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Technical Efficiency and Its Dynamics in Indian Manufacturing: An Inter-State Analysis

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Abstract

This paper analyzes state level data from the manufacturing sector in India for the period 1986-87 to 1999-00 to study the efficiency dynamics of a ”typical” firm in individual states during the pre- and post reform years. Using the non-parametric method of Data Envelopment Analysis we utilize super-efficiency models to rank the states in terms of their performance and investigate the dynamics of the efficiency rankings over time. We find no major change in the efficiency ranking of states after the reforms. Nor is there any evidence of convergence in the distribution of efficiency in the post-reform period.

Journal of Economic Literature Classification: D24, L6

Keywords: super efficiency, convergence, Markov chains.

TECHNICAL EFFICIENCY AND ITS DYNAMICS IN INDIAN MANUFACTURING: AN INTER-STATE ANALYSIS

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1. Introduction

In the present era of increasing globalization and easy access to modern communications technology, firms in all countries are under pressure to improve their production efficiency in order to survive and thrive in the face of competition from newly emerging domestic firms on the one hand and foreign competition on the other. India initiated major economic reforms in 1991 in an attempt to make a systematic shift toward an open economy along with privatization of a large segment of its economy (Ahluwalia, 2002). These reforms were phased in over a number of years and many aspects of the reforms are only recently being implemented. Moreover, there has been considerable variation in the speed and extent of implementation of the reform measures across the different states. In view of the fact that the major focus of the reforms was on industry in general and manufacturing in particular, an analysis of the regional variation in manufacturing efficiency and its dynamics is especially important.

Given India's colonial past, the hinterland areas of the port cities of Bombay, Madras, and Calcutta attained a higher level of industrial development compared to the rest of the country because of natural advantages (like easy access to raw materials and better transportation facilities). Consequently, in the corresponding states of Maharashtra, Tamilnadu, and West Bengal manufacturing accounts for a higher proportion of the gross state product. However, an interesting question is whether 'typical' firms located in the leading industrial states also perform at a higher level of technical efficiency compared to those in other states.

In the empirical literature, labor productivity or output per worker is often taken as an index of efficiency of a firm. By this criterion, a state with higher labor productivity is more efficient. This, of course, is a partial measure of performance because it ignores the role of non-labor inputs. More sophisticated studies measure technical efficiency relative to a production frontier constructed from actual input-output data and takes into account all the inputs in the production process. The method of Data Envelopment Analysis (DEA) provides a nonparametric measure of efficiency without any explicit specification of a production function. In this sense, it is often considered preferable to stochastic production frontier analysis. As is explained below, a problem with conventional DEA is that it fails to discriminate between observations all of which are rated to be at 100% technical efficiency. A relatively new variant of DEA measures *super-efficiency* and permits a complete ranking of all firms in a sample.[1]

Very few studies have examined the question of efficiency in the Indian manufacturing sector. Ray (2002) examines the multifactor productivity growth and efficiency of Indian states for the period 1986-87 to 1995-96. Also Mitra et al. (2002) study the total factor productivity and technical efficiency of Indian states for the period 1976 to 1992 and examine the role of infrastructure in determining performance. However, neither of these two studies investigates the dynamics of efficiencies over time. In the present paper we analyze the data from the Annual Survey of Industries for the

[1] In the absence of constant returns to scale and/or when zero input values are encountered, a feasible solution may not exist for the relevant DEA problem for measuring super-efficiency.

years 1986-87 through 1999-2000 to construct year-by-year super-efficiency rankings of the states and union territories of India. Specifically, we address the following questions:

- Are the major industrial states also more efficient than others?
- Is the efficiency ranking of states stable over time?
- Did the economic reforms introduced in the 1990s alter the efficiency ranking of the states?
- Is there a convergence in the technical efficiency of the states over the time period considered?
- What is the long run distribution of efficiency across states?

Our study, thus, extends the literature on Indian manufacturing in that we measure *super-efficiency* (rather than the conventional measure of efficiency), which allows us to completely rank the states in order of performance. Further, our focus is on the dynamics of the efficiency rankings of the states over a time period that includes the pre-reform and post-reform years. In addition, our study period includes more recent years of data as compared to the two studies mentioned above.

Our results show that although a handful of states (Goa, Delhi, and Chandigarh) feature at the top of the efficiency ranking over the years, they do not include the major industrial states like Maharashtra and Gujarat. Also, several states (like Andhra Pradesh, Haryana, West Bengal, and Punjab) are at the lower end of the table for most years. Overall, in spite of specific instances of upward and downward mobility, there has been no major change in the efficiency ranking of individual states after the reforms. Also, our statistical analysis does not show that there has been a convergence in the distribution of technical efficiency across states. To a large extent technical efficiency of firms in a state is affected by the infrastructure and overall political-economic environment in the state where it is located. Apparently, the economic reforms especially in the form of liberalization of government control and greater reliance on market forces have, so far, failed to create an environment conducive to efficient utilization of resources in many states.

The rest of the paper unfolds as follows. Section 2 provides the theoretical background and describes the DEA methodologies for measuring (conventional) technical efficiency and super-efficiency. Section 3 describes the data and presents the findings from the DEA models. Section 4 considers the dynamics of the efficiency distribution (across states) over time through concordance analysis, convergence analysis and Markov chain analysis. Section 5 concludes.

2. The Theoretical Background

2.1 Efficiency and its Measurement

In parametric models, one specifies an explicit functional form for the frontier and econometrically estimates the parameters using sample data for inputs and output. Hence the validity of the derived technical efficiency measures depends critically on the appropriateness of the functional form specified.

In contrast, the method of DEA introduced by Charnes, Cooper and Rhodes (CCR) (1978) and further generalized by Banker, Charnes, and Cooper (BCC) (1984) provides a nonparametric alternative to parametric frontier production function analysis. In DEA, one makes only a few fairly weak assumptions about the underlying production technology. In particular, no functional specification is necessary. Based on these assumptions a production frontier is empirically constructed using mathematical programming methods from observed input-output data of sample firms. Efficiency of firms is then measured in terms of how far they are from the frontier.

Consider an industry producing a scalar output, y, from a bundle of m inputs, $x=(x_1,x_2,\ldots,x_m)$. Let (x^j, y^j) be the observed input-output bundle of firm j $(j= 1,2,\ldots, N)$. The technology is defined by the production possibility set

$$T=\{(x, y): y \text{ can be produced from } x\}.$$

An input-output combination (x^0, y^0) is feasible if and only if $(x^0, y^0) \in T$.

We make the following assumptions about the technology:

- All observed input-output combinations are feasible. Thus, $(x^j, y^j) \in T$ $(j = 1,2,\ldots,N)$.
- The production possibility set, T, is convex. Hence, if $(x^1, y^1) \in T$ and $(x^2, y^2) \in T$, then $(\lambda x^1+(1-\lambda)x^2, \lambda y^1+(1-\lambda)y^2)\in T$, $0\leq\lambda\leq 1$.

  In other words, weighted averages of feasible input-output combinations are also feasible.
- Inputs are freely disposable. Hence, if $(x^0, y^0)\in T$ and $x^1 \geq x^0$, then $(x^1, y^0)\in T$. This rules out negative marginal productivity of inputs.
- Output is freely disposable. Hence, if $(x^0, y^0)\in T$ and $y^1 \leq y^0$, then $(x^0, y^1)\in T$

  Varian (1984) pointed out that the smallest set satisfying the above assumptions is;

$$S = \{(x, y) : x\geq \sum_{j=1}^{N}\lambda_j x^j ; y \leq \sum_{j=1}^{N}\lambda_j y^j ; \sum_{j=1}^{N}\lambda_j = 1; \lambda_j \geq 0; j = 1,2,\ldots,N\}.$$

Let $\bar{x} = \sum_{j=1}^{N}\lambda_j x^j , \bar{y} = \sum_{j=1}^{N}\lambda_j y^j ; \sum_{j=1}^{N}\lambda_j = 1; \lambda_j \geq 0$. By virtue of convexity $(\bar{x},\bar{y})$ is feasible. Then, for any $x \geq \bar{x}, (x,\bar{y})$ is feasible. Finally, for any $y \leq \bar{y}, (x, y)$ is also feasible. If we assume constant returns to scale (CRS), for any $(x, y)\in T, (kx, ky)\in T$ for any $k \geq 0$. In that case, the λ_j s will be only restricted to be non-negative and would not have to add up to unity. The CRS production possibility set would then be

$$S^C = \{(x, y) : x \geq \sum_{j=1}^{N} \lambda_j x^j ; y \leq \sum_{j=1}^{N} \lambda_j y^j ; \lambda_j \geq 0; j = 1,2,..., N\}.$$

Under the CRS assumption, the output oriented technical efficiency of any firm producing output y^0 from input x^0 is $1/\phi^*$, where

$$\phi^* = \max \ \phi : (x^0, \phi y^0) \in S^C.$$

To compute technical efficiency[2] one solves the following linear programming problem:

$$\begin{aligned}
&\phi_k = max \quad \phi && k \in (1,..., N) \\
\text{s.t} \quad &\sum_{j=1}^{N} \lambda_j x_i^j \leq x_i^k && i = 1,..., m \\
&\sum_{j=1}^{N} \lambda_j y^j \geq \phi y^k && \qquad\qquad (1) \\
&\lambda_j \geq 0. && j = 1,2,..., N
\end{aligned}$$

2.2 Super-efficiency and its Measurement

The standard DEA models – both the CCR model for CRS and the BCC model for variable returns to scale (VRS) – provide measures of technical efficiency of a firm relative to the others within the same sample. Firms that are found to be technically inefficient can be ranked in order of their measured levels of efficiency. Firms that are found to be efficient are, however, all ranked equally by this criterion. Andersen and

[2] Under constant returns to scale the output- and input-oriented technical efficiency measures coincide.

Petersen (1993) suggest a criterion that permits one to rank order firms that are all found to be at 100% technical efficiency by DEA. The underlying idea behind this criterion is quite simple. Consider the single-input, single-output case. Suppose that a firm with input-output (x_0, y_0) has been found to be technically efficient in an output-oriented DEA problem. Obviously, if its output had been any larger than y_0, it would have remained efficient. But a small reduction in its output may not necessarily lower its technical efficiency rating from 100%. In that sense, this firm may suffer some deterioration in its performance without becoming inefficient. In other words, its observed output exceeds what is necessary for this firm to be considered efficient relative to other firms in the sample. In that case, the firm may be regarded as *super-efficient.* Naturally, between two firms both of which are technically efficient, the one with the greater room for reducing its output without becoming inefficient is, in a sense, more *super-efficient* than the other.

In the general case of *N* firms with the observed input-output bundle (x^j, y^j) for firm *j* (*j*=1, 2,…,*N*), for each technically efficient firm *k*, we solve the following DEA problem:

$$\bar{\phi}_k = max \quad \phi \qquad\qquad k \in (1,...,N)$$

$$\text{s.t} \quad \sum_{\substack{j=1 \\ j \neq k}}^{N} \lambda_j x_i^j \le x_i^k \qquad (i = 1,...,m)$$

$$\sum_{\substack{j=1 \\ j \neq k}}^{N} \lambda_j y^j \ge \phi y^k \qquad\qquad (2)$$

$$\lambda_j \ge 0. \qquad (j = 1,2,...,N; j \neq k)$$

The output bundle $\bar{y}_k = \bar{\phi}_k y^k$ is what the firm k needs to produce from the input bundle x^k in order to remain (output-oriented) technically efficient relative to the other firms in the sample. Thus, $\frac{1}{\bar{\phi}_k}$ is a measure of its *super-efficiency.* Hence, between two technically efficient firms i and j, both technically efficient, j is ranked above i, if $\bar{\phi}_j < \bar{\phi}_i$.[3]

A potential problem of feasibility with these *super-efficiency* models has been noted by Dulá and Hickman (1997), Xue and Harker (2002), and Seiford and Zhu (1999). For some efficient observations there may not exist any input- or output-oriented projection on to a frontier that is constructed from the remaining observations in the data set under the VRS assumption. For example, if the firm k under evaluation has the smallest quantity of any individual input in the sample, there cannot be *any* convex combination of the input bundles of the other firms that would satisfy the relevant input constraint in the problem (2) above. Thus, one cannot measure the level of *super-efficiency* of such a firm. This, however, is not a problem under the CRS assumption so long as all input bundles include positive quantities of every input.

3. The DEA Application

3.1 Data Description

In this paper, we examine state-level data from the Indian manufacturing sector for the years 1986-87 through 1999-00. The period up to 1990-91 is regarded as "pre-reform" and the subsequent period in the sample is regarded as "post-reform". The data for different states come from the Annual Survey of Industries (ASI) for the relevant

[3] Note that when efficiency <1 the super-efficiency measure is equal to the efficiency measure, whereas when efficiency =1 the super-efficiency measure is $\geq$ 1.

years. We conceptualize a single-output, 5-input production technology for the total manufacturing sector in India. Output is measured by the gross value of manufacturing production in the state. The inputs include (i) production workers, (ii) non-production workers, (iii) capital, (iv) fuels, and (v) materials. In light of inter-state differences in the output-mix, use of gross value to measure output may appear problematic. However, as shown in Ray (2002), under the assumption of identical output prices for different kinds of manufactured products across the nation, the value of aggregate output in manufacturing can serve as a quantity index of output. All inputs and output were divided by the number of establishments (factories) in that state so that we are examining and comparing the technical efficiency of a 'typical firm' within each state. It may be noted that under the CRS assumption DEA models using aggregate data and those using "per firm" data yield the same optimal solution. Nonetheless, there are two advantages to using per-firm data. First, although the total output would vary widely across states due to differences in their sizes, the per-firm data are more directly comparable and one can readily observe the differences in the output scales of typical firms across states. Secondly, even though the CCR model is invariant to a change in scale, in practical implementation a large variance in any one output or input often creates a problem for the simplex solution algorithm[4]. Use of per firm data considerably alleviates this problem.

3.2 Findings from the DEA application

Table 1a shows the summary statistics for the output oriented technical efficiency measures for the Indian states during the pre-reform period. During this period the

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[4] Ali (1994) characterized this as an "ill conditioned data" problem.

average efficiency was 0.96 indicating that on average the manufacturing sector could increase its output by 4% while using the same level of inputs. Of the pre-reform years the average efficiency was lowest in 1990-91, the year before the reform. Also the variation between states as measured by the coefficient of variation was highest in that year. Similar summary statistics for the post reform period are presented in Table 1b. We find that the average efficiency across states and across years for the post-reform period was 0.936 which is lower than the average for the pre-reform period. Delhi, Chandigarh, and Goa were efficient in every year over the entire sample period. The states of Maharashtra and Bihar were also efficient in every year during the pre-reform period.

For each year several states are found to be 100% efficient. Hence it is difficult to compare the relative performance of these states based on their efficiency measures. We therefore measure the super-efficiency for each state during each year in the sample period. Based on the super efficiency measures we are able to rank all the states in our sample in each year. Table 2 shows that while Delhi, Chandigarh, and Goa consistently ranked at the top over the entire sample period as well as in the two sub-periods, states like West Bengal, Andhra Pradesh, Haryana, and Punjab ranked consistently at the bottom. We also see that Maharashtra fell behind Delhi, Chandigarh, and Goa in terms of *super efficiency*. Further, Gujarat's performance is about average in terms of its ranking although its ranking improved after the initial post-reform period. Our results show that the 'typical' manufacturing firms in Maharashtra, Gujarat, Tamilnadu, and West Bengal, the four leading industrial states of the country[5], are not at the top in terms of technical

[5] Table 1 of Mitra et al. (2002) shows that in the year 1985 (that is the year right before the start of our sample period) the top four industrialized states in terms of the ratio of the state's manufacturing to Indian manufacturing sector as well as in terms of the share of manufacturing in the state domestic product were Maharashtra, Gujarat, Tamilnadu, and West Bengal.

efficiency. Of the four, only Maharashtra was at full technical efficiency by the conventional measure. Among the other three, Gujarat and Tamilnadu attained full efficiency in some years but West Bengal performed at less than 100% efficiency in every year in our sample period. This indicates that these states could further increase their manufacturing production by improving the technical efficiency of operation of the typical firm.

A question that naturally arises in this context is: If the states acclaimed to be the industrial leaders do not rank at the top in terms of efficiency, then what accounts for their leadership position in terms of overall manufacturing? In general, the industrial success of a state depends on its ability to attract and sustain a broad spectrum of industrial activities over years. The locational desirability of a state depends on a variety of factors that, along with technical efficiency and human capital, also affect the long run profitability of any venture. These include *political* factors like political stability and governance, regulations, tax laws, and trade unionism; *geographical* factors like access to markets, agglomeration economies, and infrastructure including transportation and power; and *economic* factors like price advantage especially with respect to labor. It is quite possible that for an individual state a lower level of technical efficiency is more than compensated by advantages in some of these other factors. But even in such a case any improvement in efficiency will only enhance the competitiveness of any particular state. Moreover, efficiency is the only one among these factors that can be improved to a large extent by the unilateral efforts of the firm.

It may be noted that, many of the above factors themselves may foster efficiency. For example, two of our best performing states, Goa and Delhi also ranked at the top two positions according to a recent study by Debroy and Bhandari[6], comparing 19 states on 46 parameters including law and order, education, infrastructure, and investment. In fact according to an earlier study by Ghosh and De (1998) too Delhi and Goa ranked among the top three positions in terms of transport and power. Among the poor performers in terms of our efficiency ranking, we find that West Bengal, which is in danger of losing its position among the industrial leaders, also appeared consistently at the lower end in the rankings by both these studies.

4. Dynamics of the Efficiency Distribution

4.1 Stability of Efficiency Ranks and Concordance Analysis

It is interesting to examine if the performance rankings of the states have been stable over time. The results of the pair wise Spearman rank correlation analysis between the rankings in the different years are presented in Table 3. We find that in general the agreement between the performance rankings of states is higher for adjacent years than for years that are further apart. To test the overall agreement among the efficiency rankings of the states across years we perform concordance analysis. The Kendall coefficient of concordance, W, measures the degree of association between multiple rankings (say m different rankings) of n observations. In other words, W represents the ratio of the actual agreement between annual rankings to the maximum possible agreement (in the case of perfect stability over years). If the efficiency rankings remain highly stable across years, the same group of states will appear at the lower, middle, or upper parts of the distribution. Hence the higher is the stability in the rankings of the efficiency scores over years, the higher will be the measured coefficient of concordance,

[6] This study and its results were reported in India Today (May, 2003)

W.[7] Results from the concordance analysis are presented in Table 4. The test statistic $\chi^2 = m(n-1)W$ follows a χ^2 distribution with n-1 degrees of freedom. Using the calculated values of W for the entire sample period as well as the various sub-periods in each case we can test the following hypothesis.

H_0 : The rankings are independent (i.e, $W = 0$)

against

H_1 : The rankings are not independent (i..e., $W \neq 0$)

The χ^2 test leads to a rejection of the null hypothesis of independence in ranking, at 1% level of significance over the entire sample period as well as for each of the two sub-periods. This implies that the efficiency rankings have been fairly stable and there is no evidence that the 1991 reforms significantly changed the relative efficiency rankings of the typical manufacturing firm from each state.

4.2 Convergence Analysis

Concordance analysis examines the stability of the ordinal ranking of the technical efficiency of the states. It is possible for the gap between a pair of states to significantly narrow down even though their ordinal ranks are not reversed. This happens when a lower ranked state improves faster than the higher ranked one. To examine the potential narrowing down of this gap we next investigate whether there is a convergence in the technical efficiency of the states over the time period under consideration in this study. Are the less efficient states improving in efficiency faster than the more efficient states over time? The concept used in the literature to describe this phenomenon is known

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[7] For a detailed discussion of Concordance analysis see Sheskin (1997)

as 'mean reversion' or 'β convergence'. Another important aspect of convergence is to examine whether the dispersion of the efficiency distribution is narrowing over time. (See Barro and Sala-i-Martin 1991, Sala-i-Martin 1994, and Quah 1993 for a discussion of these concepts of convergence).

To test for mean reversion one could run the regression (see Lichtenberg 1994 for details of the following discussion):

$$\ln(Y_{t+j}) - \ln(Y_t) = \alpha + \beta \ln(Y_t) + u \tag{3}$$

and test for $\beta < 0$.

Alternatively, we can rewrite (3) as

$$\ln(Y_{t+j}) = \alpha + (1+\beta)\ln Y_t + u \tag{4}$$

$$= \alpha + \pi \ln(Y_t) + u$$

where $\pi = 1 + \beta$. In this case the test for mean reversion is to test for the hypothesis

$H_0 : \pi \geq 1$ (no mean reversion)

against

$H_1 : \pi < 1$

The above hypothesis can be tested through a *t* test.

On the other hand convergence (i.e., σ convergence) implies that

$$\frac{d\left[\mathrm{var}(\ln Y_t)\right]}{dt} < 0 \tag{5}$$

or, in terms of two discrete points of time

$$\frac{\left[\mathrm{var}(\ln Y_t)\right]}{\left[\mathrm{var}(\ln(Y_{t+j})\right]} > 1 \tag{6}$$

From (4) this can be tested as

$$H_0 : \frac{R^2}{\pi^2} = 1 \text{ (no convergence)}$$

against

$$H_1 : \frac{R^2}{\pi^2} > 1 .$$

The above hypothesis can be tested by an F test.

Table 5 shows the results of the mean reversion and convergence tests over the entire sample period as well as for the pre-reform and post-reform periods based on the super-efficiency measures. Tests conducted for each sub-period failed to reject the null hypothesis of 'no convergence' even at the 5% level of significance. Hence we find no evidence of convergence in the efficiency performance of the states and union territories. For the test of 'mean reversion' we are unable to reject the null hypothesis of 'no mean reversion' for the entire period 1986-87 through 1999-00 or for the post-reform period (1991-92 through 1999-00) even at the 5% level of significance. However, for the pre-reform period (1986-87 through 1990-91) we are able to reject the null hypothesis of 'no mean reversion' at the 5% level of significance (although not at the 1% level of significance). Thus we find some evidence of mean reversion during the pre-reform period.

4.3 Markov Chain Analysis

The concordance analysis in section 4.1 indicates that the rankings of states were fairly stable over the sample period. However the values of the concordance coefficient W also tell us that there is room for some mobility across years. The convergence analysis gave us no significant evidence of convergence from the pre-reform to the post-reform period. However, this does not tell us much about the intra-distributional movements of efficiencies from one level (low, medium, or high) to another. We can get insights into this by performing a Markov chain analysis.[8] We first of all classify the efficiencies into three groups[9]: group1 - low efficiency (super efficiency < 0.9)[10]; group 2 - medium efficiency (0.9 $\leq$ super efficiency <1); and group 3 - high efficiency (super efficiency $\geq$ 1). The distribution of the efficiency scores in each of the three groups for the years 1986-87 to 1999-00 are presented in Table 6. The Markov chain analysis focuses on the transition probabilities p_{ij}^{t} that an Indian state whose efficiency is in group i in period t-1 will move to group j in period t, (where i, j = 1, .., r)[11]. Since these transition probabilities are time dependent, we compute the maximum-likelihood estimate of the transition probabilities for each of our three periods of interest – the entire sample period (1986-87 through 1999-00), the pre-reform period (1986-87 through 1990-91), and the post-reform period (1991-92 through 1999-00) using the following method after Anderson and Goodman (1957):

Let n_{ij}^{t} denote the number of Indian states whose efficiency was in group i in period t-1 and transitioned to group j in period t.

$$n_{ij} = \sum_{t=2}^{T} n_{ij}^{t}$$

In our application T = 14 for the entire sample period, whereas T = 5 for the pre reform period, and T= 9 for the post reform period.

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[8] Bartelsman and Dhrymes (1998) applied Markov chain analysis to study the productivity dynamics in U.S. manufacturing using establishment level data.

[9] In the literature, the standard term used to refer to these groups is 'states'. In order to avoid potential confusion with our use of the term state to refer to the geographical areas in India we chose to use the term groups instead.

[10] An efficiency score of less than 0.9 represents a shortfall of more than 10% from the benchmark and is therefore classified as low efficiency here.

We also obtain the maximum likelihood transition probabilities, $\hat{p}_{ij} = \dfrac{n_{ij}}{\sum_{j=1}^{r} n_{ij}} \geq 0$

The matrix $\hat{P}$ whose elements are $\hat{p}_{ij}$ s is the maximum-likelihood estimate of the transition matrix. This matrix satisfies the properties: $0 \leq \hat{p}_{ij} \leq 1$ and $\sum_{j=1}^{r} \hat{p}_{ij} = 1$ and is therefore a Markov matrix. The $\hat{P}$ matrix for the period 1986-87 through 1999-00 is presented in Table 7a and similar matrices corresponding to the pre-reform period and post-reform periods are presented in Table 7b and Table 7c respectively. From each of these three matrices we find that there is a high probability that an Indian state belonging in a certain efficiency group will remain in that same group. For instance in Table 7a the probability of moving from group 1 to group 1 is 0.526, the probability of moving from group 2 to group 2 is 0.612, and the probability of moving from group 3 to group 3 is 0.761. Similar results are seen from Table 7b and 7c. We also see that there is very low probability that a state belonging to group 3 (high efficiency) will move to a low efficiency or medium efficiency group but there is a reasonable probability that a state belonging in group 1 (low efficiency) will move to group 2 (medium efficiency). This was especially so for the pre-reform period.

A Markov chain represents a stationary process if after a sufficiently large number of transitions the transition probabilities remains constant over time. The estimated transition matrix ($\hat{P}$ matrix) can be tested for the null hypothesis of stationarity (against the alternative hypothesis of non-stationarity) by applying a χ^2 test, the test statistic for which is given by

[11] Where r is the total number of groups. In our application r = 3.

$$\chi^2_{r(r-1)(m-1)} = \sum_{t=2}^{T}\sum_{i=1}^{r}\sum_{j=1}^{r} n_i^{t-1}\left[\frac{(p_{ij}^t - \hat{p}_{ij})^2}{\hat{p}_{ij}}\right],$$

where *m* is the number of transition matrices.

For the entire sample period 1986-87 through 1999-00 the calculated test statistic is χ^2 = 88.228249, with 72 degrees of freedom. The calculated test statistic for the pre-reform period 1986-87 through 1990-91 is χ^2 = 14.848041, with 18 degrees of freedom whereas for the post-reform period it is χ^2 = 53.086283, with 42 degrees of freedom. In each of these cases we are unable to reject the null hypothesis of stationarity even at the 5% level of significance. From these three stationary matrices we are able to obtain the long-run probabilities of efficiencies falling in the three groups defined above.[12] We find that in the long-run, there is equal probability that the efficiencies of the manufacturing sector in the 22 Indian states and union territories will be in any of the three efficiency groups i.e., the long-run probability for each of the groups is 0.33333. This implies that the long run efficiency distribution will not be bimodal.

The main findings of the study may be summarized as follows:

- A 'typical' firm from a leading industrial state is not necessarily more efficient.
- Despite some mobility, the efficiency ranking of individual states has been persistent over time.
- The economic reforms have not altered the relative efficiency rankings in a significant manner.
- There is no evidence of σ-convergence (in the sense of lower variance) and only a weak evidence of mean reversion prior to the reforms.

[12] See Simon and Blume 1994.

- The long run distribution of efficiency is uniform rather than bimodal.

5. Summary

In this paper we analyzed state level data for the aggregate manufacturing sector in India (constructed from the Annual Survey of Industries) for the period 1986-87 to 1999-00 to study the efficiency dynamics of individual states. Using the non-parametric method of Data Envelopment Analysis we utilized super-efficiency models to rank the states in terms of their performance. The results show considerable variation in efficiency across states. Further, there has been little movement across ranks.

One caveat is that our findings are based on the analysis of the total manufacturing sector and may hide variation across industries within manufacturing. A more detailed sector-by-sector analysis would provide more insight into the effect of the reforms on the relative efficiency of each state's manufacturing sector.

Also, use of per firm or average data may hide changes in efficiency caused by reallocation of production across firms operating at different levels of efficiency within any state. This limitation can be addressed only in a study using panel data at the plant level.

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Table 1a: Summary of efficiencies (Pre-reform).

stat	eff8687	eff8788	eff8889	eff8990	eff9091	eff8691
mean	0.973868	0.972501	0.94834	0.959391	0.94814	0.960448
min	0.89339	0.89849	0.85265	0.88696	0.85132	0.85132
max	1	1	1	1	1	1
stdev	0.03434	0.035631	0.051464	0.044512	0.055017	
cv	0.035261	0.036639	0.054267	0.046396	0.058026	

Note: eff8691 gives the overall summary statistics for the pre-reform period.

Table 1b: Summary of efficiencies (Post-reform)

stat	eff9192	eff9293	eff9394	eff9495	eff9596	eff9697	eff9798	eff9899	eff9900	eff9100
mean	0.973	0.970	0.926	0.968	0.961	0.961	0.908	0.857	0.902	0.936
min	0.888	0.877	0.784	0.866	0.847	0.852	0.761	0.697	0.721	0.697
max	1	1	1	1	1	1	1	1	1	1
stdev	0.036	0.039	0.066	0.039	0.049	0.047	0.085	0.097	0.090	
cv	0.037	0.040	0.071	0.041	0.051	0.048	0.093	0.113	0.099	

Note: eff9100 gives the overall summary statistics for the post-reform period.

Table 2: Efficiency Rankings for overall period and sub-periods.

		Sample Period	Pre-Reform	Post-Reform	Initial Post-Reform	Later Post-Reform
Obs	**STATE**	**Rank 8600**	**Rank 8691**	**Rank 9100**	**Rank 9196**	**Rank 9600**
1	AP	21	21	20	20	21
2	AS	14	7	18	13	20
3	BI	5	5	4	5	5
4	GU	10	13	10	15	6
5	HA	19	20	19	21	18
6	HP	4	3	5	4	7
7	JK	7	14	6	3	13
8	KA	15	11	14	10	16
9	KE	13	12	13	14	12
10	MP	11	10	12	11	10
11	MH	6	6	7	7	8
12	OR	8	8	8	9	9
13	PU	22	22	21	22	17
14	RA	18	19	16	17	11
15	TN	16	15	15	12	14
16	UP	17	17	17	16	15
17	WB	20	18	22	18	22
18	AN	9	9	11	8	19
19	CH	2	1	2	2	3
20	DE	3	4	3	6	1
21	GO	1	2	1	1	2
22	PO	12	16	9	19	4

Note: The states and union territories included in this study are Andhra Pradesh (AP), Assam (AS), Bihar (BI), Gujarat (GU), Haryana (HA), Himachal Pradesh (HP), Jammu and Kashmir (JK), Karnataka (KA), Kerala (KE), Madhya Pradesh (MP), Maharashtra (MH), Orissa (OR), Punjab (PU), Rajasthan (RA), Tamilnadu (TN), Uttar Pradesh (UP), West Bengal (WB), Andaman and Nicobar Islands (AN), Chandigarh (CH), Delhi (DE), Goa (GO), and Pondicherry (PO).

Table 3: Spearman Rank Correlations.

	8687	8788	8889	8990	9091	9192	9293	9394	9495	9596	9697	9798	9899	9900
8687	1	0.67	0.81	0.72	0.55	0.5	0.63	0.7	0.5	0.7	0.5	0.67	0.65	0.52
8788		1	0.67	0.6	0.84	0.62	0.84	0.84	0.68	0.64	0.68	0.49	0.44	0.32
8889			1	0.81	0.57	0.46	0.67	0.61	0.52	0.84	0.55	0.6	0.4	0.59
8990				1	0.68	0.68	0.75	0.68	0.59	0.81	0.54	0.46	0.5	0.53
9091					1	0.84	0.91	0.93	0.74	0.72	0.67	0.45	0.4	0.26
9192						1	0.83	0.82	0.85	0.62	0.75	0.44	0.28	0.17
9293							1	0.87	0.85	0.7	0.82	0.59	0.43	0.39
9394								1	0.77	0.75	0.68	0.56	0.48	0.25
9495									1	0.64	0.89	0.64	0.18	0.25
9596										1	0.56	0.51	0.36	0.46
9697											1	0.72	0.16	0.37
9798												1	0.36	0.63
9899													1	0.55
9900														1

Table 4: Results of Concordance Analysis

	1986-87 to 1999-00	1986-87 to 1990-91	1991-92 to 1999-00	1991-92 to 1995-96	1996-97 to 1999-00
W	0.629035	0.75792	0.609316	0.815246	0.597826
χ^2	184.94	79.58	115.16	85.6	50.22

Note: 1. All the χ^2 values are significant at the 1% level of significance.
2. The period 1991-92 through 1995-96 is the initial post-reform period whereas the period 1996-97 through 1999-00 is the later post-reform period

Table 5: Results from convergence analysis

	Entire Period 1986-87 to 1999-00	Pre-Reform 1986-87 to 1990-91	Post- Reform 1990-91 to 1999-00
π (standard error)	1.23449 (0.21896)	0.68268 (0.15838)	0.62431 (0.32652)
R^2	0.6138	0.4816	0.1545
Calculated *t*	1.070926	-2.003536	-1.150588
Test for mean reversion	Cannot reject null hypothesis at 5% or 1% level of significance	Reject null hypothesis at 5% level of significance	Cannot reject null hypothesis at 5% or 1% level of significance
Calculated $\frac{R^2}{\pi^2}$	0.402765	1.033361	0.396395
Test for convergence	Cannot reject null hypothesis at 5% or 1% level of significance	Cannot reject null hypothesis at 5% or 1% level of significance	Cannot reject null hypothesis at 5% or 1% level of significance

Table 6: Distribution of efficiencies

	Group 1 Efficiency < 0.9	Group 2 $0.9 \leq$ Efficiency <1	Group 3 Efficiency ≥ 1
1986-87	1	10	11
1987-88	1	10	11
1988-89	4	11	7
1989-90	3	10	9
1990-91	5	8	9
1991-92	1	10	11
1992-93	2	11	9
1993-94	6	9	7
1994-95	2	10	10
1995-96	3	9	10
1996-97	4	9	9
1997-98	11	5	6
1998-99	14	4	4
1999-00	8	9	5

Table 7a: Transition Probabilities Matrix (P& Matrix) for 1986-87 through 1999-00

To → / From ↓	Group 1	Group 2	Group 3
Group 1	0.526316	0.403509	0.070175
Group 2	0.241379	0.612069	0.146552
Group 3	0.053097	0.185841	0.761062

Table 7b: Transition Probabilities Matrix (P& Matrix) for 1986-87 through 1990-91

To → / From ↓	Group 1	Group 2	Group 3
Group 1	0.333333	0.555556	0.111111
Group 2	0.219512	0.634146	0.146341
Group 3	0.026316	0.210526	0.763158

Table 7c: Transition Probabilities Matrix (P& Matrix) for 1991-92 through 1999-00)

To → / From ↓	Group 1	Group 2	Group 3
Group 1	0.604651	0.325581	0.069767
Group 2	0.283582	0.582090	0.134328
Group 3	0.075758	0.196970	0.727273