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THE COMPONENTS OF OUTPUT GROWTH: A CROSS-COUNTRY ANALYSIS

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THE COMPONENTS OF OUTPUT GROWTH:

A CROSS-COUNTRY ANALYSIS

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ABSTRACT: This paper uses a stochastic frontier analysis to investigate sources of output and productivity growth in 17 OECD countries. Empirical results indicate that no one individual component predominates as an explanation of output growth; and in this sense, we conclude that no single key explanation exists as to why countries grow. Overall, input and technical change explain most of the output growth observed in our sample of countries. Efficiency growth also appears to play an important role in several low to middle income countries. Our conclusions, however, must be qualified by the fact that our estimates of the components of output growth have substantial standard deviations and that several findings are sensitive to changes in model structure.

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1. Introduction

Comparable economic agents can be assumed to operate according to a common technology. This, at least, is the idea that underlies the literature on production frontiers for firms in a given industry ("frontier" here meaning the maximum technically feasible output given inputs). This idea can also be applied in a macroeconomic context in which countries are producers of output (e.g. GDP) given inputs (e.g. capital and labor). Accordingly, countries can be thought of as operating either on or within the frontier; and the distance from the frontier as reflecting inefficiency. Over time, a country can become less inefficient and "catch up" to the frontier or the frontier itself can shift over time, indicating technical progress. In addition, a country can move along the frontier by changing inputs. Hence output growth can be thought of in terms of three different components: efficiency change, technical change and input change. Economists often refer to the first two components collectively as "productivity change".

This decomposition provides a framework for addressing a number of questions that lie at the heart of many modern macroeconomic debates. Typically, such issues involve answering questions like: Which countries are making most efficient use of their inputs? Is economic growth driven by countries removing inefficiencies and moving closer to the world production frontier? Or is it driven by movements of or along the frontier itself? These questions are especially topical in light of recent research into issues of country convergence ((Barro (1991) and Barro and Sala-i-Martin (1992)) and endogenous growth (Romer (1993, 1994)). For instance, if countries are lying on or near different parts of the frontier, then observed differences in GDP per capita should be due largely to input mix. Policies that prescribe increases in incomes should then focus on changing the input mix, perhaps by increasing the stock of capital. On the other hand, if inefficiencies are found to play a role, policy prescriptions should stress the need for improvements in productive efficiency (eg. improving the legal system, establishing political and macroeconomic stability, welcoming transnational corporations with greater organizational skills, and so on).

At the outset, an important distinction must be made. We do not attempt to explain growth in terms of explanatory variables, as e.g. in Barro (1991), but rather to decompose it into its constituent components. Whereas Barro and Sala-i-Martin (1992) find evidence of unconditional convergence across 48 U.S. states, Barro (1991) can not achieve this conclusion on the basis of a much more heterogeneous sample of countries. Similarly, our data do not suggest such unconditional convergence. Figure 1 plots 1979 GDP per capita levels against actual growth of GDP per capita. The straight line indicates the OLS linear regression line. An examination of this figure indicates that there is no evidence of convergence (termed β-convergence in Barro and Sala-i-Martin (1992)) of GDP for this set of countries over the admittedly short time span encompassed by this study. Some countries that were relatively poor in 1979 saw GDP per capita grow very rapidly (Japan and Finland) but some poor countries also grew relatively slowly (Greece and Ireland). Similarly, there were some rich countries which grew quickly (U.S., Canada, Australia and Norway) but also some (Germany and France) which exhibited slow growth.

In this paper, we attempt to shed light on some of these wider macroeconomic questions by examining changing productivity patterns within a subset of OECD countries. We have chosen our countries under the reasonable assumption that these would have access to a common technology, and thus, possess a common production frontier.[1] Empirical results based on a panel of 17 countries for the period indicate that: i) GDP growth occurs to a large extent because of increases in inputs and technical change but efficiency growth also appears to play an important role in explaining productivity growth in a few countries (U.K., Italy, Japan, Finland and, to a lesser extent, Sweden). In

[1]This is not to assume that this frontier applies necessarily to countries very different from those in our sample. However, with some abuse of terminology, we shall call the frontier a "world frontier".

particular, Japan and Finland, among the poorest countries in 1979, achieved respectively about 20% and 10% of their subsequent fast growth by improving efficiency. The U.K. derives about half its GDP growth from efficiency increases. However, poor countries (e.g. Ireland and Greece) are not necessarily inefficient so that a policy focused on improving efficiency in poor countries is no panacea for economic growth. ii) Economies with high levels of per capita GDP find most of their GDP growth in input changes. For these countries, input growth provides a substantial explanation for both high and low rates of overall GDP growth. iii) Technical change varies across countries and occurs in a way which seems uniformly beneficial to rich and poor countries alike. But the poorest countries (Greece and Ireland), which benefitted from technical change, also suffered the most severe losses in efficiency levels in the period under study.
iv) The marginal productivity of labor with respect to the marginal productivity of capital decreased slowly over the sample period in the U.S., where only moderate growth of the capital-labor ratio occurred. v) Although very low (with some growth over the period) for Japan, the efficiency level for the U.S. was very high and constant. vi) Huge differences between countries exist in elasticities of labor and capital, but returns to scale seems very constant across countries, always indicating increasing returns to scale. Over time, these returns to scale seem to decrease somewhat. vii) Overall, few general lessons can be learned, either from countries that achieved fast growth or from those that stagnated during the time period of the study. Indeed, each of the three components of GDP growth are important in explaining observed successes and failures in countries over time.

These conclusions are based on a Bayesian stochastic frontier analysis developed in this paper, partly building on our earlier work with individual effects models (see Koop, Osiewalski and Steel (1994)). The analysis enables us to: i) Obtain exact small sample results in a way that is particularly appropriate for the treatment of this paper's very small data set. (ii) Focus on any quantity of interest and derive its full posterior distribution; and in particular, the full posterior distribution of any individual efficiency or function of efficiencies. This focus, in turn, enables us to calculate standard deviations and make inferences about whether one country's efficiency change, say, is statistically different from that of another. An analysis using classical econometric methods could not allow for inferences on inefficiencies to be made in this manner (see van den Broeck, Koop, Osiewalski and Steel (1994)). (iii) Easily integrate out parameters since each is assigned a probability distribution. Thus, we can take into account parameter uncertainty, a characteristic which is bound to be important since the small sample size will tend to prohibit precise estimation. iv) Easily impose (unlike classical methods) economic regularity conditions on the production function.

We use recently developed numerical methods based on Markov chain random sampling, in particular, the Gibbs sampler (see e.g. Gelfand and Smith (1990)), to conduct the actual calculations. Note that all models can be easily handled using a 486 personal computer. Details on the Gibbs sampler can be found in the Appendix.

The remainder of the paper is organized as follows: Section 2 briefly compares general methodologies for productivity analysis, and Section 3 formalizes the ideas discussed in the introduction with respect to decomposing output and productivity growth. Section 4 provides the models used in the paper; Section 5 presents our empirical results; and Section 6 concludes and discusses some directions for future research.

2. Methodologies of Productivity Analysis

In a recent article, Fare, Grosskopf, Norris and Zhang (1994) address similar questions from a deterministic angle, applying mathematical programming techniques, known as "Data Envelopment Analysis" (DEA) to the same sample as used in this study. (Fare, Grosskopf and Lovell (1994) provides an excellent summary of DEA methods as applied to production frontiers). In contrast, we use a stochastic frontier analysis which approaches the inference problem using statistical methods. This method is implemented in a composed error framework, pioneered by Meeusen and van den Broeck (1977) and Aigner, Lovell and Schmidt (1977). Let us begin by considering important features of both methods. If we let Y_{ti}, K_{ti} and L_{ti} be real output, capital stock and labor in period t (t=1,..,T) in country i (i=1,..,N), respectively, and assume a frontier common to all countries in a given period, then the types of models considered take the form:

$$Y_{ti}=f_t(K_{ti},L_{ti})\,\tau_{ti}w_{ti}, \tag{1}$$

where τ_{ti} is the efficiency (i.e. $0<\tau_{ti}\leq 1$ and $\tau_{ti}=1$ implies full efficiency) and w_{ti} reflects measurement error. The DEA analysis Fare, Grosskopf, Norris and Zhang carry out assumes implicitly that: i) there is no measurement error (i.e. $w_{ti}=1$); ii) the frontiers are defined by a piecewise linear envelope; and iii) the frontiers are completely unrelated over time.

By way of intuition, consider Figure 2 (adapted from the Fare, Grosskopf, Norris and Zhang study), which plots the DEA frontiers for 1979 and 1988 in the case of constant returns to scale, an assumption that underlies most of their results. In the case of the U.S. the shift in the output-labor ratio between 1979 and 1988 moves the frontier considerably, and this single observation completely determines the frontier for both time periods. Advocates stress that DEA does not require an explicit functional form for the frontier but since it ignores measurement error, a researcher could easily be led astray by outlying observations, as Figure 2 illustrates. For instance, if the US data were subject to measurement error the whole frontier (and thus the efficiency measures of all firms) would be shifted. Britto and Akiba (1993) argue that the capital stock as given by the Penn World Tables (used in the present study and in Fare, Grosskopf, Norris and Zhang) is mismeasured and the U.S. should have a higher capital to labor ratio than Japan. This would clearly induce a dramatic change in the frontier of Figure 2. The sensitivity of DEA to outliers is no doubt one of the biggest weaknesses of the DEA approach Fare, Grosskopf, Norris and Zhang use but other aspects of their study can also be criticised. In particular, many economists would argue that production technology should be smooth and that the piecewise linear function used in DEA is inappropriate. In addition, their assumption that the frontiers are unrelated over time is almost certainly incorrect: From a statistical point of view, imposing structure linking the frontiers over time in some way, should improve estimation of the frontier. (In other words, knowledge of last period's frontier should provide some information about this period's frontier).

In a stochastic frontier analysis, the model has to be entirely specified by making assumptions about functional form and the distribution of efficiency and measurement error. Note that the inclusion of measurement error makes stochastic frontier analysis far less sensitive to outliers. This characteristic is illustrated in Figures 3-8, which present a translog frontier, with exponentially distributed inefficiencies and a Normally distributed measurement error and a separate linear time trend for each coefficient[2]. In Figure 3 we have retained the assumption of constant returns to scale, which underlies Figure 2 as well. We shall subsequently show, however, that this restriction is strongly rejected by the data. Unlike DEA, our stochastic framework makes explicit testing possible. If we impose constant returns to scale anyway, we find that the large difference between the U.S. and other countries is mainly attributed to measurement error and not to changes in scale. This makes the observations for the U.S. appear like "outliers" in Figure 3. Note that now data points could potentially be situated above the posterior mean of the frontier, which reflects the fact that the frontier itself is stochastic and measurement error is allowed for. For DEA analyses measurement error does not exist, and one merely considers a convex hull of the observations. Thus, the technology will be determined only by such outlying observations. In Figures 4-8 we allow for variable returns to scale. Rather than drawing the three-dimensional surface in Y, K and L, we plot slices in Y/L, K/L space for different values

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[2]The frontier depicted in Figures 3-8 corresponds to the posterior means of the coefficients of the linear trend model as described in Subsection 3.2 with $\tau^{*}=0.75$.

of L. In each graph we also plot these countries that use comparable amounts of labor input (in thousands of workers) and are thus operating at that slice of the frontier. Following this analysis, we observe a quite different shift in the frontier from 1979 to 1988 than that found in Figure 2. The frontier is now not exclusively determined by the extreme observation, and we notice that the observations for the U.S. are again important in defining the frontier (see Figure 4), but especially the frontier for 1988 is also pushed upwards by the observations for Australia and Canada (Figure 7). Our stochastic frontier approach does not allow the frontier to be determined by only one observation. The high output-labor ratio of the U.S. has an influence on the location of the frontier, but so do the observations for the other countries. Clearly, the inference on efficiency, which is measured using the (relative) vertical distance from the frontier, can be dramatically different in both approaches.

A number of later findings already become apparent through a more careful analysis of Figures 4-8: i) Measurement error seems quite small as all drawn data points are below the posterior mean of the frontier. ii) The flexibility of the approach allows the frontier to change shape over time. iii) There are large differences in efficiencies between countries; in particular, Japan and Spain are quite inefficient in 1979 and do not seem to improve, whereas the U.S., Canada and Sweden retain a very high level of efficiency, each at a different level of labour inputs. iv) The assumption of constant returns to scale seems untenable in view of the rather marked differences between the frontiers corresponding to large and small countries. If we take into account scale effects, the U.S. no longer appears an outlier as in Figure 3.

DEA advocates criticize stochastic frontier analysis on the grounds that functional form and distributional assumptions must be made.[3] Note, however, that the underlying emphasis of our paper is on robustness (i.e. on how sensitive results are to our assumptions) and that we begin with a model with very little

[3]It should be stressed that the one (strong) distributional assumption DEA imposes is that measurement error does not exist.

structure imposed, gradually tightening it as we go along. This emphasis, and a comparison of our results with those in the Fare, Grosskopf, Norris and Zhang study, allows us to analyze robustness in a formal manner.

3. Decomposing Output and Productivity Growth

Throughout this paper, we assume variants on a translog production frontier. Given the short span of the data (10 years, 17 countries), the translog provides adequate flexibility. Under this assumption a loglinear model based on (1) is obtained:

$$y_{ti}=x_{ti}'\beta_t+v_{ti}-u_{ti}, \tag{2}$$

where $u_{ti}=-\ln(\tau_{ti})$ is a nonnegative random variable, $v_{ti}=\ln(w_{ti})$ and is assigned a symmetric distribution with mean zero,

$$x_{ti}=(1 \quad k_{ti} \quad l_{ti} \quad k_{ti}l_{ti} \quad k_{ti}^2 \quad l_{ti}^2)',$$
$$\beta_t=(\beta_{t0}\ldots\beta_{t5})',$$

and lower case letters (y,l,k) indicate natural logs of upper case letters (Y,L,K). Note that the production frontier changes over time (i.e. β has a time subscript). In all cases, regularity restrictions are imposed to ensure that capital and labor elasticities are nonnegative at all observed input levels. That is:

$$\begin{aligned} EK_{ti}&\equiv\frac{\partial y_{ti}}{\partial k_{ti}}=\beta_{t1}+\beta_{t3}l_{ti}+2\beta_{t4}k_{ti}\geq 0, \\ EL_{ti}&\equiv\frac{\partial y_{ti}}{\partial l_{ti}}=\beta_{t2}+\beta_{t3}k_{ti}+2\beta_{t5}l_{ti}\geq 0, \end{aligned} \tag{3}$$

for all i and t (see the Appendix for practical details regarding the imposition of (3)). The elasticity of scale is a reasonable measure of local returns to scale (see Varian (1992), p. 16). For the translog model this takes the form:

$$ERTS_{ti}=EK_{ti}+EL_{ti}=\beta_{t1}+\beta_{t2}+(\beta_{t3}+2\beta_{t4})\,k_{ti}+(\beta_{t3}+2\beta_{t5})\,l_{ti}.$$

In our translog framework, constant returns to scale correspond to imposing the three restrictions:

$$\beta_{t1}+\beta_{t2}=1,\ \beta_{t4}=\beta_{t5},\ \beta_{t3}=-2\beta_{t4}.$$

Finally, the frontier will reduce to a Cobb-Douglas specification once we restrict β_{t3}, β_{t4} and β_{t5} to zero.

Given the world frontiers in periods t and t+1, and the inputs and inefficiencies of country i in both periods, the expected increase in the log of country i's GDP is:

$$(x'_{t+1,i}\beta_{t+1}-x'_{ti}\beta_t)+(u_{ti}-u_{t+1,i}),$$

where the first term is due to both world technical progress and changes in the input use in country i (i.e. changes in allocation and scale) and the second term reflects changes in efficiency. Note that the first term can be written as

$$\frac{1}{2}(x_{t+1,i}+x_{ti})'(\beta_{t+1}-\beta_t)+\frac{1}{2}(\beta_{t+1}+\beta_t)'(x_{t+1,i}-x_{ti}). \tag{4}$$

In (4), the first component reflects technical progress, whereas the second captures changes in inputs.

Leaving input change aside for the present, we begin by considering productivity change. Note that, if the explanatory variables were fixed at some level x_{*i}, we would be able to measure the productivity change of country i as:

$$\exp[x'_{*i}(\beta_{t+1}-\beta_t)]\exp(u_{ti}-u_{t+1,i}),$$

which is the product of two terms; one measuring the effect of a shift in the world frontier (pure technical change); and the other, individual efficiency change. Since inputs vary over time, we measure the effect of changes in world technology on the productivity of country i as a geometric average of pure technical changes for $x_{*i}=x_{ti}$ and $x_{*i}=x_{t+1,i}$. In other words,

$$TC_{t+1,i}=\exp[\frac{1}{2}(x_{t+1,i}+x_{ti})'(\beta_{t+1}-\beta_t)]. \tag{5}$$

The total increase in productivity of country i is then defined as:

$$PC_{t+1,i}=TC_{t+1,i}\times EC_{t+1,i}, \tag{6}$$

where $EC_{t+1,i}=\exp(u_{ti}-u_{t+1,i})$ is the efficiency change (i.e. $\tau_{t+1,i}/\tau_{t,i}$). Note that $PC_{t+1,i}$ is the output-based Malmquist productivity change index used in Fare, Grosskopf, Norris and Zhang (1994).

Cumulated productivity changes and their components are given by

$$CPC_i=CTC_i\times CEC_i, \tag{7}$$

where

$$CTC_i=\prod_{t=1}^{T-1} TC_{t+1,i}, \tag{8}$$

and

$$CEC_i=\prod_{t=1}^{T-1} EC_{t+1,i}=\exp(u_{Ti}-u_{1i}). \tag{9}$$

Average changes are defined as geometric averages of annual changes. In other words,

$$\begin{aligned} APC_i &= (CTC_i)^{\frac{1}{T-1}}\times(CEC_i)^{\frac{1}{T-1}} \\ &= ATC_i\times AEC_i. \end{aligned} \tag{10}$$

Now let us return to the decomposition in (4). With the definition of $PC_{t+1,i}$ adopted in (6) the change in expected GDP of country i, is exactly equal to

$$GC_{t+1,i}=IC_{t+1,i}\times TC_{t+1,i}\times EC_{t+1,i}, \tag{11}$$

where

$$IC_{t+1,i}=\exp\left[\frac{1}{2}(\beta_{t+1}+\beta_t)'(x_{t+1,i}-x_{ti})\right], \tag{12}$$

which captures the input change. Again, the measure in (12) is a geometric average of two "pure" input change effects: One measured with respect to the old frontier; and the other, the new frontier. Note that Fare, Grosskopf, Norris and Zhang's DEA analysis does not consider input change. Cumulated and average values for both GDP and input change are defined analogously to those for productivity growth (see equations (7) to (10)), and are denoted by CGC, AGC, CIC and AIC, respectively.

To reiterate, we expect output to grow due to input change, technical change and efficiency change. Equation (11) provides the formal decomposition of expected GDP change into these three factors. To facilitate interpretation, we use average annual percentage growth rates in our empirical section: APG=100x(APC-1), ATG=100x(ATC-1), AEG=100x(AEC-1), AIG=100x(AIC-1) and AGG=100x(AGC-1). Each of these features of interest we discuss in succession below.

4. The Models

All models in this paper are versions of the specification given in (2). We make the usual assumption that the v_{ti}'s are i.i.d. $N(0,\sigma_t^2)$ with the variances possibly time-specific, and assume that the u_{ti}'s are independent of each other and of the v_{ti}'s. Since interest centers on the robustness of results to variation in structure, we use several different models, beginning with the most unstructured and successively impose more structure.

4.1 Time Specific (TS) Model

The approach Fare, Grosskopf, Norris and Zhang use assumes that frontiers are totally independent across time. Our TS model is similar to theirs in spirit in that it is formally identical to T independent cross-sectional stochastic frontier models. In other words, each period has a different translog frontier, measurement error distribution and efficiency distribution. The efficiency distribution of $u_{ti}=-\ln(\tau_{ti})$ must be one-sided to ensure that τ_{ti} lies between zero and one, and u_{ti} here is taken to be exponential[4] with mean λ_t (see e.g. DeGroot (1970) for formal

[4]The exponential distribution is a fairly flexible one-sided distribution that should be able to capture a wide variety of inefficiency behavior. A more flexible distribution (which nests the exponential) is the Gamma. The use of Gamma inefficiency distributions with stochastic frontier models has been severely criticized by Ritter and Simar (1994). Stochastic frontier analysis tries to decompose deviations from the frontier into two

definitions of this, and other distributions used in this paper). These assumptions suffice to specify the likelihood function which, when combined with a prior distribution, yields the Bayesian model. Details on prior specification and derivation of the posterior conditional distributions needed to set up the Gibbs sampler are located in the Appendix. Note that we always impose the regularity conditions given in (3) through the prior.

A restricted version of this model that imposes more structure is obtained by allowing only the frontier parameters to be time-specific, and to assume that both the variances of the measurement error, σ_t^2, and the mean of the exponentially distributed inefficiency error, λ_t, are constant over time. This model is in between the TS model and the one presented in the next Subsection in which even more structure will be imposed.

4.2 Trending Frontier Models

The TS model is extremely "parameter rich", with no less than 80 parameters for 170 observations. As we shall see, this characteristic induces some inferential and computational problems. Furthermore, the assumption of independence for the frontier over time is undoubtedly unreasonable since, in practice, the frontiers are surely related over time. Thus, we propose the more structured specification for the J=6 elements of β_t:

$$\beta_t=\beta^* + t\beta^{**},$$

and

parts: one having a symmetric distribution (v_{ti}); and the other, a one-sided distribution (u_{ti}). Intuitively, this decomposition is poorly defined unless some fairly tight structure is placed on the two kinds of errors. Generally, the Gamma distribution becomes too similar to the Normal when it moves far away from the exponential. DEA surmounts this problem by placing an extremely tight structure on the measurement error: it is always zero. We do not choose to address the problems raised by this footnote in this manner but only note here that measurement error doubtlessly plays an important role and should not be ignored.

$$\sigma_1^2=..=\sigma_T^2=\sigma^2.$$

The assumption that the σ_t^2's are constant over time can be relaxed quite easily. In addition, for u_{ti} we now assume independent exponential distributions with the same mean λ. Note that this model is still fairly flexible, in that the frontier can change substantially over time (this was illustrated in Figures 4-8), but that the number of parameters has been reduced to 14. We shall denote this model by the linear trend (LT) model.

An obvious extension of the LT model is to include higher order trends: using a quadratic rather than a linear trend for describing the dynamic behaviour of β_t will define the quadratic trend (QT) model. Here we have a bit more flexibility in the time behaviour of the frontier at the expense of having 20 parameters.

The above models are considerably more flexible than those common to the stochastic frontier literature[5]. For this reason, we can consider other models which impose even more structure by restricting technical progress to occur only through shifts in the intercept. For the LT model, this restricted version assumes that slope parameters of the frontier are constant over time, but that

$$\beta_{t0}=\beta_0^* + t\beta_0^{**},$$

where β_{t0} is the first element of β_t. Note that the latter model has the potentially undesirable property that it imposes technical change to be the same for all countries. In other words, since the frontier moves only through the intercept it moves the same amount for all countries regardless of input mix.

As an extreme case, we could adopt a model where no change at all is allowed in the frontier, thus using only 8 parameters in total in the linear trend case.

In another direction, one could think of restricting these

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[5]This literature usually incorporates the assumption that technical progress is confined to changes in β_{t0}. Note that Cornwell, Schmidt and Sickles (1990) use a quadratic trend whereas Perelman and Pestieau (1994) impose a linear trend.

models based on the translog to constant returns to scale, thus effectively reducing the number of parameters for the LT specification to 8. The resulting model will be called the LT-CRTS model.

Finally, we can also think of imposing a Cobb-Douglas technology by simply restricting β_{t3}, β_{t4} and β_{t5} to zero, thus leaving the LT model with 8 parameters.

Thus, we have four different basic models (TS, QT, LT, LT-CRTS) which impose an increasing amount of structure on the data. Admittedly, our extreme models could be somewhat unreasonable in that the TS model may be over-parameterized and the LT-CRTS model or the constrained versions of the LT model too restrictive. However, our approach does have the strength that it considers a wide variety of models so that we can investigate robustness by seeing whether any particular issue differs significantly across models. Although in our case it is likely that the data is not very informative for resolving some issues, we can at least be confident in results that are constant across reasonable model and prior specifications.

5. Empirical Results

We apply our methods to a sample of OECD countries over the period 1979-1988.[6] Aggregate output (Y) we measure by real GDP; labor (L), by total employment; and capital stock (K) we calculate from capital stock per worker.[7]

The focus of this paper is on the components of output and productivity growth and the robustness of findings to prior and model assumptions. Subsection 5.1 discusses this latter issue while Subsection 5.2 discusses some of the economic implications of our results.

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[6]The commonly used Penn World Tables (Mark 5) provided the data set used in this study and it is identical to that in Fare, Grosskopf, Norris and Zhang (1994).

[7]This capital stock measure includes gross investment in producer durables and nonresidential construction but excludes residential construction.

5.1. Model Choice and Robustness

The emphasis of this paper is not exclusively on choosing one "correct" model. Rather, we are interested in seeing how robust results are to the choice of different reasonable models. Nevertheless, it is worth discussing which of our models seems to provide a better window for viewing the data in order to answer questions about productivity growth and its components. Note that we avoid the use of posterior odds (which is the standard Bayesian tool for model selection) since their calculation requires the use of informative proper priors over parameters not common to all models. They require, for instance, that we place proper priors on the frontier coefficients and enlist a degree of subjectivity likely to be unappealing to many readers. Consequently, our discussion of model choice proceeds along more "eclectic" lines.

Since the biggest difficulty we encountered was in decomposing productivity growth into technical growth and efficiency growth[8], this issue provides a convenient focus for the following discussion on robustness. If robustness across models and priors can be found in this dimension, then we can no doubt be confident of our results. Another challenging criterion is the within-sample fit that a model can generate. Average growth rates in our sample of countries vary from 0.93% for Ireland to 3.75% for Japan. Table 1 presents the average (over countries) posterior correlation between the components of average productivity growth (the average efficiency growth (AEG) and average technical growth (ATG)) for the four basic models. Clearly, the less negative this correlation is, the easier and numerically more stable is our decomposition. AEG averaged over all countries[9] is also reported, to evaluate how much posterior precision is left after the decomposition, and the in-sample fit

[8]For all models, this decomposition proves more difficult than that of overall growth into input and productivity growth.

[9]Note that the tables contain posterior means (and standard deviations) of features of interest. To simplify the discussion we often drop the term "posterior mean" such that in place of the phrase "the posterior mean of the efficiency change" we write merely "efficiency change".

is presented for the two extreme countries, Ireland and Japan, as well as for the U.K., which has shown average growth over this period. We measure this fit by the difference between the observed and fitted average GDP growth (AGG). Posterior means of all these quantities are presented, and posterior standard errors are denoted in parentheses.

The four basic models show important differences. First of all, the TS model leads to a very poor fit. Remember that this unstructured model consists of T=10 independent cross-sectional stochastic frontier models, each with only N=17 observations to determine 8 parameters. The sampler quickly finds values of β_t and u_t that attribute all the deviations from the frontiers to inefficiency (indicating no measurement error), but lead to nonsensical results for the changes over the years. The three more sparsely parameterized models do better on this score. There are no formal identification problems of the parameters, but the QT model finds it virtually impossible to distinguish between the components of APG, thus failing to accomplish one of the main goals of this study. It does fit very well within sample, but at the expense of unreasonably low efficiency levels: all countries are much below the frontier, which essentially deprives the latter of its interpretation. Also, the decomposition of APG is largely arbitrary, leading to a posterior mean of the average efficiency growth of -2.88% (which is, of course, very badly determined). Without sacrificing much of the within-sample fit (the standard deviations are still very low), we obtain a much better decomposition of productivity growth by using the LT model. AEG averaged over all countries has a posterior mean of -0.24% with a much smaller standard deviation than for QT. The correlation between AEG and ATG is high on average (especially for Greece, Ireland and Norway, where the posterior correlation coefficient is in between -0.97 and -0.98), but does not preclude a sensible decomposition of the productivity growth. If we restrict the model further by assuming constant returns to scale, we clearly impose too much, as the model has lost the flexibility to fit the sample well. Despite an almost zero correlation between AEG and ATG, average AEG is still very badly determined, as the model does very poorly in explaining the total GDP growth. Thus, the choice of the basic model to pursue the further analysis with, has to be in favour of the LT model, which seems to provide a very useful balance between flexibility and parsimony.

If the posterior of β^* and β^{**} would be Normal, we could easily construct a Highest Posterior Density test for the more restricted versions of the LT model, by using the fact that the standardized inner product should have a χ^2 distribution. Of course, this Normality does not really hold, but we shall base an approximate χ^2 test on this idea. That should give us at least a rough idea of the appropriateness of certain simplifications. If we then test the restriction of constant returns to scale (which corresponds to the LT-CRTS model), we obtain the value 2257 for this inner product, which should have an approximate χ^2_6 distribution under the null hypothesis of constant returns to scale, thus strongly corroborating the earlier evidence that the LT-CRTS model is not supported by the data. For the hypothesis that the linear trend only affects the constant term β_{t0}, we have to compare the value 119.8 with a χ^2_5 distribution, which again leads to very strong rejection of the null, and for the even stronger hypothesis that no trend at all should be present in the LT model, we obtain 410.4 to test for six restrictions. Also, when we test the restrictions leading to the Cobb-Douglas form of the frontier, we have to compare the value 567.8 with a χ^2_6 posterior distribution. Thus, none of these extra restrictions seem to have any data credibility, and our preferred model will clearly be the full translog LT model. If we start such a testing procedure from the more general TS model where σ_t^2 and λ_t are assumed constant over time, we can actually test for the LT model; i.e. the null hypothesis of a linear trend. As this implies 48 restrictions on the parameters, we should compare the value 45.87 with a χ^2_{48} distribution, which clearly provides even more evidence in favour of the LT model.

As discussed in the Appendix, the priors are all quite flat. One of the key prior hyperparameters is the prior median efficiency, τ^*. We select τ^*=0.75, which implies that the median of the (relatively noninformative) prior efficiency distribution is 0.75. Since this is an important dimension in which to investigate prior sensitivity, we also consider the very different values $\tau^*=0.5$ and $\tau^*=0.95$. Ideally, we would like the inference on crucial quantities like ATG and AEG with our preferred model to be relatively insensitive to this prior input. For the sake of brevity, we present only results for Japan, Ireland and the U.K. in Table 2. All three countries represent extremes of behavior. Ireland was a poor country that experienced little growth; Japan, a somewhat poor country that experienced rapid growth; and the U.K., a rich country that experienced average growth. Table 2 (ERTS) also contains the averages of the posterior means and standard deviations for the returns to scale $ERTS_{ti}$ (the arithmetic averages over years and countries).

Overall, Table 2 indicates that the LT model displays an impressive degree of robustness across these very different priors. We should stress that by considering the decomposition of APG into ATG and EAG we are examining the dimension where we would expect to find the least amount of robustness. Apart from indicating that, on average, the results on $ERTS_{ti}$ are very stable across priors, Table 2 also adds to the evidence against the LT-CRTS model, as returns to scale clearly seem increasing.

In the previous paragraphs we have attempted to choose the most appropriate of all the models we have tried in this paper. It is also worthwhile to discuss briefly other possible models that could have been but were not attempted. First, we selected a translog form for our frontier. Given the short data span and the local flexibility of the translog, we felt that choosing more flexible functional forms would be counterproductive (i.e. the overparameterization problem would far outweigh any benefits derived from greater flexibility). Less flexible specifications based on a Cobb-Douglas technology are, of course, possible, but in view of the clear rejection of the Cobb-Douglas form of the frontier, the latter seems a futile exercise.

5.2 Discussion of Results

This section discusses the economic implications of our results in more detail. For the sake of brevity, we present only those results for the preferred LT model with $\tau^{*}=0.75$. Before proceeding, two qualifiers are in order. First, the standard deviations of all our average growth measures are often substantial, and thus, our conclusions contain a certain degree of uncertainty. This is not surprising. Indeed, it would be even more surprising to expect our small data set to answer the kinds of complicated questions we are posing with any high degree of accuracy. The advantages over DEA of using a statistical approach in general, and a Bayesian stochastic frontier approach in particular cannot be stressed enough for small samples. More specifically, our method allows us to formally summarize the uncertainty that arises from using a small sample in such studies. Second, although we feel confident about our chosen model, and most results appear to be robust to model choice, the previous section's discussion does indicate some lack of robustness, which is another issue often overlooked by practitioners of DEA.

i) Growth Decomposition

A key aim of this paper is to relate our results to some of the major macroeconomic debates alluded to in the introduction. In the broadest sense, our interest is in investigating why and how some countries grow faster than others. To investigate these issues in further detail we have decomposed expected GDP growth into its three components: input growth, technical growth and efficiency growth (measured by AIG, ATG and AEG, respectively). Table 3 presents posterior means and standard deviations of these three measures along with expected GDP growth (i.e. AGG, see equation (11)), which is approximately equal to the sum of AIG and APG), actual GDP growth[10], and productivity growth (i.e. APG,

[10]We calculate these using a geometric average. Note that these results differ somewhat from the growth rates reported by Fare, Grosskopf, Norris and Zhang in their Table 1. It would appear that they have used the exponent 1/T rather than 1/(T-1) to compute the geometric average.

which is approximately ATG+AEG) for the 17 countries under consideration.

Table 3 indicates that our model fits the data very well in that expected and actual average GDP growth are almost identical and standard errors of AGG are quite small. Not surprisingly, decomposing output growth into its components does not yield any "secret" to fast growth. A general pattern appears to be that input change and technical change provide the major impetus for growth for most countries, and that changes in efficiency play a relatively minor role. However, the two poor countries that failed to grow, Ireland and Greece, suffered severe decreases in efficiency levels. Ireland experienced high input growth (as a result of a rapidly growing labor force and capital stock) in addition to high technical growth but saw all these effects offset completely by a very large drop in efficiency. Table 4, which presents efficiency levels for the 17 countries in 1979 and 1988, shows that Ireland was a rather efficient economy in 1979, but had reached a very low level of efficiency in 1988. Greece also experienced a less dramatic, but nonetheless large, drop in efficiency. Moreover, efficiency had a positive role to play in four "middle-income" countries--Japan and Finland, which achieved fast growth--and Italy and the U.K., where growth was less rapid.

For fast growing rich countries, efficiency gains did not appear to play any role in economic growth, and most growth seems to be linked to input changes. Australia, Canada and the U.S. achieved fast GDP growth largely through input growth, while Norway relied more heavily on technical, as opposed to input change, to achieve its growth. Conversely, for those rich countries that experienced relatively slow GDP growth (i.e. Belgium, France and Germany), slow growth in inputs would appear to be the culprit since technical change was roughly average. Belgium and, to a lesser extent, France, suffered some decline in efficiency.

ii) Convergence Issues

Table 4 presents the efficiency levels of the 17 countries for both the first and last years of the sample. A consideration of the 1979 level of efficiency suggests some possible clues to growth, but these are far from conclusive. The relatively poorer countries that achieved rapid GDP growth (Japan and Finland), began the period with very inefficient economies while other poor countries which did not perform as well (Austria, Greece, and Ireland) began the period with above average efficiencies. It is tempting to conclude that economic growth, and, thus, convergence of incomes to rich country levels, comes easier for poorer countries that are also very inefficient. Perhaps it is easier to eliminate inefficiencies than to encourage technical or input growth. However, this conclusion must be qualified by Spain, which was very inefficient and achieved moderate GDP growth without eliminating inefficiencies. This suggests that the maxim that inefficiencies must be removed in order for growth to be achieved in as short as span of time as possible is not a universally binding one, although it would appear to be relevant for both Japan and Finland.

Our technical change results do not indicate any conclusive findings for researchers searching for evidence of income convergence. In particular if we consider the poorest countries, technical growth (see Table 3) appears to be higher than average for Ireland, Finland and Japan, but below average for Austria and Greece and especially Spain. These six countries had the lowest incomes in 1979. Technical change seems to be shifting the world production frontier outward in a way which benefits some of the the poorer countries, but also Norway. Of course, Ireland, Greece and, to a much lesser extent, Austria saw this advantage disappear as a result of losses in efficiency.

iii) The Nature of Technical Progress

An important aspect of technical growth is whether it is driven largely by an increase in the marginal productivity of labor or of capital, or by both to the same degree. The latter case is known as factor-neutral technical progress whereas "capital-saving" is the term commonly used to describe the case when technical progress involves the marginal productivity of labor increasing faster than that of capital. In order to investigate this issue more closely, we divide the marginal productivity of labor by that of capital so as to define, thereby, the marginal rate of technical substitution (MRTS) of capital for labor. Posterior moments for this quantity do not exist, but Figure 9 plots the 5th, 50th and 95th percentile of the posterior distributions over the sample period for the MRTS for the U.S. An examination of this graph reveals a pronounced tendency of MRTS to decrease over time, indicating labor-saving technical progress. We can also deduce from the figure that some left skewness characterizes the posterior distributions for MRTS whereas spread (indicating our uncertainty) somewhat decreases.

iv) The Input Mix

There are substantial differences in the proportions of the production factors used over our sample of countries (see also Figures 3-8). The capital/labor ratio (K/L) in 1988 ranges from 15.45 for Greece to 52.82 for Norway. Countries with high capital/labor ratios all attain fast growth, except for Belgium. If we focus instead on the change in K/L over the sample period, we notice that all countries that have achieved at least 3% annual growth have done so through large changes in K/L, except for Australia. Thus, we can at least state that those countries where both the level and the growth of K/L are high (namely Canada, Finland, Japan and Norway) have seen their GDP grow quickly.

Another question of interest concerns the capital and labor elasticities, denoted by EK_{ti} and EL_{ti} respectively in (3), as well as the returns to scale $ERTS_{ti}$, for the different countries and years. Table 5 contains the averages over all the periods in the sample, for each country, of all three quantities. It turns out that there is relatively little difference in returns to scale: all countries indicate increasing returns to scale, with very small standard errors. The decomposition over the factors, however, is very different in the sample. Capital elasticity ranges from a low of 0.048 for Japan to a high of 0.91 for Greece. Clearly the countries with high K/L (Canada, Belgium, Finland, Japan and Norway) are exactly those with very low capital elasticities. Conversely, the highest values for EK_i are found for Greece and Ireland, where the capital-labor ratio is lowest. Given that $ERTS_i$ is more or less the same for all i, we have exactly the opposite situation for labor elasticity, where Japan and Norway reach posterior mean values above unity, and for Greece we find 0.19. Table 6 reports the evolution of the country averages of these quantities over time. There is a clear tendency for EL_t to decrease over time, which is partly offset by an increasing capital elasticity, but the resulting returns to scale $ERTS_t$ is decreasing somewhat over time. In addition, the posterior uncertainty concerning returns to scale tends to go up over time, as evidenced by the standard errors.

Note, incidentally, that again we face the situation that the aggregate returns to scale is much easier to determine than its components.

v) Conclusions

It is somewhat difficult to compare our results to those of the Fare, Grosskopf, Norris and Zhang study since they do not formally model input change, and their techniques imply that only three levels of technical change exist: one for the U.S. and one for two sets of eight countries which achieved identical levels of technical change above/below the U.S. figure.[11] Furthermore, the model closest in spirit to that used by Fare, Grosskopf, Norris and Zhang, the TS model, is strongly rejected by the data in favour of our preferred LT model. Since their DEA does not take measurement error into account either, it would be worthwhile to see how sensitive their results are to outliers or to changes in the observed data points. With just 17 countries for each year, one would expect robustness properties to be poor. More importantly, unlike this paper, Fare, Grosskopf, Norris and Zhang base most of their results on a model which assumes constant returns to scale technology. In particular, they compute

[11] The finding that identical technical change levels exist for large groups of countries is an artifact of the DEA methodology. Since as few as one or two countries can determine the frontier, it moves over time in the same way over large regions.

productivity, technical and efficiency change with respect to the constant returns to scale technology (see their p.74-75). They then decompose efficiency change under constant returns to scale into scale change and efficiency change under variable returns to scale. Thus, their productivity index and its decomposition is always based on an assumption which we find to be strongly rejected by the data.

With these limitations in mind, however, we note that some results of their study (in particular, the ordering of productivity growth) are qualitatively similar to our own but that, unsurprisingly, important differences exist. Ireland and Denmark, for instance are classified in the Fare, Grosskopf, Norris and Zhang study as having low rates of technical change; and Italy, high technical growth. In addition, due to its imposition of constant technical change for large groups of countries, their DEA methodology does not adequately capture extremes in technical growth, which we found to be high for Norway and low for the U.K. For efficiency growth the main differences are for Ireland, where they find zero growth under variable returns to scale, and for Denmark, Italy, Spain and the U.K., where they find 0.47%, 0.37%, -1.06% and 0.06%, respectively. Using our measures of posterior uncertainty, given by the standard deviations, we can indeed conclude that these differences are quite substantial (in fact, they exceed 3.5 standard deviations). In addition, for both technical (under constant returns to scale in their framework) and efficiency growth, the ordering over countries is quite different. This is exactly, as mentioned previously, the most challenging decomposition in this type of analysis. Interestingly, APG (only presented under constant returns to scale) is very different for Australia, Austria, Denmark, Sweden and the U.K., where they obtain growth rates of at least 0.5% less, corresponding to a difference of at least 7 posterior standard deviations.

Keeping in mind the limitations of the models and data, and the fact that standard deviations attached to our efficiency measures are fairly substantial, we draw the following tentative conclusions with regard to growth: i) GDP growth occurs largely due to increases in inputs and technology; however, for a few key countries more efficient use of inputs also has an important role to play. ii) For some countries that were very inefficient in 1979 (Japan, Finland, Italy and the U.K.), efficiency improvements played an important role in productivity and GDP growth. However, our results also demonstrate that poorer countries need not be inefficient (e.g. Ireland and Greece in 1979) so that a policy focussed solely on improving efficiency will not necessarily guarantee fast growth. iii) For economies with higher levels of GDP per capita, performance with respect to input change appears to be a crucial factor in determining overall growth since in all these countries input growth accounted for more than 50% of overall GDP growth. One exception was Norway, where a great deal of technical change took place.

With respect to the issue of convergence, we draw the following tentative conclusions: i) Just looking at the data, unconditional convergence of incomes does not seem to be occurring in our sample of 17 OECD countries over 1979-1988. ii) Some convergence of efficiency, however, does appear to be occurring among some "middle-income" countries, such as Japan, Finland, Italy and the U.K. However, the opposite situation appears to hold for countries at the lowest income levels; a case in point here is that of Ireland, where efficiency dropped in a spectacular way. iii) In essence, we find that many countries are converging to different points on the world production function, and that the world frontier itself is moving outwards over time in a way that appears not uniformly more beneficial to poorer or to richer countries.

Overall, we offer an eminently sensible but basically unhelpful conclusion about growth: There exists no one unique key for achieving it. Some rich and poor countries grew quickly as a result of input changes (Australia, Canada and Spain) while others (Finland and Norway) grew as a result of technical change. Italy and the U.K. received a substantial portion of their growth from efficiency improvements while Japan grew quickly in all three categories. Moreover, no rich country achieved fast growth through efficiency improvements alone, which is not a surprising finding given that no rich country was particularly inefficient in 1979. For those countries with GDP per capita in 1979 over \$10,000, input changes were the most important factor in explaining both successes and failures in growth.

It is an open question whether these results can be generalized to a wider set of countries. It should also be emphasized that the previous discussion is somewhat speculative in that some of our results are not very robust to changes in the model specification. Nonetheless, we do believe that our results are suggestive and merit further investigation in addition to providing a statistical framework within which to treat more extensive data sets.

6. Concluding Remarks

In this paper we adopt a Bayesian stochastic frontier framework for measuring the components of output growth in a set of 17 OECD countries. Empirical results indicate that all three components play an important role in explaining output growth. However, it was difficult to find a general pattern which could form the basis for universal policy conclusions with respect to productivity growth.

Our work is similar in spirit to the growth accounting literature. Although too voluminous to cite here (see Maddison (1987) for a survey), this literature tends to lump the unexplained residual under the rubric "technical change". Using a stochastic frontier model, however, enables us to analyse efficiency issues formally and it allows us to give a structural interpretation to our unexplained residual. Thus, we address the issue of output growth in a more fundamental way than in the growth accounting literature.

Our work also relates to the enormous literature that seeks to explain economic growth using cross-country regressions (eg. Barro (1991), DeLong and Summers (1991), Levine and Renelt (1992), Persson and Tabellini (1994)). Unlike this literature, however, we focus on measurement rather than explanation, using a simple economic model and then seeing what insights can be derived through the use of careful statistical methods. This is in contrast to cross-sectional regression approaches that seek to consider a myriad of possible deeper "structural" reasons for empirical findings. In statistical terms, we are interested in investigating the properties of the distribution of output conditional on capital and labor. Researchers who perform cross-country growth regressions implicitly argue that the distribution of output conditional on capital, labor, and many other complex variables, is the more appropriate focus for studies into productivity growth. However, the investigation of such a distribution typically involves selecting out only a few of the potentially enormous number of conditioning variables. For computational ease researchers engaged in cross-country growth studies will assume a linear relationship along with minimal dynamics and a simple error structure. Given the restrictiveness of such a statistical model and the lack of robustness in cross-country growth regressions (Levine and Renelt (1992)), we would argue that our approach is a sensible complement.

An obvious extension to this paper would be to consider a wider set of countries for a longer time period. At present, data limitations prohibit this research but with improved data sets appearing regularly such limitations will no doubt prove to be less troublesome in the future. A further extension would be to use a more sophisticated production relationship, perhaps one involving a measure of human capital, or to allow the parameter of efficiency distributions to depend on country characteristics so as to provide a more formal explanation of one of the components of productivity growth. The latter extension would involve trivial changes in the computational demands encountered in this paper. Provided these country characteristics are zero-one dummy variables, a Gibbs sampler could be easily set up. In cases where zero-one dummies were inappropriate, such an extension would involve somewhat more sophisticated Markov chain random sampling methods.

Allowing for model and parameter uncertainty is of enormous importance in any empirical study since it enables the researcher to guard against drawing strong conclusions from weak evidence. In this paper, we have made many conclusions and recommendations based on our empirical results but have stressed that both model and parameter uncertainty must lead us to qualify significantly the recommendations we make. That is, substantial standard deviations for quantities of interest and a certain degree of sensitivity to model choice means that our conclusions should be taken tentatively and within the full understanding of these limitations. Note, however, that these limitations are not specific to our particular approach since any sensible study would doubtlessly reveal a similar sensitivity. The limitations of the present data allow us to draw only tentative conclusions about the macroeconomic debates we consider, and to pretend otherwise would surely be misleading.

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Appendix

Bayesian analysis requires both the specification of a likelihood function and a prior distribution for the parameters. The assumptions given in the body of the paper define the likelihood function. Throughout this paper, we use a traditional flat, noninformative, prior (see, e.g., Zellner (1971), p. 60) for $\ln(\sigma_t^{-2})$. The prior for β_t is flat but truncated to ensure that the economic regularity conditions hold at all points in the sample. In order to avoid degenerate behavior of the posterior, informative priors must be placed on the λ_ts. The use of the traditional flat prior for $\ln(\lambda_t)$ causes the posterior to be improper, with an asymptote at full efficiency (see Ritter and Simar (1993)). We elicit the prior in such a fashion so as to allow it to be dominated by the sample.

In order to evaluate posterior properties of the models, we use Gibbs sampling methods. (See Gelfand and Smith (1990) and Casella and George (1992) for an introduction). Essentially, Gibbs sampling involves taking random draws from conditional posterior distributions, and then allowing these draws to converge to draws from the joint posterior. Once draws from the joint distribution have been obtained, any posterior feature of interest can be calculated.

<u>Time Specific Model</u>

Our first Bayesian model is:

$$\prod_{t=1}^{T} f_N^N(y_t \mid X_t\beta_t - u_t, \sigma_t^2 I_N)\, p(\beta_t, \sigma_t^{-2})\, p(\lambda_t) \times \prod_{i=1}^{N} f_G(u_{ti} \mid 1, \lambda_t^{-1}), \qquad \textbf{(A1)}$$

where $f_N^M(.\mid a,B)$ denotes the M-variate Normal distribution with mean a and covariance matrix B, $y_t=(y_{t1},..,y_{tN})'$, $X_t=(x_{t1},..,x_{tN})'$, and $u_t=(u_{t1},..,u_{tN})'$. The prior on the frontier parameters in (A1) is given by:

$$p(\beta_t, \sigma_t^{-2}) \propto \sigma_t^2 p(\beta_t),$$

where $p(\beta_t)=1$ if period t capital and labor elasticities of output are nonnegative for all countries in the sample and 0 otherwise (see (3)). The prior for λ_t is given by:

$$p(\lambda_t^{-1}) = f_G(\lambda_t^{-1} \mid \lambda_{01}, \lambda_{02}),$$

where $f_G(.\mid a,b)$ denotes the Gamma distribution with shape parameter a and scale parameter b, the mean being a/b. λ_{01} and λ_{02} are prior hyperparameters. A detailed justification of, and suggestions for, prior elicitation are given in van den Broeck, Koop, Osiewalski and Steel (1994). It is sufficient to note here that we choose $\lambda_{01}=1$, which implies a very flat prior, and that by choosing $\lambda_{02}=-\ln(\tau^*)$, we also ensure that τ^* is the prior median efficiency, which is a natural quantity to elicit in practice. We typically choose $\tau^*=.75$ (which indicates, *a priori*, that we expect the median of the efficiency distribution to be .75) but we also consider other values for our sensitivity analysis. Unless otherwise specified, $\tau^*=.75$ throughout the paper.

The Gibbs sampler draws from the following conditional posterior distributions. The draw for β_t is taken from:

$$p(\beta_t \mid Data, u_t, \lambda_t^{-1}, \sigma_t^{-2}) \propto p(\beta_t)\, f_N^J(\beta_t \mid \hat{\beta}_t, \sigma_t^2 (X_t' X_t)^{-1}), \tag{A2}$$

where

$$\hat{\beta}_t = (X_t' X_t)^{-1} X_t' (y_t + u_t).$$

This distribution is multivariate Normal, truncated to be nonnegative only in the region where regularity conditions are satisfied.

Similarly, the draw for σ_t^{-2} is taken from:

$$\begin{aligned} &p(\sigma_t^{-2} \mid Data, \beta_t, u_t, \lambda_t^{-1}) \\ &= f_G(\sigma_t^{-2} \mid \frac{N}{2}, \frac{1}{2}[y_t - X_t\beta_t + u_t]' [y_t - X_t\beta_t + u_t]). \end{aligned} \tag{A3}$$

And for λ_t^{-1} from:

$$p(\lambda_t^{-1} \mid Data, \beta_t, u_t, \sigma_t^{-2}) = f_G(\lambda_t^{-1} \mid \lambda_{01} + N, \lambda_{02} + \sum_{i=1}^{N} u_{ti}). \tag{A4}$$

Finally, for u_t we draw from:

$$p(u_t \mid Data, \beta_t, \lambda_t^{-1}, \sigma_t^{-2}) \propto \prod_{i=1}^{N} f_N^1(u_{ti} \mid x_{ti}'\beta_t - y_{ti} - \frac{\sigma_t^2}{\lambda_t}, \sigma_t^2)\, I(u_{ti} \geq 0), \tag{A5}$$

where I(.) is the indicator function. In other words, the u_{ti}'s are truncated Normal.

<u>Linear Trend Model</u>

This model can be written as:

$$y = X^* \beta - u + v, \tag{A6}$$

where $y=(y_1' \ldots y_T')'$, $u=(u_1' \ldots u_T')'$, $v=(v_1 \ldots v_T)'$, $\beta=(\beta^{*\prime}\ \beta^{**\prime})'$, and

$$X^* = \begin{bmatrix} X_1 & X_1 \\ . & . \\ X_t & tX_t \\ . & . \\ X_T & TX_T \end{bmatrix}.$$

Note that β is a 2Jx1 vector (where J=6 is the number of parameters in the basic translog specification).

Our Bayesian model can be written as:

$$f_N^{TN}(y \mid X^*\beta-u, \sigma^2 I_{TN})\, p(\beta, \sigma^{-2})\, p(\lambda^{-1}) \prod_{t=1}^{T}\prod_{i=1}^{N} f_G(u_{ti} \mid 1, \lambda^{-1}), \qquad \textbf{(A7)}$$

where

$$p(\lambda^{-1}) = f_G(\lambda^{-1} \mid 1, -\ln(\tau^*)),$$

$$p(\beta, \sigma^{-2}) \propto \sigma^2 p(\beta),$$

and $p(\beta)=1$ if the regularity conditions are satisfied and =0 otherwise. Under this prior structure, the conditionals for the Gibbs sampler can be derived. For β we obtain:

$$p(\beta \mid Data, u, \sigma^{-2}, \lambda^{-1}) \propto p(\beta)\, f_N^{2J}(\beta \mid \hat{\beta}, \sigma^2 (X^{*\prime}X^*)^{-1}), \qquad \textbf{(A8)}$$

where

$$\hat{\beta} = (X^{*\prime}X^*)^{-1}X^{*\prime}(y+u).$$

The next conditional is:

$$\begin{aligned} &p(\sigma^{-2} \mid Data, \beta, u, \lambda^{-1}) \\ &= f_G(\sigma^{-2} \mid \frac{TN}{2}, \frac{1}{2}[(y-X^*\beta+u)'(y-X^*\beta+u)]). \end{aligned} \qquad \textbf{(A9)}$$

Then, we get

$$\begin{aligned} &p(u \mid Data, \beta, \sigma^{-2}, \lambda^{-1}) \\ &\propto f_N^{TN}(u \mid X^*\beta-y-\frac{\sigma^2}{\lambda}\iota, \sigma^2 I_{NT})\, I(u_{ti}\geq 0), \end{aligned} \qquad \textbf{(A10)}$$

where ι is a TNx1 vector of ones, and the full conditional for λ^{-1} is

$$p(\lambda^{-1} \mid Data, \beta, u, \sigma^{-2}) = f_G(\lambda^{-1} \mid 1+NT, -\ln(\tau^*) + \sum_{t=1}^{T}\sum_{i=1}^{N} u_{ti}). \qquad \textbf{(A11)}$$

<u>Computational Issues</u>

The results for the preferred model are based on a sequential Gibbs sampler with 500,000 included and 5,000 burn-in passes. That is, for various starting values, we generated 505,000 passes and discarded the first 5,000 to eliminate possible start-up effects. The reader is referred to Koop, Steel and Osiewalski (1994) for a discussion of various implementations of the Gibbs sampler and techniques for assessing convergence in the context of stochastic frontier models.

Table 1: Growth Decomposition and In-Sample Fit
Posterior means (standard deviations)

	Av.Cor AEG, ATG	Av. AEG	Ireland AGG-actual	Japan AGG-actual	U.K. AGG-actual
TS	-0.850	-0.13 (0.65)	-5.41 (1.58)	0.03 (1.38)	2.10 (0.94)
QT	-0.999	-2.88 (1.35)	0.00 (0.02)	0.00 (0.02)	0.00 (0.02)
LT	-0.851	-0.24 (0.21)	0.00 (0.08)	0.00 (0.09)	0.00 (0.08)
LT CRTS	-0.086	-0.02 (0.84)	1.10 (1.40)	-0.51 (1.29)	-0.43 (0.81)

Table 2: Prior Sensitivity

τ^*	ERTS	Ireland		Japan		U.K.	
		ATG	AEG	ATG	AEG	ATG	AEG
0.5	1.0741 (0.0140)	1.75 (0.41)	-3.12 (0.43)	1.49 (0.36)	0.62 (0.30)	-0.29 (0.33)	1.01 (0.30)
0.75	1.0818 (0.0084)	1.78 (0.39)	-3.23 (0.37)	1.92 (0.24)	0.64 (0.28)	-0.26 (0.27)	1.07 (0.25)
0.95	1.0827 (0.0091)	2.21 (0.41)	-3.65 (0.40)	2.05 (0.19)	0.28 (0.27)	-0.37 (0.28)	1.09 (0.30)

Table 3: Growth Rate Components for Preferred Model

Country	GDP growth	AGG	AIG	ATG	AEG	APG
Australia	3.01	3.01 (0.06)	2.51 (0.02)	0.58 (0.08)	-0.09 (0.07)	0.49 (0.06)
Austria	2.04	2.04 (0.07)	1.44 (0.02)	0.92 (0.14)	-0.32 (0.16)	0.60 (0.07)
Belgium	1.52	1.52 (0.07)	0.73 (0.02)	1.66 (0.18)	-0.86 (0.19)	0.78 (0.07)
Canada	3.00	3.01 (0.07)	2.09 (0.06)	1.10 (0.10)	-0.20 (0.09)	0.90 (0.08)
Denmark	1.92	1.92 (0.08)	1.10 (0.02)	1.19 (0.20)	-0.38 (0.22)	0.81 (0.08)
Finland	3.49	3.49 (0.09)	1.08 (0.06)	1.99 (0.30)	0.39 (0.33)	2.38 (0.10)
France	1.62	1.62 (0.08)	1.16 (0.04)	1.00 (0.13)	-0.54 (0.14)	0.46 (0.09)
Germany	1.62	1.62 (0.09)	0.80 (0.04)	1.01 (0.13)	-0.19 (0.14)	0.82 (0.09)
Greece	1.40	1.40 (0.08)	1.76 (0.03)	0.72 (0.36)	-1.06 (0.37)	-0.35 (0.08)
Ireland	0.93	0.93 (0.08)	2.47 (0.04)	1.78 (0.39)	-3.23 (0.37)	-1.51 (0.09)
Italy	2.60	2.59 (0.08)	1.02 (0.02)	0.60 (0.11)	0.95 (0.13)	1.56 (0.08)
Japan	3.75	3.75 (0.09)	1.14 (0.13)	1.92 (0.24)	0.64 (0.28)	2.58 (0.16)
Norway	3.32	3.32 (0.07)	1.16 (0.07)	2.32 (0.38)	-0.18 (0.40)	2.14 (0.10)
Spain	2.03	2.03 (0.08)	2.17 (0.03)	0.12 (0.14)	-0.25 (0.15)	-0.13 (0.09)
Sweden	2.18	2.18 (0.06)	1.32 (0.02)	0.65 (0.09)	0.20 (0.10)	0.85 (0.07)
U.K.	2.30	2.30 (0.08)	1.48 (0.05)	-0.26 (0.27)	1.07 (0.25)	0.80 (0.09)
U.S.	2.87	2.87 (0.07)	1.80 (0.05)	1.06 (0.15)	-0.01 (0.14)	1.05 (0.09)
average	2.33	2.33 (0.08)	1.48 (0.04)	1.08 (0.20)	-0.24 (0.21)	0.84 (0.09)

Table 4: Efficiency Levels for Preferred Model

Country	1979		1988	
Australia	0.985	(0.009)	0.978	(0.008)
Austria	0.910	(0.011)	0.884	(0.009)
Belgium	0.950	(0.009)	0.879	(0.012)
Canada	0.983	(0.009)	0.965	(0.008)
Denmark	0.819	(0.011)	0.791	(0.013)
Finland	0.752	(0.009)	0.779	(0.020)
France	0.825	(0.011)	0.786	(0.009)
Germany	0.762	(0.011)	0.750	(0.009)
Greece	0.939	(0.019)	0.853	(0.020)
Ireland	0.905	(0.017)	0.674	(0.018)
Italy	0.821	(0.011)	0.894	(0.011)
Japan	0.582	(0.010)	0.617	(0.013)
Norway	0.981	(0.010)	0.966	(0.030)
Spain	0.723	(0.011)	0.707	(0.011)
Sweden	0.963	(0.010)	0.980	(0.006)
U.K.	0.803	(0.015)	0.884	(0.018)
U.S.	0.980	(0.012)	0.979	(0.011)
average	0.863	(0.011)	0.845	(0.013)

Table 5: Year Averages of Factor Elasticities and Returns to Scale

Country	EK_i	EL_i	$ERTS_i$
Australia	0.386 (0.017)	0.679 (0.021)	1.083 (0.006)
Austria	0.455 (0.018)	0.628 (0.025)	1.082 (0.010)
Belgium	0.111 (0.025)	0.960 (0.031)	1.071 (0.010)
Canada	0.164 (0.022)	0.913 (0.022)	1.078 (0.004)
Denmark	0.397 (0.019)	0.683 (0.026)	1.080 (0.011)
Finland	0.114 (0.028)	0.957 (0.035)	1.070 (0.012)
France	0.177 (0.024)	0.903 (0.023)	1.080 (0.003)
Germany	0.179 (0.025)	0.902 (0.024)	1.080 (0.004)
Greece	0.905 (0.038)	0.193 (0.044)	1.098 (0.013)
Ireland	0.608 (0.026)	0.477 (0.034)	1.084 (0.016)
Italy	0.278 (0.022)	0.805 (0.022)	1.083 (0.003)
Japan	0.048 (0.034)	1.031 (0.030)	1.079 (0.008)
Norway	0.057 (0.032)	1.011 (0.040)	1.068 (0.014)
Spain	0.479 (0.021)	0.609 (0.025)	1.088 (0.004)
Sweden	0.540 (0.020)	0.546 (0.026)	1.086 (0.010)
U.K.	0.583 (0.031)	0.510 (0.034)	1.094 (0.005)
U.S.	0.275 (0.037)	0.813 (0.037)	1.088 (0.010)
average	0.338 (0.026)	0.743 (0.029)	1.082 (0.008)

Table 6: Country Averages of Factor Elasticities and Returns to Scale

Year	EK_t	EL_t	$ERTS_t$
1979	0.317 (0.028)	0.783 (0.029)	1.100 (0.006)
1980	0.314 (0.024)	0.781 (0.025)	1.095 (0.005)
1981	0.314 (0.022)	0.777 (0.023)	1.090 (0.005)
1982	0.321 (0.020)	0.766 (0.022)	1.086 (0.006)
1983	0.331 (0.021)	0.751 (0.023)	1.083 (0.006)
1984	0.341 (0.022)	0.738 (0.026)	1.079 (0.008)
1985	0.350 (0.025)	0.726 (0.030)	1.076 (0.009)
1986	0.358 (0.028)	0.715 (0.034)	1.073 (0.011)
1987	0.366 (0.032)	0.704 (0.039)	1.070 (0.013)
1988	0.372 (0.037)	0.694 (0.044)	1.067 (0.014)
Average	0.338 (0.026)	0.743 (0.029)	1.082 (0.008)

Figure 1: GDP Growth vs. GDP

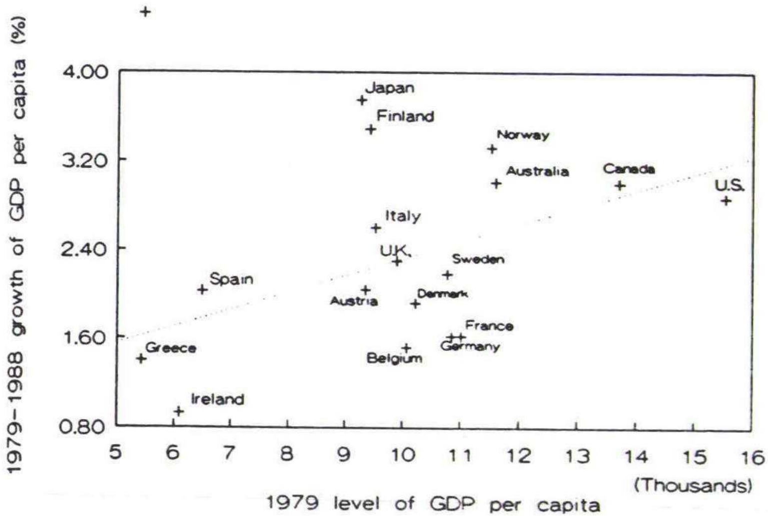


Figure 2: DEA Frontiers

constant returns to scale

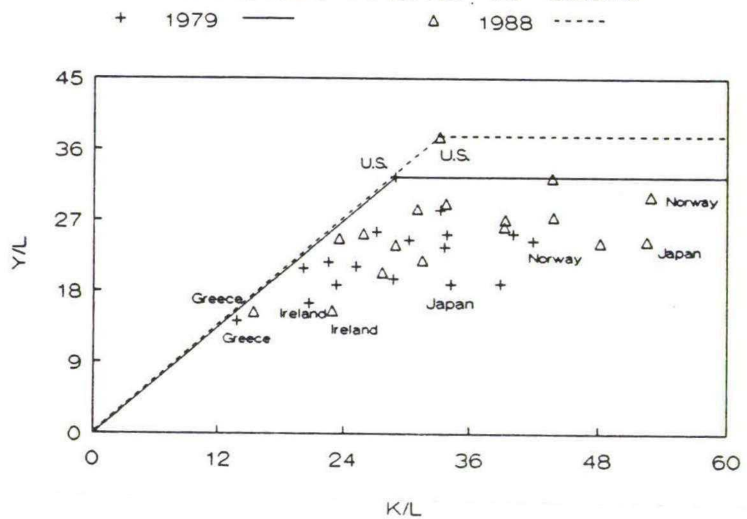


Figure 3: Stochastic Frontiers
constant returns to scale

+ 1979 ——— Δ 1988 -----

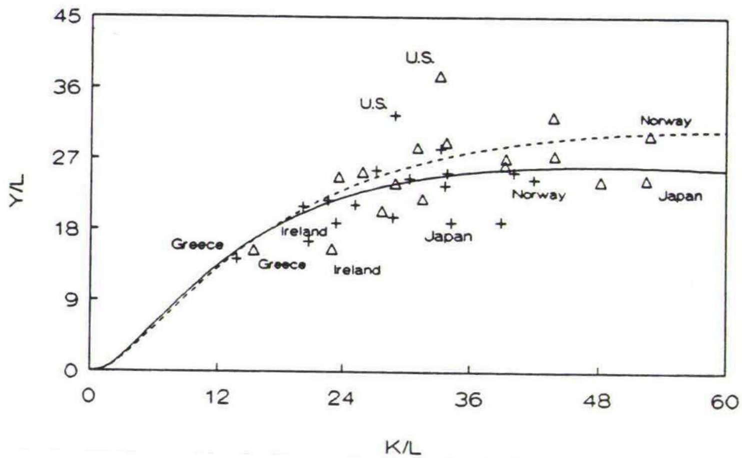


Figure 4: Stochastic Frontiers

L=114000 (US)

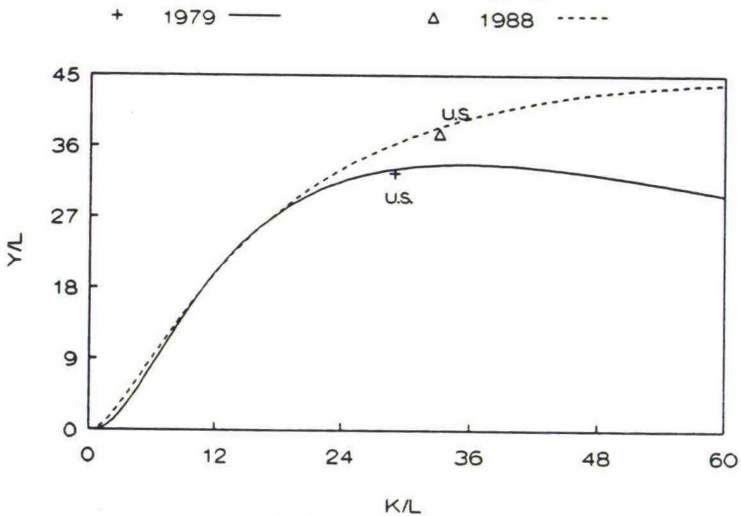


Figure 5: Stochastic Frontiers

L=59000 (Japan)

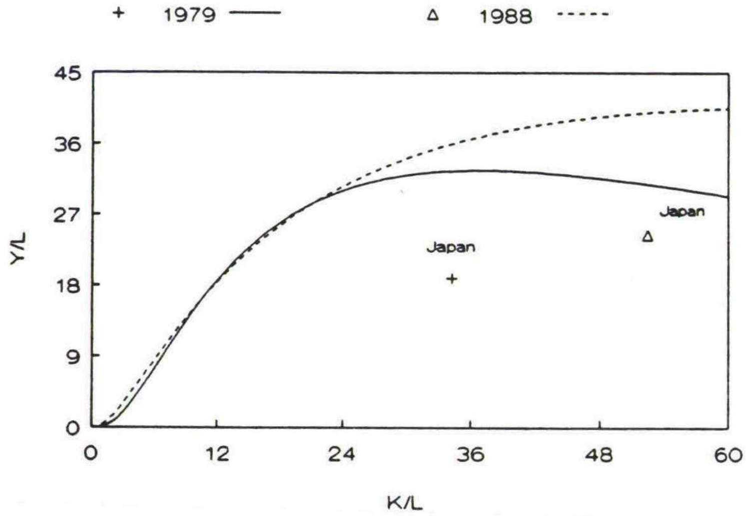


Figure 6: Stochastic Frontiers
L=27000 (France, Germany and UK)

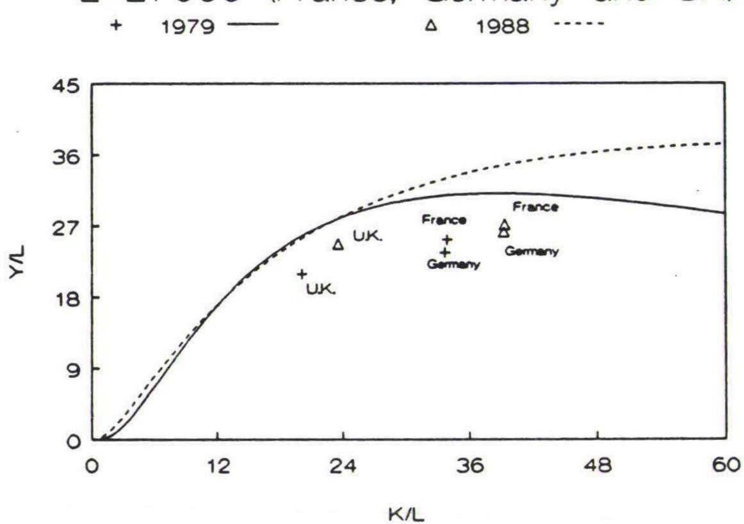


Figure 7: Stochastic Frontiers

L=11000 (Australia, Canada and Spain)

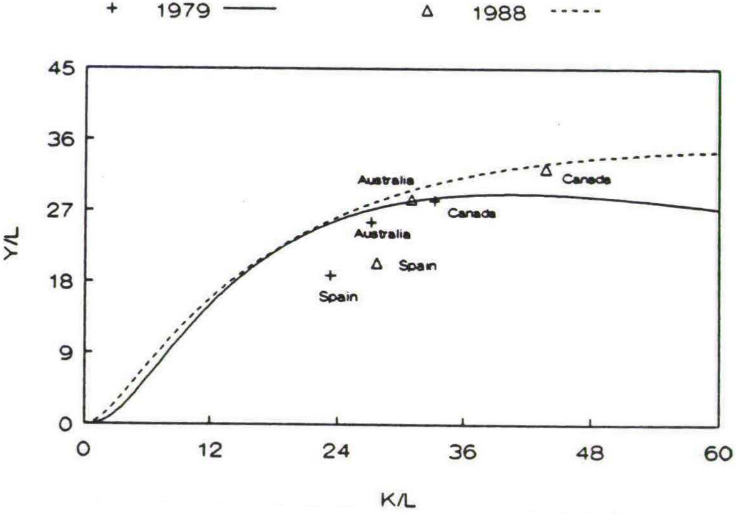


Figure 8: Stochastic Frontiers

L=3800(Austria, Belgium, Greece, Sweden)

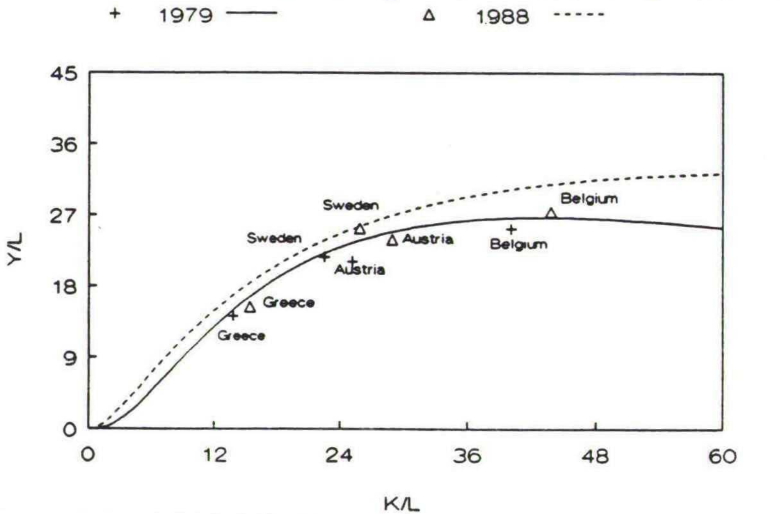
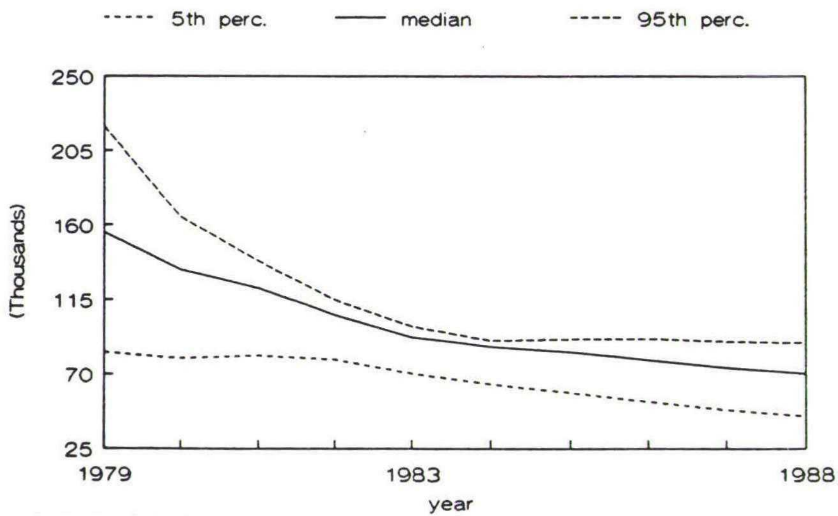


Figure 9: MRTS for U.S.



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