z_{sit} + \omega_{it}, \quad u_{it} \geq 0$.

where z variables are treated as determinants of technical efficiency, and where z_{it} is a (1×M) vector of observable explanatory variables, whose values are fixed constants; and where δ is an (M×1) vector of unknown scalar parameters to be estimated, which would generally be expected to include an intercept parameter. Two special cases of the production function are in order. First, $\sum_s \delta_s z_{sit} = \delta_0$ implies that u_{it} is the truncated normal distribution considered by Stevenson (1980), and, second, $\sum_s \delta_s z_{sit} = 0$ gives the original formulation of Aigner, Lovell, and Schmidt (1977). The parameters of this production function can be estimated by the Maximum-Likelihood method. The likelihood function and estimation issues are discussed in Battese and Coelli (1995). The technical efficiency for the *i-th* countries in the *t-th* time period is defined by

(4.7) $TE_{it} = \exp(-\mu_{it})$

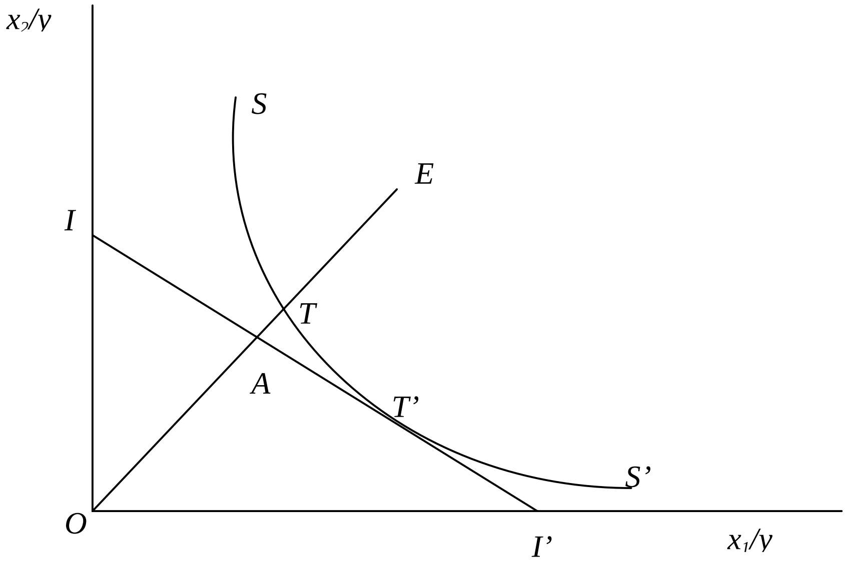
where the generalized likelihood-ratio test for the null hypothesis is $H_0: \gamma = 0$, where $\gamma = \sigma^2 / \left(\sigma_v^2 + \sigma^2\right)$. The likelihood function is evaluated for a number of values of the γ parameter between 0 and 1. If γ equals 0, this indicates that deviations from the frontier are attributable entirely to noise.[57] If γ equals 1, this indicates that all deviations are attributable entirely to economic inefficiency, and hence the stochastic frontier production function is not significantly different from the deterministic frontier production function with no random error.[58] The generalized likelihood ratio test for the null hypothesis that the γ and the β parameters are jointly equal to zero is calculated by using the values of the log-likelihood function for estimating the full frontier production function and that obtained from an *OLS* regression of the production function. This statistic has a mixed chi-square distribution.

4.3.2 Nonparametric Data Envelopment Analysis

Farrell (1957) proposes a measure of the efficiency of a firm that consists of two components: technical efficiency, which reflects the ability of a firm to obtain maximal output from a given set of inputs, and allocative efficiency, which reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices. These two measures are then combined to provide a measure of total economic efficiency. Farrell illustrates this concept using a simple example involving firms that use two inputs (x_1 and x_2) to produce a single output (*y*), under the assumption of constant returns to scale.

[57] Previous studies use a standard econometric methodology that, in this author's opinion, is entirely correct in their implicit assumption of economic efficiency.
[58] Kneller and Stevens (2002) find that, in practice, the γ parameter is statistically significant in the range of 0.80 to 0.85.

Fig. 4.7 Technical and Allocative Efficiencies from an Input Orientation



In Fig. 4.7, *SS'* represents the unit isoquant of a fully efficient firm, and *II'* represents the slope of the isocost line. If a given firm uses quantities of inputs, defined by the point *E*, to produce a unit of output, the technical inefficiency of that firm can be represented by the distance *TE*, which is the amount by which all inputs could be reduced proportionally without a reduction in output, as reflected in the following equations:

(4.8) $$TE_i = OT/OE .$$

(4.9) $$AE_i = OA/OT .$$

(4.10) $$EE_i = OA/OE .$$

where TE_i, AE_i and EE_i represent the technical efficiency, allocative efficiency and total economic efficiency, respectively. In the input-orientated case above, the *DEA* method defines the frontier by seeking the maximum possible proportional reduction in input usage, with output levels held constant, for each country. By contrast, in the output-orientated case, the *DEA* method seeks the maximum proportional increase in output production, with input levels held fixed.[59]

The analysis developed in Chames et al. (1978) assumes Constant Returns to Scale (*CRS*) in their approach. *CRS* model assumes there are data on *x* inputs and *y* outputs for each of *z* firms. The $x \times z$ input matrix, *X*, and the $y \times z$ output matrix, *Y*, represent the data for all *z* firms. The *DEA* formulation, via the ratio form, can be obtained as the maximum of a ratio of weighted outputs to weighted inputs subject to the constraint.

$$(4.11) \quad \max_{u,v}\left(u' y_i / v' x_i\right), \qquad \text{st} \quad u' y_j / v' x_j \leq 1, \; j=1,2,\ldots,z \qquad u, v \geq 0.$$

where u is an $y \times 1$ vector of output weights and v is a $x \times 1$ vector of input weights. One problem with this ratio formulation is that it has an infinite number of solutions. This can be avoided by imposing the constraint, $v' x_i = 1$, which provides the following multiplier form of the *DEA* linear program.

$$(4.12) \quad \max_{u,v}\left(\mu' y_j\right), \qquad \text{st} \quad v' x_i = 1, \qquad \mu' y_j - v' x_j \leq 0, \; j=1,2,\ldots,z \qquad u, v \geq 0.$$

Using the duality in linear programming, the form in equation 4.12 can derive an equivalent envelopment form as following.

59 Fare and Lovell (1978) point out that, under Constant Returns to Scale, the input-orientated and output-orientated measures of technical efficiency are equivalent.

$$(4.13) \qquad \min_{\theta,\lambda} \theta,$$
$$\text{st} \quad \begin{aligned} &-y_i + Y\lambda \geq 0, \\ &\theta x_i - X\lambda \geq 0, \\ &\lambda \geq 0. \end{aligned}$$

where θ is a scalar and λ is a $z \times 1$ vector of constants.

Alternatively, Fare et al. (1985) introduce a Variable Returns to Scale (*VRS*) approach, which corrects *CRS* approach weakness.[60] They add the convexity constraint, $z1'\lambda = 1$, on the *CRS* model to modify the linear programming problem.[61]

$$(4.14) \quad \min_{\theta,\lambda} \theta,$$
$$\text{st} \quad \begin{aligned} &-y_i + Y\lambda \geq 0, \\ &\theta x_i - X\lambda \geq 0, \\ &z1'\lambda = 1, \\ &\lambda \geq 0. \end{aligned}$$

where $z1$ is an $z \times 1$ vector of ones.

Recent years have seen a great variety of applications of *DEA* for evaluating the performances of many kinds of entities engaged in various activities [Lovell (1993), Fulginiti and Perrin (1997), Rao and Coelli (1998), as well as Nin et al. (2003)]. *DEA* has opened up possibilities for use in cases that have been resistant to other approaches because of the complex nature of the relations between the multiple inputs and multiple outputs involved in many of these activities. *DEA* techniques are flexible and adaptable. This approach is simply compatible with the linear programming methods and concepts. *DEA* does not distinguish between technical inefficiency and statistical noise effects, and *DEA* does not account for noise.

[60] Fare et al. (1983), Byrnes et al. (1984), and Banker et al. (1984) provide the evidence that *CRS* analysis is biased by scale efficiencies.
[61] Coelli et al. (1995) point that the convexity constraint ensures that an inefficient firm is only 'benchmarked' against firms of a similar size.

4.4 Empirical Results

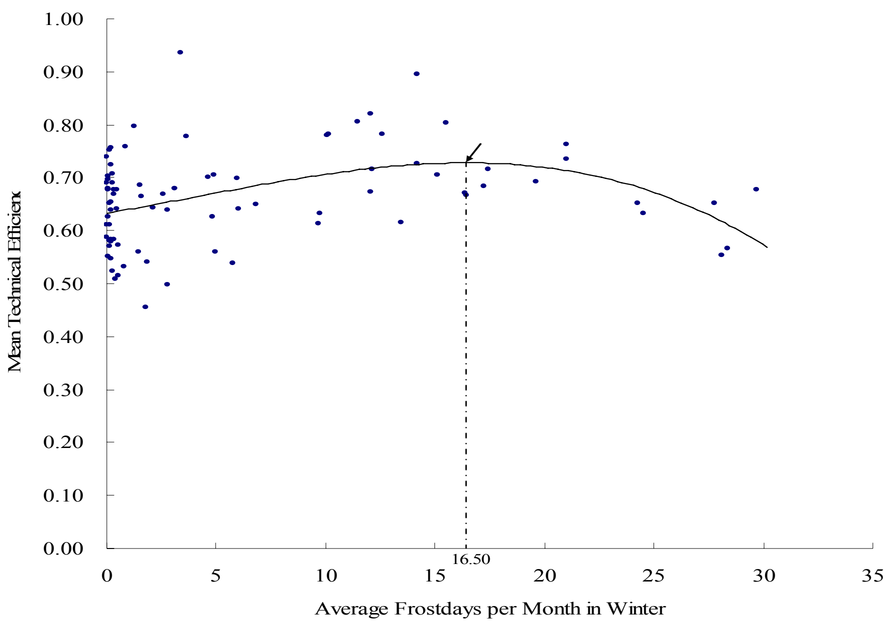
In this paper, the stochastic frontier production functions are applied to a sample of agricultural productivity in developed and developing countries over a period of 34 years. The sample covers 83 countries, 24 are in Africa, 20 are in South and Central America, 16 in Asia, 16 in Europe, four in Oceania, and three in North America. The Translog and Cobb-Douglas stochastic frontier production functions, defined by equations 4.2 and 4.3, contain 20 β-parameters and the eight additional parameters associated with the distributions of the v_{it} and u_{it} random variables. Maximum-likelihood estimates of these parameters of four stochastic frontier production functions are obtained by using the FRONTIER computer program, are given in Table 4.3.[62] Column 1 has a Cobb-Douglas functional form. All the remaining production functions have a Translog functional form. Column 2 excludes explanatory variables for the technical inefficiency function. In Column 3, frostdays is assumed to be a linear variable, whereas it hypotheses a nonlinear effect in Column 4. Finally, Column 4 is the basic production function. It assumes a Translog functional form, technical inefficiency effects, geography, historical, trade, institutional, and nonlinear frostdays effects in the technical inefficiency component.

The signs of most β-estimates in the basic production function are as expected and statistically significant, with the exception of the negative estimate of the variables for land and tractors. The negative elasticity for land may be caused by the fact that rapid population growth and the resulting need for human settlement and increased urbanization. The parameter γ is estimated approximate to 1.0, suggesting that the technical inefficiency effects are highly significant. The estimates of frostdays, the Africa dummy, as well as Middle East (*ME*) and North Africa (*NA*) dummy variables in the inefficiency production function indicate that there exist significant climatic and geographical disadvantages for countries with fewer frostdays in the winter.[63] The significance of the forstdays variables indicates a nonlinear climate effect: as the number of frostdays increases, the efficiency becomes larger, which is same as previous

[62] The *FRONTIER* computer programs is available on The Centre for Efficiency and Productivity Analysis http://www.uq.edu.au/economics/cepa/software.htm

Chapter 2. The scatter plot of mean technical efficiency against the frequency of frost is shown in Fig. 4.8. The maximum point in the data occurs at around 16.50 frostdays in the winter on the smooth convex curve, with a slight increase of technical efficiency up to the threshold, but a sharp decline beyond. The threshold occurs at different point in previous study. Chapter 2 shows the break point is around at 2.11049 frostdays in the winter, which is negatively correlated with growth in the tropical sub-sample but positively correlated in the temperate sub-sample.[64]

Fig. 4.8 Frost Frequency and Mean Technical Efficiency, 1961-1994



[63] The geography dummy variables are defined by the World Bank.

[64] The difference of points is the upshot of using different dataset and methodologies. In Chapter 2, we assume the annual frostdays has a significant impact on growth rate in Solow Model; in this Chapter, the annual frostdays plays a significant role in logarithm production function in agriculture.

Table 4.3 The Maximum-Likelihood Stochastic Frontier Production Functions

Variable	Cobb-Douglas		Translog 1		Translog 2		Basic P.F.	
Frontier Function	**Coef.**	**t-stat.**	**Coef.**	**t-stat.**	**Coef.**	**t-stat.**	**Coef.**	**t-stat.**
Constant	2.435	33.633	2.505	7.606	1.699	5.681	2.503	9.722
Land	-0.005	-0.416	-0.461	-4.919	-0.371	-4.157	-0.267	-4.215
Fertilizer	0.081	10.470	0.432	6.753	0.625	10.640	0.706	12.257
Livestock	0.371	17.738	-0.182	-0.964	0.211	1.223	0.091	0.602
Tractors	0.165	11.206	-0.301	-3.893	-0.635	-8.285	-0.710	-10.206
Labor	0.339	21.448	1.586	23.610	1.356	21.569	1.227	19.800
$(\text{Land})^2$			-0.062	-4.296	-0.035	-2.637	-0.034	-2.725
$(\text{Fertilizer})^2$			0.093	16.329	0.095	17.509	0.082	16.246
$(\text{Livestock})^2$			0.108	3.379	0.047	1.611	0.059	2.422
$(\text{Tractor})^2$			0.069	9.779	0.089	12.386	0.061	9.256
$(\text{Labor})^2$			0.101	11.025	0.102	12.230	0.123	15.760
Land × Fertilizer			0.029	1.972	0.041	3.054	0.066	4.968
Land × Livestock			0.044	1.291	0.035	1.085	-0.008	-0.369
Land × Tractors			0.000	-0.004	-0.045	-3.008	-0.003	-0.280
Land × Labor			0.134	9.233	0.126	9.187	0.090	6.785
Fertilizer × Livestock			-0.131	-6.579	-0.164	-9.008	-0.186	-9.690
Fertilizer × Tractors			-0.092	-8.140	-0.088	-8.304	-0.062	-6.299
Fertilizer × Labor			-0.017	-1.536	-0.041	-4.027	-0.051	-7.486
Livestock × Tractors			0.115	5.103	0.178	8.222	0.191	9.489
Livestock × Labor			-0.280	-12.743	-0.201	-9.648	-0.150	-7.273
Tractors × Labor			-0.117	-9.281	-0.147	-12.552	-0.176	-17.513
Inefficiency Production Function								
Constant	0.633	4.994			-0.239	-5.300	0.321	10.890
Frostdays	0.013	2.779			0.018	10.129	-0.008	-3.161
Frostdays Square	-0.003	-7.599					0.000	0.864
Frostdays Cube	0.000	9.016					0.000	1.760
Africa Dummy	0.031	1.984			0.459	9.872	0.165	16.850
ME and *NA* Dummy	0.066	1.332			0.035	0.824	0.040	3.710
Legal Origin Dummy[65]	0.040	4.020			-0.012	-0.760	0.054	8.817
Openness	-0.126	-7.956			-0.132	-4.154	-0.031	-3.028
Civil Liberty	0.032	8.182			-0.002	-0.301	0.016	5.782
Variance Parameters								
$\sigma_v^2 + \sigma^2$	0.030	21.264	0.026	10.159	0.016	15.813	0.013	39.433
$\gamma = \sigma^2/(\sigma_v^2 + \sigma^2)$	1.000	13.034	0.551	5.952	0.285	3.930	1.000	1582
Countries	83		83		83		83	
Time periods	34		34		34		34	
Log-Likelihood	980		1735		2109.1		2179	

65 The legal origin dummy variable is equal to one if the country adopts the British common law, and zero otherwise.

Several LR-tests are presented in Table 4.4. It starts by testing the Cobb-Douglas production function against the Translog production function. The results indicate that the Cobb-Douglas functional form is rejected. The remaining tests consider restrictions on the parameters in the inefficiency production function. The countries operating under British common law have a significantly lower level of agricultural productivity than countries with German, Scandinavian, or those of socialist legal origins. The negative estimate for trade openness and positive estimate for civil liberty variables imply that countries with better trade and institutional policies tend to be more efficient. Early empirical publications, Battese and Coelli (1995), Hjalmarsson et al. (1996), and Wiebe et al. (2000), have other appropriate explanatory variables for the technical inefficiency effects in Agriculture. Their results indicate that human capital, land quality, water indicators, and time trend are significant components in the technical inefficiency production function. It is notable that those four variables are insignificant in my estimation and are deleted from the basic production function in Table 4.3. In this application, the Translog production function is a better fit for the underlying data. The inefficiency effects in the stochastic frontier are clearly stochastic and are related to climate, geography, historical, trade, and institutional variables.

Table 4.4 Likelihood-Ratio Tests for Parameters in the Frontier Production Function

Null Hypothesis	Log Likelihood	Critical Value	Decision
	2179.26		
$H_0: \beta_{ij}=0$, i,j = 1,....,5 (Cobb-Douglas)	979.77	26.30	Reject H_0
$H_0:\ \delta_1 = \delta_2 = \delta_3 = 0$ (no climate effect)	2060.24	9.49	Reject H_0
$H_0: \delta_7 = 0$ (no trade effect)	2172.00	3.84	Reject H_0
$H_0: \delta_8 = 0$ (no institutional effect)	2151.10	3.84	Reject H_0
$H_0: \delta_4 = \delta_5 = 0$ (no regional effect)	2042.50	7.81	Reject H_0
$H_0: \delta_6 = 0$ (no legal origin effect)	2150.42	3.84	Reject H_0
$H_0:\ \gamma = \delta_i = 0, i = 1,...,8$ (no inefficiency effects)	1734.86	16.27	Reject H_0

Notes: the statistic has a mixed chi-square distribution. All the tests are carried out using 5% significance level.

Table 4.5 provides average technical efficiency scores for each of the countries for the years 1961-1994. The results show that the average technical efficiency score of 0.662 over 34 years implies that 83 countries are, on average, producing 66.2% of the output that could potentially be produced using the observed input quantities. Among the developed countries in Table 4.5 are a larger number of countries that have technical efficiencies exceeding the mean efficiency level. Efficient technology promotes favorable agricultural productivity. Most countries with lower technical efficiency over the sample period are in Asia and Africa, as supported in Lusigi and Thirtle (1997), Fulginiti and Perrin (1998, 1999), as well as Nin et al. (2003).[66]

[66] Lusigi and Thirtle (1997) estimate the *DEA* of 47 African countries.

Table 4.5 Mean Technical Efficiency of 83 Countries by *SFA*, 1961-1994

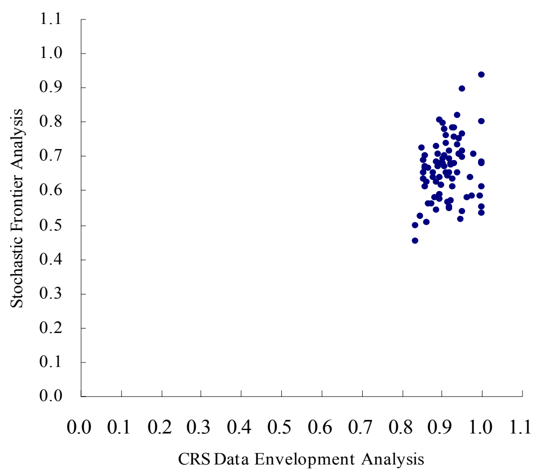
Country	TE	Country	TE	Country	TE
Zambia	0.454	Austria*	0.632	Ghana	0.698
Zimbabwe	0.499	Uruguay*	0.639	Mexico*	0.700
Tanzania	0.508	Trinidad and Tobago*	0.639	Portugal*	0.701
Malawi	0.515	Tunisia	0.640	Malaysia*	0.704
Kenya	0.523	Indonesia	0.641	Cyprus*	0.705
Central African Rep.	0.533	Bolivia	0.643	New Zealand*	0.706
Botswana*	0.538	Iraq	0.650	Costa Rica*	0.708
Swaziland	0.541	United States*	0.652	Denmark*	0.717
Mozambique	0.547	Nigeria	0.652	France*	0.717
Benin	0.551	Sweden*	0.653	Colombia	0.725
Norway*	0.554	Venezuela*	0.654	Chile*	0.727
Angola	0.559	Peru	0.665	Switzerland*	0.735
Algeria	0.560	Iran, Islamic Rep.	0.667	Philippines	0.739
Finland*	0.566	India	0.669	Paraguay	0.753
Senegal	0.571	Guatemala	0.669	Nicaragua	0.756
Madagascar	0.573	United Kingdom*	0.670	Dominican Republic	0.759
Cameroon	0.578	Jordan	0.673	Japan*	0.763
Sri Lanka	0.581	Guyana	0.677	Egypt	0.778
Zaire (Congo, Dem Rep.)	0.584	Honduras	0.677	Syrian Arab Republic	0.779
Uganda	0.584	Jamaica	0.678	Spain*	0.782
Bangladesh	0.587	Canada*	0.678	Greece*	0.783
Fiji	0.611	Australia*	0.680	Ecuador	0.796
Mauritius*	0.611	Suriname	0.681	Belgium and Luxembourg*	0.802
South Africa	0.613	Turkey	0.685	Argentina*	0.806
Ireland*	0.616	Papua New Guinea	0.685	Italy*	0.821
Morocco	0.626	Brazil	0.690	Netherlands*	0.896
El Salvador	0.626	Thailand	0.691	Israel*	0.936
Pakistan	0.632	Germany*	0.692	Mean Efficiency	0.662

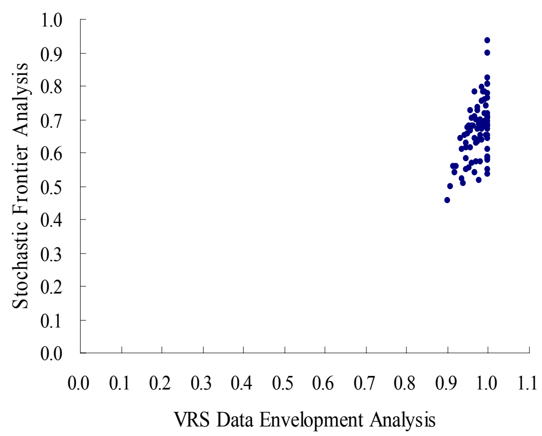
Notes: Developed countries with "*", defined by World Bank[67].

[67] In general, the term "developing economics" has been used to denote the set of low and middle income economics. The Bank's income categories (low, middle, high income) are based on the Bank's operational lending categories. www.worldbank.org

To test the robustness of the *SFA* results, this study considers an alternative specification of the frontier production function using *DEA* methods on the same agricultural inputs and output dataset. The computer program DEAP is concerned with the use of *DEA* method to construct a nonparametric piecewise frontier over the data to calculate efficiency relative to this frontier surface.[68] The DEAP program constructs *DEA* frontiers for the calculation of *CRS* technical efficiency and *VRS* technical efficiency, as well as for the calculation of efficiency scores and technical change. Table 4.6 presents the level of technical efficiency resulting from the application of the *DEA* methodology. Fig. 4.9 compares the average scores in technical efficiency using the *SFA*, *CRS DEA*, as well as *VRS DEA* methods.[69] The similarity in efficiency scores suggests that the SFA results are quite robust in the choice of methodology. The outliers are Botswana, Cameroon, the Central African Republic, and Nicaragua. The difference between two production functions may be due to the fact that the *DEA* method can envelope the observations in a more flexible way than the *SFA* method.

Fig. 4.9 Mean Technical Efficiency, *DEA* vs. *SFA*





[68] The DEAP computer programs is available on The Centre for Efficiency and Productivity Analysis http://www.uq.edu.au/economics/cepa/software.htm

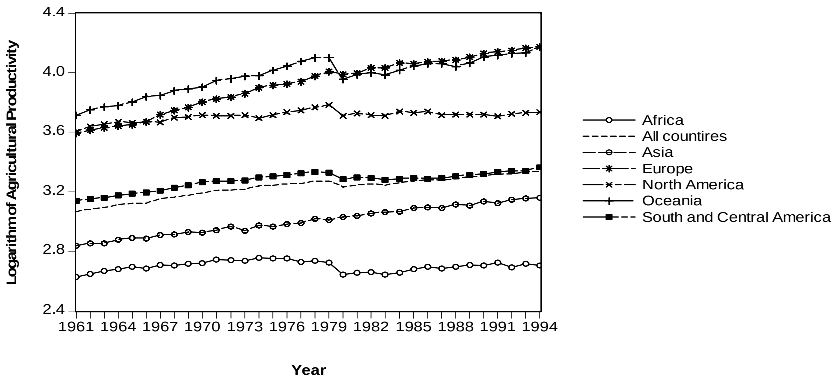
Table 4.6 Average Technical Efficiency of 83 Countries by *DEA*, 1961-1994

Country	*CRS*	*VRS*	Country	*CRS*	*VRS*	Country	*CRS*	*VRS*
Zimbabwe	0.834	0.908	Bangladesh	0.896	1.000	Greece*	0.930	0.987
Zambia	0.836	0.900	Madagascar	0.896	0.969	Nicaragua	0.931	0.986
Kenya	0.845	0.936	Ireland*	0.900	0.955	Guyana	0.933	0.954
Colombia	0.852	0.973	Ecuador	0.901	0.986	Sweden*	0.938	0.980
Brazil	0.853	0.984	Honduras	0.902	0.965	Italy*	0.940	1.000
Venezuela*	0.854	0.948	Thailand	0.904	0.992	Switzerland*	0.941	0.973
Pakistan	0.855	0.972	Egypt	0.906	0.999	Paraguay	0.941	0.984
India	0.857	1.000	U.K.*	0.906	0.986	Malaysia*	0.943	0.999
Mexico*	0.859	0.969	Portugal*	0.907	0.962	New Zealand*	0.944	1.000
Peru	0.859	0.957	Syrian Arab Rep.	0.909	0.966	Malawi	0.945	0.976
South Africa	0.860	0.945	Dominican Rep.	0.910	0.991	Botswana*	0.949	0.967
Morocco	0.860	0.945	Philippines	0.910	0.996	Netherlands*	0.950	1.000
Tanzania	0.861	0.940	United States*	0.910	1.000	Denmark*	0.950	0.993
Iran, Islamic Rep.	0.866	0.957	Finland*	0.914	0.961	Japan*	0.950	1.000
Algeria	0.868	0.920	Bolivia	0.914	0.967	Ghana	0.951	0.981
Angola	0.874	0.914	Indonesia	0.916	0.999	Cameroon	0.964	1.000
Tunisia	0.880	0.931	Germany*	0.917	1.000	Trinidad and Tobago*	0.971	0.983
Iraq	0.880	0.943	Mozambique	0.917	0.946	Uganda	0.976	1.000
Sri Lanka	0.883	0.946	France*	0.918	0.999	Cyprus*	0.980	0.998
El Salvador	0.885	0.969	Nigeria	0.919	0.996	Zaire	0.997	1.000
Turkey	0.885	0.976	Norway*	0.920	0.952	Central African Rep.	0.998	0.999
Swaziland	0.886	0.918	Senegal	0.922	0.980	Israel*	0.999	1.000
Chile*	0.887	0.958	Jamaica	0.923	0.960	Belgium and Luxembourg*	1.000	1.000
Costa Rica*	0.890	0.968	Jordan	0.924	0.948	Benin	1.000	1.000
Guatemala	0.892	0.972	Canada*	0.924	0.992	Mauritius*	1.000	1.000
Australia*	0.893	1.000	Fiji	0.925	0.935	Papua New Guinea	1.000	1.000
Uruguay*	0.893	0.975	Spain*	0.926	0.990	Suriname	1.000	1.000
Argentina*	0.895	1.000	Austria*	0.927	0.974	Mean Efficiency	0.915	0.974

[69] Coelli and Rao (2003) argue that VRS technology is too sensible to aggregate cross-sectional data.

Given the finding that efficiency varies significantly across countries, an obvious issue is whether these differences are associated with agricultural productivity. This present paper examines global agricultural productivity trends using data from 83 countries for the years between 1961 and 1994. The seven series in Fig. 4.10 show agricultural productivity indices from 1961 to 1994 for the different regions. From the figure, it is evident that Europe has a higher agricultural productivity level by 1994, followed by Oceania and Asia. Europe, Oceania, and Asia exhibit higher growth than the global growth levels in agricultural productivity. Africa and North America retain their position as the lowest groups. This provides evidence to refute the result of declining agricultural productivity in less developed countries by Fulginiti and Perrin (1993, 1998). The findings of the agricultural productivity level are that African countries made some progress in the 1960s, suffered a regression during the 1970s, and recovered after the mid-1980s, supporting by previous findings by Block (1995), Lusigi and Thirtle (1997), as well as Fulginiti et al. (2003),

Fig. 4.10 Logarithm of Agricultural Productivity, 1961-1994[70]



Coelli and Rao (2003) point out that those countries in Asia and Africa with the lowest mean technical efficiency scores in 1980 achieved the largest increases in mean technical

[70] In Fig 4.7, there is a slump in all curves between 1979 and 1980, which is due to the change of FAOSTAT frameworks.

efficiency over the period 1980-2000. Fig. 4.11 plots the mean technical efficiency scores of the entire set of countries over the 15 year period. It indicates that the overall mean technical efficiency changes in Asian and African countries are rather disappointing. Over the 15-year period, there is, overall, a 2.34% increase in African countries and a 0.70% increase in Asian countries in mean technical efficiency. At a global level, African countries have the lowest level of productivity and a slightly positive productivity trend. Asian countries currently have lower level of agricultural productivity, but, in terms of technical progress, these regions are well on their way to closing the persistent productivity gap. This result confirms the earlier findings of a wide productivity gap between developed and developing countries. Fig. 4.12 shows the growth rate of technical efficiency of 83 countries over two sub-sample time periods. It is worth noting that there is weak evidence for convergence or catch-up in efficiency levels in agriculture. Furthermore, the results suggested a stronger tendency for convergence over the period 1961-1980 in agricultural technical efficiency across countries, while a convergence tendency between 1980 and 1994.

Fig. 4.11 Mean Technical Efficiency of 83 Countries, 1980 – 1994

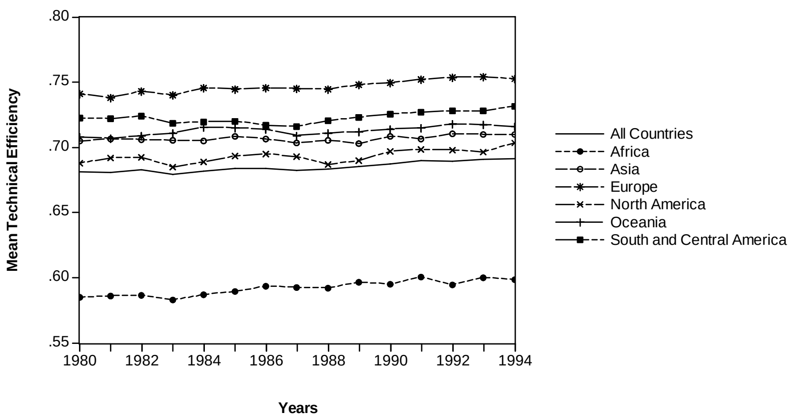
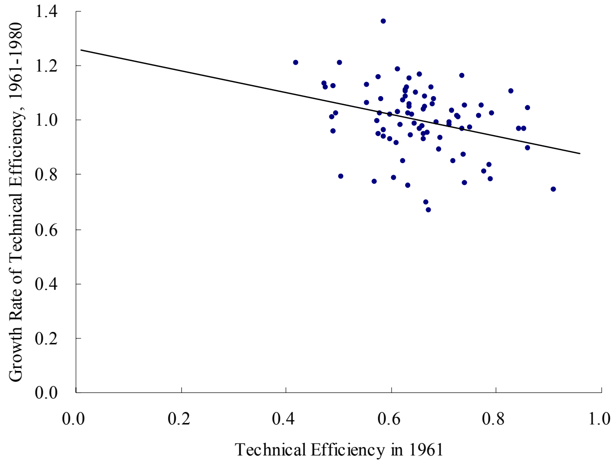


Fig. 4.12 The Relationship between Growth Rate of Technical Efficiency and Initial Technical Efficiency Levels of 83 Countries



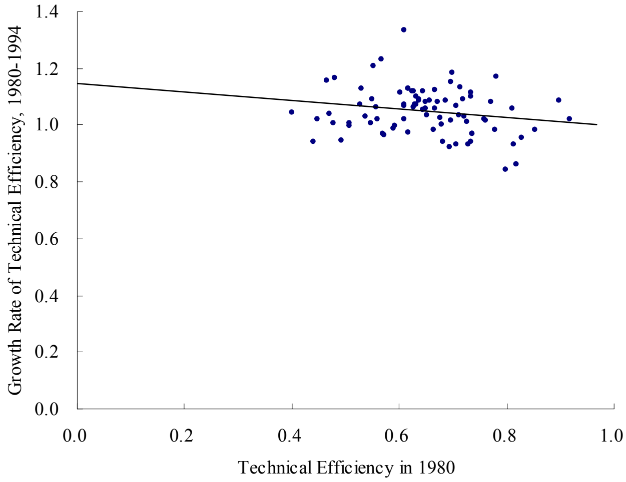


Fig. 4.13 Logarithm of Agricultural Productivity, 1961-1994

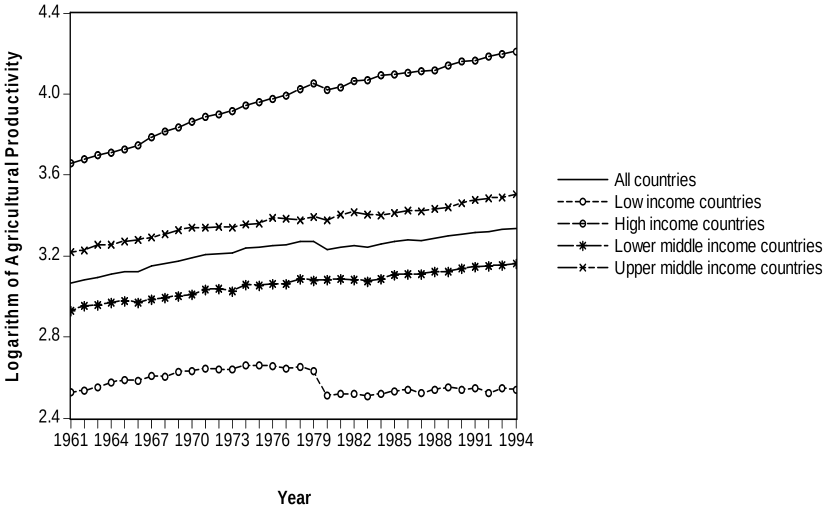
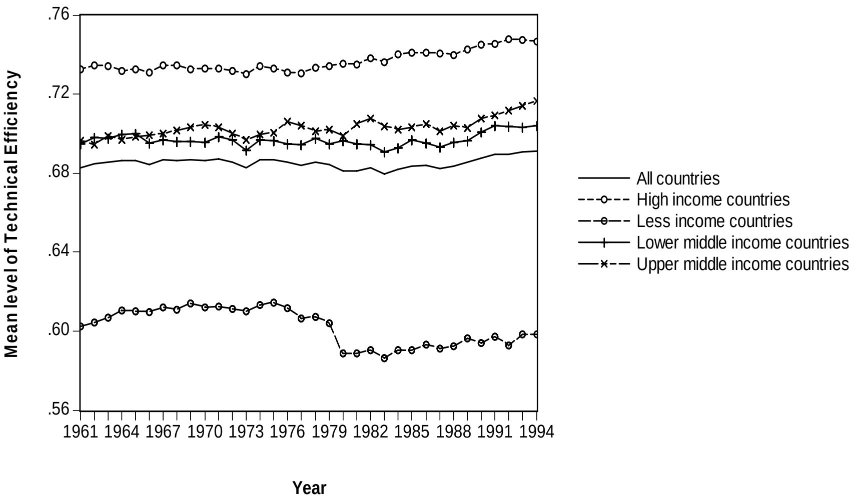


Fig. 4.14 Mean Technical Efficiency, 1961-1994



Notes: GNI per capita is the World Bank's main criterion for classifying countries. For example, economies are considered upper middle-income economies if their per capita GNI is higher than the World Bank's operational threshold for 15-year IBRD loans and lower than the threshold for high-income economies.

Furthermore, the hypothesis about positive correlation efficiency between efficiency levels and agricultural productivity is confirmed by these samples. This implies that the empirical evidence in Fig. 4.13 does exhibit a degree of catch-up in productivity levels between developed and developing countries. The five series graphed in Fig. 4.14 illustrates that the technical inefficiency production function has a strong influence on the level and trend of agricultural productivity in the sample. The result indicates that developing countries with lower agricultural productivity can reach higher levels through improvements in efficiency. The continuing development of international trade policy serves as the evidence bridging the agricultural productivity gap.

4.5 Conclusion

One objective of this chapter focuses on the technical efficiency of both developing and developed countries in agriculture. The paper examines the impact of stochastic production frontiers on technical efficiency and agricultural productivity in 83 countries over the period 1961 – 1994.

The results support the idea that legal origin remains an important factor in shaping initial agricultural productivity. The negative estimate for trade openness and positive estimates for civil liberty variables imply that countries with better trade and institutional policies tend to be more technically efficient. Average technical efficiencies for developed countries are higher than those for developing countries.

The other objective focuses on whether annual frostdays robustly matter for technical efficiency in agriculture. Two determinants, climate and geography of technical efficiency are statistically significant. The estimates indicate that countries' relative agricultural technical efficiency scores are higher because of favorable climate and geography.

CHAPTER 5

CONCLUSION

> *First, by the skill, dexterity, and judgment with which its labour is generally applied; and , secondly, by the proportion between the number of those who are employed in useful labour, and that of those who are not so employed. Whatever be the soil, climate, or extent of territory of any particular nation, the abundance or scantiness of its annual supply must, in that particular situation, depend upon those two circumstances. The abundance or scantiness of this supply too seems to depend more upon the former of those two circumstances than upon the latter.*
>
> *Adam Smith (1776)*

Modern economists started building up economic models based on Adam Smith roughly half century ago. In the initial years thereafter, economists dealt with theoretical economic growth models. Numerous publications dealt with empirical studies while the computing difficulties were globally solved three decades later. Furthermore, seminal publications have examined economic performance recently.

This dissertation provides insights into the annual hard frosts and economic growth nexus. The relevance of the dissertation's findings of this dissertation is strengthened by the use of econometric methodologies.

The threshold technique and model uncertainty analysis provide robustness results that climate plays different roles in tropical and temperate countries in its impact on the economic growth model. The application of the quantile regression model in the field of the economic growth model clearly provides an additional advantage. The agricultural technical efficiency model developed in this dissertation has demonstrated its relevance in supporting the climate in determining efficient technology.

Therefore, the results presented in this work provide a more reliable and appropriate indication that climate is one of the key determinants of an economy. The findings of this study are valuable in establishing the strategic framework for promotion policies, which should be adopted by governing bodies responsible for development planning. Accordingly, governing bodies should invest in human capital and accomplish efficient trade policies which are so important to developing countries.

Every study is by its nature limited; however, these several findings are expected to make a small contribution to the fast-growing empirical studies on economic development.

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