ESSAYS ON FIRM AND AGGREGATE PRODUCTIVITY AND EFFICIENCY

by

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(Under the Direction of David R. Kamerschen)

ABSTRACT

In the past decade, researchers have been increasingly examining productive efficiency as an explanation for observed economic phenomena. The aim of this research is to further this practice on two fronts. My first emphasis is on firm efficiency. While numerous empirical studies have investigated whether efficiency is behind firm growth and industry market structure, there is little theoretical justification for this practice. I develop an endogenous model of firm innovation that explicitly defines firm efficiency as the principal driver of firm growth and market structure. I then test some of its implications through a stochastic frontier analysis of manufacturing firms from the COMPUSTAT database. My second emphasis is on aggregate technology frontiers. I argue that economy-wide technology frontiers estimated with aggregate measures of output are downward biased. In response to this bias, I propose a micro-macro approach that estimates a "better" frontier that more closely emulates the underlying heterogeneous technologies.

INDEX WORDS: Firm Efficiency, Demsetz Hypothesis, Firm R&D and Innovation, World Technology Frontier, International Productivity Comparisons, Stochastic Frontier Analysis

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CHAPTER 1

INTRODUCTION

In the past decade, researchers have been increasingly examining productive efficiency as an explanation for observed economic phenomena. The aim of this research is to further this practice on two fronts. Our first emphasis is on firm efficiency. While numerous empirical studies have investigated whether efficiency is behind firm growth and industry market structure, there is little theoretical justification for this practice. In Chapter 2, we develop a theoretical model of endogenous firm growth that conforms to empirical regularities found in the literature and explicitly defines firm efficiency as the principal driver of firm growth and market structure. This model can serve as unified framework for additional theoretical and empirical work that explicitly incorporates both innovation and firm efficiency. We then test some of its implications in Chapter 3 through a stochastic frontier analysis of manufacturing firms from the COMPUSTAT database.

My second emphasis is on aggregate technology frontiers. Chapter 4 addresses the estimation of aggregate technology frontiers as used in international productivity comparisons. Researchers of regional and international productivity comparisons are increasingly adopting various frontier approaches to examine convergence and the possible causes of productivity differences. We argue that economy-wide technology frontiers estimated with aggregate measures of output are downward biased. This bias extends not only to estimates of the technology frontier, but also produces incorrect measures of technical change and efficiency change. We propose a micro-macro approach that estimates a “better” frontier that more closely emulates the underlying technologies.

In Chapter 5, we employ the technique described in Chapter 4 on an unbalanced panel of 12 OECD countries from 1980-2001. We reveal that traditional frontiers estimated with aggregate measures of output underestimate the available best-practice technology from 10.36%-134.80%, with an average underestimation of 53.96%. The previously unmeasured increased output potential present within the sample countries is largely due to inefficiency in the sectors possessing both the largest returns from labor and increasing returns-to-scale, which is consistent with the development of cutting-edge labor-saving technologies, such as information technologies, that have yet to rapidly diffuse.

CHAPTER 2

INNOVATION, FIRM EFFICIENCY, AND MARKET STRUCTURE

Introduction

Of long standing interest has been the relationship between a firm's innovative efforts, efficiency and market structure. Research on these themes have typically either evaluated Schumpeter's (1942) notion of market power encouraging firm innovation or Demsetz's (1973) hypothesis that dominant firms owe efficiency and not market power for their position. While numerous, and often controversial, empirical studies[1] have produced mixed results in these areas, there are few theoretical models that account for the patterns observed in the data. Where models of R&D and innovation are found they are "typically based on econometric models without much theoretical content….[or] focusing on macro issues and a few stylized facts (Klette & Griliches, 2000)." Following recent efforts that borrow from macroeconomic theories of endogenous growth, we develop an endogenous model of firm innovation that: (i) generates larger market shares for efficient firms; and (ii) drives firm growth through static and dynamic inefficiency produced, and not imposed, by the model. This model can serve as unified framework for additional theoretical and empirical work that explicitly incorporates both innovation and firm efficiency into models of firm growth and market structure.

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[1] Cohen & Levin (1989), Bresnahan (1989), & Schmalensee (1989) are thorough reviews of the empirical literature.

Like previous theoretical models of firm innovation and growth (Klette & Griliches, 2000; Klette & Kortum, 2004), this paper seeks to evaluate a number of the stylized facts found in the empirical literature. However, our contribution is unique in that our model considers firm efficiency to be the driver of firm growth. Specifically, the stylized facts we wish to address are[2]:

(i) R&D expenditures rise proportionally with firm size and with R&D intensities independent of firm size

(ii) The number of patents and innovations per dollar of R&D tends to decrease with firm size

(iii) Persistent differences in firm sizes (Klette & Griliches, 2000)

(iv) Smaller firms tend to grow faster than larger firms, although among larger firms growth rates are unrelated to past growth or firm size.

The last stylized fact requires a few words. This is a refinement of Gibrat's law which held that firm growth and size are uncorrelated. However, recent empirical work[3] rejects this hypothesis for very small firms. This is important because Gibrat's law is often imposed into theoretical models of firm growth (e.g. Klette & Griliches, 2000). Since firm growth is determined by firm efficiency in our model, it is desirable that our model is consistent with the analogous observation that smaller firms are more efficient than large firms[4]. Our model reconciles this observation with Demsetz's hypothesis of

[2] Detailed references and surveys behind these facts can be found in Appendix A of Klette & Kortum (2004).

[3] see Sutton (1997) for a survey.

[4] recent empirical evidence is Dhawan (2001)

large, efficient firms by considering separate measures of technical efficiency and allocative efficiency[5].

The rest of the paper is organized as follows. As the literatures on firm innovation and firm efficiency have largely developed along separate lines, we will briefly discuss the current thought on firm size, market structure, and innovation and then efficiency and market structure. This is followed by our endogenous model of firm innovation, efficiency, and growth. We conclude with a discussion of implications and future research.

Literature Review

1. Firm size, market structure, and innovation

Cohen & Klepper (1996) develop a model of firm innovation and firm size designed to address the stylized facts that: (i) R&D expenditures rise proportionally with firm size and with R&D intensities independent of firm size; and (ii) The number of patents and innovations per dollar of R&D tends to decrease with firm size. These empirical regularities have traditionally been interpreted to mean that large firms possess no advantage in R&D. In light of the apparent diminishing returns to R&D implied above, in seems peculiar that large firms would continue to perform R&D at relatively high nominal rates. Cohen & Klepper (1996) account for this discrepancy by developing a model where firm size conditions the returns to R&D by spreading the costs over the

[5] There is a trade-off between our measures of technical and allocative efficiency. As we will show this trade-off implies that a statically allocative efficient firm reduces a portion of expected future technical efficiency, indicating that such a firm may be allocatively inefficient in a dynamic context. However, an additional component of technical efficiency is beyond the control of a given firm.

output of a given product. This cost spreading approach generates an advantage to R&D for firms with large market shares but does not address the larger issue of firm growth and market structure.

Seeking to explain both questions of why dominant firms perform relatively more research and the persistence of monopoly, Etro (2004) develops a theoretical model of patent races under Stackleberg competition. Under the assumption of free entry, Etro finds that dominant firms must aggressively innovate to avoid market decline. Further, markets characterized by the continuous leapfrogging of new patent holders must possess some barriers to entry, suggesting that persistence of monopoly actually indicates competitive markets. While this result appears counter-intuitive, it is actually in line with Demsetz's (1973) idea that dominant firms are far from basking in the quiet life, but earn their dominance through superior performance, which we append are maintained by continual innovation. Empirically testing whether dominant firms have greater incentives to innovate, Blundell *et. al.* (1999) find that dominant firms who innovate actually receive higher stock market valuations than those who do not, which could account for their high rate of innovation despite decreasing returns per dollar of R&D.

Borrowing from the quality ladder models of macroeconomic growth, Klette and Griliches (2000) develop a endogenous model of firm growth where firms receive stochastic innovations due to R&D investment. Firm growth is dependent upon the receipt of monopoly profits until the next innovation arrives. This generates results consistent with Gibrat's law as well as the stylized facts presented previously. Klette and Kortum (2004) extend this model to a general equilibrium framework and by assuming that firm innovations accumulate into its stock of knowledge capital. Additional implications of their model are that R&D intensity is positively related to productivity and that larger firms can offset diminishing returns to R&D investment through ever increasing stocks of knowledge capital.

2. Concentration, market power, and efficiency

This literature begins with Demsetz (1973), who posits that industry concentration may occur because of firm efficiency. The rationale is that firm specific effects, such as team production or reputation, may exist which can not be obtained by deconcentration in an industry. Segregating firms from the U.S. Census of Manufactures into strategic groups based upon their market shares, Martin (1988) states that efficiency and market power may not be competing theories of industry concentration, finding evidence that both effects are present in his data. Developing a new empirical industrial organization (NEIO) model that separates market power from efficiency effects, Lopez *et. al.* (2002) examine the effects of concentration in U.S. food processing industries. Their results are mixed, with one-third of their sample experiencing cost efficiency effects from concentration and the balance being dominated by market power effects that reinforce cost inefficiency. They note, however, that only industries characterized by product homogeneity and large economies of size experience such cost efficiencies in their sample. A rare theoretical paper on efficiency and market structure, Pires and Brito (2003) demonstrates with models of Cournot-Nash competition and product differentiation where efficient firms begin with larger market shares, that it is possible for changes in efficiency to generate inverse changes in market share, particularly in the presence of dominant firms. This implies that whether the Demsetz hypothesis holds or not, this hypothesis can not be extended to variations in efficiency.

A Simple Model of Endogenous Firm Innovation

With regards to the literature, our model is closest to that of Cohen & Klepper (1996), although we employ a stochastic, rather than deterministic innovation process. A significant departure from previous efforts is our assumption regarding the body of knowledge firms acquire over time. Prior to Klette & Kortum (2004), models have relied upon flows of R&D investment to generate new innovations. Like Klette & Kortum (2004), we assume that firms carry a stock of knowledge over time, however, we allow all firms to utilize the updated aggregate body of knowledge in periods subsequent to the arrival of new innovations. This is due to another key departure from the literature in our model.

Current models of endogenous firm innovation are variations of the quality ladder models utilized in macroeconomic growth (Grossman & Helpman, 1991; Aghion & Howitt, 1992). These variations specify that new innovations are *drastic*[6] in nature, with firm growth driven by the monopoly profits received by the innovating firm until the stochastic arrival of the next innovation. However, as Mansfield *et. al.* (1981) note, many patents are either successfully imitated, or imitated around, within 1 year and most in less than 3 years. Further, this interpretation of innovation is largely focused upon the creation of distinctly new products that can supplant previous products in the market.

Our model of innovation primarily considers the development of process improvements and new technology that is applied in the production process. Firms are

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[6] Arrow (1962) defines *drastic* innovations as those that completely supplant existing products or technology and *nondrastic* innovations as those that are constrained by competition from previous products or technology. When *nondrastic* innovations are considered in the literature (e.g. Klette & Griliches, 2000), competitors are still driven out of the market by the setting of a limit price on the part of the monopolist.

hardly inefficient because they fail to produce products enjoying patent protection. However, success or failure in the discovery and utilization of new, innovative manufacturing technologies, for example, standardized parts, assembly lines, Just-in-Time (JIT) inventory systems, etc., may often dictate the growth and performance of firms, particularly in competitive industries. These kinds of innovations are often difficult to protect through formal patents, generating technology spillovers that may quickly diffuse, especially in industries with high levels of turnover and labor mobility.

Coupling this interpretation of innovation with the empirically observed short effective life of patents, we follow Cohen and Klepper (1996), and limit an innovator's monopoly return to new innovation to one period before updating the aggregate body of knowledge available to all firms. One practical implication of this assumption is that no firm possesses an advantage in innovation over other firms, except with regards to their physical capability to invest in R&D. An additional unique characteristic of our model is that given our assumption of *nondrastic* innovations, all firms may simultaneously receive innovations at a given point in time. It is this stochastic innovation process that allows us to define measures of firm efficiency that drive firm growth and ultimately market structure.

Consider a model of firm production, where a given firm i at time t produces output, Y_{it}, with its input endowments of capital K_{it} and labor L_{it}:

(2.1) $$Y_{it} = A_{it} F(K_{it}, L_{it}).$$

A_{it} represents an index of the technology that a given firm can bring to bear on its resource endowments in the production process. Employing a Cobb-Douglas functional form for convenience[7], equation (2.1) can be rewritten as:

(2.2) $Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{1-\alpha}$.

An improvement in the technology available to a firm in time t is stochastic process that is governed by the research efforts of the firm. We assume that a firm can undertake research to develop superior technology in the next period by investing resources to obtain an instantaneous probability of innovation p, with $0 \le p \le 1$. The instantaneous probability of innovation is directly related with the resources allocated to research, $K_{it}^{r} \in (0, K_{it})$ and $L_{it}^{r} \in (0, L_{it})$:

(2.3) $p_{it} = F(K_{it-1}^{r}, L_{it-1}^{r})$,

with $p_{it}(0,0) = 0$, $\dfrac{\partial p_{it}}{\partial K_{it-1}^{r}}, \dfrac{\partial p_{it}}{\partial L_{it-1}^{r}} > 0$, and $\dfrac{\partial^2 p_{it}}{\partial K_{it-1}^{r\,2}}, \dfrac{\partial^2 p_{it}}{\partial L_{it-1}^{r\,2}} < 0$. Advances in the technology index are then discrete random variables Z_{it} where $P(Z_{it} = z_t) = p_{it}$, $P(Z_{it} = 0) = (1 - p_{it})$, and with z_t representing the value of the new innovation's improvement on the technology index. We shall employ Z_{it}^{*} to denote the realization of random variable Z_{it}. Given the assumption of *drastic* innovations in much of the literature, it is usually important to carefully consider the timing before the next innovation, with researchers typically utilizing either a Poisson (e.g. Klette & Griliches, 2000; Etro, 2004; Klette & Kortum, 2004) or exponential (Reinganum, 1989) distribution

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[7] The assumption of a Cobb-Douglas functional form is for expositional ease and is not necessary for the arguments to be developed in this model.

for the probability of an innovation arriving within a specific interval. Since our model, like Cohen and Klepper (1996), relies upon *non-drastic* innovations that are universally disseminated the period after arrival, the specific probability distribution is not crucial beyond standard assumptions that it be continuously twice differentiable.

As all firms freely obtain the new innovation in the subsequent period, increases in the technology index does not convey an advantage in research to any particular firm. While we could consider the probability of a new innovation to be conditional upon the ever increasing index of technology, this would not contribute to our evaluation of firm heterogeneity in R&D and market share. In light of this, we assume that future innovations are entirely determined by present allocations of resources to R&D. Thus, in period t the expected technology index for the ith firm is:

(2.4) $$A_{it} = E[Z_{it}] + A_{t-1} = p_{it}(K^r_{it-1}, L^r_{it-1})z_t + A_{t-1}$$

or more explicitly,

(2.5) $$A_{it} = p_{it}(K^r_{it-1}, L^r_{it-1})z_t + \sum_{s=1}^{t-1}\sum_{j=1}^{n} Z^*_{js},$$

with A_{t-1} capturing the aggregate body of knowledge available to all firms in time t. Substituting equation (2.5) into equation (2.2), we produce the following model for the ith firm's expected production in time t:

(2.6) $$Y_{it} = \left(p_{it}(K^r_{it-1}, L^r_{it-1})z_t + \sum_{s=1}^{t-1}\sum_{j=1}^{n} Z^*_{js} \right)(K_{it} - K^r_{it})^{\alpha}(L_{it} - L^r_{it})^{1-\alpha}.$$

Assuming that output markets can be initially characterized by perfect competition, each firm's objective function is simply (2.7), with each firm choosing (K^r_{it}, L^r_{it}):

(2.7) $\max_{K_{it}^r, L_{it}^r} \sum_t Y_{it} \delta^t$

where δ represents the discount rate for future production. The first order conditions are:

(2.8)
$$\left(p'_{it+1}(K^r_{it|L^{r*}_{it}}, L^{r*}_{it})z_{t+1}\right)(K_{it} - K^r_{it})^{\alpha}(L_{it} - L^r_{it})^{1-\alpha} = p_{it}(K^r_{it-1}, L^r_{it-1})z_t + \sum_{s=1}^{t-1}\sum_{j=1}^{n} Z^*_{js}$$

(2.9)
$$\left(p'_{it+1}(K^{r*}_{it}, L^r_{it|K^{r*}_{it}})z_{t+1}\right)(K_{it} - K^r_{it})^{\alpha}(L_{it} - L^r_{it})^{1-\alpha} = p_{it}(K^r_{it-1}, L^r_{it-1})z_t + \sum_{s=1}^{t-1}\sum_{j=1}^{n} Z^*_{js}$$

which are increasing in the value of innovations and the probability of receiving an innovation and decreasing in the aggregate body of knowledge, as would be expected. Because of our assumptions about $p_{it}(K^r_{it}, L^r_{it})$, our second order conditions reduce to $-p'_{it}(K^r_{it|L^{r*}_{it}}, L^{r*}_{it},)z_{it}, -p'_{it}(K^{r*}_{it}, L^r_{it|K^{r*}_{it}})z_{it} < 0$, thereby assuring a global maximum.

Innovation and Firm Efficiency

For any time t the maximum attainable output, Y^F_{it}, of each firm, given their resource endowment, (K_{it}, L_{it}), is $Y^F_{it} = A_t K^{\alpha}_{it} L^{1-\alpha}_{it}$, where

(2.10) $A_t = \sum_{j=1}^{n} Z^*_{it} + \sum_{s=1}^{t-1}\sum_{j=1}^{n} Z^*_{js}$.

The first sum captures the probability of the ith firm receiving an innovation during time t and the subsequent summations, again, capture the aggregate value of previous innovations. This yields each firm's boundary of production,

(2.11) $Y^F_{it} = \left(\sum_{j=1}^{n} Z^*_{it} + \sum_{s=1}^{t-1}\sum_{j=1}^{n} Z^*_{js}\right)(K_{it} - K^r_{it})^{\alpha}(L_{it} - L^r_{it})^{1-\alpha}$.

However, a given firm may not produce at this boundary due to the idiosyncratic arrivals of innovation and/or a firm's decision to undertake research, which governs the innovation process. We define measures of firm inefficiency that incorporate these possibilities as follows. Considering, again, the i th firm's boundary of production:

(2.12) $Y_{it}^{F} = A_t K_{it}^{\alpha} L_{it}^{1-\alpha}$.

The actual production of the i th firm in time t is:

$$\textit{potential output} \times \textit{technical efficiency} \times \textit{allocative efficiency}$$

(2.13)
$$Y_{it} = A_t K_{it}^{\alpha} L_{it}^{1-\alpha} \times \frac{A_{it} K_{it}^{\alpha} L_{it}^{1-\alpha}}{A_t K_{it}^{\alpha} L_{it}^{1-\alpha}} \times \frac{A_{it}(K_{it} - K_{it}^{r})^{\alpha}(L_{it} - L_{it}^{r})^{1-\alpha}}{A_{it} K_{it}^{\alpha} L_{it}^{1-\alpha}}$$

Rewriting (2.13) yields:

(2.14)
$$\begin{aligned} Y_{it} &= A_t K_{it}^{\alpha} L_{it}^{1-\alpha} \times \frac{A_{it}}{A_t} \times \frac{(K_{it} - K_{it}^{r})^{\alpha}(L_{it} - L_{it}^{r})^{1-\alpha}}{K_{it}^{\alpha} L_{it}^{1-\alpha}} \\ &= A_{it}(K_{it} - K_{it}^{r})^{\alpha}(L_{it} - L_{it}^{r})^{1-\alpha} \end{aligned}$$

which is the quantity of output produced using the firm's available technology in time t, as opposed to the best available technology, and productive resources not dedicated towards research. We formally define our measures of firm inefficiency as:

(2.15) $\dfrac{A_{it}}{A_t} \equiv \dfrac{1}{u_{itz}} \in (0,1)$

and

(2.16) $\dfrac{(K_{it} - K_{it}^{r})^{\alpha}(L_{it} - L_{it}^{r})^{1-\alpha}}{K_{it}^{\alpha} L_{it}^{1-\alpha}} \equiv \dfrac{1}{u_{itx^{r}}} \in (0,1)$.

u_{itz} is a measure of technical inefficiency equivalent to the potential output lost when a firm does not receive an innovation nor can exploit the innovations of other firms[8]. Because our model assumes simultaneous non-drastic innovations, a firm will always possess some technical inefficiency in this model unless no other firm receives an innovation or no firm receives an innovation at a given time t, in which case every firm produces with the current body of knowledge, A_{t-1}. The other inefficiency identified in our model, u_{itx^r}, is a measure of allocative inefficiency which is equal to the production lost in time t by allocating resources to research. Because firms may maximize their output over time by undertaking research to improve their productive capacity[9], this measure of allocative inefficiency is only true in a static sense. However, it provides a plausible explanation that may link some of the observed stylized facts, such as larger firms investing more heavily in R&D, small firms being observed to produce with greater efficiency, and with the persistence of larger firms' market shares, nonetheless.

In short, consistent with Martin's (1988) findings, sloth and efficiency may not be mutually exclusive states for dominant firms. Dominant firms may be efficient as Demsetz (1973) suggests, albeit dynamically through their investment in future productive potential, and yet vulnerable, inefficient targets for small and lean producers at a given point in time. These smaller, efficient firms must then quickly steal away market share before the next innovation strikes, always leaving them a step behind due to their technical inefficiency, u_{itz}. Of course, as they survive and grow, they too may trade

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[8] Recall that we assume all firms may simultaneously receive non-drastic innovations which are included in the body of knowledge in time $t+1$.

[9] This depends on the actual distribution of $p(K_{it}^r, L_{it}^r)$ and the value of z_t

off some u_{itx^r} to reduce u_{itz} depending upon the specific distribution of $p(K_{it}^r, L_{it}^r)$ and the value of z_t. Formally including our measures of technical and allocative efficiency into a single model of firm production produces:

(2.17) $Y_{it} = A_t K_{it}^{\alpha} L_{it}^{1-\alpha} u_{itz}^{-1} u_{itx^r}^{-1}$.

We feel that this stochastic model of firm innovation and efficiency serves as a needed foundation for empirical and additional theoretical work on firm efficiency and growth. In the next section we use this model to investigate how the innovation process drives firm growth and ultimately market structure.

An Analysis of Firm Growth and Market Structure

Before we can examine how our model of firm innovation and efficiency may affect market structure, we must explicitly incorporate firm growth into the model. Suppose an industry consists of n identical firms endowed with resources (K_0, L_0). The initial index of technology available to all firms is A_0. Analogous to Cohen and Klepper (1996), we will simplify our model by assuming that some fixed proportion[10] g of the value of firm output is retained to acquire resources for further production:

(2.18) $R_t K_{it} + W_t L_{it} = g P_{t-1} Y_{it-1}$,

where R_t, W_t, and P_{t-1} are the market prices of capital, labor, and output, respectively, and with firms acquiring additional capital K_{it} and labor L_{it} such that $R_t \dfrac{\partial Y_{it}}{\partial K_{it}} = W_t \dfrac{\partial Y_{it}}{\partial L_{it}}$.

We will denote c_t as the proportion of firm revenues $g P_{t-1} Y_{it-1}$ that is used to acquire

[10] Allowing the portion of firm revenues to vary over time and firm are obvious extensions to this model.

additional capital inputs in time t as, with the remainder, $(1-c_t)$, being allocated toward additional labor inputs[11]. Assuming that the distribution of $p(K_{it}^r, L_{it}^r)$ and the value of z_t are sufficient to induce firms to innovate, each firm allocates a portion of firm resources towards R&D investment: $K_{it}^r = k_{it}K_{it}$ and $L_{it}^r = l_{it}L_{it}$, with $k_{it}, l_{it} \in (0,1)$. Firms grow through an iterative process of producing ever larger quantities of output which generates ever larger revenues from which to acquire more resources for production.

Because we are considering identical firms in perfectly competitive markets, if we momentarily suspend the possibility of firm inefficiency, A_{it}, k_{it}, and l_{it} are reduced to A_t, k_t, and l_t, respectively. Suppressing factor and output prices, the output of firm i in time 0 and time 1 are, respectively:

$$(2.19)\quad Y_{i0} = A_0\left(K_0 - k_0K_0\right)^{\alpha}\left(L_0 - l_0L_0\right)^{1-\alpha} = A_0K_0^{\alpha}L_0^{1-\alpha}(1-k_0)^{\alpha}(1-l_0)^{1-\alpha}$$

$$(2.20)\quad \begin{aligned} Y_{i1} &= A_1\left(c_1gY_{i0}\right)^{\alpha}\left((1-c_1)gY_{i0}\right)^{1-\alpha}(1-k_1)^{\alpha}(1-l_1)^{1-\alpha} \\ &= gK_0^{\alpha}L_0^{1-\alpha}A_0A_1(1-k_0)^{\alpha}(1-l_0)^{1-\alpha}(1-k_1)^{\alpha}(1-l_1)^{1-\alpha}(1-c_1)^{\alpha}(1-c_1)^{1-\alpha} \end{aligned}.$$

Solving through iteration yields the ith firm's output in time t:

$$(2.21)\quad Y_{it} = g^tK_0^{\alpha}L_0^{1-\alpha}\prod_{m=0}^{t}A_mc_m^{\alpha}(1-c_m)^{1-\alpha}(1-k_m)^{\alpha}(1-l_m)^{1-\alpha}$$

and its market share:

$$(2.22)\quad MS_{it} = \frac{g^tK_0^{\alpha}L_0^{1-\alpha}\prod_{m=0}^{t}A_mc_m^{\alpha}(1-c_m)^{1-\alpha}(1-k_m)^{\alpha}(1-l_m)^{1-\alpha}}{\sum_{i=1}^{n}\left[g^tK_0^{\alpha}L_0^{1-\alpha}\prod_{m=0}^{t}A_mc_m^{\alpha}(1-c_m)^{1-\alpha}(1-k_m)^{\alpha}(1-l_m)^{1-\alpha}\right]}.$$

[11] In theory, each firm's initial factor endowments came from a similar budget allocation of seed capital.

Thus, if we assume away the stochastic innovation process embedded in A_m, each firm comprises a $1/n$ share of the market.

Returning our stochastic innovation process to the model we can examine how firm efficiency influences firm growth and market structure. Retaining our assumption of an industry of n identical firms, we begin with each firm allocating the same proportion k_t and l_t of capital and labor resources to R&D investment. The ith firm's output in time t is now:

$$(2.23)\quad Y_{it} = g^t K_0^\alpha L_0^{1-\alpha} A_{it} \prod_{l=0}^{t-1} A_l \prod_{m=0}^{t} c_m^\alpha (1-c_m)^{1-\alpha} (1-k_m)^\alpha (1-l_m)^{1-\alpha},$$

or alternatively,

$$(2.24)\quad Y_{it} = g^t K_0^\alpha L_0^{1-\alpha} \prod_{m=0}^{t} \left[A_m c_m^\alpha (1-c_m)^{1-\alpha} (1-k_m)^\alpha (1-l_m)^{1-\alpha} \right] u_{itz}^{-1}$$

and its market share:

$$(2.25)\quad \begin{aligned} MS_{it} &= \frac{g^t K_0^\alpha L_0^{1-\alpha} A_{it} \prod_{l=0}^{t-1} A_l \prod_{m=0}^{t} c_m^\alpha (1-c_m)^{1-\alpha} (1-k_m)^\alpha (1-l_m)^{1-\alpha}}{\sum_{i=1}^{n} \left(g^t K_0^\alpha L_0^{1-\alpha} A_{it} \prod_{l=0}^{t-1} A_l \prod_{m=0}^{t} c_m^\alpha (1-c_m)^{1-\alpha} (1-k_m)^\alpha (1-l_m)^{1-\alpha} \right)} \\ &= \frac{g^t K_0^\alpha L_0^{1-\alpha} \prod_{m=0}^{t} \left[A_m c_m^\alpha (1-c_m)^{1-\alpha} (1-k_m)^\alpha (1-l_m)^{1-\alpha} \right] u_{itz}^{-1}}{\sum_{i=1}^{n} \left(g^t K_0^\alpha L_0^{1-\alpha} \prod_{m=0}^{t} \left[A_m c_m^\alpha (1-c_m)^{1-\alpha} (1-k_m)^\alpha (1-l_m)^{1-\alpha} \right] u_{itz}^{-1} \right)} \end{aligned}.$$

As previously discussed, even when all firms receive an innovation they are inefficient relative to the aggregate index of technology they could potentially bear on their resources and *will get to bear on their resources in the next period*. However, if all firms, or no firms, receive innovation z_t, i.e. $u_{itz} = u_{jtz}\ \forall i, j$, their respective market shares remain unchanged with each firm receiving an even share of the market.

Now let's consider that firm i does not receive an innovation with the remaining j firms such that $u_{itz} > u_{jtz}$. Suppressing the u_{jtz} term of the innovative firms to ease our exposition, the market share of firm i is now:

(2.26)

$$MS_{it} = \frac{g^t K_0^\alpha L_0^{1-\alpha} \prod_{m=0}^{t} \left[A_m c_m^\alpha (1-c_m)^{1-\alpha} (1-k_m)^\alpha (1-l_m)^{1-\alpha} \right] u_{itz}^{-1}}{\sum_{j=1}^{n-1} \left(g^t K_0^\alpha L_0^{1-\alpha} \prod_{m=0}^{t} \left[A_m c_m^\alpha (1-c_m)^{1-\alpha} (1-k_m)^\alpha (1-l_m)^{1-\alpha} \right] \right) + g^t K_0^\alpha L_0^{1-\alpha} \prod_{m=0}^{t} \left[A_m c_m^\alpha (1-c_m)^{1-\alpha} (1-k_m)^\alpha (1-l_m)^{1-\alpha} \right] u_{itz}^{-1}}$$

with the market share of the remaining firms:

(2.27)

$$MS_{jt} = \frac{g^t K_0^\alpha L_0^{1-\alpha} \prod_{m=0}^{t} \left[A_m c_m^\alpha (1-c_m)^{1-\alpha} (1-k_m)^\alpha (1-l_m)^{1-\alpha} \right]}{\sum_{j=1}^{n-1} \left(g^t K_0^\alpha L_0^{1-\alpha} \prod_{m=0}^{t} \left[A_m c_m^\alpha (1-c_m)^{1-\alpha} (1-k_m)^\alpha (1-l_m)^{1-\alpha} \right] \right) + g^t K_0^\alpha L_0^{1-\alpha} \prod_{m=0}^{t} \left[A_m c_m^\alpha (1-c_m)^{1-\alpha} (1-k_m)^\alpha (1-l_m)^{1-\alpha} \right] u_{itz}^{-1}}.$$

Assuming that all firms receive innovations each period from this point forward[12], the deviation in market shares will persist, despite the fact that all firms will exploit the exact same technology in subsequent periods. This is because of firm i's diminished resource base from which to produce or conduct research. The larger firms now have an enhanced incentive to undertake research, since each innovation can be brought to bear on a much larger resource base[13]. However, small firms may be able to recapture these

[12] And that firm i's optimal resource allocation hasn't changed due to its diminished market share, although doubtless it would. Exploration of this issue through formal simulation shall be explored in future research.

[13] This is analogous to Cohen & Klepper's cost spreading (1996).

losses by reallocating resources from research to production and thus reducing their static allocative inefficiency u_{itr}[14].

Conclusion

We have presented a theoretical model of endogenous firm growth that conforms to empirical regularities found in the literature and explicitly defines firm efficiency as the principal driver of firm growth and market structure. This model can hopefully serve as a much needed foundation for empirical work regarding firm size, firm growth, and firm efficiency. While our analysis of market structure was restricted to a highly stylized case of identical firms, the model can be easily extended to accommodate heterogeneous assumptions of the innovation process, innovation values, and initial market shares. In particular, extending the model to permit firm entry and exit should provide a richer set of conclusions that better emulate what is observed in the data. Additional model implications and testing would be best performed through formal simulations of the model, which will likely shed considerable insight on the dynamics of firm growth and market structure.

[14] An evaluation of the changes in market structure because of u_{itr} is analogous to that produced by u_{itz} and is not formally presented due to its dependency on the distribution of $p(X_{it}^{r})$ and the value of z_{it}.

CHAPTER 3

R&D, MARKET STRUCTURE, AND FIRM EFFICIENCY: A STOCHASTIC FRONTIER APPROACH

Introduction

A recurring theme in industrial economics is whether market power is a product of firm efficiency. In Demsetz's (1973) seminal paper, he finds loose evidence that dominant firms may have firm specific efficiencies that would be lost under deconcentration. Examining data from from the U.S. Census of Manufactures, Martin (1988) finds that efficiency and market power may not be competing theories of industry concentration, discovering evidence of both effects in his data. In an effort to better understand the complex relationship between market power and efficiency, we developed a model of endogenous firm growth that generates firm inefficiency as a byproduct of the innovative process (Chapter 2). Using this theoretical framework as a guide, we estimate a stochastic frontier model using manufacturing firm data from Standard and Poor's COMPUSTAT database that can explicitly estimate a firm's efficiency relative to the technology frontier and examine determinants of the inefficiency effect. As predicted by our theoretical model, we find firm market shares and firm size to be highly positively correlated with firm efficiency and research intensity to decrease firm efficiency.

Following our model (Chapter 2) of firm innovation and efficiency, firm production can be characterized by:

$$(3.1) \quad Y_{it} = A_t K_{it}^{\alpha} L_{it}^{1-\alpha} u_{itz}^{-1} u_{itx^r}^{-1}$$

where Y_{it} represents the output produced by the i th firm in period t; X_{it} is a vector of resources available to firms; A_t represents an index of the technology that a given firm can bring to bear on its resource endowment in the production process; u_{itz} is a measure of technical inefficiency that captures lost production from the use of inefficient/obsolete technology; and u_{itx^r} represents allocative inefficiency in period t resulting from a firm's decision to invest resources on R&D as opposed to current production.

If we consider a firm's market share equation:

$$(3.2)\, MS_{it} = \frac{g^t K_0^{\alpha} L_0^{1-\alpha} \prod_{m=0}^{t} \left[A_m c_m^{\alpha} (1-c_m)^{1-\alpha} (1-k_m)^{\alpha} (1-l_m)^{1-\alpha} \right] u_{itz}^{\;-1} u_{itx^r}^{\;-1}}{\sum_{i=1}^{n} \left(g^t K_0^{\alpha} L_0^{1-\alpha} \prod_{m=0}^{t} \left[A_m c_m^{\alpha} (1-c_m)^{1-\alpha} (1-k_m)^{\alpha} (1-l_m)^{1-\alpha} \right] u_{itz}^{\;-1} u_{itx^r}^{\;-1} \right)}$$

we would expect efficient firms to grow in size and inefficient firms to shrink relative to the overall market. However, there is a tradeoff between the static allocative inefficiency u_{itx^r} and more dynamic technical inefficiency u_{itz}, since it is investments in R&D today that generate tomorrow's technological progress. Which effect dominates firm growth must be drawn from empirical work. Our contribution is to examine the static implications of this model as a foundation for future empirical work.

This endogenous model of firm growth implies that a firm's R&D investment generates observable inefficiency in a static context. It also predicts that firms with larger market shares will be observed to be less efficient than those will smaller market shares, since it is innovation and efficiency that drives firm growth. Because we are interested in directly examining firm efficiency, we are able to use the stochastic frontier approach to estimate a production function that also produces estimates of how efficient a firm is relative to the best practice frontier. Since R&D expenditures are typically employed as an input rather than an output it has often proven to be an unreliable instrument to evaluate the relationship between innovation and market share (Blundell *et. al.*, 1999). This technique is especially beneficial for our purposes because it allows us to incorporate R&D investments and market share as a determinant of efficiency as opposed to inputs to the production function.

With regards to technique and motive, that being the application of a stochastic frontier model to COMPUSTAT data to determine the causes of productive inefficiency, our paper is similar to Baek (2004). Baek (2004) utilized this approach to determining whether international diversification was related to a firm's productive efficiency. Other similar studies include Dhawan (1997), who applied a stochastic frontier model to evaluate the technical progress of firms in the COMPUSTAT database and favorably compared the results to those obtained from traditional estimates of Solow residuals.

Method

We evaluate the relationships between a firm's size, market dominance, R&D strategy, and productive efficiency implied by equations (3.1) and (3.2) by employing the stochastic frontier model proposed by Battese & Coelli (1995). Stochastic frontier models, first introduced by Aigner *et al* (1977) and Meeusen & van den Broeck (1977)[15], estimate production frontiers using a composite error component that directly estimates a firm's inefficiency relative to frontier while also accounting for random noise. The

[15] A comprehensive treatment is Kumbhakar and Lovell (2000)

Battese & Coelli (1995) formulation accommodates panel data and also allows for the evaluation of the determinants of technical inefficiency:

(3.3) $\ln Y_{it} = \ln f(X_{it};\beta_t) + v_{it} - u_{it}$

where Y_{it} is the output for firm i in the t th period; $f(X_{it};\beta_t)$ is a deterministic function of a vector of input quantities, X_{it}, and a vector of unknown parameters, β_t; v_{it} are independent and identically distributed $(i.i.d.)$ random errors with a $N(0,\sigma_V^2)$ distribution; u_{it} are independently, but not identically, distributed non-negative truncated normal errors, with mean μ_u and variance σ_u^2, associated with inefficiency in production.

Rewriting the firm production function (Equation 3.1) derived from our model of stochastic innovation and firm efficiency in logarithms yields:

(3.4) $\ln Y_{it} = \ln A_t + \alpha \ln K_{it} + (1-\alpha)\ln L_{it} - \ln u_{itz} - \ln u_{itx^r}$.

As equation (3.3) shows, our model of firm efficiency can be directly estimated through the Battese and Coelli (1995) framework, although the estimates for firm inefficiency,

(3.5) $\ln u_{it} = \ln u_{itz} + \ln u_{itx^r}$,

capture total firm inefficiency. However, the Battese and Coelli (1995) model allows us to estimate determinants of firm inefficiency. Since u_{itx^r} only represents firm inefficiency resulting from the allocation of productive resources to research and development, we can directly estimate the effects of firm R&D on the total inefficiency term u_{it}. We interpret the unexplained portions of the inefficiency term as representing the technical inefficiency defined by u_{itz}.

To examine explanations of firm efficiency, the efficiency effect, u_{it}, can be specified as:

(3.5) $$u_{it} = z_{it}\delta + w_{it}$$

where z_{it} is a vector of observable explanatory variables; δ is the vector of parameters to be estimated; and $w_{it} \sim N(0, \sigma_w^2)$ with the distribution of w_{it} being bounded by the variable truncation point $-z_{it}\delta$.

Equations (3.4) and (3.5) are jointly estimated through maximum likelihood, with the likelihood function maximized in terms of the variance parameters, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma^2$. Estimates of the efficiency of the ith firm in time t is given by

(3.6) $$TE_i = \exp(-u_{it}) = \exp(-z_{it}\delta - w_{it}),$$

which is interpreted as the degree which output falls short of its potential given a specific technology and level of inputs. It can be predicted by

(3.7) $$E[\exp(-u_{it}) \mid (v_{it} - u_{it})] = \left[\exp\left(-u_{it}^* + \frac{1}{2}\sigma^{*2}\right)\right] \times \left[\frac{\Phi\left[\left(u_{it}^* / \sigma^*\right) - \sigma^*\right]}{\Phi\left(u_{it}^* / \sigma^*\right)}\right]$$

where $u_{it}^* = \dfrac{\sigma_v^2(z_{it}\delta) - \sigma_u^2(w_{it})}{\sigma_v^2 + \sigma_u^2}$ and $\sigma^{*2} = \dfrac{\sigma_v^2\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)}$.

Using firm level data, we will estimate the following Cobb-Douglas production function:

(3.8) $$\ln Y_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \alpha_1 t + \alpha_2 SMALL + \alpha_3 I_{it} + v_{it} - u_{it}$$

where Y_{it} is the value added of production for firm i in time t; L_{it} is the number of employees; and K_{it} is the value of fixed assets. $SMALL_{it}$, I_{it}, and t are indicator variables to control for firm size, industry effects and time, respectively. Following our hypothesis about the relationships between a firm's size, research efforts, market dominance and its efficiency, the z_{it} variables we will use to examine firm efficiency are: $SMALL_{it}$, an indicator variable for the size of a given firm; MS_{it}, a firm's market share; RDS_{it}, a firm's R&D intensity; and RDI_{it}, a firm's R&D intensity relative to their industry. As previously discussed, the estimates of RDS_{it} and RDI_{it} capture the portion of u_{it} accounted for by u_{itx^r} with the remainder attributed to technical inefficiency u_{itz}.

Data

We utilize a balanced panel of firm level data extracted from Standard and Poor's COMPUSTAT database for the period of 1994-2003. The panel covers all active and inactive manufacturing firms, as identified by 1-digit Standard Industrial Classification (SIC) Codes 2 & 3, that were listed on the New York, American, NASDAQ, and regional stock exchanges during this period. The raw unbalanced panel contains 108,208 observations for the period of 1994-2003 and spanning 6,763 firms, due to the appearance and disappearance of firms at different years in the panel. After removing observations with variables for which no data was reported, we were left with an unbalanced panel of 25,584 observations spanning 3,550 firms. This was further reduced to a balanced panel of 6,920 observations, covering 692 firms from 1994-2003. While a longer, albeit thinner, panel could have been used, we feel that this analysis benefits from the increased firm heterogeneity that a wider panel provides. We note that any variables calculated from the data were calculated using the full raw panel of 108,208 observations. Therefore, despite their omission, we are able to account for some degree of the variance these additional observations may have exerted in our analysis.

Value-added, defined as net sales less the cost of goods sold plus the change in inventory, is employed for each firm's output. Value-added was converted into real 2000 dollars using the GDP deflator. Labor inputs are defined as the number of employees as reported to shareholders each year. We use fixed assets, defined as the market value of total assets less current assets, as our measure of capital. Following standard practice, the reported book values are converted into market values using the Salinger and Summer (1983) perpetual inventory method described in Whited (1992). Finally, we deflate our measure of capital stock with the Producers Price Index.

Each firm's market share in time t is defined as firm sales divided by total industry sales, with each industry defined by 3-digit SIC codes. We utilize two different measures of R&D: the ratio of reported R&D expenses to firm sales and firm R&D intensity relative to industry, defined as each firm's R&D to sales ratio divided by the industry's R&D to sales ratio. R&D intensities greater (less) than 1 indicate that a firm commits relatively more (less) resources to R&D than the industry as a whole, after controlling for firm size. Industry effects are controlled through indicator variables for the 83 3-digit SIC codes represented in our data. Figure 3.1 presents the distribution of firms in each industry.

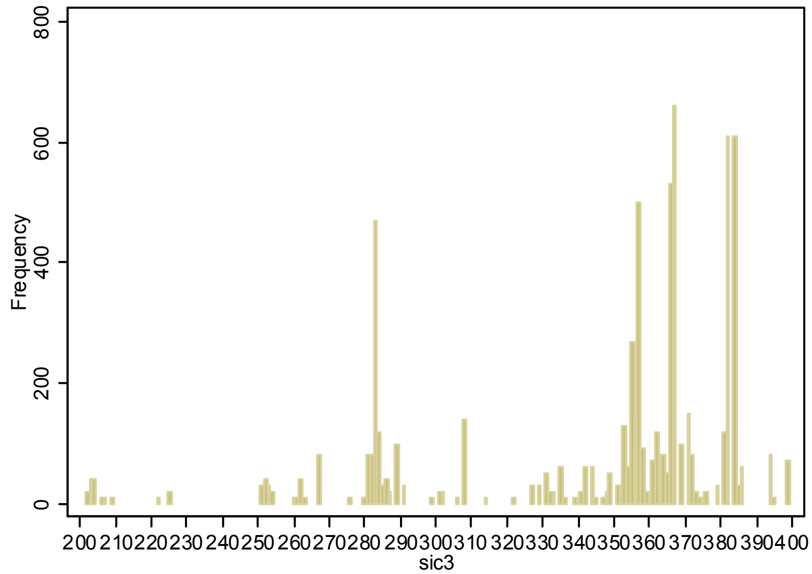

Figure 3.1. Distribution of Firms by Industry

Finally, indicators are employed to denote small and large firms, using Gertler & Gilchrist's (1994) definition of small firms as those with average assets of less than $25 million in 1982 dollars[16]. 2,730 observations or 39% of the sample are classified as small firms by this definition. Summary statistics for balanced panel are presented below in Table 3.1.

Table 3.1 Summary Statistics of the Variables

Variable	Sample Mean	Standard Deviation	Minimum	Maximum
Value-Added (Y)	758.662	2427.848	.015	37542.64
Fixed Assets (K)	1298.243	5477.028	.008	119025.1
Employees (L)	8.218	26.866	.002	728
Market Share (MS)	.061	.144	0	1
R&D to Sales (RDS)	.081	.148	0	4.116
R&D Intensity (RDI)	1.932	11.955	.005	472.343

Notes: 6920 Observations (t=10, n=692)

Figure 3.2 shows a series of scatter-plots between ln(output), market share, R&D to sales ratio, and firm R&D intensity relative to industry. These echo common regularities found in firm data: (i) there is no relationship between firm size and research efforts; (ii) no relationship between a firm's market share and R&D; and (iii) no relation between a firm's R&D intensity and their relative R&D intensity with respect to their industry[17]. Figures 3.3 & 3.4 present the same scatter-plots for the small and large sub-samples and reveal that these findings are consistent for both groups.

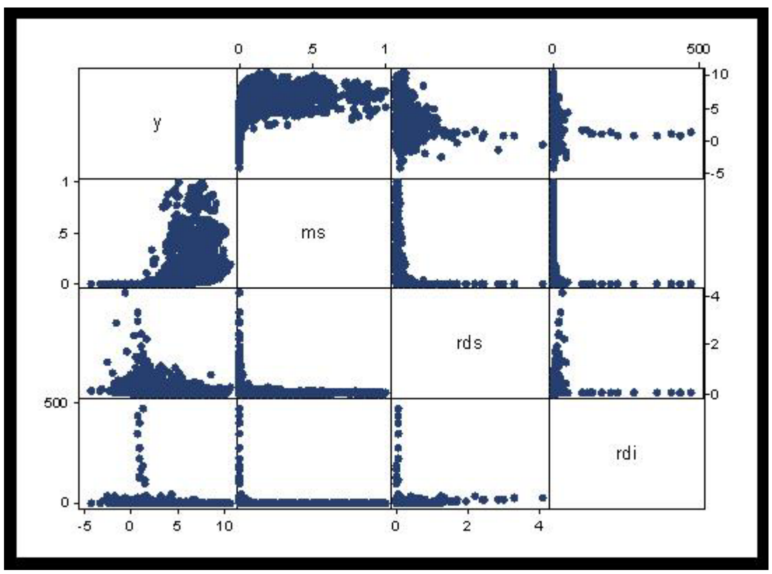

Figure 3.2. Scatter-plot of Select Variables (All Firms)

[16] While this is an arbitrary definition, Dhawan (2001) found no qualitative difference in results when using cut-off levels of $35 million, $50 million, and $100 million to examine firm size and productivity differentials.

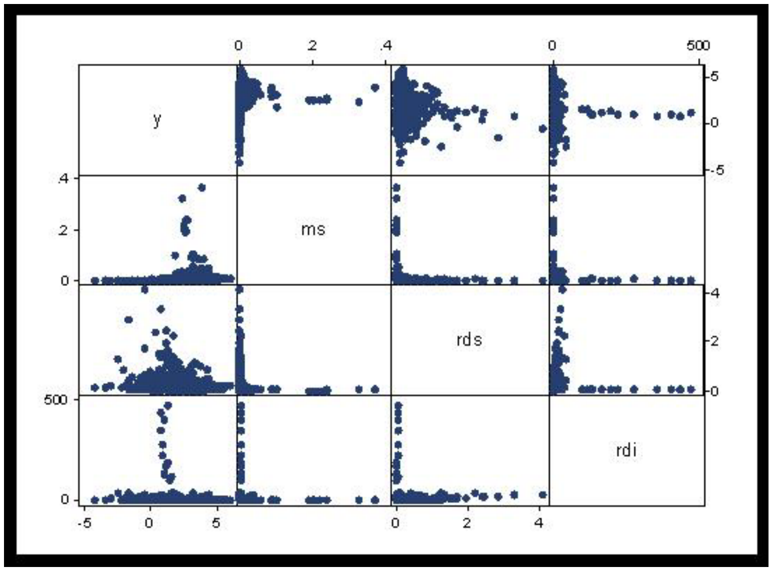

Figure 3.3. Scatter-plot of Select Variables (Small Firms)

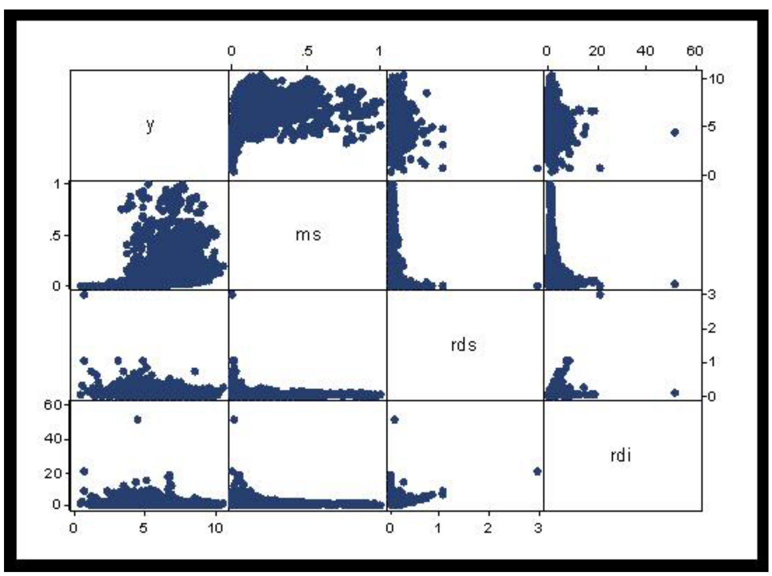

Figure 3.4. Scatter-plot of Select Variables (Big Firms)

[17] We find these patterns are robust to alternative measures of firm size, such as sales, assets, and employees. We also find nominal R&D expenditures to be positively related to firm size.

Results

Table 3.2 presents the estimates for the stochastic frontier model in equation (3.5). Table A.1 includes estimates for the time and sector control variables.

Table 3.2. Maximum Likelihood Estimates for Firm Stochastic Frontier Model

Variable	Coefficient (Std Error)	Variable	Coefficient (Std Error)
K	.334*** (.009)	σ^2	.831*** (.050)
L	.591*** (.011)	σ_v^2	.163*** (.006)
SMALL	-.153*** (.023)	σ_u^2	.668*** (.052)
Constant	3.240*** (.083)	γ	.803*** (.015)
Num Obs.	6920	Avg. TE score: .685	
Log-likelihood	-5666.791		
H_O: γ=0			
Test Statistic	862.075		
Decision	Reject		

Notes: *t*-ratios are asymptotic. *** $p < .001$; ** $p < .05$; * $p < .1$

The estimate for γ, which is calculated as $\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$, indicates to what degree deviations from the frontier can be attributed to inefficiency as opposed to statistical noise. The null hypothesis that γ equals zero is rejected suggesting that inefficiency is present within the data. The average technical efficiency score of the sample is .685 which is in the range of estimated average score efficiency scores, .627 - .724, Baek (2004) received with similar COMPUSTAT data.

Table 3.3 presents our estimates with the inclusion of explanatory variables z_{it} for the technical inefficiency term $\exp(-u_{it})$. We find Model 1.5 to dominate the other model specifications through log-likelihood testing. Some care must be taken in the interpretation of the estimated z_{it} s for the inefficiency term u_{it}. Since u_{it} represents deviations from the efficient frontier, a positive (negative) estimated coefficient indicates that this explanatory factor decreases (increases) the efficiency of the firm.

Table 3.3. Maximum Likelihood Estimates of Inefficiency Effects

Variable	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4	Model 1.5
K	.338*** (.009)	.345*** (.010)	.349*** (.009)	.370*** (.010)	.363*** (.011)	.369*** (.053)
L	.488*** (.012)	.483*** (.019)	.475*** (.012)	.459*** (.013)	.471*** (.015)	.461*** (.073)
SMALL	-.163*** (.023)	-.160*** (.023)	-.150*** (.023)	.192** (.069)	.257** (.106)	.221 (.643)
Constant	3.208*** (.073)	3.091*** (.073)	2.990*** (.071)	2.954*** (.074)	2.915*** (.000)	2.985*** (.000)
μ:						
Constant	.681*** (.053)	.536** (.247)	.599*** (.053)	.467*** (.076)	.578*** (.069)	.583*** (.327)
MS	-29.274*** (1.877)	-27.817*** (2.918)	-28.137*** (1.761)	-27.095*** (1.923)	-26.065*** (2.338)	-27.308*** (7.203)
RDS		.706*** (.117)	.645*** (.077)	.582*** (.072)		.573*** (.125)
RDI			.001 (.001)	.001 (.001)		
SMALL				.600*** (.084)	.669*** (.111)	.564*** (.662)
σ^2	.666*** (.025)	.620*** (.123)	.627*** (.021)	.580*** (.027)	.543*** (.035)	.578*** (.212)
σ_v^2	.084*** (.004)	.094*** (.007)	.092*** (.004)	.080*** (.005)	.077*** (.004)	.074*** (.018)
σ_u^2	.582*** (.025)	.526*** (.118)	.535*** (.020)	.500*** (.026)	.466*** (.033)	.503*** (.194)
γ	.874*** (.007)	.848*** (.023)	.853*** (.008)	.862*** (.008)	.858*** (.010)	.872*** (.018)
Log-likelihood	-5184.546	-5144.909	-5146.440	-5084.126	-5118.405	-5086.361

Notes: *t*-ratios are asymptotic. *** $p < .001$; ** $p < .05$; * $p < .1$

As Table 3.3 reveals, the estimates for capital K and labor L are quite close regardless of model specification. Although the indicator for small firms has a highly significant, negative effect on output when it is not considered a determinant of firm inefficiency, we find it to be a highly significant determinant of firm inefficiency. Since $SMALL$ has a positive, yet statistically insignificant effect on output when the indicator is employed in both the production function and as a determinant for firm inefficiency, this implies that any negative influence firm size may have exerted on firm output in Models 1.0 – 1.2 is captured under the inefficiency effect[18]. We can interpret this to mean that firm size has little effect on firm production and that larger firms are characterized by greater efficiency, a prediction of our model.

While we can not formally decompose the total inefficiency estimate u_{it} into its comprising technical efficiency u_{itz} and allocative inefficiency u_{itx^r}, our estimate of RDS identifies the degree to which u_{itx^r} influences total inefficiency u_{it}. As our model predicts, allocating resources to research is a highly significant contributor to total firm inefficiency. However, the magnitude of this estimate is dwarfed by the role of market share on firm efficiency. Since, the remaining inefficiency not explained by firm investment in R&D can be attributed to sheer technical inefficiency u_{itz}, we can see that technical inefficiency plays a much larger role in firm production that the allocation of resources to research.

We can also observe evidence of another important implication of our model in our results. Our model of firm innovation implies that technical inefficiency and allocative inefficiency can also be thought of as a tradeoff between dynamic (technical) and static (allocative) efficiency. A common stylized fact (Klette & Kortum, 2004) is that R&D expenditures increase proportionally with firm size, despite the presence of

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[18] Model specifications that did not include the indicator variable for small firms in the production function were all rejected through log-likelihood testing and are not reported.

decreasing returns to R&D. As our results indicate that firm efficiency increases with firm size and decreases with investments in R&D, which grow proportionally with firm size, this would provide some evidence that larger firms are indeed trading off static efficiency for dynamic efficiency, while smaller firms focus on near term increases in output as they attempt quickly to grow and survive.

Conclusion

As predicted by our theoretical model in Chapter 2, a firm's market share, size, and R&D intensity are highly significant as determinants of a firm's efficiency. Specifically, we that firm efficiency increases with higher market shares. It is clear from our results that small firms exhibit a significant inefficiency effect, as well as, firms that undertake higher levels of R&D. This is consistent with the notion that research detracts resources from productive activities. This supports our model's prediction that firms face a tradeoff between dynamic (technical) and static (allocative) efficiency. Further research is required to capture the dynamic efficiency gains that firms should receive from their sacrifice of static efficiency and the formal decomposition of these two effects from estimates of total firm efficiency.

CHAPTER 4

AGGREGATE TECHNOLOGY FRONTIERS

Background

Since the introduction of productivity and efficiency analysis to the growth literature by Fare, Grosskopf, Norris, and Zhang (1994), researchers of regional and international productivity comparisons are increasingly adopting various frontier approaches to examine convergence and the possible causes of productivity differences. Recent studies employing this approach include examining aggregate labor productivity and capital deepening (Kumar & Russell, 2002), the effects of public capital on efficiency (Puig-Junoy, 2001), and factor accumulation as the source of East Asia's rapid growth (Kruger, Cantner, & Hanusch, 2000). Bound partly by data constraints and partly by convention, most economy-wide inter-regional comparisons are conducted with single aggregate measures of output. While frontiers estimated with such aggregate measures provide considerable insight, recent research indicates the presence of substantial productivity differences within and between regions at the industry/sector level (Harrigan, 1999; Bailey & Solow, 2001). In light of these findings, it is important to examine how well the aggregate outputs typically employed characterize the underlying technologies of diverse, multi-sector economies.

We argue that economy-wide technology frontiers estimated with aggregate measures of output are downward biased. This bias extends not only to estimates of the technology frontier, but also produces incorrect measures of technical change and efficiency change. We propose a micro-macro approach that estimates a “better” frontier that more closely emulates the underlying technologies. This better frontier can be used to produce more precise measures of technical change and efficiency change. Applying our better frontier to an unbalanced sample of 12 OECD countries from 1980-2001, we reveal that traditional frontiers estimated with aggregate measures of output underestimate the available best-practice technology by an average of 53.96%. We find that this previously unmeasured output potential is largely due to inefficiency in sectors possessing technologies characterized by higher elasticities of output with respect to labor than capital and increasing returns-to-scale.

Researchers of growth and productivity have primarily employed the growth accounting approach introduced by Solow (1957) that measures productivity growth through an aggregate production function. In its most general form this function is

$$(4.1) \quad Y = f(K, L, A)$$

where, Y is aggregate output, K is total capital stock, L is total labor, and A is a “residual” that captures shifts in production over time. Making standard assumptions about functional form and the effects of technical progress (e.g. a Cobb-Douglas function with *neutral* technical change), this equation can be restated in terms of growth rates,

$$(4.2) \quad \lambda_Y = \lambda_K + (1-\alpha)\lambda_L + \lambda_A .$$

Estimates of the growth rate of A, i.e. λ_A, are commonly referred as total factor or multifactor productivity. While this framework has been extended considerably since its introduction as researchers have sought to examine growth rate convergence and endogenize the unexplained productivity represented by A, the fundamental basis of analysis is essentially unchanged.[19]

As this growth accounting framework was being introduced, Farrell (1957) noted that since individual producers may be inefficient in production, from either mis-management or some other reason, traditional econometric analysis of production functions may not be adequate for estimating and comparing production across producers. Proposing to explicitly measure the degree to which producers are inefficient, Farrell defined input and output oriented measures of technical inefficiency that are bounded by 0 and 1. Producers with technical efficiency scores less than unity are inefficient.

Figure 4.1 considers a producer facing a decreasing returns to scale production function. If the producer's output is inside of the production function mapped by $f(x)$, i.e. the producer is inefficient, there are two orientations for evaluating the producer's inefficiency, an output orientation and an input orientation. For example, if the firm's actual output is indicated by point D, then the firm could have either produced more (Point C) given its input use (Point E) or produced the same level of output with fewer inputs (Point B).[20] Using the above graph, Farrell's output-oriented measure of

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[19] This literature is voluminous; a recent exposition of traditional TFP measurement is Hulten (2001).

[20] For completeness, we should note that the producer could hypothetically choose to both increase production and decrease input usage, producing between points B and C along the frontier. However, this

technical efficiency would be the ratio ED/EC, while the Farrell input-oriented measure of technical efficiency would be the ratio AB/AD. We note that the two measures are equivalent under constant returns to scale. Again, if a producer were observed to produce on the frontier the resulting input and output ratios would be equal to unity.

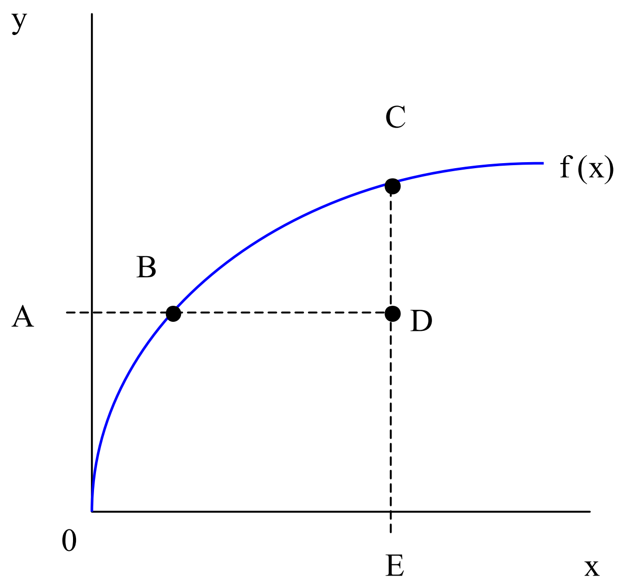

Figure 4.1. Input and Output Measures of Technical Efficiency

This idea of explicitly examining technical efficiency was largely ignored until the development of *stochastic frontier analysis* (Aigner, Lovell, & Schmidt, 1977; Meeusen & van den Broeck, 1977) and *data envelopment analysis* (DEA) (Charnes, Cooper, & Rhodes, 1978) in the late 1970s.[21] Since their introduction, these techniques have spawned a growing field of study dedicated to productivity and efficiency analysis.

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assumes that the producer is maximizing profit as a ratio of revenues per cost, i.e.

$\max_{y,x} \hat{\pi} = \text{revenues/cost}$, rather than the traditional assumptions of minimizing cost given output or maximizing output given cost.

[21] A thorough survey of production frontiers and empirical techniques is Lovell (1993).

The underlying basis of this research, however, draws heavily from the micro-economic theory of production. Accordingly, these techniques were almost exclusively used for firm and industry level analyses.

Recognizing that the growth accounting methods used to examine international comparisons of productivity growth assumed technical efficiency on the part of entire economies, Fare, Grosskopf, Norris, and Zhang (1994) introduced the use of production frontiers to the growth literature. Using data envelopment analysis (DEA) to calculate distance functions that capture Farrell's measure of technical efficiency, they estimate Malmquist indices that explicitly characterize the world technology frontier. Comparing individual observations to the frontier, they produce productivity measures that can be further decomposed into measures of technical change and efficiency change.

This new approach to aggregate productivity measurement quickly spurred research along three distinct lines: the decomposition of Malmquist indices,[22] alternative frontier estimation techniques,[23] and empirical studies of productivity growth and convergence for regional economies.[24] However, this new literature has overlooked how well the aggregate outputs employed characterize the underlying technologies of diverse, multi-sector economies. Interestingly, this critique has been addressed by traditional researchers of total factor productivity (TFP). They have found that while aggregate

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[22] See Lovell (2002) for an examination of this controversial literature.

[23] Primarily, the econometric technique of stochastic frontier analysis (SFA), e.g. Koop, Osiewalski, and Steel (1999) introduce SFA to the growth literature, albeit with a Bayesian twist, and Atkinson, Cornwell, and Honerkamp (2003) take a GMM approach that can be decomposed into analogous FGNZ measures of technical and efficiency change.

[24] Jaume Puig-Junoy (2001) provides a brief review of this young literature.

productivity appears to converge, convergence does not occur across many important sectors such as manufacturing (Bernard & Jones, 1996). Likewise, aggregate productivity rankings ignore the widely disparate levels of productivity revealed at the sector level and that most countries in empirical samples tend to possess a productivity advantage in some sector over the aggregate best-practice country (Harrigan, 1999; Bailey & Solow, 2001). Examining TFP growth in the U.S. farm sector, Ball *et al.* (1999) discovered that despite stable TFP growth at the aggregate level, considerable volatility was exhibited by the individual states. Acknowledging that "aggregate productivity calculations can say nothing about the deeper causes" of productivity differences, Bailey and Solow (2001) have issued a call for researchers to seek the determinants of international productivity differences in micro-data.

This paper intends to address this gap in the aggregate frontier literature. Employing sector data, we propose a two-stage micro-macro approach to calculate an aggregate frontier that more closely emulates the underlying technologies. This "better" frontier demonstrates that technology frontiers generated from aggregate measures of output for regions that are characterized by multiple outputs of heterogeneous technology are unequivocally downward biased and will distort measurements of technical change and efficiency change. This is not surprising to the literature, which readily admits that the best-practice frontiers estimated are but approximations to the true underlying technology (Fare *et al.*, 1994; Koop, Osiewalski, & Steel, 1999; Kruger, Cantner, & Hanusch, 2000). However, these studies frequently produce results indicating that a single best-practice country is solely responsible for shifts in world technology. Given the evidence presented above in the TFP literature and the growing popularity of aggregate frontier studies it is important to examine whether this best-practice approximation is a reasonable representation of the true frontier. Our better frontier can be used to test the robustness of traditional aggregate measures and further produce measures of technical change and efficiency change that more closely capture both intra-sector and inter-sector productivity differences in aggregate economies.

Traditional Aggregate Technology Frontiers

Let a multi-output, multi-input production technology be characterized by the technology set,

(4.3) $T \equiv \{(K, L, \mathbf{Y}) : (K, L) \; can \;\; produce \;\; \mathbf{Y}\}$,

which transforms aggregate inputs, i.e. capital, K, and labor, L, into an output vector, $\mathbf{Y} = (Y^1, \ldots, Y^S)$, of various sectors, $s = (1, \ldots, S)$. The output of any given sector, Y^s, is assumed to be produced with a distinct heterogeneous technology with respect to the other sectors. This production set, T, can also be defined using output set, $P(K, L)$, which denotes all combinations of outputs, $\mathbf{Y}$, that can be produced given input (K, L),

(4.4) $P(K, L) \equiv \{\mathbf{Y} : (K, L, \mathbf{Y}) \in T\}$.

We choose this representation because it seems more likely that large, multi-product economies, such as regions or countries, act as output maximizers given their fixed factor endowments rather than cost-minimizers given a fixed level of output. The output distance function is defined on the output set, $P(K,L)$, as

$$(4.5)\quad D_o(\mathbf{Y},K,L)=\inf_{\boldsymbol{\theta}}\{\boldsymbol{\theta}:(\mathbf{Y}/\boldsymbol{\theta})\in P(K,L)\},$$

with $\boldsymbol{\theta}$ indicating the inverse of the factor by which output vector $\mathbf{Y}$ can be increased given (K,L) and still be feasible.[25] The technology frontier is typically defined as the vectors $\mathbf{Y}$ such that $D_o(\mathbf{Y},K,L)=1$. It is from this point that all previous studies in the literature begin their departures into empirical measurement or productivity decompositions, albeit using an aggregate single output. This output is invariably a price-weighted aggregation, Y_{Agg}, such as GDP, with $Y_{Agg}=\mathbf{YP}'$ where $\mathbf{P}=(P^1,\ldots,P^S)$ is a vector of output prices for each sector. Rewriting equations (4.3) - (4.5) to reflect the aggregate output actually employed, the technology set, output set, and distance function are respectively,

$$(4.6)\quad T\equiv\{(K,L,Y_{Agg}):(K,L)\ can\ produce\ \ Y_{Agg}\},$$

$$(4.7)\quad P_{Agg}(K,L)\equiv\{Y_{Agg}:(K,L,Y_{Agg})\in T_{Agg}\},\ \text{and}$$

$$(4.8)\quad D_o^{Agg}(Y_{Agg},K,L)=\inf_{\theta}\{\theta:(Y_{Agg}/\theta)\in P(K,L)\}.$$

[25] We should note we make the usual assumptions about such output sets and the corresponding properties of the distance functions (Fare & Primont, 1995), chiefly among them that the output set be convex and that inputs and outputs are at least weakly disposable.

The aggregate technology frontier represented by $P_{Agg}(K,L)$ is shown in Figure 4.2. Consider a region producing at point A. The line $\overline{0B}$ represents all attainable outputs given the region's fixed input endowment. The region's efficiency score as estimated by the distance function described in equation (4.8) would be equal to the value of $\theta = 0A/0B$.

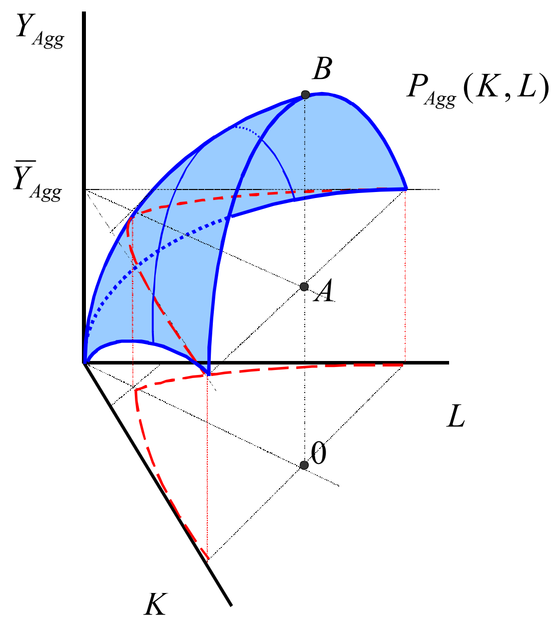

Figure 4.2. Traditional Aggregate Technology Frontiers

When inefficiency is estimated, as currently practiced, with the price-weighted aggregate output, Y_{Agg}, using the distance function in equation (4.8), the inefficiency present within its comprising sectors is not explicitly considered. Only if all of the sectors are produced with identical technologies will this technique accurately reflect the degree of efficiency within each region. Since, the measurement of efficiency with this approach serves only as an approximation of the relative efficiency within each region, we must ask whether this is an adequate approximation.

Problems with Multi-Output Frontier Estimation

Ideally, one would circumvent the problems posed by aggregate technology frontiers by directly estimating the multi-output distance function in equation (4.5). The multi-output approach would successfully identify the separate dominant technologies that may be masked by the aggregate data. However, this requires detailed disaggregate sector data that captures the full heterogeneity of outputs and inputs. Lovell (1993) details the DEA approach for multi-output firms. While this approach is technically feasible a number of problems often arise. First, there is typically a paucity of output quantity data at the sector level. Second, even if this data were available, the number of regions deemed efficient tends to increase with the number of outputs[26] (Coelli, Rao, & Battese, 1998; Button & Weyman-Jones, 1992). This occurs because as the number of outputs increases, the dimensions of the input/output space increase relative to the sample size of regions. This leaves few free dimensions for comparison absent very large samples. The result is that each region is determined to efficiently produce their relatively "unique" output bundle.

Gstach (1999) reviews techniques for estimating multi-output technical efficiency in noisy settings. In addition to considering a stochastic DEA approach that suffers from the same problems outlined above, he presents the multi-output parameterization of stochastic frontier models detailed in Grosskopf and Hayes (1993) and Coelli and Perelman (1996). These models transform the multi-output problem into scalar comparisons that can be solved through straightforward parametric methods. This

[26] This is true for inputs as well. Fare and Zelenyuk (2002) and Tauer (2001) address the biases produced by the use of aggregate inputs to circumvent this problem.

transformation, however, must assume that the various outputs can be represented by a common technology for all sectors. Unfortunately, it is the heterogeneous technologies underlying each sector's output that produce the downward bias of traditional aggregate frontiers.

A "Better" Technology Frontier

Assuming that the various sectors comprising output vector $\mathbf{Y}$ are separable in production,[27] we can evaluate the suitability of the relative efficiency scores currently estimated. Rather than estimate the relative efficiency of a region's aggregate output after a price-weighted aggregation of its individual sectors' observed output, we propose that efficiency is estimated initially in each sector. The individual technology set, output set, and distance function for each sector are defined in equations (4.9)-(4.11), respectively:

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[27] Some notes on this assumption: Functional separability and the existence of consistent aggregate input indices are already implied by using value-added outputs (Yuhn, 1991), which are recommended by the OECD (2001a) for regional productivity comparisons and prevalent throughout the current aggregate frontier productivity literature. In the absence of output separability, the effects of the joint production of value-added outputs, which by definition exclude intermediate inputs in the production process, is a question of economies of scope between the various disaggregate sectors. Estimates of an individual sector's productivity with regard to its explicit input allocations would be upward biased in the presence of significant scope economies. However, this is mitigated, in part or whole, as these scope economies are ignored when the sectors are combined into an aggregate output. Whether or not value-added outputs are used, the absence of significant economies of scope at the macroeconomic sector level must be assumed to conduct individual sector analysis with macroeconomic sector "slices" of aggregate data sets, e.g. Bernard & Jones (1996), Gouyette and Perelman (1997), Harrigan (1999), and Shestalova (2003).

(4.9) $T^s \equiv \{(K^s, L^s, Y^s) : (K^s, L^s)\ can\ produce\ \ Y^s\}, \quad s = 1, \ldots, S$,

(4.10) $P^s(K^s, L^s) \equiv \{Y^s : (K^s, L^s, Y^s) \in T^s\}$, and

(4.11) $D_o^s(Y^s, K^s, L^s) = \inf_{\theta^s}\{\theta^s : (Y^s / \theta^s) \in P^s(K^s, L^s)\}$.

As in equation (4.5), θ^s indicates the inverse of the factor by which output Y^s can be increased given (K^s, L^s) and still be feasible. This distance function may be estimated using either a DEA or stochastic frontier approach to produce efficiency scores and relative efficiency rankings. Using regional data that decompose each region's aggregate output and available inputs into their comprising sectors, individual estimates of productivity and efficiency can be estimated for each sector across regions. That is, given panel data of the form $(Y_r, Y_r^1, \ldots, Y_r^s, K_r, K_r^1, \ldots, K_r^s, L_r, L_r^1, \ldots, L_r^s)$ such that $Y_r = \sum_{s=1}^{S} Y_r^s$, $K_r = \sum_{s=1}^{S} K_r^s$, $L_r = \sum_{s=1}^{S} L_r^s$, we may estimate S sector distance functions for each region r, producing efficiency scores for each sector in the economy. Having performed the separate productivity analyses for each sector, we can scale each region's output in each sector to the best-practice frontier for that sector. As individual θ_r^s s are estimated, each region's sectoral outputs can be scaled to the sector's technology frontier through

(4.12) $Y_r^{s*} = Y_r^s (\theta_r^s)^{-1}$.

It is at this point that we construct price-weighted aggregates that explicitly consider inefficiency at the sector level. The best-practice *adjusted sector outputs,* Y_r^{s*}, previously constructed for each region can be aggregated to form best-practice *adjusted aggregate outputs* as follows,

$$(4.13)\quad Y_r^* = \sum_{s=1}^{S} P^s Y_r^{s*} ,$$

where P^s is, again, a price index for each sector. This new aggregate measure of output can be used to estimate aggregate technology frontiers that reflect the heterogeneous technologies of its comprising sectors.

Considering the technology set and output set of the new *adjusted aggregate outputs*,

$$(4.14)\quad T^* \equiv \{(K, L, Y^*) : (K, L)\ can\ produce\ \ Y^*\}$$

and

$$(4.15)\quad P^*(K, L) \equiv \{Y^* : (K, L, Y^*) \in T^*\} ,$$

we are able to estimate the distance function,

$$(4.16)\quad D_o^*(Y^*, K, L) = \inf_{\theta}\{\theta : (Y^* / \theta) \in P(K, L)\} ,$$

where θ represents the efficiency score for each region. Because the output of each region is scaled to the maximum level of output attainable, given its input endowments and allocations, in a world where it uses the best available technology in each of its comprising sectors, $P^*(K,L) \geq P_{Agg}(K,L)$ by definition. $P^*(K,L) = P_{Agg}(K,L)$ if the output in every sector is produced using the same technology or if each region produces efficiently in every sector. Estimates of this "better" frontier, $P^*(K,L)$, which explicitly considers the heterogeneous technologies of its underlying sectors and defined as the outputs Y^* such that $D_o^*(Y^*,K,L) = 1$, can be used to evaluate the aggregate technology frontiers currently estimated in the literature.

To ascertain the efficiency scores and efficiency rankings of each region relative to the better technology frontier, we must estimate the distance function in equation (4.16) using pooled *adjusted aggregate output*, Y_r^*, and actual aggregate output, Y_r, data for each region. The efficiency rankings obtained for each region's actual aggregate output indicate their relative efficiency to the better technology frontier that is mapped by the Y_r^*s. Figure 4.3 demonstrates the better technology frontier and its relation to the aggregate technology frontiers currently estimated. Again, consider a region producing at Point A. The traditional aggregate frontiers previously discussed would estimate the region's efficiency as the value of $\overline{0A}/\overline{0B}$ instead of $\overline{0A}/\overline{0C}$ as estimated with the better frontier. Recalling that $P^*(K,L) \geq P_{Agg}(K,L)$, it is feasible that the estimated frontiers are identical or that the traditional aggregate frontier is an adequate approximation of the better frontier. We investigate this empirical question with OECD data described in the next chapter.

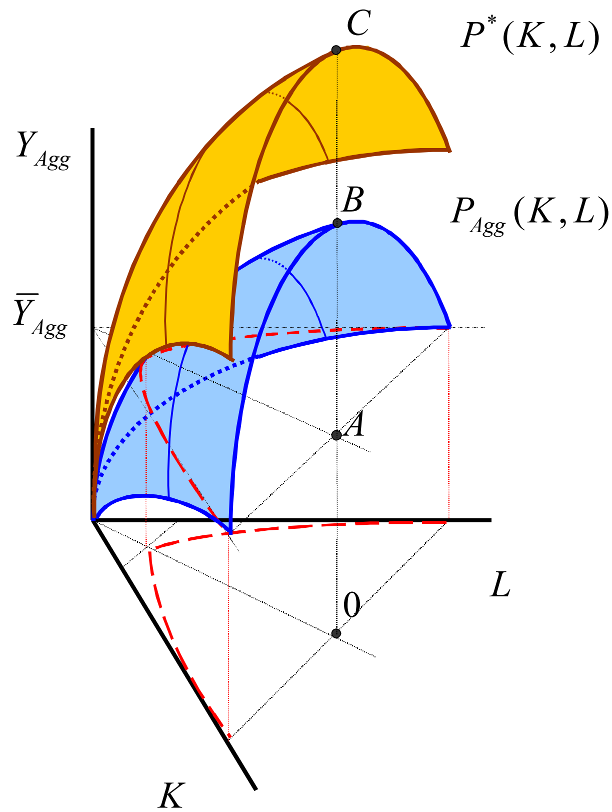

Figure 4.3. Better Technology Frontier

CHAPTER 5

ESTIMATING A BETTER TECHNOLOGY FRONTIER

Method

We estimate efficiency at both the sector and aggregate level using the time-varying stochastic frontier model for unbalanced panel data proposed by Battese and Coelli (1992),

(5.1) $Y_{rt} = f(X_{rt};\beta_t)e^{(V_{rt}-U_{rt})}$

and

(5.2) $U_{rt} = \eta_{it}U_{rt} = \exp[-\eta(t-T)]U_r$,

where Y_{rt} is the output for the r th region in the t th period; $f(X_{rt};\beta_t)$ is a deterministic function of a vector of input quantities, X_{rt}, and a vector of unknown parameters, β_t; V_{rt} are independent and identically distributed $(i.i.d.)$ random errors with a $N(0,\sigma_V^2)$ distribution; U_{rt} are half-normal, $N(0,\sigma_U^2)$ distributed errors associated with inefficiency in production; and η is an unknown scalar parameter indicating the presence of efficiency changes over time. As Battese and Coelli (1992) note, the exponential specification of the behavior of the regional effects over time (equation 5.2) implies that technical efficiency must either increase at a decreasing rate $(\eta > 0)$, decrease at an increasing rate $(\eta < 0)$, or remain constant $(\eta = 0)$. Should $\eta = 0$ variation in efficiency only occurs across regions and reduces U_{rt} to U_r.

Technical efficiency for the r th region in the t th time period is defined as

(5.3) $$TE = E[\exp(-U_{rt}) \mid V_{rt} - U_{rt}].$$

Traditionally, $\exp(-U_{rt})$ is interpreted as the degree through which output falls short of its potential given a specific technology and level of inputs. However, this interpretation assumes that all regions are producing with the best-available technology, explicitly specified as $f(X_{rt}; \beta_t)$, and that all deviations from the frontier not attributed to stochastic noise represent an inefficient implementation of this technology. This stringent assumption about the production technology available to regions has led many researchers to adopt the DEA approach, which makes no assumptions about available technology beyond the convexity and disposability assumptions previously made. We note, however, this assumption is only one interpretation about the nature of the frontier and the technical inefficiency term $\exp(-U_{rt})$.

Another interpretation is that the technology frontier represents an envelope of all feasible technologies available in the production of a given output. This envelope maps the maximum output attainable through efficient production with the best-practice technology for all feasible input allocations and endowments. We choose this interpretation of the functional form of the stochastic frontier, with the inefficiency term defined by equation (5.3) representing production inefficiencies caused either by the use of inappropriate technology given a region's inputs, poor implementation of best-practice technology, or both.

While flexible functional forms such as the translog are commonly used for estimating efficiency, the estimated output elasticities are not reliable due to severe multi-collinearity in the data (Yuhn, 1991; Vijverberg, Vijverberg, & Gamble, 1997; Murillo-Zamorano & Vega-Cervera, 2001; Puig-Junoy, 2001). This is not considered a problem if the desired result is to produce relative efficiency rankings (Puig-Junoy, 2001). However, as we must use our estimates to transform our initial sector outputs into *adjusted sector outputs*, we must produce estimates robust to multi-collinearity. Testing translog, translog with time-trend, Cobb-Douglas, and Cobb-Douglas with time-trend model specifications for multi-collinearity using the condition index,[28] we find only the two Cobb-Douglas specifications are robust to multi-collinearity. Further, the translog functional form does not globally satisfy monotonicity, which requires the marginal products to be positive for all inputs. Checking for positive monotonicity for each data point in the sample, we present the results for each sector in Table 5.1.

Table 5.1. Percent of Observations Satisfying Monotonicity of the Translog

	Input		
Sector	Capital (K)	Employment (E)	Year (T)
Aggregate Output	100.0%	100.0%	56.9%
Agriculture	100.0%	82.8%	56.9%
Mining and Quarrying	100.0%	73.5%	0.0%
Total Manufacturing	100.0%	100.0%	61.6%
Electricity, Gas, and Water Supply	100.0%	0.0%	80.6%
Construction	100.0%	100.0%	56.9%
Wholesale and Retail Trade	100.0%	100.0%	51.7%
Transportation and Communication	100.0%	97.8%	58.6%
Finance, Insurance, and Real Estate	100.0%	100.0%	46.6%
Community, Social, and Personal Services	100.0%	89.2%	56.9%

[28] Condition number values in excess of 20 indicate severe multi-collinearity. The translog and translog with time trend models produced values in excess of 400.

Given the substantial number of observations that fail to satisfy positive monotonicity and the severe multi-collinearity present when using the translog functional form in this sample, we employ Cobb-Douglas and Cobb-Douglas with time-trend model specifications for our analysis.

Data

We use an unbalanced panel of 12 OECD countries spanning the period 1980-2001 for a total of 232 observations, using data from the OECD STAN database for Industrial Analysis (OECD, 2001b). Table 5.2 indicates the countries and years included in this analysis.

Table 5.2. Sample OECD Countries and Years

Austria	1986-2001	France	1980-2000	Sweden	1980-2000
Belgium	1985-2000	Italy	1980-1999	United Kingdom	1981-2000
Canada	1980-1999	South Korea	1980-2000	United States	1980-2001
Finland	1980-2000	Norway	1980-2001	West Germany	1980-1991

The OECD STAN database contains measures of output, labor, and capital investment at the aggregate and industry level covering all activities within the *International Standard Industrial Classification of all Economic Activities, Revision 3* (ISIC Rev.3). This current version of the STAN database, which includes service industries and better accommodates technology/knowledge based industries, represents a substantial revision of the original, which exclusively covered the manufacturing sector. Because all of the sector data must directly sum into the aggregate data reported in our panel, we are constrained to the use of nine major industrial sectors.

Adhering to current practice (OECD, 2001a, 2002b), we use value added as our measure of output. This measure, often referred to as GDP by industry, represents an industry's contribution to GDP and excludes the production of intermediate inputs consumed. Inputs are measured as employees and gross capital stocks. Since the STAN database contains capital investment data from the 1970s, capital investments are converted into capital stocks using the perpetual inventory method employed by Harrigan (1999). This ensures that the resulting capital stocks sum into the separately calculated aggregate capital stocks required by our approach.

Values are converted to a common base year 2000 U.S. dollar by first deflating current year values with purchase power parity (PPP) deflators from the OECD Economic Outlook database (OECD 2003). The results are then converted into 2000 base year dollars using the United States GDP deflator. Although it is widely agreed that current price deflators are inadequate for meaningful international productivity comparisons (van Ark, 1996; Bernard & Jones, 2001; Sorensen, 2001), the focus of this research is not on the actual relative productivity rankings but on the appropriate estimation of the frontier. While different price deflators may change the nominal levels of estimated frontiers, it will not bias the relationship between the aggregate and "better" frontiers we examine. Table 5.3 presents summary statistics for the variables included in our analysis for each sector and the economy-wide aggregate.

Table 5.3. Summary Statistics for Aggregate and Sector Variables

Sector	Value Added Output (millions 2000$)				
	Sample Mean	Sample Median	Standard Deviation	Minimum	Maximum
Aggregate Output	1411582.33	820920.71	1990900.91	49029.77	9115204.00
Agriculture	35666.64	24803.95	38030.18	2643.16	149321.84
Mining and Quarrying	37091.16	5100.61	63998.64	243.25	336530.48
Total Manufacturing	277410.00	150120.70	365123.89	12355.93	1474493.02
Electricity, Gas, and Water Supply	36042.98	21580.51	48738.54	1033.93	196579.66
Construction	72112.93	44825.27	90113.18	3770.20	456874.51
Wholesale and Retail Trade	201454.45	109511.44	311843.64	7227.54	1480206.00
Transportation and Communication	101038.03	59803.39	133899.18	3916.69	616669.00
Finance, Insurance, and Real Estate	329318.78	183650.87	516524.33	4516.65	2767713.04
Community, Social, and Personal Services	319986.84	168379.46	471400.31	6341.52	2147023.35

Sector	Capital Stocks (millions 2000$)				
	Sample Mean	Sample Median	Standard Deviation	Minimum	Maximum
Aggregate Output	1566681.74	800419.00	1752235.73	50155.00	8089409.00
Agriculture	61334.44	47408.00	61859.79	4806.00	300102.00
Mining and Quarrying	86491.78	9036.00	147606.14	189.00	539905.00
Total Manufacturing	250450.71	140342.50	283011.21	13954.00	1163928.00
Electricity, Gas, and Water Supply	97989.30	61549.00	119321.29	3627.00	478411.00
Construction	27858.22	16797.50	28841.03	1285.00	129157.00
Wholesale and Retail Trade	140611.47	69041.00	235187.75	2014.00	1183125.00
Transportation and Communication	167235.94	96155.50	197210.29	4855.00	1025392.00
Finance, Insurance, and Real Estate	439336.81	184272.00	441016.96	11647.00	1943737.00
Community, Social, and Personal Services	293600.05	157493.50	361803.96	7537.00	1718975.00

Sector	Employment (1000s)				
	Sample Mean	Sample Median	Standard Deviation	Minimum	Maximum
Aggregate Output	35710.84	24186.00	31170.96	11121.00	149731.00
Agriculture	2041.03	1461.00	1557.26	509.00	7301.00
Mining and Quarrying	179.03	105.00	215.75	41.00	1186.00
Total Manufacturing	6589.35	5215.00	4560.07	1810.00	20795.00
Electricity, Gas, and Water Supply	285.82	205.00	223.13	31.00	965.00
Construction	2190.55	1795.00	1593.06	683.00	8598.00
Wholesale and Retail Trade	7340.16	4501.00	8057.82	2561.00	36909.00
Transportation and Communication	2125.56	1686.50	1490.23	607.00	7646.00
Finance, Insurance, and Real Estate	4149.77	2630.50	4829.07	332.00	25130.00
Community, Social, and Personal Services	10809.62	7262.50	10347.30	1489.00	48294.00

Results

Cobb-Douglas and Cobb-Douglas with time-trend specifications of the Battese and Coelli (1992) stochastic frontier model were estimated for each sector and for aggregate output through maximum likelihood estimation. Likelihood ratio tests were used to select the appropriate model specification for each sector and the aggregate output. We present the results for our preferred models in Table 5.4[29].

Table 5.4. Maximum Likelihood Estimates and Specification Tests for Preferred Stochastic Frontier Model for each Sector and Economy-wide Aggregate

	Aggregate and Sector Coefficients (Standard Errors)									
Variables	Aggregate Output	Agriculture	Mining and Quarrying	Total Manufacturing	Electricity, Gas, and Water Supply	Construction	Wholesale and Retail Trade	Transportation and Communication	Finance, Insurance, and Real Estate	Community, Social, and Personal Services
Constant	.380	4.862***	1.300***	-1.180	-.403	-1.125*	.327	.355	.508	.465***
	(.762)	(1.176)	(.306)	(.950)	(.356)	(.662)	(1.132)	(.785)	(.511)	(1.967)
Capital (K)	.699***	.478***	.758***	.629***	.701***	.505***	.569***	.643***	.321***	.627
	(.050)	(.047)	(.020)	(.055)	(.045)	(.060)	(.053)	(.062)	(.063)	(.069)
Employment (L)	.376***	.139	.238***	.720***	.474***	1.054***	.646***	.486***	1.052***	.495
	(.097)	(.099)	(.058)	(.150)	(.068)	(.109)	(.180)	(.155)	(.107)	(.316)
Year (t)	.012***	--	-.021	.016***	.032***	--	--	--	--	.003
	(.004)		(.007)	(.005)	(.005)					(.011)
σ^2	.507**	1.398**	.292**	1.002*	.434**	1.604**	.884**	.411*	1.575**	.417
	(.230)	(.668)	(.115)	(.520)	(.204)	(.705)	(.415)	(.212)	(.663)	(.280)
σ_v^2	.028***	.033***	.072***	.025***	.033***	.042***	.030***	.036***	.030***	.032***
	(.003)	(.003)	(.007)	(.002)	(.003)	(.004)	(.003)	(.004)	(.003)	(.003)
σ_u^2	.479**	1.365**	.220*	.977*	.401*	1.559**	.854**	.375*	1.545**	.385
	(.230)	(.668)	(.115)	(.520)	(.204)	(.705)	(.415)	(.213)	(.663)	(.280)
η	-.009	-.004	.020*	-.007	-.042**	.007***	-.005*	.010**	.004	.008
	(.007)	(.003)	(.012)	(.006)	(.016)	(.002)	(.003)	(.004)	(.003)	(.011)
γ	.945***	.977***	.753***	.975***	.923***	.994***	.966***	.913***	.981***	.924***
	(.026)	(.012)	(.099)	(.014)	(.037)	(.012)	(.017)	(.047)	(.008)	(.054)
Num Obs.	232	232	211	232	232	232	232	232	232	232
Log-likelihood	60.120	35.505	-39.963	68.209	44.560	6.603	47.806	32.838	44.535	44.763
H$_O$: γ=0										
Test Statistic	187.035	196.766	137.223	144.399	108.389	238.324	233.912	153.355	437.168	139.072
Decision	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject	Reject
H$_O$: η=0										
Test Statistic	1.926	1.863	2.865	1.378	17.804	7.294	2.869	4.353	2.099	.0851
Decision	Accept	Accept	Accept	Accept	Reject	Reject	Accept	Reject	Accept	Accept

[29] Complete maximum likelihood estimates for all model specifications, including translog, in each sector are presented in Appendix B (Tables B.1-B.10).

Hypothesis tests were performed for the presence of inefficiency and its trend. The estimate for γ, which is calculated as $\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$, indicates to what degree deviations from the frontier can be attributed to inefficiency as opposed to statistical noise. The null hypothesis that γ equals zero is rejected across all regions suggesting that some inefficiency is present in each of the sectors and in the aggregate output. We fail to reject the null hypothesis that $\eta = 0$ for the aggregate output and 6 of the 9 sectors. This indicates that inefficiency is not varying over time in these sectors, i.e. inefficiency only varies across countries in the sample. For the three sectors where time-varying inefficiency is statistically accepted, we find technical efficiency increasing in the Construction and Transportation and Communication sectors and technical efficiency decreasing in the Electricity, Gas, and Water Supply sector.

Average technical efficiency scores and relative rankings, given the preferred model for each sector and the aggregate output, are presented for each country and the country average in Table B.2. Like Harrigan (1999), our results indicate that there may be some problems with the OECD data. For example, estimated efficiency scores for the United States are beneath the sample country average in four of the nine sectors. While we are not troubled by the high relative rankings Canada received, leading the sample in 2/3 of the sectors and in the aggregate output, the gap between Canada's estimated efficiency scores and the 2nd and 3rd ranked country in these sectors is surprisingly large. Fortunately, the principal aim of this paper is to examine potential downward bias in current estimates of aggregate technology frontiers as opposed to the international efficiency comparisons in the sample. While the econometric results may be biased by measurement error in the data, this will not bias the relationship between the two frontiers we must estimate to evaluate whether traditional aggregate frontiers are appropriate representations of the unobservable technology frontier.

Table 5.5. Average Efficiency Scores and Rankings by Country (1980-2001)

Country	Aggregate Output	Agriculture	Mining and Quarrying	Total Manufacturing	Electricity, Gas, and Water Supply	Construction	Wholesale and Retail Trade	Transportation and Communication	Finance, Insurance, and Real Estate	Community, Social, and Personal Services
Austria	0.295 (11)	0.136 (12)	0.354 (10)	0.439 (10)	0.387 (12)	0.111 (12)	0.221 (11)	0.288 (12)	0.108 (11)	0.365 (12)
Belgium	0.340 (10)	0.196 (11)	0.839 (2)	0.442 (9)	0.566 (10)	0.117 (11)	0.224 (10)	0.348 (10)	0.097 (12)	0.367 (11)
Canada	0.964 (1)	0.533 (4)	0.625 (7)	0.966 (1)	0.917 (2)	0.940 (1)	0.958 (1)	0.948 (1)	0.952 (1)	0.964 (1)
Finland	0.295 (11)	0.197 (10)	0.315 (11)	0.411 (12)	0.409 (11)	0.147 (10)	0.219 (12)	0.310 (11)	0.115 (10)	0.367 (10)
France	0.732 (4)	0.661 (3)	--	0.897 (3)	0.909 (3)	0.470 (3)	0.769 (4)	0.793 (5)	0.540 (5)	0.806 (3)
Italy	0.722 (5)	0.495 (6)	0.820 (3)	0.720 (7)	0.816 (6)	0.355 (6)	0.793 (3)	0.843 (2)	0.551 (4)	0.757 (5)
South Korea	0.400 (9)	0.345 (9)	0.700 (4)	0.431 (11)	0.736 (9)	0.282 (9)	0.339 (9)	0.441 (9)	0.292 (9)	0.403 (9)
Norway	0.671 (7)	0.499 (5)	0.958 (1)	0.762 (6)	0.943 (1)	0.713 (2)	0.855 (2)	0.663 (7)	0.675 (2)	0.682 (7)
Sweden	0.675 (6)	0.756 (2)	0.643 (6)	0.674 (8)	0.811 (7)	0.341 (7)	0.613 (6)	0.836 (4)	0.502 (6)	0.781 (4)
United Kingdom	0.755 (3)	0.379 (8)	0.656 (5)	0.852 (4)	0.866 (4)	0.394 (5)	0.428 (8)	0.770 (6)	0.309 (8)	0.742 (6)
United States	0.831 (2)	0.956 (1)	0.587 (9)	0.929 (2)	0.797 (8)	0.283 (8)	0.472 (7)	0.838 (3)	0.327 (7)	0.912 (2)
West Germany	0.671 (8)	0.421 (7)	0.588 (8)	0.775 (5)	0.831 (5)	0.405 (4)	0.691 (5)	0.656 (8)	0.629 (3)	0.673 (8)
Average	0.613	0.465	0.644	0.692	0.749	0.380	0.549	0.645	0.425	0.652

The inverse of each region's efficiency score for each year in each sector was multiplied to the respective observed output to produce *adjusted sector output*. The *adjusted sector outputs,* which scales each region's output in each sector to the estimated best-practice frontier for each sector, for all nine sectors in each region is summed to produce the *adjusted aggregate output* for each region.[30] The *adjusted aggregate output* represents the total amount of value-added output feasible if each country efficiently applied best-practice technology in each sector given existing input endowments and allocations to each sector. Pooling the *adjusted aggregate output* with the observed output data, we estimate the better frontier, again, with the Battese and Coelli (1992) stochastic frontier model with Cobb-Douglas and Cobb-Douglas with time-trend model specifications with maximum likelihood estimation. We present the maximum likelihood estimates of our better frontier in Table 5.6.

Table 5.6. Maximum Likelihood Estimates for Better Frontier

Variable	Coefficient (Std Error)	Variable	Coefficient (Std Error)
Constant	-2.453** (.810)	σ^2	.679*** (.199)
Capital (K)	.614*** (.028)	σ_v^2	.027*** (.002)
Employment (L)	.813*** (.070)	σ_u^2	.651*** (.199)
Year (t)	.009*** (.003)	η	-.002 (.003)
		γ	.060*** (.012)
Num Obs.	464		
Log-likelihood	118.649		
H_O: γ=0			
Test Statistic	899.043		
Decision	Reject		
H_O: η=0			
Test Statistic	.277		
Decision	Accept		

Notes: *t*-ratios are asymptotic. *** $p < .001$; ** $p < .05$; * $p < .1$

The null hypothesis that $\gamma = 0$ is rejected through log-likelihood testing and the coefficient estimate is found to be highly significant indicating that there is some

[30] Since we are already using value-added outputs converted to a common base-year, purchase power parity adjusted dollar, we do not have to apply the price weights included in equation (13).

inefficiency present in the sample. However, the estimated coefficient of γ is quite small, reflecting the fact that half of the observations, i.e. the *adjusted aggregate outputs*, should lie on the efficient frontier. Like our estimate using the traditional aggregate output, we fail to reject the null hypothesis that $\eta = 0$, indicating again that efficiency is not varying over time in this sample. Table 5.7 shows the average efficiency scores and relative rankings of each country and the country average estimated with the traditional and better technology frontiers.

Table 5.7. Average Efficiency Scores and Rankings (1980-2001)

Country	Traditional Aggregate Frontier	Better Aggregate Frontier	Rank Tests	
Austria	0.295 (11)	0.163 (12)	Spearman's Rho	0.771
Belgium	0.340 (10)	0.192 (11)	Prob > |z|	0.003
Canada	0.964 (1)	0.875 (1)		
Finland	0.295 (11)	0.195 (10)		
France	0.732 (4)	0.550 (2)	Kendall's Tau	0.626
Italy	0.722 (5)	0.524 (3)	Prob > |z|	0.006
South Korea	0.400 (9)	0.295 (9)		
Norway	0.671 (7)	0.521 (4)		
Sweden	0.675 (6)	0.410 (7)		
United Kingdom	0.755 (3)	0.496 (5)		
United States	0.831 (2)	0.354 (8)		
West Germany	0.671 (8)	0.477 (6)		
Average	0.613	0.421		

As we expect, the average efficiency scores are lower in comparison to the better frontier than to the frontier estimated with traditional aggregate measures of output. While Canada remains the most efficient producer in our sample, there is variation between the relative efficiency rankings estimated from each of the frontiers. Dramatically, we find that the United States falls from 2nd to 8th in relative efficiency in the sample. We present Spearman's rho statistic and Kendall's tau statistic along with the estimated efficiency rankings in Table 5.7. Both coefficients reject the null hypothesis of no significant correlation at the 1 percent significance level. Thus, while estimated efficiency does fall relative to the better technology frontier we find no significant change in each country's efficiency ranking relative to this better frontier. Adjusting each country's observed aggregate output to the technology frontier estimated with traditional aggregate measures of output and the better technology frontier constructed from sector data, we evaluate the total output feasible in each region. Table 5.8 displays the average percentage increase in output available to each country if they were producing on the traditional technology frontier estimated from aggregate measures of output and the estimated better frontier constructed from sector data.

Table 5.8. Comparison of Average Potential Output as Estimated by Traditional and Better Technology Frontiers

Country	Average % increase from observed aggregate output to traditionally estimated technology frontier	Average % increase from observed aggregate output to better technology frontier	Average % increase between estimated traditional and better technology frontiers
Austria	239.18	512.79	80.67
Belgium	194.31	421.36	77.15
Canada	3.75	14.50	10.36
Finland	238.79	413.53	51.57
France	36.54	81.92	33.23
Italy	38.49	90.74	37.74
South Korea	149.89	239.36	35.80
Norway	48.96	92.05	28.92
Sweden	48.22	144.02	64.63
United Kingdom	32.52	101.64	52.16
United States	20.29	182.44	134.80
West Germany	49.06	109.48	40.53
Average	91.67	200.32	53.96
Weighted Average	36.81	78.18	30.24

Notes: Weights are output shares of total sample output.

The average potential increase in output across countries during 1980-2001 as measured by the traditional aggregate technology frontier is 91.67%. The analogous average potential increase estimated by the better technology frontier is 200.32%, representing an underestimation of 53.96% when employing traditional aggregate technology frontiers. Given the substantial variation in country size, it is more valuable to examine a weighted-average of potential output where the weights are each country's share of the total sample output. Also reported in Table 5.8, this weighted-average reveals a potential increase in output of 36.81% and 78.18% for the traditional and better technology frontiers, respectively. Using the weighted-average, we find that the traditional technology frontier underestimates the better frontier by 30.24%. Even Canada, the dominant producer in this sample, exhibits a substantial increase in potential output available when it is compared to the better technology frontier, exhibiting a 10.36% underestimate of the underlying technology frontier when it is estimated with aggregate measures of output.

Having demonstrated that aggregate productivity frontiers estimated with simple price-weighted aggregate data are downward biased and obscure the inefficiency that may be present within its comprising sectors, we must ask why the difference between the two frontiers is so large. Examining the estimated output elasticities of the traditional and better aggregate frontiers, we find that production on the traditional frontier is very close to a constant returns-to-scale technology while the better frontier exhibits increasing returns-to-scale with a substantially higher labor elasticity of output . As the sector results in Tables 5.4 & 5.5 reveal, the least efficient sectors in our sample, Construction and Finance, Insurance, & Real Estate (F.I.RE), also happen to be characterized by both the largest labor elasticities of output and increasing returns-to-scale technologies in the sample. Since the least efficient sectors experience the greatest increase in potential output, we would expect them to greatly influence the adjusted aggregate technology represented in the better frontier. Table 5.9 shows the percent increase in output experienced by each sector as it was adjusted to the sector's estimated best-practice frontier.

Table 5.9. Average Percent Increase from Observed to Adjusted Sector Output

Country	Agriculture	Mining and Quarrying	Total Manufacturing	Electricity, Gas, and Water Supply	Construction	Wholesale and Retail Trade	Transportation and Communication	Finance, Insurance, and Real Estate	Community, Social, and Personal Services
Austria	637.1	182.6	127.7	167.3	804.5	352.7	248.6	827.0	173.6
Belgium	410.7	19.1	126.2	78.9	757.8	346.6	188.1	931.3	172.5
Canada	87.5	59.9	3.5	9.1	6.4	4.4	5.5	5.0	3.7
Finland	408.1	217.2	143.5	157.5	584.3	356.3	224.3	767.4	172.5
France	51.2	--	11.4	10.1	113.0	30.1	26.1	85.1	24.1
Italy	137.8	70.2	29.1	20.4	147.3	44.7	52.5	59.0	48.5
South Korea	102.1	22.0	38.9	22.8	182.0	26.1	18.7	81.4	32.0
Norway	189.9	42.8	132.0	36.8	255.7	194.8	127.3	242.1	148.4
Sweden	100.2	4.4	31.2	6.1	40.3	16.9	50.9	48.0	46.7
United Kingdom	32.3	55.5	48.4	23.6	194.1	63.1	19.7	99.3	28.0
United States	163.7	52.4	17.4	15.6	154.3	133.7	29.9	223.8	34.8
West Germany	4.6	70.3	7.6	25.9	254.8	111.8	19.3	205.4	9.7
Average	193.8	72.4	59.7	47.8	291.2	140.1	84.2	297.9	74.5
Weighted Average	68.3	37.7	24.5	24.5	202.7	89.9	31.6	167.0	25.3

Notes: Weights are output shares of total sample output.

Looking at the weighted-average of each sector's potential increase in output, we see that the Construction and F.I.RE sectors, with respective weighted-average increases in output of 202.7% and 167.0%, are primarily driving the increase in aggregate output. The average output increase of the seven remaining sectors is substantially less at 43.11%, even after weighting by their output shares of the sample. One possible explanation for the most inefficient sectors possessing significant increasing returns-to-scale technologies and substantially higher labor elasticities of output is that the best-practice technologies in these sectors utilize cutting-edge labor-saving and labor-augmenting technologies, e.g. information technologies, that have yet to mature and diffuse through-out the broader economy, both within and between regions. The effects of these two largely inefficient sectors on the simple price-weighted aggregate output and adjusted aggregated output is clearly seen when we consider each sector's output share. Table 5.10 displays each sector's average share of aggregate output from 1980-2001 for each country in the sample.

Table 5.10. Average Sector Shares of Total Output (1980-2001)

Country	Agriculture	Mining and Quarrying	Total Manufacturing	Electricity, Gas, and Water Supply	Construction	Wholesale and Retail Trade	Transportation and Communication	Finance, Insurance, and Real Estate	Community, Social, and Personal Services	Total
	Observed Output Shares									
Austria	2.89	0.49	20.81	2.82	7.45	17.12	7.52	19.95	20.96	100.00
Belgium	1.92	0.31	20.69	3.07	5.12	13.76	6.89	24.67	23.57	100.00
Canada	3.14	5.16	17.66	3.12	6.15	13.77	7.54	22.23	21.24	100.00
Finland	6.11	0.39	24.23	2.58	5.99	12.47	9.23	17.57	21.42	100.00
France	3.67	0.00	20.83	2.39	5.51	12.81	6.50	26.49	21.81	100.00
Italy	1.73	0.91	29.81	2.40	5.83	11.43	6.00	22.02	19.87	100.00
South Korea	3.99	0.54	23.93	1.94	6.00	17.07	7.26	20.63	18.64	100.00
Norway	9.98	0.98	27.76	2.50	9.30	13.54	7.28	14.10	14.55	100.00
Sweden	3.24	15.28	13.11	2.97	4.84	12.44	9.76	17.43	20.93	100.00
United Kingdom	3.17	0.40	21.24	2.78	5.55	11.83	7.55	21.39	26.09	100.00
United States	1.80	3.97	21.78	2.58	5.54	13.64	7.78	21.85	21.06	99.70
West Germany	1.99	2.03	18.68	2.49	4.51	15.67	6.76	24.30	23.28	100.00
Average	3.64	2.54	21.71	2.64	5.98	13.79	7.51	21.05	21.12	99.98
Weighted Avg.	2.53	2.63	19.65	2.55	5.11	14.27	7.16	23.33	22.67	99.90
	Adjusted Sector Output Shares									
Austria	4.36	0.28	9.67	1.50	13.69	15.81	5.36	37.63	11.70	100.00
Belgium	1.95	0.07	9.27	1.07	8.71	12.15	3.93	50.15	12.69	100.00
Canada	5.34	7.47	16.60	3.09	5.94	13.06	7.22	21.25	20.02	100.00
Finland	7.12	0.28	13.52	1.48	9.48	13.03	6.83	34.89	13.36	100.00
France	3.86	0.00	16.12	1.83	8.17	11.56	5.69	34.00	18.77	100.00
Italy	2.71	1.02	25.37	1.90	9.52	10.90	6.03	23.10	19.45	100.00
South Korea	5.25	0.43	21.63	1.57	11.05	14.02	5.61	24.41	16.03	100.00
Norway	10.65	0.52	23.69	1.25	12.07	14.69	6.11	17.72	13.29	100.00
Sweden	4.79	11.82	12.70	2.32	5.02	10.74	10.87	19.06	22.68	100.00
United Kingdom	2.62	0.38	19.64	2.13	10.23	12.02	5.62	26.55	20.80	100.00
United States	2.46	3.16	13.19	1.53	7.28	16.37	5.20	36.22	14.59	100.00
West Germany	1.13	1.88	10.86	1.68	8.62	17.88	4.35	39.83	13.75	100.00
Average	4.35	2.28	16.02	1.78	9.15	13.52	6.07	30.40	16.43	100.00
Weighted Avg.	2.39	2.03	13.74	1.78	8.68	15.21	5.29	34.95	15.94	100.00
	Change in Output Shares after Adjustment to Sector Best-Practice Frontier									
Austria	1.47	-0.21	-11.14	-1.31	6.24	-1.31	-2.15	17.68	-9.26	0.00
Belgium	0.03	-0.24	-11.42	-2.00	3.59	-1.61	-2.96	25.48	-10.87	0.00
Canada	2.20	2.31	-1.06	-0.02	-0.21	-0.71	-0.32	-0.98	-1.21	0.00
Finland	1.01	-0.11	-10.71	-1.10	3.49	0.56	-2.40	17.31	-8.06	0.00
France	0.19	0.00	-4.71	-0.57	2.66	-1.25	-0.81	7.52	-3.03	0.00
Italy	0.98	0.11	-4.45	-0.50	3.69	-0.52	0.03	1.07	-0.42	0.00
South Korea	1.25	-0.11	-2.30	-0.37	5.06	-3.05	-1.65	3.77	-2.61	0.00
Norway	0.67	-0.47	-4.07	-1.24	2.77	1.15	-1.17	3.62	-1.26	0.00
Sweden	1.55	-3.46	-0.41	-0.65	0.18	-1.70	1.11	1.63	1.75	0.00
United Kingdom	-0.56	-0.01	-1.60	-0.64	4.67	0.19	-1.92	5.16	-5.29	0.00
United States	0.66	-0.81	-8.59	-1.05	1.74	2.73	-2.58	14.37	-6.47	0.00
West Germany	-0.87	-0.14	-7.81	-0.81	4.12	2.21	-2.41	15.53	-9.53	0.30
Average	0.72	-0.26	-5.69	-0.86	3.17	-0.28	-1.44	9.35	-4.69	0.02
Weighted Avg.	-0.14	-0.60	-5.92	-0.77	3.57	0.94	-1.87	11.62	-6.73	0.10

Only the Construction, Wholesale and Retail Trade, and F.I.RE sectors increase their shares of aggregate output after the sectors have been adjusted to their respective best-practice frontiers. These sectors' combined increase of 16.13% of aggregate output was largely at the expense of the Manufacturing (-5.92%) and Community, Social, and Personal Services (-6.73). That the Manufacturing sector comprises a smaller share of aggregate output on the better technology frontier is in line with this sector's observed decreasing importance over time among the countries in this sample. Table 5.11 shows how each sector's share of aggregate output has changed on average over time in the sample.

Table 5.11. Average Sector Shares 1980-2000

Year	Agriculture	Mining and Quarrying	Total Manufacturing	Electricity, Gas, and Water Supply	Construction	Wholesale and Retail Trade	Transportation and Communication	Finance, Insurance, and Real Estate	Community, Social, and Personal Services	Total
1980	5.92	3.53	24.13	2.36	6.64	13.72	7.73	16.51	19.30	99.85
1981	5.54	4.00	23.57	2.55	6.35	13.41	7.72	16.86	19.91	99.90
1982	5.43	4.03	22.86	2.65	6.29	13.49	7.68	17.21	20.36	99.99
1983	5.03	4.13	22.73	2.78	6.16	13.45	7.53	17.70	20.35	99.86
1984	4.93	4.32	23.07	2.76	5.98	13.50	7.51	17.80	20.07	99.95
1985	4.54	3.92	22.85	2.87	5.76	13.53	7.39	18.55	20.55	99.97
1986	4.28	2.28	22.83	2.93	5.85	14.19	7.52	19.30	20.73	99.91
1987	3.98	2.12	22.72	2.91	5.95	14.32	7.41	19.82	20.77	99.99
1988	3.83	1.77	22.87	2.75	6.19	14.27	7.47	20.30	20.62	100.07
1989	3.80	2.00	22.41	2.64	6.37	14.03	7.45	20.66	20.61	99.97
1990	3.62	2.16	21.53	2.56	6.52	13.97	7.46	21.08	21.04	99.95
1991	3.29	2.03	20.53	2.66	6.39	13.98	7.63	21.70	21.76	99.97
1992	3.31	2.08	19.41	2.74	6.16	13.96	7.79	22.02	22.47	99.93
1993	3.18	2.06	19.39	2.74	5.76	13.79	7.81	22.70	22.47	99.91
1994	3.20	2.09	19.92	2.66	5.67	13.83	7.73	22.68	22.15	99.92
1995	3.06	2.11	20.61	2.64	5.58	13.77	7.57	22.79	21.83	99.96
1996	2.92	2.54	19.94	2.60	5.60	13.61	7.50	23.31	21.93	99.96
1997	2.75	2.51	20.06	2.52	5.60	13.65	7.56	23.71	21.61	99.96
1998	2.65	1.84	20.25	2.47	5.54	13.70	7.72	24.25	21.61	100.03
1999	2.56	2.18	19.98	2.36	5.49	13.75	7.63	24.54	21.55	100.04
2000	2.37	3.38	19.79	2.15	5.50	13.37	7.54	24.49	21.56	100.16

Conclusion

As frontier estimation techniques have become increasingly popular for examining production in aggregate economies, it is important to evaluate whether the aggregate frontiers currently employed adequately capture the richness of the various heterogeneous production processes subsumed in aggregate measures. Demonstrating that frontiers estimated with aggregate measures of output that are characterized by multiple outputs of heterogeneous technology are downward biased, we propose a better frontier constructed with sector data that explicitly addresses the underlying technologies while avoiding the complications of direct multi-output estimation.

Applying our better frontier to an unbalanced sample of 12 OECD countries from 1980-2001, we reveal that traditional frontiers estimated with aggregate measures of output underestimate the available best-practice technology from 10.36%-134.80%, with an average underestimation of 53.96%. The previously unmeasured increased output potential present within the sample countries is largely due to inefficiency in the sectors possessing both the largest returns from labor and increasing returns-to-scale. This is consistent with the development of cutting-edge labor-saving technologies, such as information technologies, that have yet to rapidly diffuse. This could explain why a country such the United States, a technology innovator, is determined to be very efficient relative to the traditional aggregate frontier but appears much less efficient when best-practice technologies are applied to all of the other countries in the sample. This link between technology diffusion at the sector level and its effects on aggregate productive efficiency and potential output requires further investigation. Our approach also demonstrates that regions identified as best-practice are also capable of substantial efficiency improvements due to individual sector inefficiencies, which is counter to the interpretation and results of conventional estimates of aggregate frontiers.

While the proposed better frontier allows researchers to more accurately represent the underlying technologies when performing comparisons across regions, its application of best-practice technology within sectors given a region's existing input allocation requires some scrutiny. In long-run equilibrium, the quantities of capital and labor allocated to each of the various sectors are endogenously determined by the value of marginal product of capital and labor within each sector. Once we have scaled sector outputs to the best-practice frontier, these marginal products likely change allowing for additional efficiency gains beyond the estimated better frontier through optimal resource allocation. Frontier estimation techniques that also allow for this allocative efficiency will facilitate more accurate estimates of the true underlying technology frontier and provides an important extension of this research.

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APPENDIX A

COMPLETE ESTIMATES FOR STOCHASTIC FRONTIER MODEL

Table A.1. Maximum Likelihood Estimates for Firm Stochastic Frontier Model

```
Stoc. frontier normal/truncated-normal model      Number of obs    =       6920
                                                  Wald chi2(94)    =  104152.68
Log likelihood =  -5666.791                       Prob > chi2      =     0.0000
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
k	.3341537	.0093667	35.67	0.000	.3157953	.352512
e	.5905485	.0113044	52.24	0.000	.5683923	.6127048
small	-.1533659	.0223894	-6.85	0.000	-.1972484	-.1094834
tdum1	-.0226611	.0287937	-0.79	0.431	-.0790956	.0337735
tdum2	.0405163	.0286402	1.41	0.157	-.0156174	.09665
tdum3	.0388662	.0285345	1.36	0.173	-.0170605	.0947928
tdum4	.0473088	.0284863	1.66	0.097	-.0085232	.1031409
tdum5	.0204056	.0284014	0.72	0.472	-.0352601	.0760713
tdum6	.0449652	.0284656	1.58	0.114	-.0108264	.1007568
tdum7	.0097154	.0284636	0.34	0.733	-.0460722	.065503
tdum8	-.0318898	.0284199	-1.12	0.262	-.0875918	.0238122
tdum9	-.0145974	.0283608	-0.51	0.607	-.0701835	.0409887
sdum1	1.324805	.1462869	9.06	0.000	1.038088	1.611522
sdum2	-.4097547	.1087146	-3.77	0.000	-.6228314	-.1966779
sdum3	.5942316	.1097425	5.41	0.000	.3791403	.8093229
sdum4	.4795475	.1748222	2.74	0.006	.1369023	.8221928
sdum5	-.0858788	.176676	-0.49	0.627	-.4321573	.2603997
sdum6	.2927408	.1751758	1.67	0.095	-.0505975	.6360791
sdum7	-.1505597	.1740657	-0.86	0.387	-.4917223	.1906029
sdum8	-.8181382	.1300465	-6.29	0.000	-1.073025	-.5632518
sdum9	-.4167395	.1143691	-3.64	0.000	-.6408988	-.1925802
sdum10	.0758764	.1051655	0.72	0.471	-.1302442	.281997
sdum11	-.6809994	.1168187	-5.83	0.000	-.9099599	-.4520389
sdum12	.0200626	.1354578	0.15	0.882	-.2454298	.285555
sdum13	-.1833849	.1772841	-1.03	0.301	-.5308553	.1640855
sdum14	-.1865388	.1755467	-1.06	0.288	-.530604	.1575263
sdum15	-.4602565	.1078729	-4.27	0.000	-.6716834	-.2488296
sdum16	-.4405218	.1750058	-2.52	0.012	-.783527	-.0975167
sdum17	.1228896	.0879602	1.40	0.162	-.0495092	.2952885
sdum18	.1006895	.1750611	0.58	0.565	-.2424239	.443803
sdum19	.0142117	.1757062	0.08	0.936	-.330166	.3585895
sdum20	-.0040684	.0878603	-0.05	0.963	-.1762715	.1681346
sdum21	-.1336142	.0885535	-1.51	0.131	-.3071758	.0399474
sdum22	.4823874	.0705528	6.84	0.000	.3441065	.6206683
sdum23	.7577255	.0819406	9.25	0.000	.5971249	.918326
sdum24	.1243337	.1139581	1.09	0.275	-.09902	.3476874
sdum25	.255416	.1048837	2.44	0.015	.0498477	.4609843
sdum26	.5689419	.1345718	4.23	0.000	.305186	.8326979
sdum27	.1950432	.0842697	2.31	0.021	.0298776	.3602089
sdum28	.3906196	.1183828	3.30	0.001	.1585936	.6226455
sdum29	.38132	.1745184	2.18	0.029	.0392703	.7233697
sdum30	.1112352	.1363484	0.82	0.415	-.1560029	.3784732
sdum31	.96432	.1367243	7.05	0.000	.6963454	1.232295

sdum32	-1.102132	.175597	-6.28	0.000	-1.446295	-.7579677
sdum33	-.2055781	.0802969	-2.56	0.010	-.3629571	-.0481992
sdum34	-.32916	.1727197	-1.91	0.057	-.6676844	.0093644
sdum35	-.5981888	.1746632	-3.42	0.001	-.9405224	-.2558552
sdum36	-.2597112	.1140716	-2.28	0.023	-.4832874	-.0361349
sdum37	-.3734563	.1160201	-3.22	0.001	-.6008516	-.146061
sdum38	-.5702668	.098756	-5.77	0.000	-.763825	-.3767086
sdum39	-.9507973	.1309563	-7.26	0.000	-1.207467	-.6941275
sdum40	-.4989846	.1323912	-3.77	0.000	-.7584665	-.2395026
sdum41	-.3728312	.0944198	-3.95	0.000	-.5578906	-.1877717
sdum42	-.1432391	.1727347	-0.83	0.407	-.4817929	.1953147
sdum43	-.5549083	.172344	-3.22	0.001	-.8926963	-.2171202
sdum44	-.6728648	.1311155	-5.13	0.000	-.9298464	-.4158833
sdum45	.1986972	.0958598	2.07	0.038	.0108155	.386579
sdum46	-.4946054	.0937469	-5.28	0.000	-.6783459	-.3108649
sdum47	-.4890615	.1699783	-2.88	0.004	-.8222129	-.1559101
sdum48	-.2245271	.1727119	-1.30	0.194	-.5630362	.113982
sdum49	-.4287704	.1332674	-3.22	0.001	-.6899696	-.1675712
sdum50	-.3154225	.0995193	-3.17	0.002	-.5104769	-.1203682
sdum51	-.2534618	.1138085	-2.23	0.026	-.4765225	-.0304012
sdum52	-.2712441	.1140054	-2.38	0.017	-.4946905	-.0477977
sdum53	-.3006498	.07988	-3.76	0.000	-.4572118	-.1440878
sdum54	.0523399	.0945985	0.55	0.580	-.1330696	.2377495
sdum55	.3042164	.0731235	4.16	0.000	.1608969	.4475359
sdum56	.1266318	.0794182	1.59	0.111	-.029025	.2822885
sdum57	.5624565	.0697772	8.06	0.000	.4256957	.6992173
sdum58	-.34486	.0861827	-4.00	0.000	-.513775	-.1759451
sdum59	-.3626616	.1306871	-2.78	0.006	-.6188036	-.1065195
sdum60	-.0214159	.177161	-0.12	0.904	-.3686451	.3258132
sdum61	-.4356212	.0907894	-4.80	0.000	-.6135652	-.2576773
sdum62	-.1655728	.0816118	-2.03	0.042	-.325529	-.0056167
sdum63	-.1338511	.1315967	-1.02	0.309	-.3917759	.1240736
sdum64	.0263946	.0877631	0.30	0.764	-.1456179	.198407
sdum65	.4350196	.1008857	4.31	0.000	.2372873	.6327518
sdum66	.2835825	.0695895	4.08	0.000	.1471896	.4199755
sdum67	.1438372	.0690739	2.08	0.037	.0084548	.2792196
sdum68	-.0707683	.0838055	-0.84	0.398	-.2350241	.0934875
sdum69	-.430666	.0785673	-5.48	0.000	-.5846552	-.2766769
sdum70	-.4022083	.0886204	-4.54	0.000	-.5759011	-.2285156
sdum71	-.9022079	.1320596	-6.83	0.000	-1.16104	-.6433758
sdum72	-.2283485	.1733863	-1.32	0.188	-.5681795	.1114824
sdum73	.4504347	.1744185	2.58	0.010	.1085807	.7922888
sdum74	-.6967847	.1309457	-5.32	0.000	-.9534336	-.4401358
sdum75	.0839505	.1174389	0.71	0.475	-.1462255	.3141265
sdum76	-.0539337	.0817576	-0.66	0.509	-.2141756	.1063082
sdum77	.2779873	.0690879	4.02	0.000	.1425775	.413397
sdum78	.2586738	.0691028	3.74	0.000	.1232349	.3941128
sdum79	-.0672409	.1172882	-0.57	0.566	-.2971216	.1626397
sdum80	.4244872	.0942863	4.50	0.000	.2396893	.609285
sdum81	.2922934	.088213	3.31	0.001	.119399	.4651878
sdum82	.210582	.1741091	1.21	0.226	-.1306656	.5518295
_cons	3.240313	.08304	39.02	0.000	3.077558	3.403069
/mu	-.7364682	.1315457	-5.60	0.000	-.994293	-.4786434
/lnsigma2	-.1849303	.0605822	-3.05	0.002	-.3036691	-.0661914
/ilgtgamma	1.40845	.0951902	14.80	0.000	1.221881	1.595019
sigma2	.8311623	.0503536			.738105	.9359517
gamma	.8035214	.0150281			.7723943	.8313211
sigma_u2	.6678566	.0515824			.5667569	.7689563
sigma_v2	.1633056	.0064598			.1506446	.1759666

H0: No inefficiency component: z = -25.325 Prob<=z = 0.000

APPENDIX B

MAXIMUM LIKELIHOOD ESTIMATES FOR ALL MODEL SPECIFICATIONS FOR EACH SECTOR AND AGGREGATE VALUE ADDED

Table B.1. Maximum Likelihood Estimates for Aggregate Value Added

	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4
K	3.082 (0.836)	3.137 (0.883)	0.801 (1.085)	0.692 (0.054)	0.670 (0.049)
E	-4.939 (1.535)	-4.316 (1.261)	3.286 (2.349)	0.511 (0.255)	0.674 (0.168)
T	0.123 (0.043)	0.063 (0.007)	-	0.012 (0.004)	-
KE	-0.301 (0.161)	-0.315 (0.160)	-0.102 (0.166)	-	-
KT	-0.007 (0.005)	-	-	-	-
ET	0.003 (0.005)	-	-	-	-
K^2	0.044 (0.077)	0.047 (0.076)	0.066 (0.070)	-	-
E^2	0.934 (0.258)	0.892 (0.257)	-0.099 (0.354)	-	-
T^2	-0.004 (0.001)	-0.005 (0.001)	-	-	-
Constant	10.97 (9.369)	7.594 (7.836)	-16.823 (10.999)	-0.785 (2.083)	136.163 (1428.075)
μ	-689.891 (9560.152)	-344.007 (2594.183)	0.908 (0.311)	0.550 (0.567)	138.769 (1428.049)
η	-0.013 (0.011)	-0.001 (0.006)	0.007 (0.003)	-0.009 (0.008)	0.000 (0.000)
σ^2	350.60 (4851.945)	152.390 (1146.881)	0.286 (0.168)	0.305 (0.242)	0.204 (0.084)
γ	1.000 (0.001)	1.000 (0.001)	0.905 (0.057)	0.910 (0.072)	0.865 (0.058)
σ_u^2	350.588 (4851.945)	152.369 (1146.881)	0.259 (0.169)	0.277 (0.242)	0.176 (0.085)
σ_v^2	0.021 (0.002)	0.021 (0.002)	0.027 (0.003)	0.028 (0.003)	0.027 (0.002)
Log-Likelihood	92.144889	90.893300	58.782992	60.165496	59.05365

Table B.2. Maximum Likelihood Estimates for Agriculture Sector

	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4
K	-0.021 (0.968)	0.489 (0.748)	3.016 (0.871)	0.500 (0.040)	0.464 (0.046)
E	-7.800 (3.824)	-2.875 (1.928)	-0.772 (1.822)	0.241 (0.095)	0.080 (0.099)
T	-0.069 (0.123)	0.074 (0.008)	-	0.305 (0.070)	-
KE	0.104 (0.081)	0.020 (0.054)	-0.040 (0.064)	-	-
KT	0.009 (0.007)	-	-	-	-
ET	0.005 (0.007)	-	-	-	-
K^2	-0.027 (0.060)	-0.009 (0.055)	-0.219 (0.059)	-	-
E^2	0.911 (0.410)	0.407 (0.238)	0.175 (0.195)	-	-
T^2	-0.006 (0.001)	-0.006 (0.001)	-	-	-
Constant	36.787 (17.902)	14.170 (7.754)	-4.119 (9.430)	18.932 (7.234)	5.537 (1.166)
μ	0.086 (1.124)	-1.287 (5.112)	1.459 (0.342)	22.373 (8.425)	1.039 (0.323)
η	0.014 (0.013)	-0.002 (0.005)	-0.003 (0.002)	-0.016 (0.003)	-0.005 (0.003)
σ^2	0.725 (0.904)	1.879 (3.756)	0.526 (0.253)	1.223 (0.598)	0.470 (0.258)
γ	0.969 (0.039)	0.988 (0.024)	0.942 (0.028)	0.981 (0.010)	0.931 (0.039)
σ_u^2	0.702 (0.904)	1.856 (3.756)	0.496 (0.253)	1.199 (0.598)	0.437 (0.258)
σ_v^2	0.023 (0.002)	0.023 (0.002)	0.030 (0.003)	0.024 (0.002)	0.033 (0.003)
Log-Likelihood	78.32271	77.554582	43.150725	65.535107	36.598313

Table B.3. Maximum Likelihood Estimates for Mining and Quarrying Sector

	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4
K	1.267 (0.196)	0.880 (0.178)	1.042 (0.275)	0.759 (0.022)	0.584 (0.074)
E	-2.777 (0.564)	-1.296 (0.423)	-1.760 (0.335)	0.234 (0.058)	0.224 (0.065)
T	0.342 (0.074)	-0.021 (0.014)	-	-0.022 (0.008)	-
KE	-0.219 (0.026)	-0.148 (0.025)	-0.139 (0.024)	-	-
KT	-0.049 (0.004)	-	-	-	-
ET	0.036 (0.012)	-	-	-	-
K^2	0.053 (0.017)	0.068 (0.022)	0.005 (0.026)	-	-
E^2	0.946 (0.131)	0.592 (0.107)	0.666 (0.086)	-	-
T^2	0.010 (0.002)	-0.001 (0.001)	-	-	-
Constant	8.285 (1.492)	4.138 (1.160)	7.805 (1.800)	1.339 (0.321)	3.477 (1.107)
μ	3.718 (1.816)	0.057 (0.439)	1.965 (0.512)	0.252 (0.324)	1.196 (0.472)
η	-0.060 (0.004)	0.037 (0.012)	-0.006 (0.002)	0.021 (0.012)	-0.008 (0.004)
σ^2	11.711 (8.798)	0.146 (0.110)	1.353 (0.867)	0.201 (0.127)	0.551 (0.395)
γ	0.997 (0.002)	0.591 (0.309)	0.963 (0.024)	0.641 (0.228)	0.876 (0.092)
σ_u^2	11.678 (8.798)	0.086 (0.110)	1.304 (0.868)	0.129 (0.127)	0.483 (0.396)
σ_v^2	0.033 (0.003)	0.060 (0.006)	0.050 (0.005)	0.072 (0.007)	0.068 (0.007)
Log-Likelihood	20.129558	-18.408077	-14.569938	-39.839707	-40.710821

Table B.4. Maximum Likelihood Estimates for Manufacturing Sector

	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4
K	0.576 (1.122)	-0.117 (0.806)	1.510 (0.737)	0.634 (0.054)	0.602 (0.046)
E	-5.431 (2.638)	-1.160 (2.413)	-1.394 (2.414)	0.783 (0.141)	0.842 (0.131)
T	-0.041 (0.082)	0.065 (0.008)	-	0.017 (0.005)	-
KE	-0.038 (0.097)	0.020 (0.094)	-0.083 (0.076)	-	-
KT	-0.008 (0.004)	-	-	-	-
ET	0.024 (0.013)	-	-	-	-
K^2	0.038 (0.078)	0.047 (0.046)	-0.018 (0.049)	-	-
E^2	0.781 (0.330)	0.218 (0.284)	0.371 (0.295)	-	-
T^2	-0.004 (0.001)	-0.005 (0.001)	-	-	-
Constant	24.363 (11.302)	10.425 (11.482)	376.259 (10.799)	-1.701 (0.877)	453.402 (0.980)
μ	0.815 (0.713)	0.929 (0.338)	374.230 (.)	0.905 (0.300)	455.834 (.)
η	-0.016 (0.010)	0.003 (0.004)	0.000 (0.000)	-0.007 (0.006)	0.000 (0.000)
σ^2	0.805 (0.702)	0.362 (0.208)	0.250 (0.105)	0.337 (0.189)	0.270 (0.113)
γ	0.977 (0.020)	0.949 (0.030)	0.902 (0.043)	0.926 (0.042)	0.908 (0.040)
σ_u^2	0.787 (0.702)	0.344 (0.208)	0.225 (0.105)	0.312 (0.189)	0.246 (0.113)
σ_v^2	0.018 (0.002)	0.019 (0.002)	0.025 (0.002)	0.025 (0.002)	0.025 (0.002)
Log-Likelihood	100.234240	99.313831	69.508148	69.338421	68.275123

Table B.5. Maximum Likelihood Estimates for Electricity, Gas, and Water Supply Sector

	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4
K	1.260 (0.224)	0.941 (0.232)	0.376 (0.259)	0.689 (0.038)	0.903 (0.044)
E	-0.241 (0.316)	0.130 (0.347)	1.722 (0.322)	0.421 (0.056)	0.298 (0.070)
T	0.215 (0.036)	0.087 (0.008)	-	0.165 (0.038)	-
KE	-0.105 (0.043)	-0.057 (0.046)	0.105 (0.047)	-	-
KT	-0.015 (0.005)	-	-	-	-
ET	0.008 (0.005)	-	-	-	-
K^2	0.343 (0.132)	0.177 (0.139)	-0.487 (0.136)	-	-
E^2				-	-
T^2	-0.004 (0.001)	-0.005 (0.001)	-	-	-
Constant	-1.722 (1.063)	-0.578 (1.090)	-2.277 (1.329)	2.621 (1.855)	-1.253 (0.454)
μ	-675.048 (2813.352)	-557.980 (.)	-0.027 (0.293)	5.916 (2.417)	0.204 (0.131)
η	-0.041 (0.008)	-0.015 (0.007)	0.079 (0.015)	-0.033 (0.008)	0.052 (0.021)
σ^2	439.933 (1835.033)	226.426 (3.521)	0.061 (0.032)	0.435 (0.206)	0.052 (0.008)
γ	1.000 (0.000)	1.000 (0.000)	0.363 (0.332)	0.939 (0.030)	0.191 (0.106)
σ_u^2	439.909 (1835.033)	226.400 (3.521)	0.022 (0.032)	0.408 (0.206)	0.010 (0.007)
σ_v^2	0.024 (0.002)	0.026 (0.002)	0.039 (0.004)	0.027 (0.003)	0.042 (0.004)
Log-Likelihood	78.355083	72.701249	29.679370	60.699266	22.87146

Table B.6. Maximum Likelihood Estimates for Construction Sector

	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4
K	1.868 (0.552)	0.929 (0.712)	3.315 (0.800)	0.500 (0.060)	0.498 (0.059)
E	-3.505 (2.343)	1.005 (1.663)	-1.681 (1.589)	1.079 (0.111)	1.086 (0.109)
T	0.068 (0.039)	0.073 (0.009)	-	0.011 (0.006)	-
KE	-0.399 (0.094)	-0.173 (0.101)	-0.344 (0.107)	-	-
KT	-0.022 (0.005)	-	-	-	-
ET	0.031 (0.009)	-	-	-	-
K^2	0.190 (0.062)	0.087 (0.056)	-0.026 (0.069)	-	-
E^2	1.075 (0.332)	0.233 (0.284)	0.778 (0.264)	-	-
T^2	-0.005 (0.001)	-0.006 (0.001)	-	-	-
Constant	8.727 (8.398)	-3.353 (4.782)	-4.012 (4.985)	-1.342 (0.655)	70.288 (819.528)
μ	-0.066 (2.181)	0.896 (0.460)	-1.252 (5.768)	1.098 (0.360)	72.659 (819.559)
η	-0.023 (0.009)	0.007 (0.004)	0.005 (0.004)	-0.001 (0.005)	0.000 (0.001)
σ^2	2.059 (2.557)	0.632 (0.424)	1.633 (3.711)	0.624 (0.367)	0.466 (0.185)
γ	0.986 (0.017)	0.952 (0.032)	0.975 (0.057)	0.934 (0.039)	0.912 (0.036)
σ_u^2	2.031 (2.557)	0.602 (0.424)	1.592 (3.711)	0.583 (0.367)	0.425 (0.185)
σ_v^2	0.028 (0.003)	0.030 (0.003)	0.041 (0.004)	0.041 (0.004)	0.041 (0.004)
Log-Likelihood	52.264553	43.996874	13.051365	9.439514	8.9496284

Table B.7. Maximum Likelihood Estimates for Wholesale and Retail Trade Sector

	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4
K	3.009 (.)	-0.397 (1.448)	-0.322 (1.200)	0.555 (0.055)	0.570 (0.053)
E	-4.693 (.)	3.503 (4.058)	2.797 (3.351)	0.634 (0.182)	0.658 (0.177)
T	1.805 (0.015)	0.047 (0.010)	-	0.005 (0.004)	-
KE	0.871 (0.077)	0.119 (0.203)	0.156 (0.201)	-	-
KT	-0.111 (0.005)	-	-	-	-
ET	-0.070 (0.006)	-	-	-	-
K^2	-0.554 (0.061)	-0.009 (0.070)	-0.039 (0.062)	-	-
E^2	-0.816 (0.096)	-0.481 (0.672)	-0.449 (0.593)	-	-
T^2	-0.016 (0.001)	-0.004 (0.001)	-	-	-
Constant	2.829 (.)	-6.648 (11.212)	-4.125 (9.979)	0.522 (1.174)	0.215 (1.124)
μ	-0.486 (.)	0.191 (1.572)	0.519 (0.598)	0.277 (0.972)	0.402 (0.697)
η	0.118 (0.003)	0.000 (0.007)	-0.005 (0.004)	-0.009 (0.005)	-0.005 (0.003)
σ^2	0.038 (.)	0.766 (1.088)	0.530 (0.443)	0.736 (0.756)	0.602 (0.541)
γ	0.170 (.)	0.967 (0.047)	0.943 (0.048)	0.959 (0.042)	0.950 (0.045)
σ_u^2	0.006 (.)	0.741 (1.088)	0.500 (0.443)	0.706 (0.756)	0.572 (0.541)
σ_v^2	0.031 (.)	0.025 (0.002)	0.030 (0.003)	0.030 (0.003)	0.030 (0.003)
Log-Likelihood	-4626.243100	65.717071	48.202504	48.561472	47.886459

Table B.8. Maximum Likelihood Estimates for Transportation and Communication Sector

	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4
K	-0.588 (0.636)	-1.774 (0.769)	1.051 (0.907)	0.553 (0.054)	0.651 (0.059)
E	3.326 (2.267)	4.118 (1.960)	-1.409 (1.958)	0.619 (0.126)	0.442 (0.097)
T	-0.008 (0.046)	0.069 (0.009)	-	-0.344 (0.080)	-
KE	-0.061 (0.154)	0.035 (0.148)	0.146 (0.166)	-	-
KT	0.004 (0.004)	-	-	-	-
ET	0.005 (0.006)	-	-	-	-
K^2	0.146 (0.092)	0.195 (0.088)	-0.127 (0.123)	-	-
E^2	-0.302 (0.369)	-0.519 (0.368)	0.012 (0.356)	-	-
T^2	-0.007 (0.001)	-0.007 (0.001)	-	-	-
Constant	-3.023 (7.174)	-0.387 (4.847)	5.210 (4.343)	28.483 (11.356)	0.540 (0.516)
μ	-0.540 (2.542)	0.593 (0.281)	-3.225 (19.922)	21.657 (9.606)	-1.517 (6.385)
η	0.020 (0.010)	0.019 (0.006)	0.005 (0.009)	0.014 (0.003)	0.010 (0.004)
σ^2	0.636 (1.233)	0.233 (0.174)	1.331 (6.680)	0.777 (0.441)	1.012 (2.708)
γ	0.962 (0.073)	0.898 (0.077)	0.973 (0.138)	0.966 (0.020)	0.965 (0.095)
σ_u^2	0.612 (1.233)	0.210 (0.174)	1.294 (6.680)	0.751 (0.442)	0.976 (2.708)
σ_v^2	0.024 (0.002)	0.024 (0.002)	0.036 (0.004)	0.026 (0.003)	0.036 (0.003)
Log-Likelihood	75.069091	74.545268	33.735901	54.470858	32.990096

Table B.9. Maximum Likelihood Estimates for Finance, Insurance, and Real Estate Sector

	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4
K	0.974 (0.800)	0.030 (0.737)	-0.300 (0.653)	0.326 (0.069)	0.330 (0.067)
E	1.643 (0.687)	1.528 (0.709)	2.120 (0.706)	1.063 (0.138)	1.044 (0.110)
T	-0.038 (0.046)	0.051 (0.011)	-	-0.001 (0.005)	-
KE	-0.142 (0.113)	-0.003 (0.094)	0.105 (0.090)	-	-
KT	0.008 (0.004)	-	-	-	-
ET		-	-	-	-
K^2	0.025 (0.073)	0.024 (0.073)	-0.014 (0.080)	-	-
E^2	0.125 (0.186)	-0.065 (0.174)	-0.309 (0.158)	-	-
T^2	-0.005 (0.001)	-0.005 (0.001)	-	-	-
Constant	-4.569 (3.158)	0.599 (2.329)	0.284 (2.181)	0.398 (0.626)	0.479 (0.518)
μ	-7.078 (.)	-0.005 (1.860)	0.260 (1.273)	0.523 (0.921)	0.509 (0.936)
η	0.012 (0.004)	0.008 (0.004)	0.006 (0.003)	0.004 (0.003)	0.004 (0.003)
σ^2	6.944 (2.295)	1.370 (1.789)	1.114 (1.242)	1.056 (1.006)	1.063 (1.018)
γ	0.997 (0.001)	0.983 (0.023)	0.974 (0.029)	0.972 (0.027)	0.972 (0.027)
σ_u^2	6.920 (2.295)	1.346 (1.789)	1.085 (1.242)	1.026 (1.006)	1.033 (1.018)
σ_v^2	0.024 (0.002)	0.024 (0.002)	0.029 (0.003)	0.030 (0.003)	0.030 (0.003)
Log-Likelihood	70.885417	68.99013	47.115843	44.633826	44.607295

Table B.10. Maximum Likelihood Estimates for Community, Social, and Personal Services Sector

	Model 1.0	Model 1.1	Model 1.2	Model 1.3	Model 1.4
K	0.757 (0.605)	1.631 (0.763)	1.331 (0.695)	0.596 (0.051)	0.619 (0.059)
E	2.895 (2.124)	-2.342 (1.053)	-0.314 (1.567)	0.770 (0.121)	0.631 (0.152)
T	-0.094 (0.057)	0.073 (0.008)	-	-0.211 (0.047)	-
KE	-0.134 (0.091)	-0.247 (0.097)	0.059 (0.108)	-	-
KT	0.007 (0.004)	-	-	-	-
ET	0.008 (0.006)	-	-	-	-
K^2	0.083 (0.072)	0.098 (0.070)	-0.107 (0.073)	-	-
E^2	-0.090 (0.297)	0.640 (0.205)	0.030 (0.259)	-	-
T^2	-0.006 (0.001)	-0.006 (0.001)	-	-	-
Constant	-10.592 (8.577)	7.087 (3.280)	-0.442 (4.544)	10.116 (4.668)	-0.499 (0.916)
μ	0.238 (0.492)	-72.673 (837.405)	0.570 (0.263)	8.077 (3.599)	0.585 (0.255)
η	0.028 (0.010)	0.007 (0.007)	0.007 (0.004)	0.022 (0.005)	0.008 (0.004)
σ^2	0.263 (0.257)	30.022 (341.933)	0.189 (0.133)	0.301 (0.155)	0.196 (0.113)
γ	0.917 (0.082)	0.999 (0.009)	0.835 (0.119)	0.920 (0.043)	0.839 (0.095)
σ_u^2	0.242 (0.258)	29.998 (341.933)	0.158 (0.134)	0.277 (0.155)	0.164 (0.113)
σ_v^2	0.022 (0.002)	0.023 (0.002)	0.031 (0.003)	0.024 (0.002)	0.031 (0.003)
Log-Likelihood	84.252941	81.53544	46.836986	67.744752	45.469704