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Essays on Foreign Direct Investment, Growth and the Environment

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Economics

by

Waner Gu

June 2011

Dissertation Committee:

Dr. R. Robert Russell , Chairperson
Dr. Richard Arnott
Dr. Jang-Ting Guo
Dr. Aman Ullah

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The Dissertation of Waner Gu is approved:

Committee Chairperson

University of California, Riverside

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ABSTRACT OF THE DISSERTATION

Essays on Foreign Direct Investment, Growth and the Environment

by

Waner Gu

Doctor of Philosophy, Graduate Program in Economics
University of California, Riverside, June 2011
Dr. R. Robert Russell , Chairperson

This dissertation is composed of three essays on the impact of foreign direct investment (FDI) on productivity growth, convergence, and the environment. Chapter 2 decomposes labor productivity growth into components attributable to technological change, technological catch-up, foreign capital deepening, domestic capital deepening, and human capital accumulation, thus separating the effects of foreign and domestic capital deepening on productivity growth and convergence. We apply nonparametric production-frontier methods to a worldwide 1980–2005 panel and find that (1) foreign capital accumulation, together with human capital accumulation, is the driving force for productivity growth and increasing international dispersion of productivity, (2) technological change is decidedly non-neutral, with most technological advancement taking place in foreign-capital-intensive countries, and (3) international polarization is brought about primarily by efficiency changes.

Chapter 3 develops a statistical procedure to select the appropriate nonparametric efficiency model in terms of its dimensionality. The change of dimensionality is categorized into three cases: nested variable changes (expansion or contraction of a variable set), additive variable changes (aggregation or disaggregation of a variable set)

and other non-nested model changes. A bootstrapping method is proposed to measure the size of the dimensionality effect. Potential bias in raw efficiency scores owing to the dimensionality effect is corrected to reflect true efficient levels. An empirical illustration is presented with the Hughes and Yaisawarng (2004) (hereafter HY) data set.

Using U.S. state-level panel data from 1980–1994, chapter 4 estimates the impact of environmental stringency on the inflows of FDI in the U.S. The stringency of environmental policy is an uncontrollable variable in the operating environment. A three-stage model is proposed to evaluate state performance with environmental variables and reassess the pollution haven hypothesis. The three-stage model combines both data envelopment analysis (DEA) and stochastic frontier analysis (SFA), and can isolate the impact of luck (statistical noise) from those of managerial efficiency and environmental effect. This paper improves the second stage SFA evaluation by using the Local Linear Least Squares (LLLS) estimator. The empirical result suggests a negative relationship between state-level environment standards and the distribution of foreign capital in the U.S.

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Chapter 1

Introduction

The resurgent interest in the studies of economic growth seeks to determine the source of economic growth and the growth path of the world's economies. The impact of FDI on the growth process is usually considered to be positive, while the extent to which it impacts productivity growth and convergence depends on its effective utilization. One of the main objectives of this dissertation is to construct a model and employ worldwide panel data to examine the role that FDI plays in economic growth and convergence. Previous empirical studies are mainly model driven, requiring assumptions about the technology, the market structure, and other relevant factors of the growth process. In chapter 2, we use the DEA method to construct the worldwide production frontier and derive associated country-level efficiency indexes. The DEA method requires no specification of the functional form for the technology and allows a more comprehensive decomposition of productivity growth. Since the elasticity of output with respect to foreign capital is different from that with respect to domestic capital, foreign capital and domestic capital are modeled as distinct factors of production. The labor productivity growth is decomposed into components attributable to technological change, technological catch-up, foreign capital deepening, domestic capital deepening, and human capital accumulation. The pent-partite decomposition can separate the effects of foreign and domestic capital deepening on productivity growth and convergence.

Quah (1993, 1996a, 1997) argues that empirical convergence studies based on parametric regressions and focusing on first moments of the distribution are not adequate. In chapter 2, we examine economic convergence by analyzing the entire distribution of labor productivity across countries and its dynamics over the sample period. Several nonparametric tests are employed to analyze the role of each growth-accounting component in the transformation of the productivity distribution. We are particularly interested to check whether foreign capital deepening is the driving force for increased international polarization and international dispersion of proclivity.

Measuring efficiencies of decision making unites (DMU's) is an important aspect of productivity analysis. Nonparametric, deterministic frontier models have been widely used to measure efficiency in production processes. These methods, including DEA and free disposal hull (FDH) analysis, are particularly powerful when there is no reliable price information in multiple input-output production processes. However, the deterministic feature makes the estimated production frontier and its associated efficiency scores sensitive to the choice of input and output variables included in the model and to the curse of dimensionality. The magnitude (number of inputs and outputs) and structure (choice of input and output variables) of the dimensionality may affect the estimated production frontier and associated efficiencies dramatically. Thus, the selection of dimensions of inputs and outputs is vital in the setup of nonparametric frontier models. Another objective of this dissertation is to develop a statistical procedure to select appropriate nonparametric efficiency model in terms of its dimensionality.

The change of dimensionality is categorized into three cases: nested variable changes (expansion or contraction of variable set), additive variable changes (aggregation or disaggregation of variable set) and other non-nested model changes. The nested case addresses the issue of whether particular input and/or output variables are irrelevant; the additive variable case addresses the issue of whether some of the input/output variables can be aggregated; and non-nested model changes allows the comparison of two models that both have distinct variables as input/output. In chapter 3, the dimensionality test proposed is able to cover all the three categories. Efficiency change is decomposed into two components when the dimensionality changes, with one component attributable to the pure dimensionality effect and the other attributable to the net technological efficiency effect.

In addition to the qualitative analysis provided in the change of efficiency measure, the problem of evaluating dimensionality change quantitatively remains unsolved in existing literature. In chapter 3, a bootstrapping method is proposed to properly measure the size of dimensionality effect, and the potential bias in raw efficiency scores is corrected to reflect true efficient levels. Monte Carlo experiments provide proper size and valid power of the test in finite sample. The dimensionality test proposed in chapter 3 can be applied to common nonparametric frontier methods, like DEA and FDH, as well as regression-based SFA methods.

Following decades of liberalization of global capital markets, considerable debate has arisen about its role in sustainable development of recipient economies. One contentious issue of concern is its potential negative externalities on the environments of host economies. The so-called pollution haven hypothesis (PHH) argues that multinational firms in pollution-intensive industries seek to relocate to the places with weaker environmental standards. The third objective of this dissertation is to analyze the relationship between environmental policy and the distribution of foreign capital in the U.S. The advantage of intra-country analysis is that different states are more comparable than different countries on nongovernmental grounds.

The stringency of environmental policy is an uncontrollable environmental valuable. Traditional DEA or SFA methods only consider inputs and outputs in the evaluation of a DMU's efficiency performance. The omission of environmental variables is a big drawback. A three-stage model is developed to evaluate the impact of operational environment on DMU's performance. It combines both DEA and SFA methods, and can completely decompose the variation in performance into the components attributable to environmental effects, managerial inefficiency and statistical noise. Chapter 4 proposes a three-stage model to evaluate state performance with environmental variables and reassess the PHH. The stage 2 SFA evaluation is extended to a semiparametric panel setting to capture the complicated feature of the underlaying technology. Compare to parametric estimators, the LLLS estimator provides expected signs and consistent results for the empirical example using U.S. state-level panel data from 1980–1994.

The remainder of this dissertation is organized as follows. Chapter 2 discusses the methodology to examine the linkage between FDI and economic convergence, and analyzes the empirical results of a worldwide panel. Chapter 3 proposes a dimensionality test, assesses the size and power of the test by Monte Carlo experiments, and applies the test to an economic example. Chapter 4 proposes a three-stage model to evaluate the impact of state-level environmental regulation on the distribution of foreign capital in the U.S. Chapter 5 summarizes and concludes the dissertation. Tables and figures presenting the results of the analysis in chapters 2–4 are included in the Appendix A–C at the end of each chapter, respectively.

Chapter 2

Foreign Direct Investment and Convergence: A Nonparametric Production Frontier Approach[1]

2.1 Introduction

Worldwide flows of FDI, abetted by increasing openness and integration of global capital markets, grew substantially during the last three decades, at rates well above those of global economic growth. The role that FDI plays in economic growth has been studied extensively at both the theoretical and the empirical level. In the 1960s, exogenous growth analysis of FDI treated foreign and domestic capital as identical inputs, which can therefore be aggregated to form a homogeneous input that enters the production function as a whole. MacDougall (1960), Kemp (1966), and Jones (1967), for example, maintain this assumption in their models of FDI and growth. Findlay (1978) provides the first attempt to model foreign capital and domestic capital as distinct

[1] This chapter is taken from Gu and Russell (2011).

factors of production, each with a separate rate of return. His work is inspired by earlier research of Hymer (1960), which regards FDI as a transfer of a "package" combining capital, management, and new technology.

Endogenous growth theory, pioneered by Romer (1986) and Lucas (1988) in the 1980s, has emphasized the extent to which physical and human capital investment are crucial to persistent economic growth. This theory has led to extensive empirical research on the role of heterogeneous capital inputs in the growth process, notably regional and worldwide regressions using time-series or cross-sectional data. Using cross-sectional data for 46 developing countries over the period 1970–1985, Balasubramanyam et al. (1996) estimates a pooled regression of labor-productivity growth on the growth of foreign capital per capita and the growth of other inputs. Their study indicates that the elasticity of output with respect to FDI exceeds the elasticity with respect to domestic capital investment, implying that FDI is the driving force in the growth process. Borensztein et al. (1998) use seemingly unrelated regressions (SUR) to examine the inflow of FDI from OECD countries to 69 developing countries over two decades (1970–1989). The result shows that FDI contributes more to economic growth than does domestic investment, but the effect of FDI depends on the level of human capital available in the host economy. Ram and Zhang (2002) pool the data for 85 countries in the 1990s, and the regression supports the hypothesis of a positive nexus between FDI and economic growth in host countries. Makki and Somwaru (2004) test the effect of FDI on economic growth in a framework of cross-country equations, utilizing data from 66 developing countries over the last three decades (1971–2000). The results suggest that FDI is a significant source of economic growth for developing countries and that its contribution is enhanced by a positive interaction with human capital, sound macroeconomic policies, and institutional stability. Much of the empirical literature on FDI-growth linkage is summarized in De Mello Jr (1997).

Two limitations of the empirical studies outlined above are evident. First, those studies are mainly model driven, requiring assumptions about the technology, the market structure, and other relevant factors of the growth process. Second, Quah (1993, 1996a, 1997) argues that empirical convergence studies based on parametric regressions and focusing on first moments of the distribution are not adequate. Kumar and Russell (2002) (hereafter KR) develop a nonparametric (deterministic) growth-accounting method to overcome the shortcomings of the approach relying on parametric regressions. Inspired partly by Färe et al. (1994), KR suggest a tripartite decomposition of labor-productivity growth, with components attributable to technological change (expansion or contraction of the world production frontier), technological catch-up (movements toward or away from the frontier), and capital accumulation (movements along the frontier). Their Data Envelopment Analysis (DEA) approach to constructing the worldwide production frontier and its associated country-level efficiency indexes is based on Farrell (1957a) and Afriat (1972). This method envelops the data in the "tightest fitting" convex cone, with the upper boundary of the set representing the "best practice" production frontier. It requires assumptions only on returns to scale of the technology and free disposability of inputs and outputs. No specification of the functional form for the technology or assumptions about market structure are needed. KR use a panel of 57 countries over the period 1965-1990, and find that both growth and increased international dispersion of productivity are driven primarily by capital deepening and that technological change is decidedly non-neutral, with all technological advancement taking place at high levels of capital intensity.

The principal limitation of KR is the absence of human capital in the decomposition. Henderson and Russell (2005) (hereafter HR) incorporate human capital into the analysis and develop a quadripartite decomposition, with components attributable to technological change, technological catch-up, and physical and human capital accumulation. They employ a panel of 52 countries over the period 1965-1990 and find that human capital accumulation, as well as physical capital accumulation, accounts for the growth of productivity. They credit the increased international dispersion of productivity to physical capital accumulation and international polarization to technological catch-up.

Numerous studies applying DEA production-frontier methods to the decomposition of labor productivity growth into different components and to the analysis of growth and convergence have followed up on KR and HR. None of these studies, however, has extended the method to incorporate foreign capital as one of explanatory components. In this paper, we introduce foreign capital into the DEA growth-accounting framework and decompose labor productivity growth into components attributable to technological change, technological catch-up, foreign capital accumulation, domestic capital accumulation, and human capital accumulation. This pent-partite decomposition enables separation of the effect of foreign capital from other factors that contribute to labor-productivity growth.

Another limitation of previous empirical studies of the FDI-growth linkage is sample selection bias, since these studies either focus on developing countries or evaluate the effects of FDI on developing countries and OECD countries separately. The limited time span and the exclusion of OECD countries hampers analysis of the convergence of the economies of the world as a whole. In our study, a broad worldwide panel with both developing countries and OECD countries over last two decades is employed.

The remainder of the chapter is organized as follows. Section 2 describes the DEA method of constructing production frontiers and the penta-partite decomposition of the contribution of the different factors on labor productivity growth. Section 3 discusses the panel data. Section 4 summarizes the empirical results and analyzes the shifts in the productivity distributions. Section 5 concludes.

2.2 Methodology

2.2.1 Data Envelopment Analysis

We follow the HR methodology to construct the worldwide production frontier and concomitantly retrieve country-specific efficiency levels. To be specific, we use DEA to envelop the data in the smallest convex cone and identify the upper boundary of the set as the "best practice" production frontier. As capital is treated as heterogeneous, separated into foreign capital (KF) and domestic capital (KD), five macroeconomic variables are needed to define the technology: aggregate output (Y) and four aggregate inputs—KF, KD, labor (L), and human capital (H). Let $\langle Y_{jt}, KF_{jt}, KD_{jt}, L_{jt}, H_{jt}\rangle$, $t = 1, \cdots, T$ and $j = 1, \cdots, J$, represent T observations on the five variables for each of the J countries. Following the standard approach in the macroeconomics literature, human capital is assumed to be a multiplicative labor augmentation. Define $\hat{L}_{jt}{=}H_{jt}L_{jt}$ as the amount of labor input measured in efficiency units in country j at time t, so that the JT observations are $\langle Y_{jt}, KF_{jt}, KD_{jt}, \hat{L}_{jt}\rangle$, $t = 1, \cdots, T$ and $j = 1, \cdots, J$.

We adopt the "sequential production set" formulation of Diewert (1980) to preclude technological degradation (potential implosion of the frontier over time). The constant-returns-to-scale reference technology for the world at time t, using all the data up to t, is defined by

$$(2.1)\mathcal{T}_t = \Big\{\langle Y, KF, KD, \hat{L}\rangle \in \mathcal{R}^4_+ \;\Big|\; Y \le \sum_{\tau\le t}\sum_j z_{j\tau}Y_{j\tau} \;\wedge\; KF \ge \sum_{\tau\le t}\sum_j z_{j\tau}KF_{j\tau}$$
$$\wedge\; KD \ge \sum_{\tau\le t}\sum_j z_{j\tau}KD_{j\tau} \;\wedge\; \hat{L} \ge \sum_{\tau\le t}\sum_j z_{j\tau}\hat{L}_{j\tau},\; z_{j\tau} \ge 0\;\forall\, j,\tau\Big\},$$

where $z_{j\tau}$ is the level of operation of a linear process for the jt observation. Every point in the technology set is a linear combination of observed input and output vectors or a point dominated by such a combination. The constructed technology is a polyhedral cone with piecewise linear isoquants, commonly referred to as a Farrell cone. The Farrell output-based efficiency index for country j at time t is defined by

$$(2.2)\qquad E(Y_{jt}, KF_{jt}, KD_{jt}, \hat{L}_{jt}) = \min\Big\{\lambda \;\Big|\; \Big\langle Y_{jt}/\lambda, KF_{jt}, KD_{jt}, \hat{L}_{jt}\Big\rangle \in \mathcal{T}_t\Big\}.$$

As the index is the inverse of the maximal proportional amount that output can be expanded and remain technologically feasible, given the input quantities and the technology, it takes a value between zero and one and equals one if and only if the jt observation lies on the period t production frontier. As the aggregate output Y_{jt} is a scalar, the Farrell output-based efficiency index is the ratio of actual to potential (production frontier) output, evaluated at the actual input levels.

2.2.2 Pent-Partite Decomposition of Labor Productivity

Define $y_t = Y_t/L_t$ to be labor productivity at period t and $\hat{y}_t = Y_t/\hat{L}_t$ to be the output per efficiency unit of labor at period t. The foreign and domestic capital per efficiency unit of labor at period t are given by $\widehat{kf}_t = KF_t/\hat{L}_t$ and $\widehat{kd}_t = KD_t/\hat{L}_t$, respectively. As the technology is characterized by constant returns to scale, the potential outputs per efficiency unit of labor in the base period (b) and the current period (c) are functions of foreign and domestic capital per efficiency unit of labor at the two time periods: $\overline{y}_b(\widehat{kf}_b, \widehat{kd}_b) = \hat{y}_b/e_b$and $\overline{y}_c(\widehat{kf}_c, \widehat{kd}_c) = \hat{y}_c/e_c$, respectively, where e_b and e_c are the values of the efficiency indexes in the respective periods. Thus, the growth of output per efficiency unit of labor is

$$\frac{\hat{y}_c}{\hat{y}_b} = \frac{e_c \cdot \overline{y}_c(\widehat{kf}_c, \widehat{kd}_c)}{e_b \cdot \overline{y}_b(\widehat{kf}_b, \widehat{kd}_b)}. \tag{2.3}$$

Denote $\overline{y}_b(\widehat{kf}_c, \widehat{kd}_c)$ to be the potential output per efficiency unit of labor at current capital intensity using the base-period technology and $\overline{y}_c(\widehat{kf}_b, \widehat{kd}_b)$ to be the potential output per efficiency unit of labor at base-period capital intensity using the current technology. Define $\widetilde{kf}_c = KF_c/H_bL_c$ as the counterfactual ratio of current-period foreign capital to labor measured in efficiency units assuming human capital were still at its base-period level, and similarly, $\widetilde{kf}_b = KF_b/H_cL_b$ as the counterfactual ratio of base-period foreign capital to efficient units of labor assuming human capital equals its current-period level. Similarly, we have the group of ratios for domestic capital: $\widetilde{kd}_c = KD_c/H_bL_c$ and $\widetilde{kd}_b = KD_b/H_cL_b$. Let $\overline{y}_b(\widetilde{kf}_c, \widetilde{kd}_c)$ be potential output per efficiency unit of labor at $\widetilde{kf}_c$ and $\widetilde{kd}_c$ using base-period technologies, and similarly let $\overline{y}_c(\widetilde{kf}_b, \widetilde{kd}_b)$ be potential output per efficiency unit of labor at $\widetilde{kf}_b$ and $\widetilde{kd}_b$ using current technologies. Multiplying the top and bottom of (2.3) by $\overline{y}_b(\widetilde{kf}_c, \widetilde{kd}_c)\overline{y}_b(\widehat{kf}_b, \widetilde{kd}_c)\overline{y}_b(\widehat{kf}_c, \widehat{kd}_c)$ decomposes the growth of $\hat{y}$ to

$$\frac{y_c}{y_b} = \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(\widehat{kf}_c, \widehat{kd}_c)}{\overline{y}_b(\widehat{kf}_c, \widehat{kd}_c)} \cdot \frac{\overline{y}_b(\widetilde{kf}_c, \widetilde{kd}_c)}{\overline{y}_b(\widehat{kf}_b, \widetilde{kd}_c)} \cdot \frac{\overline{y}_b(\widehat{kf}_b, \widetilde{kd}_c)}{\overline{y}_b(\widehat{kf}_b, \widehat{kd}_b)} \cdot \frac{\overline{y}_b(\widehat{kf}_c, \widehat{kd}_c)}{\overline{y}_b(\widetilde{kf}_c, \widetilde{kd}_c)}. \tag{2.4}$$

Multiplying the top and bottom of (2.3) by $\overline{y}_c(\widetilde{kf}_b, \widetilde{kd}_b)\overline{y}_c(\widehat{kf}_c, \widetilde{kd}_b)\overline{y}_c(\widehat{kf}_b, \widehat{kd}_b)$ yields an alternative decomposition:

$$\frac{y_c}{y_b} = \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(\widehat{kf}_b, \widehat{kd}_b)}{\overline{y}_b(\widehat{kf}_b, \widehat{kd}_b)} \cdot \frac{\overline{y}_c(\widetilde{kf}_c, \widetilde{kd}_b)}{\overline{y}_c(\widehat{kf}_b, \widetilde{kd}_b)} \cdot \frac{\overline{y}_c(\widehat{kf}_c, \widetilde{kd}_c)}{\overline{y}_c(\widehat{kf}_c, \widehat{kd}_b)} \cdot \frac{\overline{y}_c(\widehat{kf}_b, \widehat{kd}_b)}{\overline{y}_c(\widetilde{kf}_b, \widetilde{kd}_b)} \tag{2.5}$$

By definition, $\hat{y}_t = Y_t/\hat{L}_t = Y_t/(H_tL_t) = (Y_t/L_t)/H_t = y_t/H_t$. The growth of labor productivity can be decomposed as

$$\frac{y_c}{y_b} = \frac{H_c}{H_b} \cdot \frac{\hat{y}_c}{\hat{y}_b}. \tag{2.6}$$

Combining (2.4) and (2.6), we get the pent-partite decomposition of the labor productivity:

$$\begin{aligned} \frac{y_c}{y_b} &= \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(\widehat{kf}_c, \widehat{kd}_c)}{\overline{y}_b(\widehat{kf}_c, \widehat{kd}_c)} \cdot \frac{\overline{y}_b(\widetilde{kf}_c, \widetilde{kd}_c)}{\overline{y}_b(\widehat{kf}_b, \widetilde{kd}_c)} \cdot \frac{\overline{y}_b(\widehat{kf}_b, \widetilde{kd}_c)}{\overline{y}_b(\widehat{kf}_b, \widehat{kd}_b)} \cdot \left[\frac{\overline{y}_b(\widehat{kf}_c, \widehat{kd}_c)}{\overline{y}_b(\widetilde{kf}_c, \widetilde{kd}_c)} \cdot \frac{H_c}{H_b}\right] \\ &=: EFF \times TECH^c \times KFACC^b \times KDACC^b \times HACC^b. \end{aligned} \tag{2.7}$$

Similarly, combining (2.5) and (2.6) yields an alternative pent-partite decomposition:

$$\begin{aligned} \frac{y_c}{y_b} &= \frac{e_c}{e_b} \cdot \frac{\overline{y}_c(\widehat{kf}_b, \widehat{kd}_b)}{\overline{y}_b(\widehat{kf}_b, \widehat{kd}_b)} \cdot \frac{\overline{y}_c(\widetilde{kf}_c, \widetilde{kd}_b)}{\overline{y}_c(\widehat{kf}_b, \widetilde{kd}_b)} \cdot \frac{\overline{y}_c(\widehat{kf}_c, \widetilde{kd}_c)}{\overline{y}_c(\widehat{kf}_c, \widehat{kd}_b)} \cdot \left[\frac{\overline{y}_c(\widehat{kf}_b, \widehat{kd}_b)}{\overline{y}_c(\widetilde{kf}_b, \widetilde{kd}_b)} \cdot \frac{H_c}{H_b}\right] \\ &=: EFF \times TECH^b \times KFACC^c \times KDACC^c \times HACC^c \end{aligned} \tag{2.8}$$

The two decompositions, (2.7) and (2.8), do not yield the same result unless technological change is Hicks neutral, in which case the proportional vertical shift in the frontier is identical at all points in $\widehat{kf} - \widehat{kd}$ space and the productivity change is path independent.[2] Solow (1957) maintains the assumption of Hicks neutrality in his decomposition of productivity growth into components attributable to technological change and capital deepening. Hicks neutrality, however, is a strong assumption, one that we argue below is inconsistent with the facts. Following KR and HR, the ambiguity is resolved by adopting the "Fisher ideal" decomposition, which is used in the earlier

[2]We should note that these two paths are not the only ones. In fact, there exist 12 possible paths: one set of six measures movement along the base-period production surface and the other set of six measures movement along the current-period surface. Each of these sets contains 3!=6 paths corresponding to the three dimensions, $\widehat{kf}$, $\widehat{kd}$, and H. Exploratory calculations indicate, however, that the primary sensitivity of the path is to the choice between the base or current period technology over which to measure changes in productivity owing to input changes, and this path dependence is taken into account in our decomposition. The outcome appears to be much less sensitive to the choice of path taken along the surface. (We might also note that the two paths considered in HR also are not unique: there exist two other possible paths. Our calculations indicate, however, that the HR results are not sensitive—even country by country—to the omission of these two paths in their decomposition.

works of Caves et al. (1982) and Färe et al. (1994). The "Fisher ideal" approach is to take geometric averages of the two measures for each growth-accounting component. Multiplying both sides of (2.7) and (2.8) together and taking the square root yields

$$
\begin{aligned}
\frac{y_c}{y_b} &= EFF \times (TECH^b \times TECH^c)^{1/2} \times (KFACC^b \times KFACC^c)^{1/2} \\
&\quad \times (KDACC^b \times KDACC^c)^{1/2} \times (HACC^b \times HACC^c)^{1/2} \\
&=: EFF \times TECH \times KFACC \times KDACC \times HACC
\end{aligned} \tag{2.9}
$$

Thus, the growth of labor productivity between the base period and the current period is decomposed into the effects of : (I) the change in efficiency (EFF); (II) technological change ($TECH$); (III) foreign capital accumulation ($KFACC$); (IV) domestic capital accumulation ($KDACC$); and (V) human capital accumulation ($HACC$). (I) represents the change in the distance from the production frontier, (II) stands for the shift in the frontier, and (III) to (V) represent movements along the frontier. Component (III) deserves special attention in our study, as it separates the effect of foreign capital accumulation on productivity growth from the other factors.

2.2.3 Construction of Counterfactual Potential Outputs

The calculations of shifts in the world production frontier ($TECH$) and movements along the frontier ($KACC$ and $HACC$) are handy in KR and HR. In these studies, the production frontiers can be reduced to $y-k$ (or $\hat{y}-\hat{k}$) space under the assumptions of constant returns to scale and labor augmentation of human capital. The empirically estimated world production frontier is always piecewise linear with kinks at efficient points. The piecewise linear function can be constructed after identifying all the efficient points in the sample data. This step is crucial to the decomposition calculation, which then is used to compute potential output levels given some counterfactual input combinations.

This approach, however, is impractical in higher dimensional input-output space owing to the difficulty of parameterizing the empirical production frontiers.

In our reduced model, after normalizing the labor into efficiency units, there remain two inputs ($\widehat{kf}$ and $\widehat{kd}$) and one output ($\hat{y}$), so that potential outputs must be constructed in a three-dimensional input-output space. Our approach to calculating the counterfactual potential outputs, which requires no direct estimation of the empirical production frontiers, is as follows. Given any counterfactual input combination $\widehat{kf}'_{jt}$ and $\widehat{kd}'_{jt}$, the efficient output level $\overline{y}_{jt}(\widehat{kf}'_{jt},\ \widehat{kd}'_{jt})$ on the frontier of technology $\mathcal{T}_t$ can be obtained by solving the following linear program:

$$\text{(2.10)} \qquad \begin{aligned} \max_{\hat{y}'_{jt},\ z_{11},\dots,\ z_{Jt}} \hat{y}'_{jt} \quad \textit{subject to} \quad \hat{y}'_{jt} &\leq \sum_{\tau\leq t}\sum_{j} z_{j\tau}\hat{y}_{j\tau}, \\ \widehat{kf}'_{jt} &\geq \sum_{\tau\leq t}\sum_{j} z_{j\tau}\widehat{kf}_{j\tau}, \\ \widehat{kd}'_{jt} &\geq \sum_{\tau\leq t}\sum_{j} z_{j\tau}\widehat{kd}_{j\tau}, \\ \sum_{\tau\leq t}\sum_{j} z_{j\tau} \leq 1,\ \forall\ j,\tau. \end{aligned}$$

This linear programming construction can be easily extended to technologies with any dimensionality of inputs. If the input has only one dimension in reduced form, we can still use this approach to locate any (counterfactual) efficient point on the empirical production frontier, and the results would be the same as those of KR and HR.

2.3 Data

The database employed for output, aggregate investment, and labor is the PWT (version 6.3) (Heston et al. (2009)), which provides a panel across 79 countries over the 1980–2005 period. The number of workers is computed as RGDPCH∗POP/RGDPWOK, where RGDPCH is per capita real GDP using the chain index, POP is the population, and RGDPWOK is real GDP per worker. Aggregate output in international dollars is RGDPCH∗POP. Real aggregate investment is calculated as RGDPL∗POP∗KI, where RGDPL is the real GDP using the Laspeyres deflation rule, and KI is the investment share of real GDP.[3]

For the foreign capital stocks, we convert the estimates of the annual World Investment Report of the United Nations Conference on Trade and Development (UNCTAD) to constant 2005 international dollars using purchasing power parity indexes for investment goods. The pricing index employed in the conversion is the Price Level of Investment (PI) from the Penn World Table (PWT)(version 6.3), which is defined as the PPP over investment divided by the exchange rate times 100.

To construct the domestic capital stock, we first subtract foreign investment from aggregate gross investment to obtain an estimate of domestic gross investment. We then use the Perpetual Inventory Method (PIM) to construct the domestic capital stock.[4]

We adopt a single depreciation rate (δ) of 7%, as in Caselli and Feyrer (2007).[5]

[3]As explained below, use of the PIM method of constructing capital stocks necessitates use of a longer time series, 1965–2005, for real aggregate investment.

[4]The implicit assumption underlying our empirical analysis—as well as the construction of foreign capital stocks by UNCTAD—is that accumulated foreign investment is qualitatively different from accumulated domestic investment. As UNCTAD emphasizes (http://www.unctad.org/Templates/Page.asp?intItemID=3146&lang=1), the "most importnt characteristic of FDI, which distinguishes it from foreign portfolio investment, is that it is undertaken with the intention of exercising control over an enterprise" and most FDI takes place between "parent and affiliate enterprises," so that multinational corporations typically wholly own the foreign subsidiary/branch.

[5]We prefer to employ the UNCTAD capital stock data (converted to a common currency) rather than to use PIM to construct the foreign capital stock ourselves because the UNCTAD approach, taking advantage of additional information and cross checking, is less mechanical and, we surmise, more reliable. We have carried out a number of robustness tests involving alternative assumptions about the depreciation rates for the two types of capital as well as alternative methods of constructing the capital stocks. Our empirical results, outlined below, are not materially altered under these alternative assumptions. These robustness tests are posted on our websites.

Country j's initial domestic capital stock (KD_{j0}) is estimated as

$$KD_{j0} = ID_{j0}/(g_j + \delta), \; j = 1, \cdots, J, \tag{2.11}$$

where ID_0^i is country j's value of gross domestic investment flow in 1970, and g is its average geometric rate of growth in the first five years that data are available. Country j's domestic capital stocks in the following sample period can then be obtained recursively by

$$KD_{jt} = (1-\delta)KD_{j(t-1)} + ID_{jt}, \; t = 1, \cdots, T; \; j = 1, \cdots, J. \tag{2.12}$$

For human capital, we adopt the Cohen and Soto (2007) education data, a panel of years of schooling across 96 countries in the 1960–2010 period.[6] The calculation of return to education is based on Psacharopoulos (1994), which is adopted by Hall and Jones (1999) and HR. Denote ϵ_{jt} to be the average number of years of education of the adult population in country j at time t. Thus, the total labor in efficiency units in country j at time t can be calculated as

$$\hat{L}_{jt} = H_{jt}L_{jt} = h(\epsilon_{jt})L_{jt} = e^{\phi(\epsilon_{jt})}L_{jt}, \tag{2.13}$$

where $h(0) = 1$ and ϕ is a piecewise linear function intercepting the origin. Its slope is 0.134 for the first four years' education, 0.101 for the next four years', and 0.068 for all years' education above eight. The rate of return to education (where ϕ is differentiable) is the slope of the function ϕ:

$$\frac{\partial \ln h(\epsilon_{jt})}{\partial \epsilon_{jt}} = \phi'(\epsilon_{jt}). \tag{2.14}$$

Thus, we have constructed a panel of four input variables and output variable across 79 countries, a reasonably good representation of the world's economy. Table 2.1

[6]The education data were collected for the beginning of each decade from 1960 to 2000 and were projected to 2010.

shows the distribution of our sample countries. Our panel data set contains 21 OECD countries, which account for more than half of the world's real GDP and inflows of FDI. This data set also includes China, which has been excluded from previous inter-country studies because of its incomplete record of foreign capital stocks.

2.4 Empirical Results

2.4.1 Production Frontier and Efficiency

Constant returns to scale and labor augmentation of human capital allow us to construct the production frontiers in 3-D ($\hat{y} - \widehat{kf} - \widehat{kd}$) space. Figure 2.1 superimposes the production frontier surfaces for 1980 and 2005. Thirteen countries are on the 1980 production frontier, while the remaining economies in the sample are inefficient and produce below their potential output levels. The 2005 frontier is defined by Sweden, USA, Norway, Ireland, and a collection of countries from earlier years.[7]

The first thing to note is the non-neutrality of technological change. Up to a foreign-capital-to-labor ratio of approximately 900 (Jordan in 1980), the 1980 and 2005 production frontiers are coincident, but for higher foreign capital intensities, the 2005 frontier is dramatically higher. Similarly, the 2005 frontier is also coincident with frontiers in other previous years (1985–2000) at low foreign capital intensity, indicating that almost all technological change occurs at high levels of foreign capitalization. This result confirms that of HR, where aggregate capital stock is not disaggregated.

Ireland experienced a 37% improvement in efficiency from 1980 to 2005 and defines the frontier for high foreign-capital-to-labor countries in 2005. A similar finding is found in Margaritis et al. (2007), and they explain the result by Ireland's impressive

[7] Recall that we employ the sequential production set formulation of Diewert (1980), using all data through 2005 to construct the 2005 frontier.

performance in the high-tech manufacturing sector. FDI inflows into Ireland increased continuously throughout the 1990s, mainly to high-tech computer and pharmaceutical companies, and peaked in 2000. The decline in FDI inflows to Ireland started in 2001 owing to the dot-com bubble burst, but Ireland's foreign capital stock per worker in 2005 still ranked as the second highest in the world.

Table 2.2 lists the efficiency scores of each of the 79 countries in our sample for 1980 and 2005. For comparison purposes, we report the efficiency levels using our model and the HR model, respectively. Table 2.2 shows that efficient countries identified by the HR model are nested in our model in both 1980 and 2005. The efficient economies in 1980 under the HR model (Greece, Mozambique, Netherlands, South Africa, Syria, United States, and Venezuela) are also on the empirical frontier constructed by our model, while six efficient countries under our model (Argentina, Cameroon, Columbia, Honduras, Italy, and Jordan) run below the frontier constructed by the HR model. A similar result is found in 2005, but the efficiency scores of these non-nested countries for 2005 with and without capital disaggregation are almost identical, since the efficiencies of non-nested efficient countries in our model are very close to 1 in the HR model.

We are primarily interested in comparisons of efficiency measurement with and without the disaggregation of capital stock in the technology. Table 2.2 reports that the mean efficiency score in 1980 increased from 0.63 to 0.70 by the disaggregation of capital input, suggesting that a good deal of the 1980 inefficiency in HR is attributable to misspecification of capital as a homogeneous input. The separation of foreign and domestic capital moves economies toward the frontier, closing the gap by about 18% on average. The biggest efficiency improvements emanating from the introduction of heterogeneity into the measurement of capital inputs in 1980 occur in the economies with very low foreign-capital-to-labor ratios: India, Honduras, China, Sudan, and Burkina Faso. The effect of separating capital input in the 2005 calculations is less pronounced. The average improvement in efficiency is around 5%, with the most notable change occurring for Haiti and India. Japan, with the lowest foreign capital per efficient unit of labor among OECD countries, shows substantial movement toward the empirical frontier under our model as compared to that of HR: by 40% in 1980 and by 20% in 2005.

Figure 2.2 plots the distributions of the efficiency index under our model in 1980 and 2005 on the left and under the HR model on the right. Both graphs suggest that the large mass in the middle of the distribution shifted away from the frontier. Such backward shifting is more prominent in our model, which is in accordance with the fact that the set of efficient economies in the HR model nests that in our model.

2.4.2 Pent-partite Decomposition

Table 2.3 shows each of the components of the relevant decomposition of productivity growth from 1980 to 2005, both with and without separation of the capital input. The first row for each country shows the country's productivity growth and the contributions to productivity growth of the five factors, efficiency change ($[EFF-1]\times 100$), technological change ($[TECH-1]\times 100$), foreign capital accumulation ($[KFACC-1]\times 100$), domestic capital accumulation ($[KDACC-1]\times 100$), and human capital accumulation ($[HACC-1]\times 100$). The second row for each country shows the contributions to productivity growth in the HR model, with foreign capital and domestic capital aggregating to total capital in the decomposition. Table 2.3 suggests that the ordering of average contributions is similar for the HR and our model. The means of efficiency change, human capital accumulation, and physical capital accumulation are not substantially different for the two models. In our heterogenous capital model, foreign capital accumulation not only is the principal driving force in the mean growth of worldwide productivity, but also contributes more than twice as much, on average, to productivity growth as does domestic capital accumulation.

Table 2.4 reports mean changes in productivity and the five growth-accounting components for seven groups of countries. The OECD and the original EU formation countries (EU-15) experienced significant productivity gains—well above the world average—primarily because of faster rates of technological progress and positive efficiency gains.

The miraculous growth rates of the Asian Tigers, which are more than five-fold that of the world average, are attributable primarily to predominant contributions of efficiency gains in Singapore and prominent foreign capital deepening in Japan and Korea. The neighboring Asian economies, especially China and India, also experienced large increases in productivity growth from 1980 to 2005. The HR model credits their productivity growth mostly to aggregate capital accumulation, but the results from our model suggest that the phenomenal contribution from foreign capital accumulation overwhelms that from domestic capital accumulation. As the production frontier remained the same at low foreign-capital-to-labor ratios, the extraordinary foreign capital deepening of the remaining Asian countries without commensurate increases in output per unit of labor moved them further away from the world frontier, which led to huge falls in efficiency. The remaining Asian economies and Latin America are the two groups that suffered the biggest efficiency losses over time.

Latin America is the only group that experienced a negative average growth rate of labor productivity. The HR model explains its poor performance by the collapse in efficiency and a lack of capital accumulation. Our results concur with HR regarding the contribution of the deterioration in efficiency but finds that foreign capital accumulation is not so anemic and in fact is close to the average over this period. Domestic capital accumulation for Latin American countries was actually slightly negative, suggesting that gross domestic investment was not sufficient to replace depreciated domestic capital.

Figure 2.3 contains plots of the six growth rates (of labor productivity and its five components) against output per worker in 1980, along with GLS regression lines. The positive but statistically insignificant slope of the regression slope coefficient in Figure 2.3a suggests (at least) that there is no absolute convergence in income per worker over the 1980–2005 period. The statistically significant positive regression slope coefficients in Figure 2.3b and Figure 2.3c indicate that relatively wealthy countries have benefited more from technological catch-up and technological change than have less-developed countries. Figure 2.3d reveals that, while foreign capital accumulation has contributed positively to growth for most countries, the pattern is very dissimilar to that of overall productivity growth, with some striking examples of foreign capital accumulation for low-income countries. The negative regression slope coefficient is statistically significant, indicating that the international pattern of foreign capital accumulation may have been the primary driving force to convergence. Figure 2.3e and Figure 2.3f evince a wide dispersion of contributions of domestic and human capital accumulation, but the slopes are statistically insignificant, suggesting that domestic capital and human capital deepening have done little to contribute to convergence. Each of these interpretations is based on first-moment characterizations of the productivity distribution and is therefore vulnerable to the Quah (1993, 1996a, 1997) critique. We therefore place more emphasis on the analysis of the distribution dynamics of labor productivity in the next sub-section.

2.4.3 Analysis of Productivity Distributions

Figure 2.4 plots the distributions of output per worker across the 79 countries in our sample in 1980 and 2005. The dashed and solid curves are, respectively, the estimated 1980 and 2005 distributions of output per worker. One fact that emerges immediately from Figure 2.4 is that the distributions in both periods are bimodal, with the "poor mode" remaining relatively stagnant while the "rich mode" moved further away from the poorer one. The rich mode, barely evident in 1980 and became more apparent over the 25-year period. The increased distance between the two modes is consistent with the finding from Figure 2.3a, supporting the view that relatively rich countries have grown faster than relatively poor ones.

We employ two nonparametric statistical tests for changes in the distribution: a test for multimodality and a test for the statistical significance of differences between actual and counterfactual distributions. For the former, we use the calibrated Silverman test; see Hall and York (2001) and Henderson et al. (2008b). Following HR, for the latter we choose the test proposed by Li (1996) and further studied by Fan and Ullah (1999) to test the null hypothesis, $\mathbf{H}_0 : f(x) = g(x)$ for all x, against the alternative, $\mathbf{H}_1 : f(x) \neq g(x)$ for some x.

Table 2.5 reports the results of calibrated Silverman test for multimodality of the counterfactual distributions by successive introduction of the five growth-accounting components. The rejection of the null hypothesis of the first and second tests at the 5% level, suggesting bimodality in both 1980 and 2005, is consistent with the finding from informal inspection of Figure 2.4. Note that the first test fails to reject the null hypothesis at the 1% level, indicating that the "poor mode" had emerged but was not very apparent in 1980. Table 2.6 and Table 2.7 summarize the Fan-Li-Ullah test results for comparisons of the counterfactual distributions and the actual 1980 and 2005 distributions, respectively. The first test in each table rejects the hypothesis that the actual 1980 and 2005 productivity distributions are identical at the 5% level, reinforcing the results of the multimodality test and reflecting the significantly increased international dispersion of labor productivity.

We aim to explore the role of each of the five growth-accounting components in the transformation of the productivity distribution from 1980 to 2005. Rewrite the pent-partite decomposition of labor productivity changes in (2.9) as follows:

$$y_c = (EFF \times TECH \times KFACC \times KDACC \times HACC) \times y_b. \tag{2.15}$$

The labor productivity distribution in 2005 can be constructed by consecutively multiplying labor productivity in 1980 by each of the five factors, which allows us to isolate the effect of each component. For example, the counterfactual 2005 productivity distribution of the variable

$$y^E = EFF \times y_b \tag{2.16}$$

isolates the impact on the distribution of changes in efficiency only, assuming a stationary world production frontier without any movement along the frontier. This counterfactual distribution is illustrated as a dotted curve in Figure 2.5a, along with the actual distributions in 1980 and 2005. The moderate loss of probability mass in the middle and the gains at the "poor" mode suggest that efficiency changes could be responsible for the intensification of bimodality during the 25-year period. This suggestion is supported by Row 3 of Table 2.5: introducing efficiency change into the 1980 productivity distribution leads to rejection of the null hypothesis, even at the 1% level. Table 2.5 also shows that efficiency change is the only component that by itself leads to bimodality at the 1% level. The result of the Li-Fan-Ullah test, however, listed in row 2 of Table 2.6, rejects the null hypothesis that efficiency change is solely responsible for shifting the 1980 productivity distribution to that of 2005.

The counterfactual 2005 productivity distribution of the variable

$$y^{ET} = (EFF \times TECH) \times y_b = TECH \times y^E \tag{2.17}$$

isolates the effects of efficiency and technology changes on productivity distribution, assuming no movement along the frontier. Figure 2.5b illustrates that neither the shape nor the mean of the distribution is obviously affected by the introduction of technology change, which reinforces the result from Table 2.3 that technological change contributes little to mean productivity growth. The results of the Li-Fan-Ullah test, presented in row 7 of Table 2.6 and Table 2.7, also suggest that technological change had little effect on the shift of the 1980 productivity distribution to that of 2005.

We are especially interested in the isolated impact of foreign capital deepening on the productivity distribution, obtained by examining the counterfactual distribution of the variable

$$y^{ETKF} = (EFF \times TECH \times KFACC) \times y_b = KFACC \times y^{ET}. \tag{2.18}$$

The resulting counterfactual distribution is drawn in Figure 2.5c. The introduction of foreign capital lowers the probability mass at the “poor mode” and increases it at high productivity countries, rendering the counterfactual distribution very close to the 2005 distribution. The Li-Fan-Ullah test in Row 17 of Table 2.6 fails to reject the null hypothesis, supporting the finding that the counterfactual distribution of y^{ETKF} and the actual 2005 distribution are similar. Note that the distribution test is rejected in

Row 17 of Table 2.7, suggesting that the counterfactual distribution, after introducing foreign capital deepening, is still close to that of 1980, which means that supplements from other factors are needed to complete the shift.

The additional effect of domestic capital accumulation on the distribution of y^{ETKF} can be observed by multiplying y^{ETKF} by $KDACC$:

$$(2.19)\quad y^{ETKFKD} = (EFF \times TECH \times KFACC \times KDACC) \times y_b = KDACC \times y^{ETKF}.$$

Figure 2.5d depicts the resulting counterfactual distribution, which is only slightly different from that in Figure 5c. Row 27 of Table 2.7 also shows that the Li-Fan-Ullah test fails to reject the identity of the counterfactual distribution and the 1980 distribution. Thus, the supplement from human capital accumulation is needed to complete the statistical shift of the distribution from 1980 and 2005.

We also examined other sequencing combinations. As illustrated in Figures 2.6–2.9, the results are not sensitive to changes in the sequencing order. The introduction of efficiency change always leads to international polarization. Foreign capital deepening, along with human capital accumulation, statistically brings the 1980 productivity distribution to that of 2005. With the absence of either foreign capital deepening or human capital accumulation in the sequence, the counterfactual labor productivity distribution is significantly different from that of 2005 (or significantly close to that of 1980.)

2.5 Conclusion

In this paper, we extend the HR decomposition of labor productivity growth by breaking physical capital accumulation into foreign capital and domestic capital. Thus, labor productivity growth is decomposed into components attributable to technological change, technological catch-up, foreign capital accumulation, domestic capital accumulation and human capital accumulation.

We employ the recently released PWT (version 6.3) to extend the HR panel to include data up to 2005, thus increasing the HR sample of countries by half. Our set of countries is a good representation of the world's economy, comprising developed, newly industrialized, developing, and transitional economies.

These extensions allow us to uncover the role foreign capital has played in international macroeconomic growth and convergence over the 1980–2005 period. Our principal conclusions are as follows:

1. The effects of foreign capital accumulation and domestic capital accumulation on productivity growth are dramatically different. Foreign capital accumulation, together with human capital accumulation, is the driving force of productivity growth; the contribution of domestic capital accumulation is much smaller.

2. Technological change is decidedly nonneutral, with most technological advancement taking place in countries that are highly foreign-capital intensive.

3. Foreign capital deepening and human capital accumulation are the primary driving forces behind increased international dispersion of labor productivity.

4. International polarization (the shift to a more obvious bimodal distribution) during the 1980–2005 period is brought about primarily by efficiency changes. Efficiency deterioration contributes to regression rather than progress on labor productivity in relatively low-productivity countries.

Of course, as in in any analysis, these conclusions are predicated on acceptance of the underlying assumptions as reasonable reflections of reality. In presentations of this paper, some skepticism has been expressed about the assumption of a "common" production frontier, or technology, for the entire world. For any economic entity—the world economy, a national economy, an industry, or even a particular firm—the production frontier is an abstraction, one that is fundamental to economic analysis but is an elusive notion for practitioners in these economic entities. We view the worldwide production frontier as the universal "state of knowledge," encapsulating the view that any technology could be adopted in any country *if it is rich enough to afford the capital intensity associated with that technology.* Of course, countries varying in capital intensity have varying technological options; thus, in fact, the relevant frontier for each country is a small subset of the worldwide frontier corresponding to a neighborhood of its capital/labor ratio. We believe this conception of technology is at least as realistic as the common macroeconomic assumption that each country faces a unique (global) technological frontier that is independent of the technologies available in other countries. Our view is that technologies, per se, are easily transferred, in principle, across nation state boundaries, but only if the recipient country is rich enough to afford the capital intensity associated with the transferable technology.

2.6 Appendix A: Tables and Figures

Table 2.1: Sample Country Distributions

Country Group		Number	Percentage	Percentage of FDI inflows (2005)
OECD		21	26.6%	57.4%
Non OECD*	Africa	27	34.2	5.3
	Asia	11	13.9	28.5
	Latin America	19	24.1	8.8

* Fiji is not in any of the three sub-groups of non-OECD countries.

Table 2.2: Efficiency Indexes for 79 Countries, 1980 and 2005

(Heterogeneous vs. Homogeneous Capital)

	Heterogeneous Capital		Homogeneous Capital (HR Model)	
Country	1980	2005	1980	2005
Algeria	0.75	0.38	0.73	0.34
Angola	0.49	0.38	0.35	0.38
Argentina	1.00	0.64	0.82	0.63
Australia	0.85	0.78	0.84	0.78
Austria	0.96	0.88	0.93	0.85
Bangladesh	0.47	0.33	0.43	0.28
Brazil	0.84	0.53	0.84	0.53
Burkina Faso	0.66	0.49	0.43	0.36
Burundi	0.66	0.32	0.66	0.31
Cameroon	1.00	0.65	0.91	0.64
Canada	0.97	0.81	0.96	0.79
Central African Rep.	0.56	0.24	0.39	0.22
Chile	0.59	0.61	0.58	0.60
China	0.48	0.34	0.21	0.32

continued

TABLE 2.2

CONTINUED

	Heterogeneous Capital		Homogeneous Capital (HR Model)	
Country	1980	2005	1980	2005
Colombia	1.00	0.52	0.74	0.50
Costa Rica	0.72	0.49	0.71	0.49
Côte d'Ivoire	0.92	0.67	0.80	0.67
Denmark	0.78	0.87	0.78	0.84
Ecuador	0.46	0.33	0.46	0.33
Egypt	0.70	0.74	0.63	0.71
El Salvador	0.48	0.42	0.48	0.41
Ethiopia	0.57	0.39	0.42	0.37
Fiji	0.67	0.45	0.66	0.44
Finland	0.78	0.80	0.68	0.79
France	0.93	0.90	0.93	0.89
Germany	0.77	0.78	0.77	0.78
Ghana	0.36	0.39	0.28	0.37
Greece	1.00	0.88	1.00	0.77
Guatemala	0.66	0.41	0.65	0.39
Guyana	0.19	0.11	0.18	0.10
Haiti	0.53	0.29	0.41	0.22
Honduras	1.00	0.28	0.40	0.28
India	0.92	0.43	0.36	0.34
Indonesia	0.45	0.32	0.37	0.30
Iran	0.71	0.71	0.68	0.64
Ireland	0.73	1.00	0.73	1.00

continued

TABLE 2.2

CONTINUED

	Heterogeneous Capital		Homogeneous Capital (HR Model)	
Country	1980	2005	1980	2005
Italy	1.00	0.96	0.97	0.85
Jamaica	0.31	0.28	0.31	0.27
Japan	0.96	0.86	0.68	0.72
Jordan	1.00	0.56	0.99	0.50
Kenya	0.48	0.35	0.40	0.32
Korea, Rep. of	0.49	0.58	0.37	0.50
Madagascar	0.56	0.47	0.48	0.46
Malawi	0.27	0.32	0.24	0.29
Malaysia	0.63	0.65	0.63	0.65
Mali	0.48	0.69	0.44	0.67
Mauritius	0.88	0.99	0.62	0.95
Morocco	0.82	0.57	0.76	0.56
Mozambique	1.00	0.71	1.00	0.70
Netherlands	1.00	0.89	1.00	0.84
New Zealand	0.76	0.71	0.75	0.71
Nicaragua	0.32	0.17	0.32	0.17
Niger	0.45	0.39	0.37	0.33
Nigeria	0.74	0.57	0.64	0.52
Norway	0.88	1.00	0.88	1.00
Panama	0.51	0.45	0.50	0.44
Paraguay	0.82	0.38	0.67	0.38
Peru	0.53	0.35	0.51	0.34

continued

TABLE 2.2

CONTINUED

	Heterogeneous Capital		Homogeneous Capital (HR Model)	
Country	1980	2005	1980	2005
Philippines	0.55	0.30	0.38	0.29
Portugal	0.69	0.63	0.69	0.59
Senegal	0.87	0.59	0.79	0.54
Sierra Leone	0.49	0.35	0.48	0.35
Singapore	0.75	0.92	0.75	0.92
South Africa	1.00	0.96	1.00	0.90
Spain	0.92	0.85	0.88	0.81
Sudan	0.81	0.25	0.39	0.25
Sweden	0.95	1.00	0.83	0.99
Syria	1.00	0.62	1.00	0.61
Tanzania	0.37	0.28	0.37	0.27
Thailand	0.31	0.29	0.24	0.29
Trinidad and Tobago	0.69	0.63	0.69	0.61
Tunisia	0.60	0.80	0.59	0.79
Turkey	0.60	0.55	0.54	0.54
United Kingdom	0.72	0.90	0.72	0.90
U.S.A.	1.00	1.00	1.00	0.97
Uruguay	0.71	0.56	0.66	0.55
Venezuela	1.00	0.69	1.00	0.68
Zambia	0.27	0.26	0.21	0.25
Zimbabwe	0.69	0.11	0.48	0.11
Mean	**0.70**	**0.57**	**0.63**	**0.54**

Table 2.3: Percentage Change of Pent-partite Decomposition Indexes, 1980-2005

(Heterogeneous Vs. Homogeneous Capital)

Country	Productivity Change	EFF	$TECH$	$KFACC$	$KDACC$	$HACC$
Algeria	-26.3%	-49.3	2.6	4.4	3.4	40.4
		-53.4	27.2	-8.2		35.5
Angola	45.4	-22.2	3.8	49.9	7.0	12.2
		9.1	5.4	9.5		15.5
Argentina	-10.4	-36.3	5.3	33.8	-3.8	3.7
		-23.7	11.1	0.1		5.5
Australia	51.8	-7.5	15.2	5.7	26.7	6.2
		-7.4	16.8	31.9		6.4
Austria	35.4	-8.0	14.7	15.1	0.9	10.4
		-8.7	31.0	4.3		8.5
Bangladesh	41.2	-30.9	2.4	8.8	62.4	13.0
		-33.1	0.4	89.4		11.1
Brazil	-22.2	-36.5	1.9	4.2	-8.4	25.9
		-36.4	5.0	7.3		25.7
Burkina Faso	32.6	-25.6	0.0	36.3	21.2	7.9
		-15.0	0.2	45.8		6.7
Burundi	-21.5	-52.3	0.0	10.7	41.5	4.9
		-53.9	0.0	63.1		4.3
Cameroon	-8.2	-35.1	1.8	13.4	9.2	12.3
		-29.6	0.1	15.4		13.0
Canada	43.8	-17.0	14.2	3.2	34.5	9.2
		-17.6	14.4	40.1		8.8

continued

TABLE 2.3

CONTINUED

	Productivity	Change				
Country	Change	EFF	$TECH$	$KFACC$	$KDACC$	$HACC$
Central African	-32.2	-56.8	0.4	36.4	0.2	14.2
Republic		-42.7	0.1	1.1		16.8
Chile	73.6	4.1	15.8	4.9	25.9	9.1
		3.2	16.2	32.7		9.1
China	393.8	-29.8	0.7	285.4	59.9	13.3
		50.3	3.9	173.0		15.9
Colombia	-8.7	-48.4	0.0	39.2	12.7	12.8
		-32.6	0.8	19.5		12.4
Costa Rica	4.3	-31.9	11.7	4.3	11.2	18.2
		-31.8	16.1	13.1		16.5
Côte d'Ivoire	-11.4	-27.4	2.8	13.3	-11.5	18.3
		-16.6	0.3	-11.1		19.1
Denmark	66.6	11.3	10.8	8.7	16.5	6.6
		8.1	13.6	26.5		7.3
Ecuador	-26.3	-27.7	3.3	4.1	-18.4	16.1
		-28.5	12.1	-18.6		13.1
Egypt	112.9	5.5	5.0	17.2	30.6	25.6
		13.5	0.8	47.9		25.8
El Salvador	0.3	-13.2	3.3	12.9	-9.2	9.2
		-14.0	9.5	-5.1		12.3
Ethiopia	-16.8	-31.6	0.0	17.1	-7.9	12.8
		-12.5	0.0	-12.6		8.8

continued

TABLE 2.3

CONTINUED

	Productivity	Change				
Country	Change	EFF	$TECH$	$KFACC$	$KDACC$	$HACC$
Fiji	1.0	-32.2	0.6	2.2	30.3	11.1
		-33.1	0.5	34.5		11.6
Finland	71.4	2.9	14.2	26.9	3.5	11.1
		16.5	21.9	9.3		10.4
France	41.2	-3.4	14.5	10.5	6.2	8.7
		-4.2	22.4	11.4		8.2
Germany	33.3	0.2	10.5	7.6	4.6	7.0
		0.2	16.9	7.3		6.1
Ghana	13.8	9.8	0.0	15.5	-15.1	5.5
		28.7	0.1	-17.3		6.7
Greece	23.2	-12.1	12.8	6.9	-0.8	17.1
		-22.9	37.0	-1.4		18.3
Guatemala	-11.0	-37.3	8.9	5.7	0.0	23.3
		-39.7	22.5	0.7		19.7
Guyana	-34.0	-44.0	5.4	11.2	-13.3	16.0
		-42.9	21.7	-15.4		12.2
Haiti	-31.4	-45.8	0.4	3.6	7.2	13.6
		-45.5	0.9	12.1		11.3
Honduras	-9.6	-71.6	3.4	173.0	5.3	7.1
		-32.1	7.8	12.9		9.4
India	123.9	-53.0	1.5	227.3	25.6	14.2
		-3.9	0.4	92.0		20.9

continued

TABLE 2.3

CONTINUED

Country	Productivity Change	EFF	$TECH$	$KFACC$	$KDACC$	$HACC$
Indonesia	72.2	-29.1	5.4	19.0	59.7	21.2
		-18.1	1.3	63.7		26.8
Iran	39.7	0.5	0.4	1.6	-4.0	42.1
		-6.1	24.9	-12.2		35.5
Ireland	111.9	36.9	38.8	1.7	2.2	7.3
		37.8	37.6	3.5		8.0
Italy	45.7	-3.7	10.4	16.8	0.2	17.1
		-12.5	36.8	6.8		14.0
Jamaica	30.0	-10.2	19.1	8.2	0.4	12.0
		-13.6	31.7	2.9		11.0
Japan	46.7	-9.7	2.0	47.6	1.2	6.7
		5.3	23.0	5.1		7.8
Jordan	-43.1	-43.9	0.0	0.0	-6.8	8.9
		-49.7	0.7	4.0		8.2
Kenya	-6.8	-27.4	1.8	8.6	-1.8	18.1
		-18.8	0.3	-2.1		16.9
Korea, Rep. of	209.5	18.4	8.9	40.7	47.6	15.5
		35.6	20.4	60.0		18.5
Madagascar	-14.0	-15.6	0.0	4.5	-14.4	13.9
		-4.3	0.0	-19.7		11.9
Malawi	29.7	17.7	0.6	4.3	-14.4	22.7
		23.6	0.2	-14.7		22.8

continued

TABLE 2.3

CONTINUED

Country	Productivity Change	*EFF*	*TECH*	*KFACC*	*KDACC*	*HACC*
Malaysia	133.2	3.4	8.5	0.6	71.6	20.4
		3.5	7.8	73.4		20.5
Mali	79.0	41.6	2.0	6.7	10.7	4.9
		53.5	0.1	11.1		4.9
Mauritius	146.2	12.4	2.9	31.3	43.8	12.8
		53.2	5.5	33.3		14.2
Morocco	7.4	-30.8	4.7	4.4	15.2	23.3
		-25.9	3.5	13.2		23.7
Mozambique	46.2	-29.3	0.0	38.7	43.8	3.7
		-30.3	0.0	102.8		3.3
Netherlands	13.6	-11.2	15.9	11.0	-7.3	7.3
		-15.5	25.4	0.5		6.7
New Zealand	26.1	-6.0	11.7	6.6	4.8	7.4
		-6.1	11.9	11.2		7.9
Nicaragua	-43.3	-46.5	2.4	8.2	-21.0	21.2
		-46.8	10.1	-18.6		19.0
Niger	-20.8	-13.7	0.5	-4.2	-10.5	6.7
		-10.8	0.5	-16.6		6.1
Nigeria	15.7	-22.0	0.1	18.4	-4.0	30.3
		-17.6	0.3	10.4		26.7
Norway	72.1	13.1	20.5	9.1	5.6	9.6
		13.2	29.7	7.7		8.9

continued

TABLE 2.3

CONTINUED

	Productivity			Change		
Country	Change	EFF	$TECH$	$KFACC$	$KDACC$	$HACC$
Panama	13.0	-11.1	3.9	0.0	10.8	10.3
		-12.9	3.1	12.7		11.6
Paraguay	-24.0	-53.5	5.1	22.1	18.6	7.5
		-43.3	0.9	24.1		7.0
Peru	-33.0	-34.7	0.1	20.5	-22.6	10.0
		-32.2	4.6	-16.4		13.0
Philippines	3.3	-45.7	2.5	45.6	17.5	8.6
		-23.6	0.5	20.8		11.4
Portugal	49.7	-8.6	17.1	10.1	8.6	17.0
		-13.6	31.3	15.1		14.6
Senegal	-2.5	-31.2	0.3	1.1	24.2	12.7
		-31.1	0.0	26.2		12.2
Sierra Leone	-37.6	-29.4	3.5	-0.3	-23.2	11.5
		-27.3	0.8	-24.0		12.0
Singapore	152.1	23.5	30.6	4.5	8.0	38.5
		23.6	36.1	11.1		34.8
South Africa	4.5	-3.8	0.0	0.1	-2.8	11.6
		-10.3	0.5	2.6		12.9
Spain	50.6	-7.8	15.2	20.6	0.0	17.5
		-8.4	38.6	1.7		16.7
Sudan	73.3	-69.1	4.3	214.7	58.7	7.8
		-37.1	5.1	142.6		8.1

continued

TABLE 2.3

CONTINUED

	Productivity			Change		
Country	Change	EFF	$TECH$	$KFACC$	$KDACC$	$HACC$
Sweden	58.9	5.0	9.7	22.9	7.7	4.1
		18.8	9.4	16.5		5.0
Syria	-14.2	-38.3	0.0	0.1	17.2	18.5
		-39.1	0.0	18.6		18.7
Tanzania	28.2	-24.5	0.0	7.0	41.2	12.3
		-25.2	0.0	54.3		11.1
Thailand	152.5	-4.7	6.9	38.3	42.4	25.7
		20.0	11.3	43.5		31.8
Trinidad & Tobago	22.4	-8.9	22.8	7.2	-3.5	5.8
		-11.4	28.5	1.3		6.1
Tunisia	68.5	34.2	14.0	2.7	-7.6	16.1
		33.9	15.0	-4.5		14.7
Turkey	98.2	-7.9	11.0	0.6	69.1	13.9
		1.1	5.2	63.6		13.9
U.S.A.	60.5	0.0	11.4	9.5	25.7	4.7
		-3.3	18.0	32.7		5.9
United Kingdom	76.2	24.8	11.0	7.4	7.2	10.5
		24.6	10.7	15.8		10.3
Uruguay	6.9	-21.0	3.6	11.3	8.0	8.6
		-16.5	6.7	8.1		10.9
Venezuela	-35.8	-31.0	3.7	18.2	-25.8	2.3
		-31.9	10.2	-16.9		3.0

continued

TABLE 2.3

CONTINUED

	Productivity			Change		
Country	Change	EFF	$TECH$	$KFACC$	$KDACC$	$HACC$
Zambia	-12.9	-4.3	0.0	30.9	-34.8	6.7
		18.4	1.7	-33.1		8.2
Zimbabwe	-57.1	-84.3	5.2	28.2	69.3	19.9
		-78.0	5.4	55.8		18.6
Mean	**33.4**	**-18.2**	**6.7**	**24.4**	**11.2**	**13.6**
		-11.5	**10.8**	**18.9**		**13.5**

Table 2.4: Mean Percentage Changes of the Pent-partite Decomposition Indices

(Country Groupings)

Country				Change		
Group	Productivity	EFF	$TECH$	$KFACC$	$KDACC$	$HACC$
OECD	61.3	0.5	13.8	13.8	12.6	10.2
		1.9	22.5	17.6		10.1
EU 15	52.1	2.0	15.1	12.8	3.8	10.9
		1.5	25.6	9.0		10.3
Asian Tigers*	136.1	10.7	13.8	30.9	18.9	20.3
		21.5	26.5	25.4		20.4
Non-OECD	23.3	-25.0	4.1	28.2	10.7	14.8
		-16.3	6.6	19.4		14.8
Asia	95.9	-22.6	5.3	57.4	32.1	20.4
		-6.9	7.9	52.5		21.4
Africa	16.1	-20.9	2.1	22.6	9.8	14.4
		-11.3	2.7	17.5		14.1
Latin America	-7.3	-31.9	6.3	20.7	-1.4	12.3
		-28.0	11.5	2.2		12.0
All Countries	**33.4**	**-18.2**	**6.7**	**24.4**	**11.2**	**13.6**
		-11.5	**10.8**	**18.9**		**13.5**

* Japan, Korea and Singapore.

Table 2.5: Modality Tests (p-values)

	Null Hypothesis (H_0)	H_0: One Mode H_A: More than One Mode	Conclusion of testing H_0
1	$f(y_{80})$	0.044	Reject
2	$f(y_{05})$	0.001	Reject
3	$f(y_{80} \times EFF)$	0.003	Reject
4	$f(y_{80} \times TECH)$	0.034	Reject
5	$f(y_{80} \times KFACC)$	0.018	Reject
6	$f(y_{80} \times KDACC)$	0.762	Fail to reject
7	$f(y_{80} \times HACC)$	0.223	Fail to reject
8	$f(y_{80} \times EFF \times TECH)$	0.003	Reject
9	$f(y_{80} \times EFF \times KFACC)$	0.001	Reject
10	$f(y_{80} \times EFF \times KDACC)$	0.016	Reject
11	$f(y_{80} \times EFF \times HACC)$	0.005	Reject
12	$f(y_{80} \times TECH \times KFACC)$	0.002	Reject
13	$f(y_{80} \times TECH \times KDACC)$	0.355	Fail to reject
14	$f(y_{80} \times TECH \times HACC)$	0.587	Fail to reject
15	$f(y_{80} \times KFACC \times KDACC)$	0.148	Fail to reject
16	$f(y_{80} \times KFACC \times HACC)$	0.276	Fail to reject
17	$f(y_{80} \times KDACC \times HACC)$	0.841	Fail to reject
18	$f(y_{80} \times EFF \times TECH \times KFACC)$	0.002	Reject
19	$f(y_{80} \times EFF \times TECH \times KDACC)$	0.009	Reject
20	$f(y_{80} \times EFF \times TECH \times HACC)$	0.012	Reject
21	$f(y_{80} \times EFF \times KFACC \times KDACC)$	0.002	Reject

continued

TABLE 2.5

CONTINUED

	Null Hypothesis (H_0)	H_0: One Mode H_A: More than One Mode	Conclusion of testing H_0
22	$f(y_{80} \times EFF \times KFACC \times HACC)$	0.001	Reject
23	$f(y_{80} \times EFF \times KDACC \times HACC)$	0.009	Reject
24	$f(y_{80} \times TECH \times KFACC \times KDACC)$	0.079	Fail to reject
25	$f(y_{80} \times TECH \times KFACC \times HACC)$	0.026	Reject
26	$f(y_{80} \times TECH \times KDACC \times HACC)$	0.616	Fail to reject
27	$f(y_{80} \times KFACC \times KDACC \times HACC)$	0.175	Fail to reject
28	$f(y_{80} \times EFF \times TECH \times KFACC \times KDACC)$	0.002	Reject
29	$f(y_{80} \times EFF \times TECH \times KFACC \times HACC)$	0.002	Reject
30	$f(y_{80} \times EFF \times TECH \times KDACC \times HACC)$	0.026	Reject
31	$f(y_{80} \times EFF \times KFACC \times KDACC \times HACC)$	0.000	Reject
32	$f(y_{80} \times TECH \times KFACC \times KDACC \times HACC)$	0.091	Reject

Table 2.6: Distribution Hypothesis Tests

(comparison year, 2005)

	Distribution	Boot p-value	H_0
1	$f(y_{05}) = g(y_{80})$	0.039	Reject
2	$f(y_{05}) = g(y_{80} \times EFF)$	0.019	Reject
3	$f(y_{05}) = g(y_{80} \times TECH)$	0.208	Fail to reject
4	$f(y_{05}) = g(y_{80} \times KFACC)$	0.065	Fail to reject
5	$f(y_{05}) = g(y_{80} \times KDACC)$	0.074	Fail to reject
6	$f(y_{05}) = g(y_{80} \times HACC)$	0.058	Fail to reject
7	$f(y_{05}) = g(y_{80} \times EFF \times TECH)$	0.027	Reject
8	$f(y_{05}) = g(y_{80} \times EFF \times KFACC)$	0.045	Reject
9	$f(y_{05}) = g(y_{80} \times EFF \times KDACC)$	0.037	Reject
10	$f(y_{05}) = g(y_{80} \times EFF \times HACC)$	0.034	Reject
11	$f(y_{05}) = g(y_{80} \times TECH \times KFACC)$	0.206	Fail to reject
12	$f(y_{05}) = g(y_{80} \times TECH \times KDACC)$	0.331	Fail to reject
13	$f(y_{05}) = g(y_{80} \times TECH \times HACC)$	0.651	Fail to reject
14	$f(y_{05}) = g(y_{80} \times KFACC \times KDACC)$	0.046	Reject
15	$f(y_{05}) = g(y_{80} \times KFACC \times HACC)$	0.082	Fail to reject
16	$f(y_{05}) = g(y_{80} \times KDACC \times HACC)$	0.058	Fail to reject
17	$f(y_{05}) = g(y_{80} \times EFF \times TECH \times KFACC)$	0.075	Fail to reject
18	$f(y_{05}) = g(y_{80} \times EFF \times TECH \times KDACC)$	0.035	Reject
19	$f(y_{05}) = g(y_{80} \times EFF \times TECH \times HACC)$	0.127	Fail to reject
20	$f(y_{05}) = g(y_{80} \times EFF \times KFACC \times KDACC)$	0.018	Reject
21	$f(y_{05}) = g(y_{80} \times EFF \times KFACC \times HACC)$	0.075	Fail to reject
22	$f(y_{05}) = g(y_{80} \times EFF \times KDACC \times HACC)$	0.034	Reject

continued

TABLE 2.6

CONTINUED

	Distribution	Boot p-value	H_0
23	$f(y_{05}) = g(y_{80} \times TECH \times KFACC \times KDACC)$	0.108	Fail to reject
24	$f(y_{05}) = g(y_{80} \times TECH \times KFACC \times HACC)$	0.126	Fail to reject
25	$f(y_{05}) = g(y_{80} \times TECH \times KDACC \times HACC)$	0.293	Fail to reject
26	$f(y_{05}) = g(y_{80} \times KFACC \times KDACC \times HACC)$	0.032	Reject
27	$f(y_{05}) = g(y_{80} \times EFF \times TECH \times KFACC \times KDACC)$	0.219	Fail to reject
28	$f(y_{05}) = g(y_{80} \times EFF \times TECH \times KFACC \times HACC)$	0.747	Fail to reject
29	$f(y_{05}) = g(y_{80} \times EFF \times TECH \times KDACC \times HACC)$	0.310	Fail to reject
30	$f(y_{05}) = g(y_{80} \times EFF \times KFACC \times KDACC \times HACC)$	0.069	Fail to reject
31	$f(y_{05}) = g(y_{80} \times TECH \times KFACC \times KDACC \times HACC)$	0.044	Reject

Table 2.7: Distribution Hypothesis Tests

(comparison year, 1980)

	Distribution	Boot p-value	H_0
1	$f(y_{05}) = g(y_{80})$	0.039	Reject
2	$f(y_{80}) = g(y_{80} \times EFF)$	0.614	Fail to reject
3	$f(y_{80}) = g(y_{80} \times TECH)$	0.856	Fail to reject
4	$f(y_{80}) = g(y_{80} \times KFACC)$	0.453	Fail to reject
5	$f(y_{80}) = g(y_{80} \times KDACC)$	0.954	Fail to reject
6	$f(y_{80}) = g(y_{80} \times HACC)$	0.952	Fail to reject
7	$f(y_{80}) = g(y_{80} \times EFF \times TECH)$	0.183	Fail to reject
8	$f(y_{80}) = g(y_{80} \times EFF \times KFACC)$	0.597	Fail to reject

continued

TABLE 2.7

CONTINUED

	Distribution	Boot p-value	H_0
9	$f(y_{80}) = g(y_{80} \times EFF \times KDACC)$	0.720	Fail to reject
10	$f(y_{80}) = g(y_{80} \times EFF \times HACC)$	0.496	Fail to reject
11	$f(y_{80}) = g(y_{80} \times TECH \times KFACC)$	0.076	Fail to reject
12	$f(y_{80}) = g(y_{80} \times TECH \times KDACC)$	0.828	Fail to reject
13	$f(y_{80}) = g(y_{80} \times TECH \times HACC)$	0.491	Fail to reject
14	$f(y_{80}) = g(y_{80} \times KFACC \times KDACC)$	0.158	Fail to reject
15	$f(y_{80}) = g(y_{80} \times KFACC \times HACC)$	0.117	Fail to reject
16	$f(y_{80}) = g(y_{80} \times KDACC \times HACC)$	0.560	Fail to reject
17	$f(y_{80}) = g(y_{80} \times EFF \times TECH \times KFACC)$	0.075	Fail to reject
18	$f(y_{80}) = g(y_{80} \times EFF \times TECH \times KDACC)$	0.259	Fail to reject
19	$f(y_{80}) = g(y_{80} \times EFF \times TECH \times HACC)$	0.129	Fail to reject
20	$f(y_{80}) = g(y_{80} \times EFF \times KFACC \times KDACC)$	0.351	Fail to reject
21	$f(y_{80}) = g(y_{80} \times EFF \times KFACC \times HACC)$	0.106	Fail to reject
22	$f(y_{80}) = g(y_{80} \times EFF \times KDACC \times HACC)$	0.479	Fail to reject
23	$f(y_{80}) = g(y_{80} \times TECH \times KFACC \times KDACC)$	0.076	Fail to reject
24	$f(y_{80}) = g(y_{80} \times TECH \times KFACC \times HACC)$	0.026	Reject
25	$f(y_{80}) = g(y_{80} \times TECH \times KDACC \times HACC)$	0.191	Fail to reject
26	$f(y_{80}) = g(y_{80} \times KFACC \times KDACC \times HACC)$	0.042	Reject
27	$f(y_{80}) = g(y_{80} \times EFF \times TECH \times KFACC \times KDACC)$	0.065	Fail to reject
28	$f(y_{80}) = g(y_{80} \times EFF \times TECH \times KFACC \times HACC)$	0.050	Reject
29	$f(y_{80}) = g(y_{80} \times EFF \times TECH \times KDACC \times HACC)$	0.134	Fail to reject
30	$f(y_{80}) = g(y_{80} \times EFF \times KFACC \times KDACC \times HACC)$	0.050	Reject
31	$f(y_{80}) = g(y_{80} \times TECH \times KFACC \times KDACC \times HACC)$	0.022	Reject

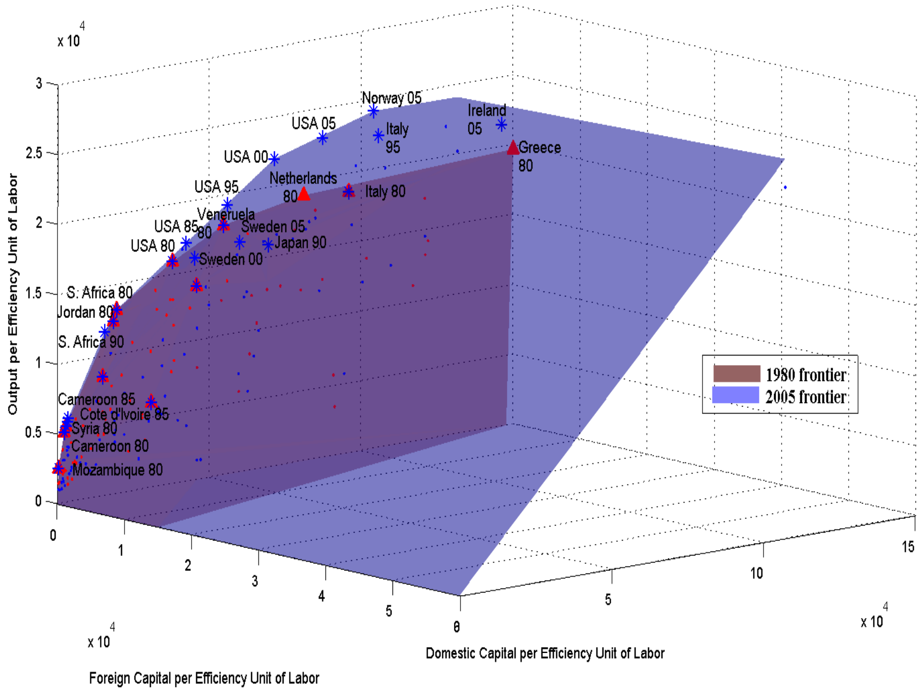


Figure 2.1: World Production Frontiers, 1980 and 2005

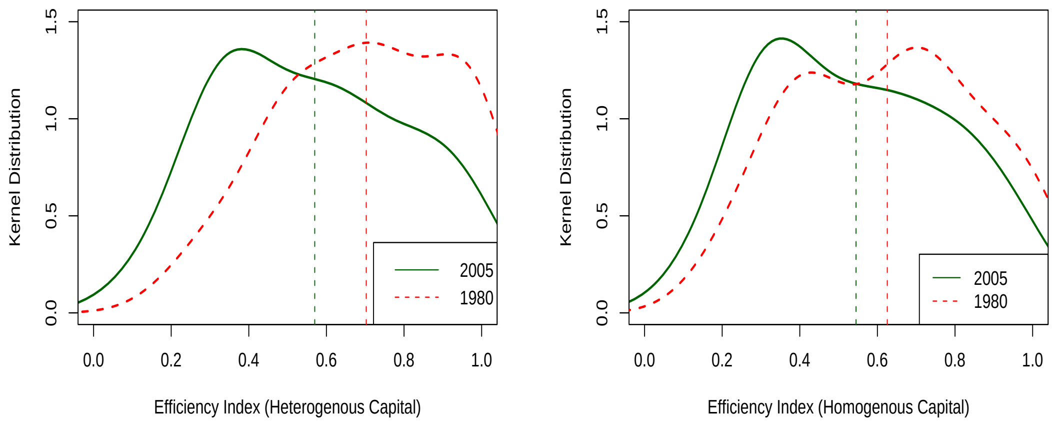
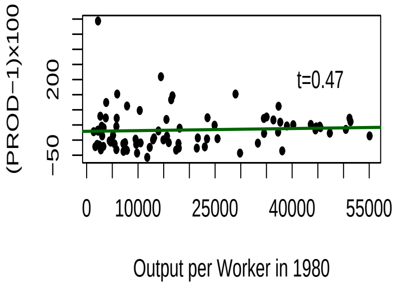
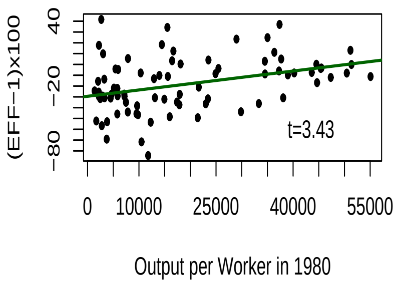


Figure 2.2: Distributions of Efficiency Indexes, 1980 and 2005

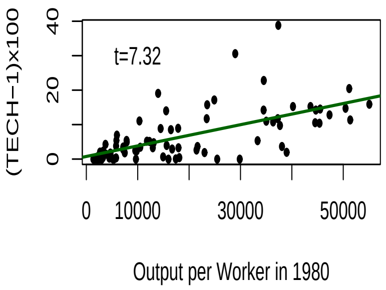
(Heterogeneous Vs. Homogenous Capital)



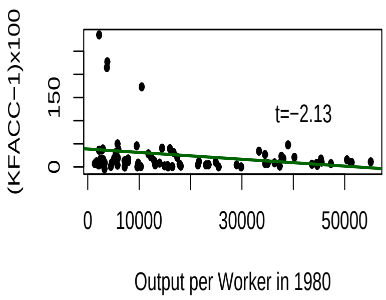
(a) Productivity Growth vs. Output per Worker



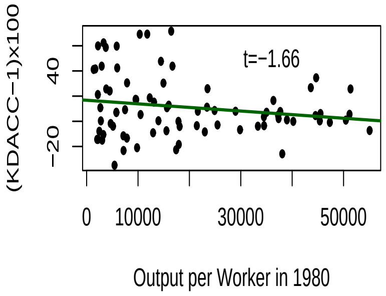
(b) Efficiency Growth vs. Output per Worker



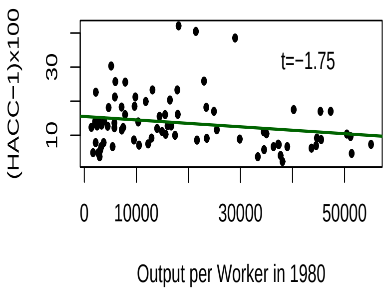
(c) Technological Growth vs. Output per Worker



(d) Foreign Capital Growth vs. Output per Worker



(e) Domestic Capital Growth vs. Output per Worker



(f) Human Capital Growth vs. Output per Worker

Figure 2.3: Percentage Change in Output per Worker and Five Decomposition Idexes (Plot against 1980 Output per Worker)

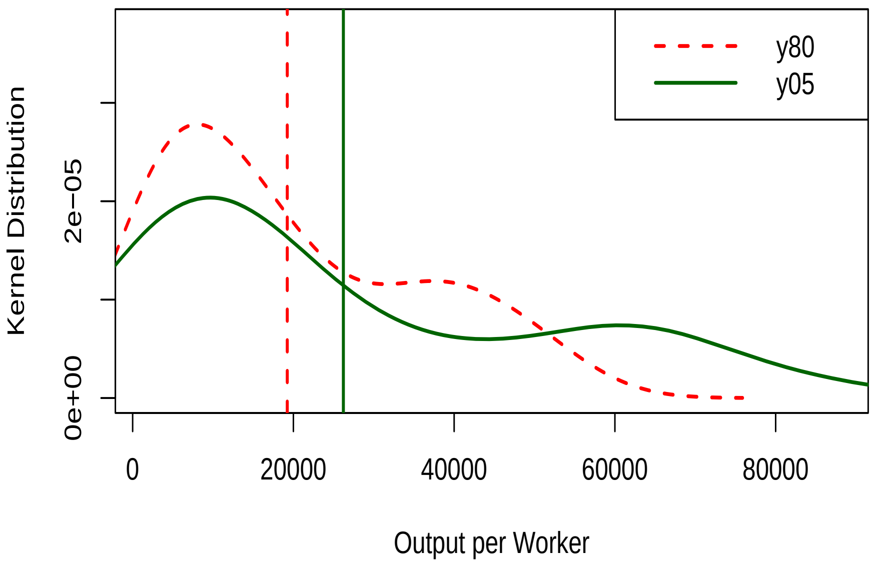
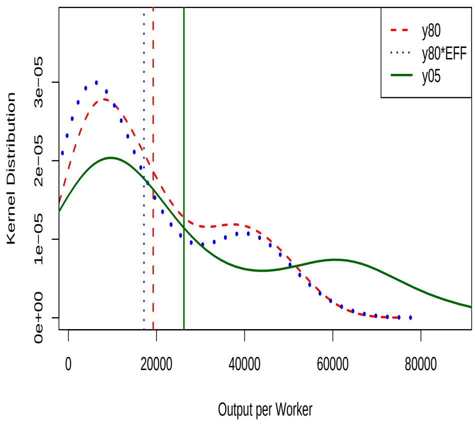
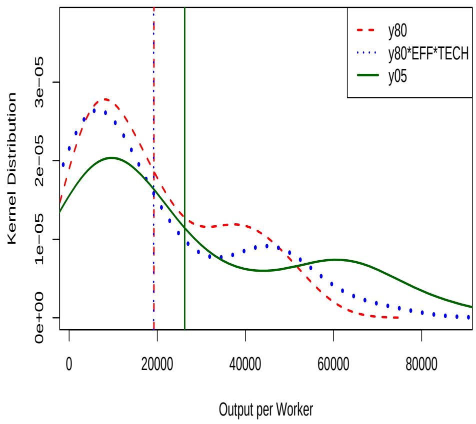


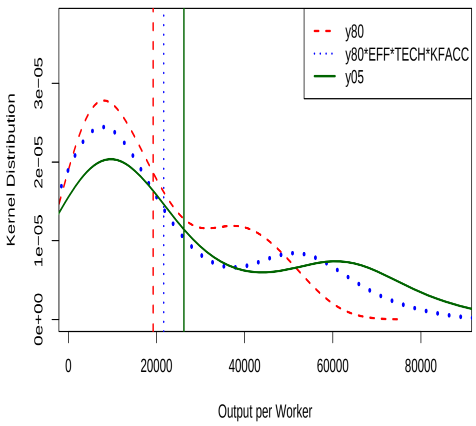
Figure 2.4: Distributions of Output per Worker, 1980 and 2005



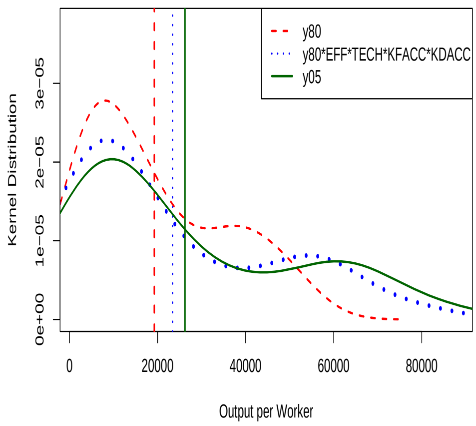
(a) Effect of Efficiency Change



(b) Effect of Technological Change



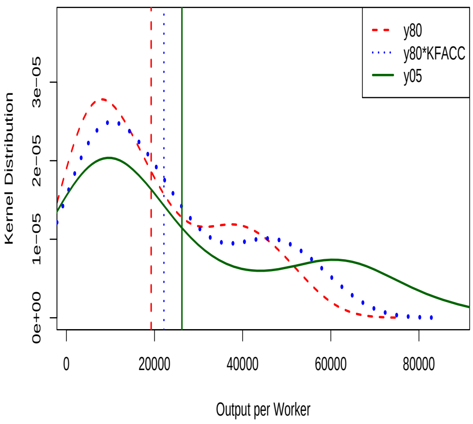
(c) Effect of Foreign Capital Deepening



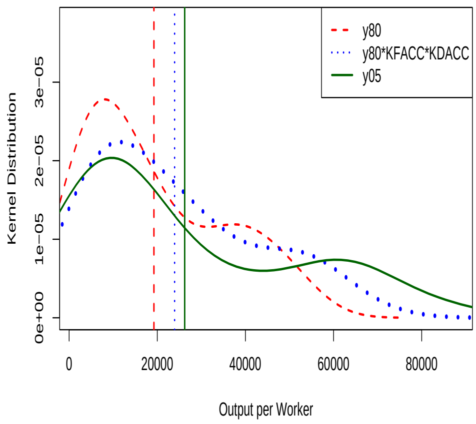
(d) Effect of Domestic Capital Deepening

Figure 2.5: Counterfactual Distributions of Output per Worker

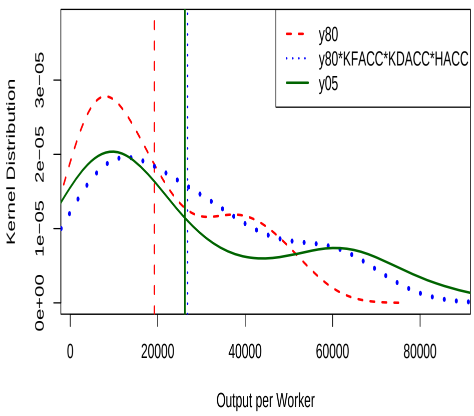
(sequence of introducing effects of decomposition: EFF, TECH, KFACC, and KDACC)



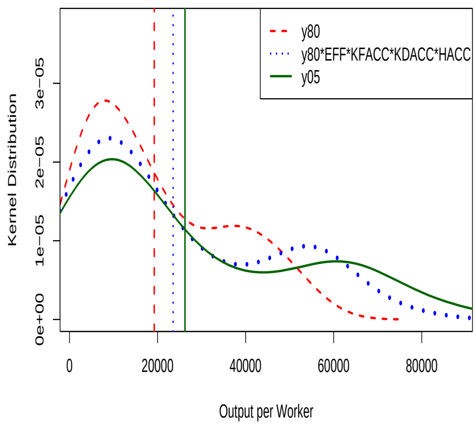
(a) Effect of Foreign Capital Deepening



(b) Effect of Domestic Capital Deepening



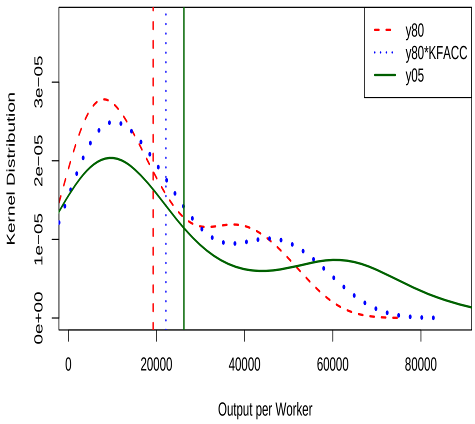
(c) Effect of Human Capital Accumulation



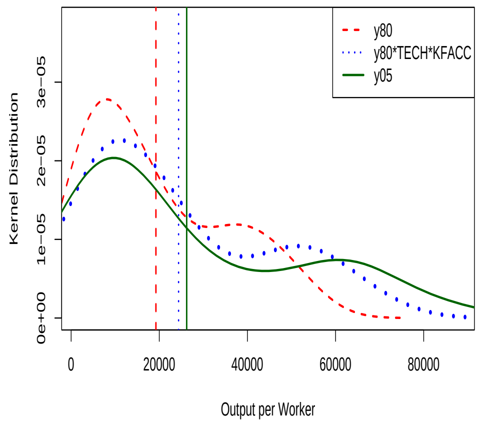
(d) Effect of Efficiency Change

Figure 2.6: Counterfactual Distributions of Output per Worker

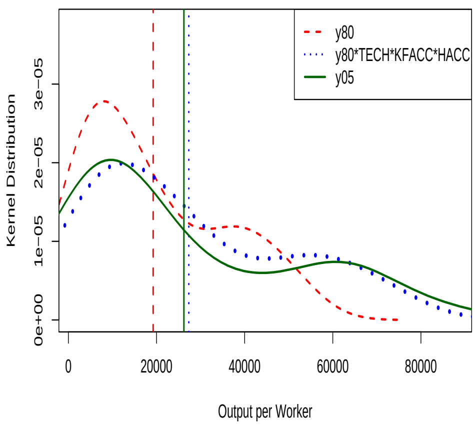
(sequence of introducing effects of decomposition: KFACC, KDACC, HACC, and EFF)



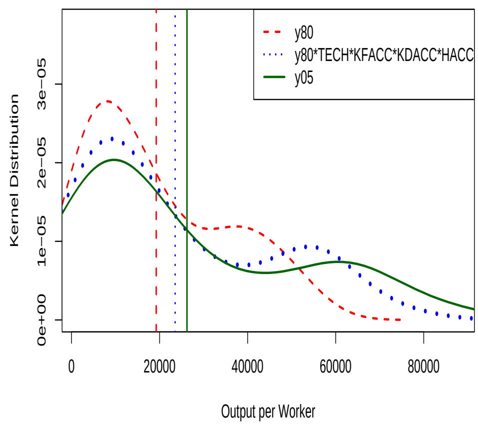
(a) Effect of Foreign Capital Deepening



(b) Effect of Technological Change



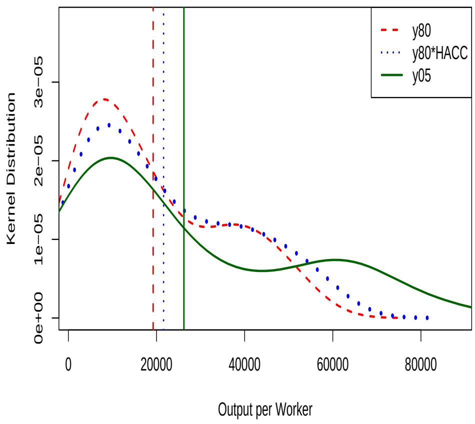
(c) Effect of Human Capital Accumulation



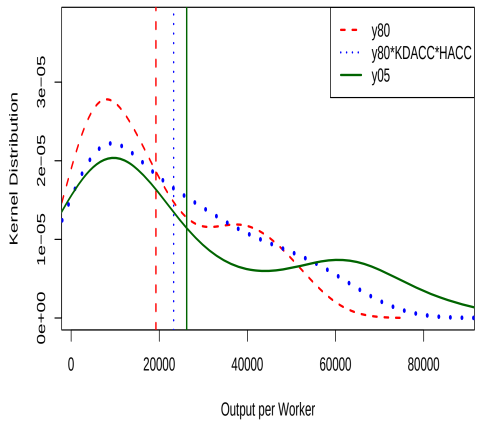
(d) Effect of Domestic Capital Deepening

Figure 2.7: Counterfactual Distributions of Output per Worker

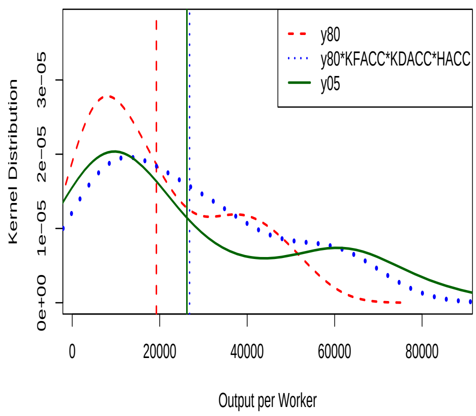
(sequence of introducing effects of decomposition: KFACC, TECH, HACC, and KDACC)



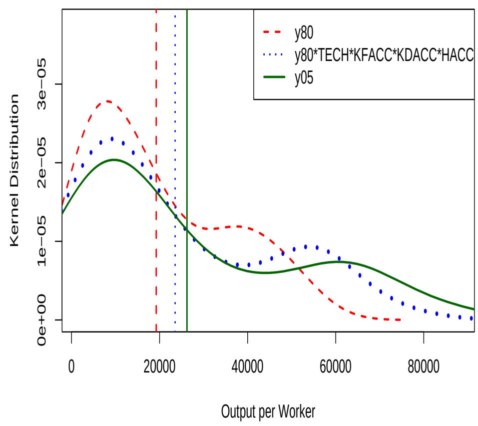
(a) Effect of Human Capital Accumulation



(b) Effect of Domestic Capital Deepening



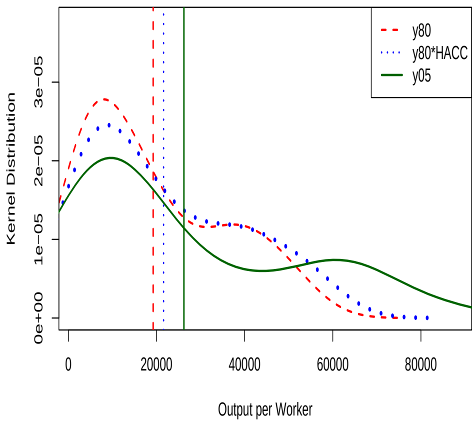
(c) Effect of Foreign Capital Deepening



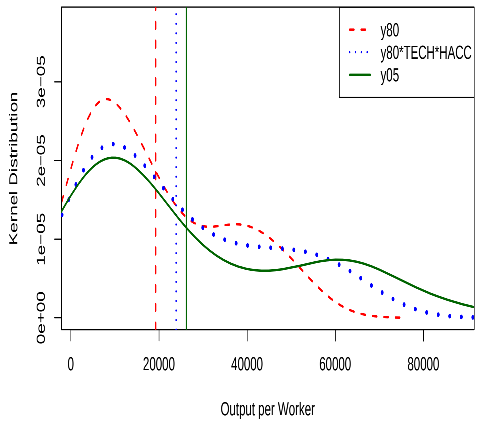
(d) Effect of Technological Change

Figure 2.8: Counterfactual Distributions of Output per Worker

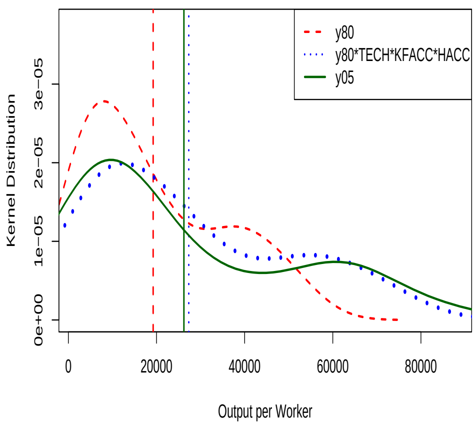
(sequence of introducing effects of decomposition: HACC, KDACC, KFACC, and TECH)



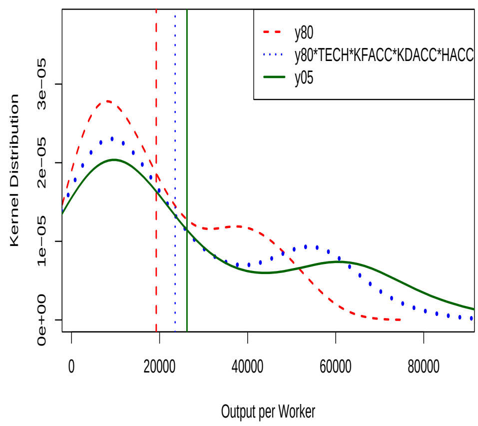
(a) Effect of Human Capital Deepening



(b) Effect of Technological Change



(c) Effect of Foreign Capital Accumulation



(d) Effect of Domestic Capital Deepening

Figure 2.9: Counterfactual Distributions of Output per Worker

(sequence of introducing effects of decomposition: HACC, TECH, KFACC, and KDACC)

Chapter 3

Model Selection in Productivity Efficiency Measurement with Dimensionality Effect[1]

3.1 Introduction

Nonparametric technical efficiency methods, pioneered by Farrell (1957b) and Charnes et al. (1978), have been widely employed over the last three decades in many areas of economics and management science. These methods, especially the data envelopment analysis (DEA), serve as standard performance evaluation tools to identify and quantify the efficiencies of the decision making units (DMU's). The DEA is a data-driven method that envelops the data in the "tightest fitting" convex cone and assigns efficiency scores to each DMU based on its performance relative to the "best practice" performers on the upper boundary of the set. It requires no specification of

[1]This chapter is taken from Gu and Tu (2011).

[1]See Emrouznejad et al. (2008) and Cooper et al. (2001) for extensive surveys of DEA literatures.

the functional form for the technology, and is particularly powerful when price information is unavailable or unreliable in multiple-dimensional production processes. As the DEA method is capable to summarize comparative assessment into a single efficiency measure, it is extensively used in public sector and nonprofit organizations involving multiple performance criteria.

The efficiency scores derived by the DEA method is measured relative to a nonparametric estimate of an unknown true frontier, and are subject to uncertainty owing to sampling variation. Because of the nonparametric multidimensional nature of the DEA estimators, statistical inference, like estimating the variance and construct confidence intervals, often relies on bootstrap strategy. The bootstrap method was introduced by Efron (1979) as a way to estimate the distribution of an estimator or test statistic. The basic idea is to treat the original sample as if it was a population and then create a bootstrap sample by resampling. If we repeat this many times and obtains lots of bootstrap samples, we can use the mean of the computed quantities as an estimate of the expected value of this bootstrapped quantity. The reliability of a bootstrap test depends on how well the bootstrapped data generating process (DGP) mimics the underlying features of the true DGP that matter for the distribution of the test statistics. See Davision and Hinkley (1997) for a balanced account of resampling methods together with their fruitful applications, and see Politis et al. (1999) for the recent development in subsampling techniques. Grosskopf (1996) provides a brief reviews of early literatures on statistical inference in DEA estimators. The drawback of a naive bootstrap is that it yields inconsistent statistical inference in nonparametric frontier models. Simar and Wilson (1998) develop a consistent bootstrap algorithm to analyze the sensitivity of the efficiency measures to sampling variation, but restrict the efficiency distribution to be homogenetic. Simar and Wilson (2000a) extend the bootstrap to heterogenetic setting by using subsampling. Kneip et al. (2008) use two bootstrap procedures, based on subsampling and smoothing, to derive asymptotic distribution of the DEA estimators.

The raw efficiency scores estimated by DEA models not only reflect technical inefficiency but also the dimensions of a variable set. For a fixed sample size, the magnitude (total number of inputs and outputs) and structure (combination of input and output variables) of the dimensionality may affect the estimated production frontier and associated efficiencies dramatically. Nunamaker (1985) justifies that the expansion of a variable set results in upward trend in efficiency scores. Thrall (1989) proposes transition conditions to underpin Nunamaker (1985)'s assertion. HY generalize the results that the increase in the dimensionality leads to higher efficiency scores and more efficient DMU's.

The difference of the dimensionality between two alternative variable sets can be categorized into three cases: nested variable changes (expansion or contraction of the variable set), additive variable changes (aggregation or disaggregation of the variable set) and other non-nested variable changes. The nested case addresses the issue of whether particular input and/or output variables are irrelevant. Tauer and Hanchar (1995) use Monte Carlo simulation to show that efficiency scores inflate when the number of input variables increase, and the dimensionality effect dominates the effect of sample size cut. Smith (1997) applies simulated data to show the underestimation of efficiency scores by the omission of relevant variables and the overestimation by the incorporation of extraneous variables. The additive case is about whether some of the input and/or output variables should be aggregated or disaggregate. The remaining non-nested cases allow a comparison of two DEA models with distinct input and/or output variables.

If the contribution of the added variables only reflects enlarged dimensionality, these variables should not be considered as part of the underlying technology set. To make the DEA results independent of the dimensionality effect, the bias in raw efficiency scores should be properly measured and corrected before any reliable policy implementation. HY provide a diagnostic test by simulating data sets from a random normal distribution with the same dimensions as the actual sample has. If the mean percentage of efficient DMU's from the observed sample is not statistically different from that of 1000 replications of simulated data, the dimensions of the DEA model are misspecified. Their estimated dimensionality effect is determined by the number of input-output variables included in the model and is homogeneous across the structure of variable set. Our paper concerns more about the marginal role of particular variables playing in the production process and allows the partial dimensionality effect to be heterogeneous. Out test utilizes the remaining observed variables and mimic the sampling distribution by bootstrap method. The comparison confirms that the index of the dimensionality constructed by observation-based simulations is more credible than that by random number generators.

In addition to measure the partial dimensionality effect caused by particular variables, our paper answers a deeper question that how to incorporate the dimensionality effect in the DEA model selection procedure. Due to the deterministic feature of nonparametric frontier model, statistical tests are not readily available. Simar and Wilson (2001) consider the nested and additive variables changes and use bootstrap method to construct test statistics. The null hypotheses of the tests assume that efficiency scores derived from correct specified model will not change if 1). irrelevant input and/or output variables are added into the model; or 2). some of the input and/or output variables are combined to be one aggregated variable. These assumptions overlook the bias in raw efficiency scores owing to the dimensionality effect. The non-zero efficiency difference between correctly specified model and misspecified model is statistically significant and reflects the partial dimensionality of the model. We follow Simar and Wilson (2001) to apply the bootstrap method to construct test statistics and correct the bias caused by the dimensionality effect. We also extend the tests to more general cases that allow for the comparison of non-nested variable changes. Monte Carlo experiments show that our tests have proper size and valid power in finite sample.

The structure of the chapter is as follows. Section 2 introduces nonparametric production frontier models and shows the effect of dimensionality. Section 3 formally states our null hypothesis and address the issue of the dimensionality change. Section 4 proposes a procedure to measure the dimensionality effect and to test change in efficiency score in this setup. Section 5 illustrates the proposed tests with HY data set. Section 6 concludes with remarks.

3.2 Nonparametric Production Models

3.2.1 Preliminaries

Consider a set of J DMU's, $j = 1, \ldots, J$, using N inputs to produce M outputs with production vectors, denoted $\langle x, y\rangle$, contained in the $\langle$input, output$\rangle$ space $\mathcal{R}_+^{M+N}$. The technology of converting inputs x into outputs y for each DMU j, can be characterized by the technology set

$$\mathcal{T} = \left\{ \langle y, x\rangle \in \mathcal{R}_+^{M+N} \;\middle|\; x \text{ can produce } y \right\}. \tag{3.1}$$

Equivalently, the same technology can be characterized by the input requirement set

$$\mathcal{L}(y) = \Big\{ x \in \mathcal{R}_{+}^{N} \;\Big|\; \langle y, x \rangle \in \mathcal{T} \Big\}, \tag{3.2}$$

or output possibility set

$$\mathcal{P}(y) = \Big\{ y \in \mathcal{R}_{+}^{M} \;\Big|\; \langle y, x \rangle \in \mathcal{T} \Big\}. \tag{3.3}$$

The theoretical literature on technical efficiency measurement puts loose regularity conditions to include a general class of technologies. We adopt assumptions by Shephard et al. (1970) and Färe et al. (1994).

Assumtion 1 *$\mathcal{T}$ is closed, convex, non-empty and bounded for all $x \in \mathcal{R}_{+}^{N}$.*

Assumtion 2 *$\langle x, y \rangle \in \mathcal{T}, \overline{y} \in \mathcal{R}_{+}^{M}$, and $\langle \overline{x}, -\overline{y} \rangle \in \langle x, -y \rangle$ implies $\langle \overline{x}, \overline{y} \rangle \in \mathcal{T}$, that is, both inputs and outputs are disposable.*

Assumtion 3 *$y > 0^{[M]} \Longrightarrow \langle 0^{[N]}, y \rangle \notin \mathcal{T}$.*

3.2.2 Inefficiency Indexes

The reference technology is defined by

$$\mathcal{T} = \Big\{ \langle x, y \rangle \in \mathcal{R}_{+}^{M+N} \;\Big|\; Y \leq \sum_{j} z_j Y_j \;\wedge\; x \geq \sum_{j} z_j x_j \;\wedge\; \sum_{j} z_j = 1,\; z_j \geq 0 \;\forall\, j \Big\}. \tag{3.4}$$

where z_j is the level of operation of a linear process for the j-th observation. Every point in the technology set is a linear combination of observed input and output vectors or a point dominated by such a combination. The constructed technology is a polyhedral cone with piecewise linear isoquants, commonly referred to as a Farrell cone. The Farrell input-based efficiency index for j-th DMU is defined by

$$\delta_j(x_j, y_j) = \min \Big\{ \delta \;\Big|\; \langle \delta x_j,\; y_j \rangle \in \mathcal{T} \Big\}. \tag{3.5}$$

As the index is the minimal proportional amount that input can be saved and remain technologically feasible, given the output quantities and the technology, it takes a value between zero and one and equals one if and only if the j observation lies on the production frontier. Similarly, The Farrell output-based efficiency index for j-th DMU is derived by

$$\theta_j(x_j, y_j) = \min\left\{\theta \;\middle|\; \langle x_j,\ y_j/\theta\rangle \in \mathcal{T}\right\}. \tag{3.6}$$

We will discuss only the input-oriented efficiencies, but the output-oriented case can be done following straightforward translation of the notation.

3.3 Null Hypothesis

In this section, we lay out our test procedures and present the properties of our test statistic. Consider a sample of observations for J DMU's, $\{y_j, x_j\}_{j=1}^{J}$, where y_j is an $M \times 1$ vector of outputs and x_j is an $N \times 1$ vector of inputs for the j-th DMU. Denote $\delta_j\,(m, n)$ as the efficiency score of the j-th DMU calculated by efficiency measures, for example, DEA, using m out of the M observed output variables and n out of the N input variables. The value of $\delta_j\,(m, n)$ usually relies on the dimension parameters m and n, which are denoted as $m \times n$ afterwards. Thus a generic question of interest is to test that, when including or excluding some observed input/output variables in the calculation of efficiency score δ_j, the change in δ_j is from the increase or decrease in dimensionality or from the existence of inefficiency. This question is appealing for theoretical concerns as well as practical reasons which, unless properly handled, usually prevent a meaningful measure of productivity and thus jeopardize the credibility of the DEA results in practical applications.

To proceed, we formulate our Null Hypothesis that the change of efficiency score of j-th DMU is owing to the change of dimensionality, but not the change in inefficiency, as follows,

$$\mathbf{H}_0 : \text{There is no efficiency change when } m_1 \times n_1 \text{ changes to be } m_2 \times n_2.$$

We test the above Null against the following Alternative,

$$\mathbf{H}_1 : \text{There is efficiency change when } m_1 \times n_1 \text{ changes to be } m_2 \times n_2.$$

We comment on the formulation of the Null and Alternative in the following remarks.

Remark 1: The Null first states that there is a change in the dimensionality of the model, from $m_1 \times n_1$ to $m_2 \times n_2$. The change in dimensionality is nondegenerate, that is, $\mathbf{1}(m_1 \neq m_2) + \mathbf{1}(n_1 \neq n_2) > 0$, where $\mathbf{1}(A)$ is 1 when the event A is true and 0 otherwise. The change of dimensionality may arise in practice for several reasons, like the availability of new observations on previously unobserved economic factors, and a change of factor inputs owing to introduction of newly found economic resource or other technical changes, etc.

Remark 2: The Null also implies that there would be a change in the value of efficiency score as dimensionality varies. It should be the case due to the stochastic sample that we observe, not to mention other reasons like dimensionality change or efficiency change. However, this variation, accounted for randomness of the observed sample, is because of the dimensionality change as stated in the Null and also the existence of efficiency change as claimed in the Alternative.

3.4 Test Statistics

The HY test focuses on the change of number of efficient DMU's. The dimension of the DEA model is misspecified if the mean percentage of efficient DMU's from the observed sample is not statistically different from that of simulated data. Our proposed test manages to use the efficiency information quantitatively from each DMU in the data set. Not only is the classification of efficient DMU's important, but also the magnitude of inefficiency matters. The idea of our proposed test is that the change in the efficiency scores $d_j = \delta_j(m_2, n_2) - \delta_j(m_1, n_1)$ (including other measures) should not be large in absolute value under the Null. Otherwise it should be rejected.

To test the proposed Null, a test statistic is in need as well as its distribution properties. Because of the multi-dimensional nature of the DEA estimators, the sampling distributions of the estimators are not handy, and the distributions of test statistics is unknown. The difficulty is to find a reasonable estimate of the underling DGP. HY simulates data sets from a random normal distribution, which eases the calculation but puts severe constraint on the type of DGP's that the test can be applied to. We employ bootstrap method to investigate sampling properties of DEA estimators. Bootstrap methodology, which assigns measures of accuracy to sample estimates through repeatedly and randomly resampling of the original data set, can be used to improve the finite-sample critical values for test statistics. There are different types of bootstrapping can be applied to DEA estimators. The reliability of a bootstrap test depends on how well the bootstrapped DGP mimics the underlying features of the true DGP. Simar and Wilson (1998) develop a smoothed bootstrap algorithm to analyze the sensitivity of the efficiency measures to sampling variation, but restrict the efficiency distribution to be homogenetic. Simar and Wilson (2001) apply it to construct critical values for the test statistics of various restrictions of a nonparametric efficiency model. Our test releases the homogenetic constraint and uses subsampling in the bootstrap algorithm to obtain consistent statistical inference.

We consider using d_j and its aggregated forms as our test statistics and bootstrap their distribution function, as in the procedures below.

Bootstrap Algorithm 1: Evaluation of Dimensionality Effect:

Step 1: Denote the input-output vector in model 1 as $\left(X^1, Y^1\right)$ and that in model 2 as $\left(X^2, Y^2\right)$. Denote $\bar{X} = X^1 \cap X^2$ as the common input variable and $\bar{Y} = Y^1 \cap Y^2$ as the common output variable used in model 1 and model 2. For $i = 1, 2$, define $\hat{X}^i = X^i \backslash \bar{X}$ and $\hat{Y}^i = Y^i \backslash \bar{Y}$. Thus, we have $X^i = \left[\bar{X}, \hat{X}^i\right]$ and $Y^i = \left[\bar{Y}, \hat{Y}^i\right]$. That is, we partitioned the input and output variables into two sets, with $\bar{X}$ and $\bar{Y}$ representing the common input and output variables, while $\hat{X}^i$ and $\hat{Y}^i$ denoting the distinct input and output variables used for model i. If some $\hat{X}^i$ and $\hat{Y}^i$ is empty, it is the case of nested variable change. the variable set of model i is nested under that of the other model.

Step 2: From the observed sample $\left\{\hat{X}_j^1\right\}_{j=1}^J$, randomly draw a sample of size $J-1$ with replacement and denote the sample as $\left\{\hat{X}_j^{1*}\right\}_{j=1}^{J-1}$. Combined the bootstrapped sample with original observations of common inputs and denote $X^{1*} = \left[\bar{X}, \hat{X}^{1*}\right]$

Step 3: Bootstrap X^{2*}, Y^{1*}, Y^{2*} similarly as been done in step 2.

Step 4: Compute the efficiency score d_j^{i*} by solving the linear programming problem (3.5) using data $\left\{X_j^{i*}, Y_j^{i*}\right\}_{j=1}^J$ for $i = 1, 2$.

Step 5: Repeat step 2-4 B times. Compute the efficiency score $d_j^{i*(b)}$, for $b = 1, \ldots, B$.

Step 6: Compute the bootstrapped dimensionality effect which is the difference between the efficiency score under model 1 and model 2:

$$DE_j\left(m_1 \times n_1,\, m_2 \times n_2\right) = \frac{1}{B} \sum_{b=1}^{B} \left(d_j^{2*(b)} - d_j^{1*(b)}\right)$$

Bootstrap Algorithm 2: p-value of the Test Statistic:

Step 1: Calculate the efficiency score $\delta_j(m_2, n_2)$ and $\delta_j(m_1, n_1)$ for the dimensionality given before and after the change. Calculate the difference of the dimensionality effect using original and bootstrapped data: $d_j = \delta_j(m_2, n_2) - \delta_j(m_1, n_1) - DE_j(m_1 \times n_1,\, m_2 \times n_2)$.

Step 2: Randomly draw a sample of size J without replacement from the given J DMU's and denote it as $\{y_i^*, x_i^*\}_{i=1}^{J}$. Use this bootstrapped sample to calculate the efficiency scores associated with the j-th DMU for both dimensionality $m_1 \times n_1$ and $m_2 \times n_2$, with each denoted by $\delta_j^*(m_2, n_2)$ and $\delta_j^*(m_1, n_1)$ respectively. Note that we use the original observations, rather than the bootstrapped values, for the j-th DMU to calculate its efficiency scores. Apply Algorithm 1 to compute the dimensionality effect $DE_j^*(m_1 \times n_1,\, m_2 \times n_2)$. Calculate the distance $d_j^* = \delta_j^*(m_2, n_2) - \delta_j^*(m_1, n_1) - DE_j^*(m_1 \times n_1,\, m_2 \times n_2)$.

Step 3: Repeat Step 2 for B times, with the distance in each run denoted as $d_j^{*(b)}$, $b = 1, ..., B$.

Step 4: Compute the test statistic value

$$\hat{\theta} = \theta(d_1, \ldots, d_J)$$

and bootstrapped test statistics value

$$\hat{\theta}^{(b)} = \theta\left(d_1^{(b)}, \ldots, d_J^{(b)}\right)$$

Step 5: Calculate the P-value

$$P = 1 - F_d(d^*) = \frac{1}{B}\sum_{b=1}^{B} \mathbf{1}\left(\hat{\theta} > \hat{\theta}^{(b)}\right),$$

where $\mathbf{1}(\cdot)$ is the indicator function as defined earlier. Reject the Null if P is less than pre-specified significance level α. Otherwise, we fail to reject the Null and thus accept the Alternative.

Remark 3: In the computation of efficiency scores, it is possible to correct the bias at Step 4 of Algorithm 1 and Step 2 of Algorithm 2, for example, as suggested by Simar and Wilson (2000a). This will involve a further bootstrap loop every time when the linear programming problem (**) is solved. This is very computationally time demanding and is usually not performed in simulations. However, when computational cost is not severe, this bias correction can be easily conducted.

Remark 4: Note that the proposed test is a global test. We need to test whether there is a change in efficiency for DMU's overall, after a change in dimensionality. However, it is easy to adapt the proposed test to be an local/individual one. This is simply done by taking $\hat{\theta} = d_j$ when testing the efficiency change of j-th DMU.

Remark 5: The aggregate function $\theta(\cdot, \ldots, \cdot)$ can take many forms, such as

$$\begin{aligned} \theta_1(d_1, \ldots, d_J) &= \left(\sum d_j^p\right)^{1/p} \text{ for } p \in \mathbb{N}, \\ \theta_2(d_1, \ldots, d_J) &= \text{median of } \{d_j\}_{j=1}^J, \end{aligned}$$

among others. The form of test statistic may affect the test result as noted by Simar and Wilson (2001), but many test statistics can deliver equivalent test results. We adopt θ_1 as the aggregate function in our empirical exercise.

3.5 Monte Carlo Simulation

We have discussed the procedures that describe our test of dimensionality for a very general setting. This section performs Monte Carlo simulation to examine the size and power of the test statistic. To compute the size of our test, we simulate data that is consistent with our null hypothesis. To compute the power of our test, we simulate data that is consistent with the alternative hypothesis. We consider the following DGPs.

DGP 1 (irrelevant input variable) :

$$\begin{aligned} x_{1i} &= 1 + 8u_{1i} \\ x_{2i} &= 1 + 8u_{2i} \\ y_{1i} &= x_{1i}^{2/3} e^{|-v_i|} \end{aligned}$$

DGP 2 (additive input variables):

$$\begin{aligned} x_{1i} &= 1 + 8u_{1i} \\ x_{2i} &= 1 + 8u_{2i} \\ y_{1i} &= (x_{1i} + x_{2i})^{2/3} e^{|-v_i|} \end{aligned}$$

where, $x_{ji}(y_{ji}, u_{ji})$ denote the jth element of x_i (y_i, u_i) and u_{ji} and v_i are independent random variables. We assume $u_{ji} \sim U[0,1]$ and $v_i \sim N(0,1)$. DGP 1 and DGP 2 are kept the same as those used by Simar and Wilson (2001).

In DGP 1, the input variable x_2 is irrelevant to the production of y_1. This design is used to study our proposed test statistic for irrelevant input variables. The question we propose is that, should there be no efficiency change when we shift from the model $\{x_1, y_1\}$ to $\{x_1, x_2, y_1\}$ computing efficiency score? Since x_{2i} is an irrelevant variable, we expect that our test statistically delivers a positive answer. While for sure there will be a change in the value of efficiency score, this difference should be resulted from either of the following two sources: the randomness of the sample we observed and the effect due to dimension change. We use bootstrap to account for the first effect and factor out the dimensionality component in the efficiency score. Consequently, computed efficiency score reflects the efficiency of units only. That is, the rejecting probability of there is a difference in efficiency score, accounting for dimensionality effect, should be close 1.

DGP 2 provides a setting from which we investigate our test for additivity of input variables. The input variable x_1 and x_2 are additive in the production of y_1. The efficiency of DMU's is therefore expected to be the same in both the model that uses $\{x_1, x_2, y_1\}$ and the one with $\{x_1 + x_2, y_1\}$. The difference in efficiency score computed from the linear programming problem should attribute to either the random sample or the dimensionality difference in the two models. Accoutring for these two effects via our proposed algorithms, the difference in efficiency score should not be significant.

We conduct 999 simulations and compute the probability of rejecting the null as portion of number of times that our test statistic exceed the simulated critical values corresponding to the significance level α (=0.01, 0.05, 0.10, 0.15). In each simulation, we conduct 999 bootstrapped samples to simulate the distribution of our statistic. We compute the dimensionality effect using 99 bootstrapped samples, given the availability of computing facility.

3.6 Empirical Illustration with NSW Data

This section illustrates our proposed approach to evaluate dimensionality effect and test changes in efficiencies with a data set that has been used in previous studies, for instance, in HY. This sample contains 161 police patrols in the State of New South Wales (NSW), Australia, in 1995 and 1996. We shortly describe the data set up to the point for our analysis, while direct readers to HY for a full data description and summary statistics. The sample is comprised of two groups of output variables, law enforcement and crime prevention activities, and two groups of inputs, labor and capital resources, which are used to deliver services to the community. Number of incidents, charges, summons and major car accidents are measures of law enforcement activities, while prevention activities are indicated by distance traveled by police cars and the number of intelligence reports prepared by front line police officers. Labor resources available include police and civilian employees measured as annual-average, full time equivalent staff and three measures of capital inputs are number of police cars, number of personal computers and area of station accommodation.

We apply our proposed approach to two cases–irrelevant case and additive case. In irrelevant case, we are concerned with the DEA modeling question that whether a given input or output variable is relevant to the efficiency measurement model or not. The result for the first case is presented in the following subsection, where three alternative models with less input variables are contrasted with the full model. The second case looks into the problem that whether two or more input or output variables should be aggregated additively in the efficiency assessment.

3.6.1 Irrelevancy of Input Variables

3.6.1.1 Model Specification and Technical Efficiency

We follow HY and consider four model specifications as follows,

M1: Include all input and output variables;

M2: Include all input and output variables except the area of station accommodation;

M3: Include all input and output variables except the number of personal computers;

M4: Include all input and output variables except the area of station accommodation and the number of personal computers.

Note that Model 1 is the largest model in terms of its dimensionality and contains 11 series. Both Model 2 and 3 contain 10 series, while Model 4 is the smallest model that only contains 9 variables. Theoretically, Model 1 should induce efficiency measures that are largest among all four models and Model 4 has smallest efficiency measures. Noticeably, dimensionality effect resulting from including more variable(s) in a larger model would seriously jeopardize efficiency measures.

Table 3.5 reproduce the results of HY (table 2, pp.416) on pure technical efficiency scores for all the four models, which are presented for comparison purpose later on. These efficiency measures were computed in R-language[2] and the R code is available upon request. We assume variable-returns-to-scale technology as formulated in equation (3.4), with different numbers of model variables as specified above. The average technical efficiency ranges from 0.901 to 0.933, while the minimum ranges from 0.518 to 0.606. The number of efficient patrol units varies from 67 to 89.

3.6.1.2 Dimensionality Effects

To account for dimensionality effect, we resort to our proposed bootstrap algorithm 1 as described in Section 3. To compute the dimensionality effect on technical efficiency score of unit $j(=1, 2, ..., 161)$ that results from including the area of station accommodation in Model 2, we bootstrap a random sample of size $m = 120$ from the original 161 patrol units. Combined it with the true observations of j-th DMU, we compute technical efficiency score for unit j using the sample of 121 units. We repeat the above process $B = 999$ times and compute efficiency score of unit j as the mean efficiency score over B bootstrapped values. The dimensionality effect, as defined earlier, is the difference between the mean efficiency score computed via bootstrapping and that computed from the original smaller model. The summary of dimensionality effects is presented in Table 3.6. The average dimensionality effect from Model 2 to Model

[2] R Development Core Team (2010), R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0. URL: http://www.r-project.org/

1 is quite close to that from Model 3 to Model 1. However, the dimensionality effect from Model 4 to Model 1 is relatively large. This finding is consistent with pre-existing concern that the larger the difference in the dimensions of two models, the greater the dimensionality effect is. The same finding applies to the maximum of dimensionality effect in these models. A closer look at the dimensionality effects computed for individual units reveals that, except for efficient units in smaller model, dimensionality effects are all positive.

We compute the corrected technical efficiencies by removing the dimensionality effect and the results are reported in Table 3.7. It is notable that the average values of technical efficiency in Model 1 after correcting the dimensionality from Model 2 and Model 3 are quite close, but the average via Model 4 bears a large difference. This finding applies to the minimum efficiency units as well. Regarding to the number of efficient patrols, Model 1 now has the same number of efficient units as Model 2, 3 and 4. That is, Model 1 bears large dimensionality effect comparing to the rest smaller models. To be specific, we illustrate this point at Model 1 and Model 2. In Model 1, without correction of dimensionality effect, the number of efficient units is 89, as displayed in Table 1. However, among these efficient units, 8 of them indicate the inflation of efficiencies, resulting from the inclusion of one additional input based on Model 2. A closer comparison of the efficiency scores in Model 1 and that after dimensionality correction reveals that, except for efficient units, efficiency scores are all inflated.

3.6.1.3 Testing Changes in Efficiency

The significant dimensionality effect found in the previous subsections distorts efficiency measures for larger models. In program evaluations, it is therefore important to account for these effects when, for example, dwelling on questions such as whether expenditures on a particular input is contributory significantly to the output. Whether there is efficiency change under such circumstances is subject to a valid statistical test[3].

We apply our bootstrap algorithm 2 proposed in Section 4 to perform inferences on the change in efficiency scores. Our null hypothesis is that there is no difference in efficiency scores computed in Model 1 and Model 2 (resp. Model 3, Model 4), while the alternative is that there is efficiency change. The test is performed in R-language with the following specifications, B=999, N=161, m=120, with 999 bootstrapped statistics that approximate the distribution of our testing statistic. The corresponding p-values for these tests are presented in Table 3.8.

P-values computed are all greater than 10%. Therefore we fail to reject the null hypothesis that there is no efficiency change when more input variables are included in the model. Note that our test result for the efficiency change from Model 4 to Model 1 is consistent with the conclusion from HY, where they conclude that Model 4 reflects pure dimensionality effect and should not be used. However, our computed p-value is significantly greater than 10%, which favors the null. This leads us to conclude that, after accounting for the dimensionality effect, Model 1 and Model 4 produce efficiency scores that are not statistically distinguishable.

3.6.2 Additivity of Input Variables

For completeness, we add a simple illustration to check the additivity of input (output) variables. We ask the question that whether some input variables can be aggregated. Particularly, we look into the labor input variables, police and civilians in NSW data set and see if the two types of labor inputs are homogeneous in nature in

[3]Varian (1990) argued that test as such should be done in economic sense, instead of statistically. This will involve a specific objective/value function for the particular problem at hand. Yet, we focus on statistical test that can be applied in a general setting and leave for future research tests from an economic point of view.

terms of efficiency measurement. We briefly state our results to save space. We consider the following model as an alternative to Model 1,

M5: Include all input and output variables but police and civilians enter the model only additively.

Model 5 contains aggregated input variables, and is not considered in HY. We reported the raw technical efficiencies in Table 3.5 and other results in Table 2-4. Under the additive-input-variable specification, the technical efficiency is bounded in between 0.919 and 0.596, with 80 units being efficient. The estimated average dimensionality effect between Model 1 and Model 5 is 0.049, and the corrected average technical efficiency is 0.870. The associated p-value to test additivity of input variables is 0.06, which leads to a rejection of the null at 10% significance level. This suggests that the police and civilian employees can be aggregated to one labor input to enter the efficiency model. The two inputs have the same unit of measurement and both deliver services to the community. As the convergence rate slows down when the input-output dimensions goes up, it is desirable to keep the dimensions low by aggregating certain inputs (outputs), if it is appropriate.

3.7 Conclusion

The comparison confirms that the index of the dimensionality constructed by observation-based simulations is more credible than that by random number generators. We also extend the tests to more general cases that allow for the comparison of non-nested variable changes.

The raw efficiency scores estimated by the DEA models not only reflect technical inefficiency but also the dimensions of a variable set. The dimensionality effect in technical efficiency models is notorious and distorts policy decisions. In this paper, we propose a measure of the dimensionality effect via a bootstrap algorithm, together with a procedure to test the change in efficiency when the dimension of a model used to perform program evaluations changes. Our test concerns more about the marginal role of particular variables playing in the production process and allows the partial dimensionality effect to be heterogeneous. The diagnostic test utilizes the remaining observed variables and mimics the sampling distribution by bootstrap method.

Our test manages to balance the computational burden and valid power in finite sample. We apply the proposed approach to NSW data set to identify efficient police patrol units, estimate dimensionality effects in models where several variables may be irrelevant or may be aggregated. In the first application, we found that there is no change in efficiency when input variables are removed from the full model, so we suggest a small scale model instead of the full model, taking the potential dimensionality effect into account. In the second application, we check the additivity of labor input variables and found that they should not enter the model additively since the change in efficiency score is significant. Last, we point out that our proposed bootstrap procedures can also be applied to non-nested efficiency models to measure the dimensionality effect and testing changes in efficiency measures when model dimension changes.

While we present our bootstrap procedures for measuring dimensionality effect and testing changes in efficiency scores, with illustrations using HY data, the theoretical aspects of the proposed procedures are still left for future research. We hope that the recent development in empirical process theory would help to tackle this theoretical challenge and some of Simar and Wilson would help to bring more fruitful work in this direction.

3.8 Appendix B: Tables

Table 3.1: Monte Carlo Estimates of Size of Test

(DGP1: Irrelevant Input Variable)

	Sample Size				
Nominal Size	25	50	100	200	400
0.01	0.003	0.009	0.016	0.013	0.008
0.05	0.038	0.044	0.036	0.052	0.049
0.10	0.071	0.069	0.082	0.092	0.126
0.15	0.092	0.103	0.130	0.142	0.146
0.20	0.162	0.159	0.177	0.194	0.203

Table 3.2: Monte Carlo Estimates of Size of Test

(DGP2: Additive Input Variables)

	Sample Size				
Nominal Size	25	50	100	200	400
0.01	0.004	0.005	0.08	0.011	0.009
0.05	0.036	0.040	0.039	0.046	0.052
0.10	0.072	0.087	0.093	0.094	0.097
0.15	0.103	0.119	0.206	0.172	0.159
0.20	0.162	0.188	0.175	0.192	0.196

Table 3.3: Monte Carlo Estimates of Power of Test

(DGP1: Irrelevant Input Variable)

	Sample Size				
Nominal Size	25	50	100	200	400
0.01	0.632	0.663	0.598	0.763	0.892
0.05	0.651	0.688	0.863	0.876	0.952
0.10	0.721	0.760	0.852	0.886	0.961
0.15	0.803	0.851	0.892	0.920	0.955
0.20	0.825	0.859	0.903	0.935	0.967

Table 3.4: Monte Carlo Estimates of Power of Test

(DGP2: Additive Input Variables)

	Sample Size				
Nominal Size	25	50	100	200	400
0.01	0.652	0.631	0.862	0.854	0.935
0.05	0.663	0.644	0.879	0.883	0.942
0.10	0.666	0.673	0.899	0.925	0.966
0.15	0.681	0.690	0.903	0.932	0.984
0.20	0.699	0.704	0.911	0.943	0.989

Table 3.5: Summary of Technical Efficiency Results

	Model				
	1	2	3	4	5
Average	0.933	0.921	0.918	0.901	0.919
Minimum	0.606	0.606	0.523	0.518	0.596
No. of efficient patrols	89	81	77	67	80

Table 3.6: Summary of Dimensionality Effects

	Model			
	$2 \rightarrow 1$	$3 \rightarrow 1$	$4 \rightarrow 1$	$5 \rightarrow 1$
Average	0.017	0.019	0.036	0.049
Maximum	0.066	0.091	0.131	0.260

Table 3.7: Summary of Efficiency Results with Dimensionality Effect Correction

	Model			
	$2 \rightarrow 1$	$3 \rightarrow 1$	$4 \rightarrow 1$	$5 \rightarrow 1$
Average	0.916	0.902	0.882	0.870
Minimum	0.542	0.537	0.491	0.649
No. of efficient patrols	81	77	67	80

Table 3.8: P-values for Testing Changes in Efficiency Scores

	Model			
	$2 \rightarrow 1$	$3 \rightarrow 1$	$4 \rightarrow 1$	$5 \rightarrow 1$
p-value	0.231	0.197	0.206	0.060

Chapter 4

Environmental Regulation and Foreign Direct Investment Inflows to U.S. States: A Three-Stage Model Approach

4.1 Introduction

Following decades of liberalization of global capital markets, considerable debate has arisen about the role of FDI in sustainable development of recipient economies. One contentious issue of concern is its potential negative externalities on the environment of host countries. The so-called pollution haven hypothesis argues that multinational firms in pollution-intensive industries seek to relocate to the places with weaker environmental standards. In order to attract more FDI, recipient economies may intend to implement lose environmental policies, which could trigger a race to the bottom, as other economies may also lower their standards to retain the FDI. Copeland and Taylor (1994) probably are the first to introduce a complete model to test the pollution haven hypothesis. However, further studies in the following decade show controversial results, as represented by the sixteen papers collected in Fullerton (2006). Despite the plausibility of the pollution haven hypothesis, empirical studies, especially those focusing on the stringency of national environmental standards, detect little evidence to support the hypothesis. Eskeland and Harrison (2003) examine the distribution of FDI across industries in four Latin American countries, but find little evidence to support the pollution haven hypothesis. Javorcik and Wei (2004) examine the pollution haven hypothesis in 25 East European countries, but find no support for it.

Another group of empirical studies concentrates on comparisons of intra-country environmental standards, as different states or provinces are more comparable than different countries on nongovernmental grounds. Levinson and Taylor (2008) use a panel of the FDI across 130 industries in Mexico over 1977-1986, and conclude that the abatement cost plays a crucial role in the pollution haven hypothesis. In the U.S., the state governments take a large fraction of the responsibility for setting environmental standards. As discussed by Keller and Levinson (2002), even if the same federal policy or standards are imposed, the state characteristics may still lead to different costs. The U.S. state-level data on environmental costs also are better and easier to obtain than those on international costs. Keller and Levinson (2002) employ state-level panel data in the U.S. and find moderate evidence on the pollution haven hypothesis. Henderson and Millimet (2007) use nonparametric methods to reassess the robustness of the conclusions in Keller and Levinson (2002). Fredriksson et al. (2003) incorporate both environmental policy and governmental corruption in the model and find empirical evident to support the pollution haven hypothesis in the U.S.

The stringency of environmental policy is an uncontrollable variable to each state. Several models have been proposed to incorporate the uncontrollable environmental effects into a DEA-based efficiency evaluation, which can be grouped into one-stage model, two-stage model, and three-stage model. First developed by Banker and Morey (1986), the one-stage (single-stage) model directly includes uncontrollable discretionary environmental variables in its linear functions along with traditional inputs and outputs, but restricts the optimization to either inputs or outputs. As it is a traditional DEA model, uncontrollable variables can be altered radially, but no random noise is accounted for. Pioneered by Timmer (1971), the two-stage model runs a regression in the second stage after a first stage DEA assessment. McCarty and Yaisawarng (1993) and Bhattacharyya et al. (1997) extend the two-stage model to adjust the first stage efficiency scores in the second stage. Fried et al. (1993) modify the two-stage model by replacing the first stage efficiency scores with its slacks in the second stage regression. Although the second stage is stochastic, the data adjustment does not account for the impact of statistical noise. Fried et al. (2002) suggest a three-stage approach, which can purge managerial inefficiency from environmental effects and statistical noise. After running the first and second stage analysis as in the two-stage model, the DEA evaluation is repeated in the third stage by using the adjusted data. The three-stage model can completely decompose the variation in performance to the components attributes to environmental effects, managerial inefficiency and statistical noise.

The stochastic frontier analysis (SFA) in the second stage is developed to distinguish the statistical noise from technical inefficiency. The parametric SFA model is first proposed by Aigner and Lovell (1977), Meeusen and van Den Broeck (1977), and

Battese and Corra (1977). These early works estimate technical efficiency by the maximum likelihood estimation (MLE) and apply the SFA to cross-sectional data. Schmidt and Sickles (1984) suggest using panel data to relax some strong assumptions on the cross-sectional framework. Pitt and Lee (1981) extend the MLE to panel data settings. Hausman and Taylor (1981) construct a panel data model that allows for time variance of some covariates. Schmidt and Sickles (1984) apply fixed effects (FE) and random effects (RE) on the estimation of time-invariant technical efficiency.

The quality of the SFA measurement depends on whether the functional form represents the true model. To relax the dependence on the parametric functional form, recent studies focus on developing semiparametric or fully nonparametric SFA models. Fan et al. (1996) consider a semiparametric cross-sectional SFA model, which has no restrictions on the functional form of the production frontier and takes the distribution of the composite error terms as known. Kneip and Simar (1996) present a general semiparametric SFA framework to deal with panel data set. The general production functional form, transforming input x_{jt} to output y_{jt} is:

$$y_{jt} = h(x_{jt}) + \alpha_j + \epsilon_{jt} \tag{4.1}$$

where $h(\cdot)$ is an unknown smooth part of production function shared by each producer, α_j captures the DMU specific effect, and ϵ represents the two sided noise component. Kneip and Simar (1996) use the Nadaraya-Watson estimator $\hat{h}$ to estimate h. This paper improves the second stage SFA evaluation by using the Local Linear Least Squares (LLLS) estimator. LLLS provides more efficient estimates of h, and can estimate both the production function and the elasticities in one step. In the first stage, the input-oriented DEA is applied to inputs and outputs only. In the third stage, the DEA evaluation is performed again, using adjusted inputs to account for the effects of environmental standards and statistical nose.

The remainder of the paper is organized as follows. Section 2 proposes the three-stage model. Section 3 discusses the panel data and presents the empirical results. Section 4 concludes.

4.2 Methodology

4.2.1 First Stage DEA

The initial evaluation of producer performance is conducted using the DEA method and traditional inputs and outputs. Although the method of efficiency measurement can be applied to analyze any number of (macro or micro) DMU's, here we will describe the special case related to my macro-level example. Capital is treated as heterogeneous and separated into foreign capital (KF) and domestic capital (KD). The technology contains four macroeconomic variables: gross state product (GSP) (Y) and three aggregate inputs–KF, KD and labor (L). The standard technology reflects the mechanism that the input vector in state j at period t, $X_{jt} = (KF_{jt}, KD_{jt}, L_{jt})$, gets transformed into Y_{jt}. Under the assumptions of constant-returns-to-scale and free disposability of inputs and outputs, the reference technology for the U.S. at time t is defined by

$$(4.2)\quad \mathcal{T}_t^1 = \left\{ \langle Y_t, KF_t, KD_t, L_t \rangle \in \mathcal{R}_+^4 \;\middle|\; Y_t \leq \sum_j \alpha_{jt} Y_{jt} \;\wedge\; KF_t \geq \sum_j \alpha_{jt} KF_{jt} \right.$$
$$\left. \wedge\; KD_t \geq \sum_j \alpha_{jt} KD_{jt} \;\wedge\; L_t \geq \sum_j \alpha_{jt} L_{jt},\; \alpha_{jt} \geq 0 \;\forall\; j \right\},$$

where α_{jt} is the level of operation of a linear process for the jt observation. Every point in the technology set is a linear combination of observed input and output vectors or a point dominated by such a combination. The constructed technology is a polyhedral cone with piecewise linear isoquants, commonly referred to as a Farrell cone (Farrell (1957a)).

The Farrell input-based technical efficiency index[1] for state j at time t is defined by

$$(4.3) \qquad E(Y_{jt}, KF_{jt}, KD_{jt}, L_{jt}) = \min \left\{ \theta \;\middle|\; \langle Y_{jt}, \theta KF_{jt}, \theta KD_{jt}, \theta L_{jt} \rangle \in \mathcal{T}_t \right\}.$$

The Farrell input-based technical efficiency index can be calculated by solving the following linear program for each observation:

$$(4.4) \qquad \begin{aligned} \underset{\theta,\ \alpha_{11},\ldots,\ \alpha_{Jt}}{min} \ \theta \quad subject\ \ to\ \ Y_{jt} &\leq \sum_{\tau \leq t} \sum_{j} \alpha_{j\tau} Y_{j\tau}, \\ \theta KF_{jt} &\geq \sum_{\tau \leq t} \sum_{j} \alpha_{j\tau} KF_{j\tau}, \\ \theta KD_{jt} &\geq \sum_{\tau \leq t} \sum_{j} \alpha_{j\tau} KD_{j\tau}, \\ \theta L_{jt} &\geq \sum_{\tau \leq t} \sum_{j} \alpha_{j\tau} L_{j\tau}, \\ \alpha_{j\tau} &\geq 0,\ \forall\ j, \tau. \end{aligned}$$

The optimal solutions to (4.4) provide preliminary performance evaluations for each state, but mix the effects attributable to managerial inefficiencies, environmental effects, and statistical noise.

4.2.2 Second Stage SFA

In this stage, the SFA method is applied to regress the first stage efficiency measures against environmental variable(s). While the regressors are operating environmental variables, there are two choices of dependent variables. One is the first stage efficiency scores, and the other is the first stage slacks. Timmer (1971) is the first to

[1] Färe and Primont (1995) proves that the assumption of constant returns to scale is equivalent to the condition that the input- and output-distance functions assign reciprocal values to each input-output combination. Thus, under constant returns to scale, the Farrell input-oriented and output-oriented indexes are equivalent.

apply limited dependent variable regression techniques to first stage efficiency scores. McCarty and Yaisawarng (1993) and Bhattacharyya et al. (1997) extend it to adjust regression residuals. As efficiency scores are bounded and frequently reach the upper bound, the choice of a regression function is very limited. Fried et al. (2002) use the SFA to regress first stage slacks against the observable environmental variables. Denote total input slack of input i from the first stage DEA for state j as s_j^i, which is the difference between the actual usage of the n-th input and the optimal projection of actual input onto the efficient input subset for output y_j.

$$s_j^i = x_j^i - \sum_l \alpha_l^i x_l^i. \tag{4.5}$$

The regressors are K observable environmental variables z_j for J states. Fried et al. (2002) set up N separate regressions, which allows environmental variables to have different impacts on each input slack.[2] The general regression form is

$$s_j^i = f^i(z_j) + v_j^i + u_j^i, \quad i = 1, \cdots, I, \; j = 1, \cdots, J. \tag{4.6}$$

where $v_j^i \sim N(0, \sigma_{vi}^2)$ captures statistical noise and $u_j^i \sim N^+(\mu^i, \sigma_{ui}^2)$ reflects managerial inefficiency. v_j^i and u_j^i are assumed to be distributed independently. Fried et al. (2002) do not impose a time dimension and parameterize (4.6) by MLE:

$$s_j^i = z_j\beta^i + v_j^i + u_j^i, \quad i = 1, \cdots, I, \quad j = 1, \cdots, J. \tag{4.7}$$

where β^i is the parameter vector reflecting the marginal effect of the environmental variable vector z_j on the input slack s_j^i.

As discussed in Fried et al. (2002), there are several advantages of using SFA in the second stage. First, we do not have to specify the direction of the effect of any

[2]Another approach is to stack the N regressions and estimate a single SFA regression model. Fried et al. (2002) suggest to run separate regressions, as the gain in flexibility outweighs the sacrifice of degree of freedom.

environmental variable prior to the analysis. Second, the statistical significance of such effect can be tested by conventional likelihood ratio tests. Third, we can test whether managerial efficiency is invariant across producers by testing the hypothesis that $\sigma_{ui}^2 = 0$. Lastly and most importantly, this setting allows managerial inefficiency, environmental variables and statistical noise to impose different effects across inputs.

However, Fried et al. (2002) have two limitations. First, they use parametric regressions in the SFA, which is expected to perform the best when the model is correctly specified. However, when the parametric model is incorrectly specified, it is expected to lead to inconsistent estimation of $f(\cdot)$ and the parameters. It is hard to believe that the underlying complicated technology is linear. Henderson and Ullah (forthcoming) conduct Monte Carlo experiments and show that nonparametric models drastically outperform the parametric model when the technology becomes nonlinear. Second, Fried et al. (2002) assume the model is time invariant and pool the data set, which ignores any commonalities or panel data effect.

This paper extends the three-stage model to a semiparametric panel setting. The feasible slack frontier is constructed by the following semiparametric model:

$$s_{jt}^i = h^i(z_{jt}) + \alpha_j^i + \epsilon_{jt}^i, \tag{4.8}$$

where $h^i(\cdot)$ is an unknown smooth function shared by each states, α_j^i captures the location effect, and the error term ϵ_{jt}^i represents the i.i.d. stochastic noise component with zero mean.

The LLLS estimator is used to estimate $h^i(\cdot)$. Taking a first-order Taylor expansion of equation (4.8) with respect to z_{jt} yields

$$s_{jt}^i \approx h^i(z) + (z_{jt} - z)\beta^i(z) + \alpha_j^i + \epsilon_{jt}^i, \tag{4.9}$$

where $\beta^i(z) \equiv \nabla h^i(z)$ is the partial derivative of $h^i(z)$ with respect to z. If s and z

are expressed in logarithmic form, then $\beta^i(z)$ represents a "local" elasticity for state j, evaluated at the point z. The estimator of $\delta^i(z) \equiv ((h^i(z), (\beta^i(z))')'$ is given by[3]

$$\hat{\delta}^i(z) = (\hat{h}^i(z), (\hat{\beta}^i(z))')' = (M'K(z)M)^{-1}M'K(z)s, \tag{4.10}$$

where $M = (1, (z_{jt} - z))$ and $K(z)$ is a diagonal matrix of kernel functions $K(b^{-1}(z_{jt} - z))$. The optimal bandwidths b can be obtained by minimizing the Least-Squares Cross-Validation (LSCV) function given by

$$CV(b) = \sum_{\tau=1}^{t}\sum_{j=1}^{J}[s_{j\tau} - \hat{h^i}_{-j}(z_{j\tau})]^2 \tag{4.11}$$

The estimator of α_j^i is given by

$$\hat{\alpha}_j^i = \frac{1}{t}\sum_{\tau=1}^{t}(s_{j\tau} - \hat{h}^i(z_{j\tau})). \tag{4.12}$$

The estimator of u_j^i is derived by means of the normalization:

$$\hat{u}_j^i = \max_j \hat{\alpha}_j^i - \hat{\alpha}_j^i. \tag{4.13}$$

4.2.3 Third Stage DEA

Before applying the DEA again, raw input data should be adjusted for the effects of environmental variable(s) and statistical noise. As in Fried et al. (2002), inputs are adjusted according to

$$\tilde{X}_{jt}^i = X_{jt}^i + \left[\max_l \left\{\hat{h}^i(z_{lt})\right\} - \hat{h}^i(z_{jt})\right] + \left[\max_l \left\{\hat{\epsilon}_{lt}^i\right\} - \hat{\epsilon}_{jt}^i\right], \tag{4.14}$$

where $\tilde{X}_{jt}^i$ is the amount of input i used in state j at time t after adjustment. The first stage DEA evaluation does not take into account the effect of relatively unfavorable

[3]We note that this estimator is inefficient because it does not take into account the variance covariance matrix of the combined error $(\alpha^i + \epsilon_t^i)$. For an efficient estimator, see Su and Ullah (2007) and Henderson and Ullah (2005). Further, if α^i is a fixed effect, then for the nonparametric estimator, see Henderson et al. (2008a) and Su and Ullah (2006).

environments and relatively bad luck. Thus, $\max_l \left\{\hat{h}^i(z_{lt})\right\} - \hat{h}^i(z_{jt})$ is the adjustment putting all states in a common operating environment, and $\max_l \left\{\hat{\epsilon}^i_{lt}\right\} - \hat{\epsilon}^i_{jt}$ is the adjustment putting all states in a common extenuating circumstance.

In the third stage, the DEA is applied on the adjusted inputs $\tilde{X}^i_{jt}$ and original outputs Y_{jt}. The results provide evaluations of purely managerial efficiency, while the effect of the operating environment and statistical noise are completely purged out.

4.3 Empirical Application

4.3.1 Data

The three-stage method is applied to a panel of 48 contiguous U.S. states[4] from 1980 to 1994. The GSP, state-by-state capital K and foreign capital stock KF are from Bureau of Economic Analysis and are converted to 1992 constant USD. Labor and the data of environmental variables are directly from Keller and Levinson (2002). The state-level environmental stringency (ES) is measured by the industry-adjusted environmental index proposed by Keller and Levinson (2002). Other environmental variables are market proximity (MKT), unionization rates (UN) and tax efforts (TAX). MKT measures the distance of each state to potential markets in other states, which is a distance-weighted average of all other states' GSP. UN is the percentage of union membership in the civilian labor force. TAX is calculated as a state's actual revenues divided by its estimated capacity to raise revenues based on a model tax code.

The summary statistics of the input-output data are presented in Table 4.1. The lowest GSP is produced by Vermont in 1980, and the highest GSP is from California in 1994. In average, 3% of each state's capital stock is consisted of foreign capital in the

[4]There is no complete data set for Alaska and Hawaii.

sample, but the share varies a lot across states. South Dakota had the lowest foreign capital stock in 1981, and Texas archived the highest foreign capital stock in 1994.

4.3.2 Empirical Results

The stage 1 DEA analysis is conducted using only the output and three inputs. Table 4.3 summarizes the stage 1 DEA evaluations. It suggests a relatively low average efficiency level and a relatively large dispersion in performance. Thus, there is considerable room for efficiency improvement by bringing up the inefficient states to the best practice frontier. However, the laggard states in the initial performance evaluations may operate in unfavorable environments, or experience unfavorable extenuating circumstances. To investigate the effect of management inefficiency from the mixed stage 1 results, stage 2 efficiency breakdowns and stage 3 re-evaluation are needed.

The effect of the environmental variables, especially that of the environmental stringency, is investigated in the stage 2 SFA analysis. No priors are imposed on the directions of the effects of environmental variables. It is expected that high MKT provides more favorable environment, while high ES, UN and TAX disfavor the managerial efficiency. Table 4.2 summarizes comparisons of stage 2 evaluations using the LLLS and MLE estimations, respectively. The first thing to note is that all the coefficients (gradients) have expected signs except those of ES with respect to KD slacks and MKT with respect to KF slacks using the MLE. The two coefficients (gradients) with unexpected signs are statistically insignificant.

We are primarily interested in the impact of state-level environmental stringency on the input slacks. The results suggest that input slacks are consistently smaller in the operation environment with higher environment standard, although the coefficient (gradient) is insignificant in the KD slacks equation. Using the semiparametric estimation provides consistent results across all the three equations, while using the MLE shows unexpected sign for KD slacks. The positive relationship between KF slacks and ES indicates that higher environment standard draws foreign capital away, and supports the pollution haven hypothesis.

The semiparametric evaluation suggests that higher market proximity narrows all of the input slacks, although the coefficient (gradient) is significant only in L slacks. The MLE evaluation provides the same results for KD and L slacks, but has opposite conclusion for KF slacks. The higher unionization rates and more tax effort both enlarge the input slacks. The results are significant for all inputs slacks under the semiparametric evaluation.

Stage 3 re-evaluates each state's performance after adjusting for the impact of the operating environment and for variation of statistical noise. Table 2.2 lists the stage 1 and 3 efficiency scores for each of the 48 states in 1994, respectively. The average efficiency score increases dramatically in stage 3 and the standard deviation narrows down about 38% after the stage 3 re-evaluation. The increase in mean efficiency supports the hypothesis that the high initial performance evaluations in some states is owing to their relatively favorable operating environments or relatively favorable extenuating circumstances. The number of efficient states increases from 2 to 6 after the adjustment, while the efficient states shuffle thoroughly in stage 3. New York keeps its efficient position on the frontier, while California falls back a little bit from the frontier in stage 3 evaluation. Arizona, Florida, South Carolina, Tennesseans, and Virginia catch up and are recognized as efficient states after the adjustment. Texas experiences efficiency decline after the stage 3 adjustment, which is consistent with the hypothesis that the relatively low stage 1 performance evaluations in some states are due to the unfavorable operating environments or relatively unfavorable extenuating circumstances.

4.4 Conclusion

The traditional DEA or SFA methods only consider inputs and outputs in the evaluation of the DMU's efficiency performance. The omission of environmental variables is a big drawback. Three-stage model is developed to evaluate the impact of operational environment on DMU's performance. This paper extends the stage 2 SFA model to a semiparametric panel setting to capture the complicated feature of the underlaying technology. Compare to the MLE, the semiparametric estimator provides expected signs and consistent results for the empirical example considered in this paper.

To test the pollution haven hypothesis across 48 contiguous states in the U.S., the stage 2 evaluation is focused on the effect of the state-level environmental stringency. The result suggests a negative relationship between environment standards and foreign capital slacks, which provides some evidence for the pollution haven hypothesis.

In our empirical example, all the environmental variables are continuous. The model itself is general and can be applied to both discrete (categorical) or mixed (continuous and discrete) data. The semiparametric estimation has significant improvement over the MLE in the stage 2 evaluation, but it still keeps the restrictive assumption that firm effect enters in linearly. The linearity can be further generalized by a fully nonparametric model. The difficulty arises from the construction of a consistent estimator.

4.5 Appendix C: Tables and Figures

Table 4.1: Descriptive Statistics of U.S. State-level Production, 1980–1994

Variables	Average	Std. Deviation	Min.	Max.
Output:				
Y	85841	112454	3031	898836
Inputs:				
KF	3150	4071	17	30131
KD	119601	14203	15672	802634
L	35714	38114	669	216800

Table 4.2: Comparisons of Stage 2 Stochastic Frontier Estimation

(Semiparametric Vs. MLE)

	Slacks		
Independent Variables	KF	KD	L
ES	0.358*	-0.840	0.389*
	*0.443**	*-0.102*	*0.473**
MKT	-0.248	-0.250	-0.300*
	0.537	*-0.132*	*-0.929**
UN	0.226*	0.406*	0.460*
	0.382	*0.305*	*0.428**
TAX	0.513*	0.234*	0.109*
	*0.519**	*0.193**	*0.712**

* Significant at the 5% level or better

Table 4.3: Comparison of Stage 1 & 3 DEA Evaluations

States	Stage 1	Stage 3
Alabama	0.260	0.968
Arizona	0.322	1.000

continued

TABLE 4.3

CONTINUED

States	Stage 1	Stage 3
Arkansas	0.164	0.859
California	1.000	0.955
Colorado	0.327	0.910
Connecticut	0.324	0.937
Delaware	0.086	0.752
Florida	0.671	1.000
Georgia	0.476	0.877
Idaho	0.097	0.742
Illinois	0.697	0.814
Indiana	0.391	0.987
Iowa	0.233	0.741
Kansas	0.215	0.733
Kentucky	0.282	0.799
Louisiana	0.344	0.823
Maine	0.098	0.490
Maryland	0.383	0.919
Massachusetts	0.489	0.910
Michigan	0.590	0.925
Minnesota	0.364	0.876
Mississippi	0.176	0.766

continued

TABLE 4.3

CONTINUED

States	Stage 1	Stage 3
Missouri	0.380	0.866
Montana	0.070	0.370
Nebraska	0.155	0.692
Nevada	0.166	0.803
New Hampshire	0.103	0.654
New Jersey	0.610	0.854
New Mexico	0.158	0.778
New York	1.000	1.000
North Carolina	0.494	0.947
North Dakota	0.055	0.485
Ohio	0.647	0.893
Oklahoma	0.232	0.751
Oregon	0.248	0.810
Pennsylvania	0.643	0.832
Rhode Island	0.087	0.732
South Carolina	0.254	1.000
South Dakota	0.066	0.518
Tennessee	0.357	1.000
Texas	0.885	0.735
Utah	0.148	0.786

continued

TABLE 4.3

CONTINUED

States	Stage 1	Stage 3
Vermont	0.051	0.585
Virginia	0.464	1.000
Washington	0.448	0.973
West Virginia	0.118	0.696
Wisconsin	0.363	0.951
Wyoming	0.054	0.674
Mean	0.339	0.816
Std. Deviation	0.245	0.152
Min.	0.051	0.370
No. of efficient states	2	6

Chapter 5

Conclusions

This dissertation analyzes the impact of FDI on productivity growth, convergence, and the environment. Chapters 2 and 4 develop the method to examine the role that FDI plays in economic growth and environment, respectively. Chapter 3 constructs a statistical test to select appropriate nonparametric efficiency model in terms of its dimensionality.

Chapter 2 extends the HR decomposition of labor productivity growth by breaking physical capital accumulation into foreign capital and domestic capital. Thus, labor productivity growth is decomposed into components attributable to technological change, technological catch-up, foreign capital accumulation, domestic capital accumulation and human capital accumulation.

The empirical evaluation using a worldwide panel across 78 countries over the 1980–2005 period indicates that the effects of foreign capital deepening and domestic capital deepening on productivity growth are dramatically different. Foreign capital accumulation, together with human capital accumulation, is the driving force of productivity growth, while the contribution of domestic capital accumulation is much smaller.

We also find that technological change is decidedly nonneutral, with most technological advancement taking place in countries that are highly foreign-capital intensive. Foreign capital deepening and human capital accumulation are the primary driving forces behind increased international dispersion of labor productivity.

Raw efficiency scores estimated by DEA method reflect not only technical inefficiency but also the dimensions of a variable set. The dimensionality effect in technical efficiency models is notorious and distorts policy decisions. In chapter 3, a measure of the dimensionality effect is proposed by a bootstrap algorithm, together with a procedure to test the change in efficiency when the dimension of a model used to perform program evaluations changes. The dimensionality test concerns more about the marginal role of particular variables playing in the production process and allows the partial dimensionality effect to be heterogeneous.

The diagnostic test utilizes the remaining observed variables and mimics the sampling distribution by bootstrap method. It manages to balance the computational burden and valid power in finite sample. The theoretical aspects of the proposed procedures are still left for future research. We hope that the recent development in empirical process theory would help to tackle this theoretical challenge.

Chapter 4 proposes a three-stage model to test the pollution haven hypothesis across 48 contiguous states in the U.S. In stage 1, preliminary performance evaluation is provided by the DEA on inputs and outputs only. The average efficiency score is relatively low and the dispersion in performance is relatively large. The stage 2 SFA method is extended to a semiparametric panel setting to capture the complicated feature of the underlaying technology. Compare to the MLE estimation, the LLLS estimator provides expected signs and consistent results for the empirical example considered in this chapter. The stage 2 evaluation is focus on the effect of state-level environmental stringency. The result suggests a negative relationship between environment standards and foreign capital slacks.

The first stage DEA evaluation does not take into account of the effect of relatively unfavorable environments and relatively bad luck. In stage 2, the variation in performance is completely decomposed to the components attributes to environmental effects, managerial inefficiency and statistical noise. After the decomposition, adjustments are applied on inputs to put each DMU in a common operating environment and common extenuating circumstance. The stage 3 DEA re-evaluation uses adjusted inputs, and the results indicate purely managerial efficiency, while the effect of the operating environment and statistical noise are completely purged out. The empirical results show that average efficiency score increases dramatically in stage 3 and the standard deviation narrows down after the stage 3 re-evaluation.

In chapter 4, all the environmental variables are continuous. The three-stage model itself is general and can be applied to discrete (categorical) or mixed (continuous and discrete) data. The semiparametric estimation has significant improvement over the MLE in stage 2 evaluation, but it still keeps the restrictive assumption that firm effect enters in linearly. Future work includes generalizing the model to a fully nonparametric panel setting. The difficulty arises from the construction of a consistent estimator. These are left for future research.

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