TECHNICAL EFFICIENCY:
AN INTERSTATE COMPARISON OF RAILWAYS IN AUSTRALIA

Dr. A.S. Godfrey Lubulwa,
School of Economics,
La Trobe University,
Victoria.

Eddie Oczkowski,
School of Economics,
La Trobe University,
Victoria.

ABSTRACT: *This paper explores the technical efficiency of the freight services divisions of Australia railways. A 'best-practice' frontier is estimated using maximum likelihood estimators with a gamma distributed error term. This frontier is then used to construct efficiency indices for the railway systems.*

When the states are ranked according to the efficiency indices, Victoria is consistently the least efficient. Queensland is the most efficient if train-kilometres is the measure of output, while South Australia is the most efficient if tonne-kilometres is the output measure. There are major divergences between the time paths of technical efficiency indices across States which might be due to random factors which are beyond the railway systems control. Apart from Western Australia and Queensland whose efficiency indices increase over time, all the other Government owned railway systems have become relatively more inefficient over time within the sample period.

ACKNOWLEDGEMENT: The research assistance of Evelyn Scopes and John Smith and the financial assistance in the form of a Commonwealth Tertiary Education Commission (CTEC) grant are gratefully acknowledged.

TECHNICAL EFFICIENCY OF RAILWAYS IN AUSTRALIA

1. Introduction

In the economics literature there are three main efficiency concepts : technical allocative (or price) and scale efficiency Technical inefficiency means that a firm uses more inputs than necessary to produce a given output Allocative (or price) inefficiency means that a firm is not equating the ratio of its factor marginal products to the relative factor prices; that is it is not cost minimising. A firm is scale inefficient if the price of its output is not equal to the firm's marginal cost. A firm is said to be operationally efficient if it is technically allocatively and scale efficient.

This paper explores the technical efficiency of the freight service divisions of the six state railway systems in Australia. In order do this a deterministic statistical 'best-practice' frontier is estimated and is then used as a reference or basis for measuring inefficiency within the freight service section of the Australian railway transport sector The frontier is deterministic in the sense that individual observations are restricted to lie on or below the production frontier Random/stochastic frontier models[1] permit observations to lie both below and above the average production frontier by arguing that the performance of a firm is affected both by factors that it can control (e g efficiency) and by factors it cannot control (e g random events like weather, strikes etc) So in the year when a firm is favourably impacted by some random factors it could perform better than average and so the firm's observation for that year would lie above the frontier Unfortunately there is no known way to date of empirically determining whether the deviation of an observation from the efficiency frontier is due to random variations or due to inefficiency. Since this paper is aimed at estimating technical efficiency for each observation there are no gains in using a more general stochastic frontier model if it is impossible to isolate the specific inefficiency of interest here[2]

[1]Sometimes referred to as composed error models. See Aigner Lovell and Schmidt (1977), Meeusen and Van den Broech (1977) A useful review is in Førsund Lovell and Schmidt (1980)

[2]In stochastic frontier models the error term comprises of two independent components, $\epsilon_i = v_i - u_i$; v_i is the random component and u_i is the non-negative component. At best, direct estimates of ϵ_i are only attainable. Recently however it has been suggested, (see Jondrow Lovell Materov and Schmidt (1982)) that the distribution of u_i conditional on the estimable ϵ_i might be used to provide point estimates of u_i It is clear that the

Deterministic frontiers have been estimated before using linear and/or quadratic programming estimation procedures which involve computing a parametric convex hull of the observed input-output ratios using a method first suggested by Farrell (1957), first applied by Aigner and Chu (1968) assuming a homogeneous Cobb-Douglas production frontier and generalised by Førsund and Jansen (1977) and Førsund and Hjalmarsson (1979) to accomodate non-homogeneous production functions

The frontier estimated in this paper is a statistical frontier in the sense that unlike the above mentioned studies its estimation involves the use of standard statistical techniques as opposed to programming sub-routines This is achieved by assuming that inefficiency is distributed across the firms according to a two parameter gamma distribution following Afriat (1972) Richmond (1974), Schmidt (1976) and Greene (1980) Then use is made of maximum likelihood estimation techniques to estimate the coefficients of the frontier The assumption imposed that no observation may lie above the efficiency frontier is equivalent to restricting the error term to be non-positive In general under this assumption maximum likelihood estimates may not be consistent and/or asymptotically efficient. Nevertheless Greene (1980) has shown that if inefficiency is distributed according to a gamma distribution as assumed in this paper then the maximum likelihood estimators of the modified model have the usual desirable asymptotic properties.

Finally the frontier estimated is a 'best practice' frontier' in the sense that it is sample specific and gives the maximal output which can be attained from a set of input quantities given the firms in the sample. It is related to the 'absolute' frontier (which gives the maximal output attainable given a set of input quantities and all firms which could concievably exist) in that as the sample size increases, the 'best-practice' converges to the 'absolute' frontier The rest of the paper is organised as follows: Section 2 discusses the main theoretical constructs employed in the study Section 3 discusses the estimation methods in greater detail and the data used in estimation. Section 4 presents and interprets the results while section 5 draws the major conclusions from the study

2. The 'Best Practice' Frontier and Inefficiency Indices

This section briefly discusses the concept of an efficiency frontier and discusses two measures of technical efficiency that are employed in later sections of the paper

2.1 The Efficiency Frontier

Take an industry where there are m firms with the ith firm producing a single output X_i from two sets of inputs capital K_i, and labour L_i according to the following production function:

$$X_i = T_i(K_i, L_i); \ i=1, \ldots, m \qquad (2.1a)$$

Efficiency measures are usually based on factor inputs required to produce one unit of output. By multiplying through by $1(X_i/X_i)$ (2.1a) is mapped into an inputs coefficients space to get:

$$X_i = t_i(k_i X_i, l_i X_i) \qquad (2.1b)$$

where k_i, l_i are the input coefficients which respectively denote the amount of capital and labour required to produce one unit of output. The efficiency frontier is defined as the set of points where the input coefficients k_i and l_i obtain their minimum values along rays from the origin (Førsund and Hjalmarsson (1974)).

Suppose a firm is observed to produce X_i^o units of output using K_i^o, L_i^o units of capital and labour. Such an observed point is inefficient if it is not on the production frontier. That is given K_i^o, L_i^o the observed inputs, one could produce a higher output X^*, $X^*>X^o$ by moving vertically to a point on the production function. Alternatively given X^o the observed output, a firm could produce the same output at some point on the frontier using input quantities K, L with $K<K^o$ and $L<L^o$.

2.2 Measures of Efficiency

There are different suggested methods of measuring efficiency, a number of them are discussed in Farrell (1957) who was the pioneer in the area, Fáre and Lovell (1978), Førsund and Hjalmarsson (1974) and Thuong (1981). In this paper use is made of the following two measures:

a) The input saving measure of technical efficiency

This is a ratio F^e/F^o where F_e are the input quantities required to produce X^o the observed output efficiently and F^o are the observed inputs associated with X^o This measure reveals the relative reduction in the quantities of inputs required to produce X_i^o with the efficiency frontier technology The measure is denoted by E_1

b) <u>The output augmenting measure of technical efficiency</u>

This measure is denoted by E_2 where

$$E_2 = \frac{\text{The observed output } X_i^o}{\text{The efficient output } X_i^*}$$

Generally E_2 is such that $0<E_2\leq 1$ and reveals how much output would be increased by moving vertically from the observed output X_i^o to the production frontier output X_i^* keeping factor inputs at K_i^o L_i^o

3. <u>The Estimation of the Efficiency Frontier</u>

This section discusses the data that is used in the estimation of the efficiency frontier Details of the empirical model can be found in the Appendix

The paper uses data in the period between 1952-53 and 1982-83 (but not for 1980/81 and 1973/74 for which no published statistics were available) on the following six government owned railway systems;

(i) The State Rail Authority of New South Wales (SRA) (N.S W)
(ii) V/Line operated by the State Transit Authority of Victoria (Vic)
(iii) Queensland Government Railways (Qld)

(iv) Western Australian Government Railways Commission (W A)
(v) South Australian Government Railways (S A)
(vi) Tasmanian Government Railways (TAS)

Australian National Railways Commission (ANRC) assumed full control over the Tasmanian and non-metropolitan South Australian railways, including those formerly managed by the Commonwealth Railways, on 1 March 1978 From 1977-78 the figures on freight movements in South Australia and Tasmania are published under the Australian National heading where they are aggregated with the figures on what was formerly the Commonwealth Railways

This aggregated data has been used here to generate the otherwise missing observations on Tasmania and South Australian Government Railway systems. The extrapolation method used assumed that from 1976-77 to 1982-83 the percentage changes and the direction of these changes in the observations on Australian National variables approximated on average the changes in the corresponding Tasmanian and South Australian variables. This method was used to generate values for Tasmania and South Australia for the years 1977-78 1978-79, 1979-80 1981-82 and 1982-83 This covers 5 years out of a 29 year sample period and affects the two smallest states in the Australian economy. All the data used is collected from Australian Bureau of Statistics publications detailed at the end of the paper

(i) OUTPUT

The output of the railway system can be measured by either train-kilometres or net tonne-kilometres Results are reported for both measures of output A train-kilometre in this paper stands for one train (that is a complete unit of locomotive and vehicles electric train set or rail motor) travelling one kilometre for the purpose of moving goods. Train-kilometres as an output measure has the inherent problem of including empty wagon-kilometres of which little is known The net tonne-kilometres measure overcomes this problem

(ii) CAPITAL

The number of goods rolling stock is used as a proxy variable for capital because it was impossible to construct capital time series corresponding to the output series for any of the six railway systems The number of goods rolling stock for all states is available over long time periods. Since these wagons are specifically for movement of goods, their use as a measure of capital while not resolving the problem at least it avoids the joint costing (with passenger traffic) problem which would arise if other measures of capital like fixed assets track open lines and signalling to mention a few are adopted. Furthermore these other measures are inappropriate because of the different accounting methods used by the different railway systems in Australia over the sample period which means that it is not clear what total assets comprises nor how depreciation of assets is handled across systems

(iii) LABOUR

Published data do not allow the total employment associated with freight to be estimated The Australian Bureau of Statistics publishes statistics based on census information for occupation and for industry neither of these captures transport adequately. In particular neither category allows analysis of freight as distinct from passenger In this study the number of workers employed in the rail system are used as a measure of the labour input in the railway system.

4 THE RESULTS

Table 1 presents the parameter estimates obtained using MOLS, the modified ordinary least squares and maximum likelihood for the full frontier with a gamma distributed error term Numbers in parenthesis are asymptotic t-ratios computed using the ratio of the estimate to the square root of the apropriate diagonal element of the estimated asymptotic covariance matrix

The MOLS estimates which are all significant suggest that the production frontier for government railways goods' freight services is:

$$\text{Train-km MOLS} = 0\ 2217e^{0\ 0183t}\, L_{it}^{0\ 651}\, K_{it}^{0\ 370} \qquad (4a)$$

$$\text{Net Tonne-km MOLS} = 0.0005e^{0.0578t}\, L_{it}^{0\ 624}\, K_{it}^{0\ 640} \qquad (4b)$$

depending on whether train kilometres or net tonne kilometres are used as the output measure.

The figures of 0 2217 and 0.0005 in (4a) and (4b) are antilogs of the estimates of α in Table 1 since $\alpha = \ln A$. The factor input elasticities estimates in (4b) are comparable to those obtained by the Transport Economics Centre (1982, p 14) where the elasticity with respect to capital is estimated to be almost as high as the elasticity with respect to labour

In (4a) one has the implied returns to scale of 1.021 while in (4b) the implied returns to scale is 1.264. The higher returns to scale associated with (4b) are precipitated by a much higher reported elasticity with respect to capital inputs in (4b) as compared to (4a). In (4a) the rate of disembodied technical change is only 1.83 percent per annum, while in (4b) the implied rate of disembodied technical change is a much higher one of 5.78 percent per annum.

The estimate of technical progress in (4a) is similar to those established by Caves et al. (1981, p 1000) for U.S. railways, 1955-1974 where it was concluded that:

> 'Over the full period productivity growth averaged approximately 2 percent per year'

The figure of 5.78% in (4b) is high even in the U.S. railways context where the highest rate of technical progress reported by Caves et al. (1981) is one of 4.2% for the sample period 1955 to 1963.

One major difference between equation (4a) and (4b) which is of importance for this study is the divergence between the values of the gamma distribution parameter P associated with the two equations. It is generally accepted that

> '... if the observations tend to be grouped close to the frontier, with only a relatively small number in the extreme range, then P should be small, the error distribution will be highly skewed and we should expect the maximum likelihood estimation to be highly efficient relative to OLS' Greene (1980, p 44).

TABLE 1

Parameter Estimates of the Efficiency Frontier

Output Measures

	Train kilometres		Net tonne-Kilometres	
	MOLS	MLG	MOLS	MLG
α	-1.506[a] (-5.289)[c]	-1.617 (-15.249)	-7.600[b] (-20.830)[c]	-7.953 (-24.274)
β_1	0.651 (10.973)	0.636 (28.843)	0.624 (8.214)	0.536 (8.426)
β_2	0.370 (4.974)	0.415 (15.003)	0.640 (6.719)	0.773 (9.689)
m	0.0183 (9.026)	0.0160 (21.285)	0.0578 (22.25)	0.0598 (27.47)
λ	6.485	6.408 (8.182)	6.646	8.492 (4.46)
P	2.214	2.304 (8.042)	3.820	6.458 (2.718)
L*	10.803	31.705	-76.538	-27.627

(a) The OLS estimate of α is -1.8472 (with an asymptoptic t-ratio of -6.488) for the production frontier with train kilometres as the output measure.

(b) The OLS estimate of α is -8.1748 (with an asymptoptic t-ratio of -22.405) for the production frontier with net tonne-kilometres as the output measure.

(c) The original OLS standard error is used to approximate the t-ratio for the MOLS intercept. Even though the original and modified OLS standard errors are assumed to be approximately equal, it follows that the t-ratios will not be equal.

The value of the gamma distribution parameter P of 2 211 associated with (4a) is almost half the value of P of 3 820 associated with (4b) This then suggests that using train-kilometers as an output measure would tend to suggest that railway systems are more efficient than would be the case if tonne-kilometres are used as a measure That is more systems would appear to be close to the frontier than would be the case if tonne-kilometres is the output measure. This difference in efficiency indices is attributable to the inclusion of train-kilometres with empty wagons in the total train-kilometres reported On the other hand net tonne-kilometres by weighing kilometres covered with tonnes actually carried eliminates the empty wagon problem

The column labelled MLG in Table 1 reports the estimation of the frontier using maximum likelihood with a gamma distributed error term. The MOLS estimates of the frontier are used as the initial estimates in the iterative estimation process The frontier suggested by MLG in Table 1 is :

$$\text{Train-km (MLG)} = 0\ 198e^{0.016t}\ L_{it}^{0\ 636}\ K_{it}^{0\ 415} \qquad (4c)$$

$$\text{Net Tonne-km (MLG)} = 0\ 00035e^{0\ 0598}\ L_{it}^{0\ 536}\ K_{it}^{0\ 773} \qquad (4d)$$

Again, the equation with train-kilometres as the measure of output, (4c), suggests returns to scale of 1.051 which is close to unity and rates of disembodied technical progress equal to 1.6 percent per annum Equation (4d) suggests much higher returns to scale (1 309) and a much high rate of disembodied technical program of 5 98 per cent per annum. One possible explanation for these high rates of Hicks-neutral technical progress is probably the way the labour input was measured.

Australian Bureau of Statistics figures on the average weekly hours worked by persons in Australia show a decline from 39.3 hours per week in 1965 to 35.3 hours per week in 1982-83 By using number of workers employed instead of average hours worked (4a)-(4d) implicitly assume a time invariant number of hours worked per week and might be underestimating the labour input elasticities while overestimating the rate of technical progress The adjustment for decreasing weekly hours worked was not done because the data on hours worked was available for only part of the sample 1965 to 1982; even then it was available for Australia as a whole and not by State and it was not possible to establish whether the railway systems experienced this decline in average weekly hours worked

Table 2 presents arithmetic means of technical efficiency indices E_1 and E_2 which were described in Section 2 In order to appreciate how E_1 and E_2 are computed find the value of a constant μ such that:

$$X^o_{it} = A\ e^{mt}\ (\mu L^o_{it})^{\beta 1}\ (\mu K^o_{it})^{\beta 2} \qquad (4e)$$

where X^o_{it} is the observed output and the left hand side of (4e) is a function of the observed inputs L^o_{it} and K^o_{it} and a scaling factor μ If $\mu = 1$ then the observed point $(L^o_{it}\ \ K^o_{it}\ \ X^o_{it})$ is efficient. If $\mu < 1$, then the observed point is technically inefficient In this paper

$$E_1 = \mu \qquad (4f)$$

Now (4e) is equivalent to:

$$X_{it} = \mu^{\beta 1+\beta 2}\ Ae^{mt}(L^o_{it})^{\beta 1}(K^o_{it})^{\beta 2} \qquad (4g)$$

Dividing both sides of (4g) by X^*_{it}, the efficient output yields E_2

$$E_2 = X^o_{it}/X^*_{it} = \mu^{\beta 1+\beta 2} \qquad (4h)$$

E_1 and E_2 would be identical only if the production function displayed constant returns to scale.

Table 2 also provides a ranking of the States It must be noted that the ranking of the States is identical whether one used E_1 or E_2 to rank them. Victoria is consistently the most inefficient state irrespective of the output measure used. The ranking of the other states is different depending on what output measures is used When train kilometres is used as a measure of output the geographically larger states dominate the ranking at the expense of the smaller states This confirms the doubts expressed earlier that this measure of output by exaggerating actual output tend to overstate the efficiency of those states which are geographically large.

When net tonne kilometres are used as a measure of output, the ranking of states dramatically changes South

7

Australia tops the list followed by New South Wales Western Australia Queensland and Tasmania in that order Furthermore the best reported average efficiency in this case is an E_1 value of 0 655 compared to the reported highest E_1 value of 842 when train kilometres are used as a measure of output

In figures 1A to 1F we present in a graph form the indices for the six states. Figures 1A to 1C are graphs of the input saving measure of efficiency E_1 when train kilometres is used as the output measure. One interesting property on the train kilometre related measure is that it is relatively stable over time for each State The pairs of States whose indices and are presented on the same graph were selected for clarity of presentation alone (minimising the criss-crossing) Given the short comings of train kilometre related measures of efficiency Figures 1A to 1C are not analysed in detail they are only presented for the sake of completeness

Figures 1D to 1F are graphs of the input saving measure of efficiency using the preferred output measure of net tonne kilometres In these figures which are computer plotted the efficiency ratio E_1 is plotted against time for each State The interpretation of E_1 of say 0.420 for Victoria for a given year is that had government owned railways in Victoria been as technically efficient as goverment owned railways in other Australian States then Victoria's observed level of freight transport services could have been produced with only 0 42 percent of the factor inputs actually used by Victoria's government railway As the graphs in Figures 1D to 1F reveal there is considerable variation in efficiency over time and between the railway systems for a given year.

While Victoria and Queensland in Figure 1D have comparable inefficiency scores up to 1965 the two States diverge from then on with Queensland becoming more efficient while Victoria becomes increasingly more inefficient In Figure 1E New South Wales and Tasmania keep an almost constant distance between their efficiency indices with New South Wales, the more efficient In Figure 1F while South Australia is more efficient than Western Australia up to the mid 1960's, there is a reversal in roles with Western Australia becoming more efficient from the late 1960s to the present

Table 3 presents the output increasing measures of efficiency, E_2 for government railways in Australia. The interpretation of these indices is as indicated earlier An index of 0 18 for Victoria in 1982/83 means that the observed production is only 18% of the output obtained by employing the same amount of inputs in the frontier function

TABLE 2

ARITHMETIC MEANS OF TECHNICAL EFFICIENCIES INDICES

OUTPUT MEASURES

	Train-km		Net Tonne-km	
	E_1	E_2	E_1	E_2
NSW	0.818 (3)	0.810 (3)	0.655 (2)	0.575 (2)
VIC	0.480 (6)	0.463 (6)	0.420 (6)	0.321 (6)
QLD	0.842 (1)	0.835 (1)	0.543 (4)	0.450 (4)
WA	0.824 (2)	0.816 (2)	0.636 (3)	0.553 (3)
SA	0.619 (5)	0.605 (5)	0.656 (1)	0.576 (1)
TAS	0.775 (4)	0.765 (4)	0.541 (5)	0.448 (5)
AUST	0.726	0.716	0.577	0.487

FIGURE 1A: E_1 STATE EFFICIENCIES (TRAIN-KM) FOR N S W. AND TAS.

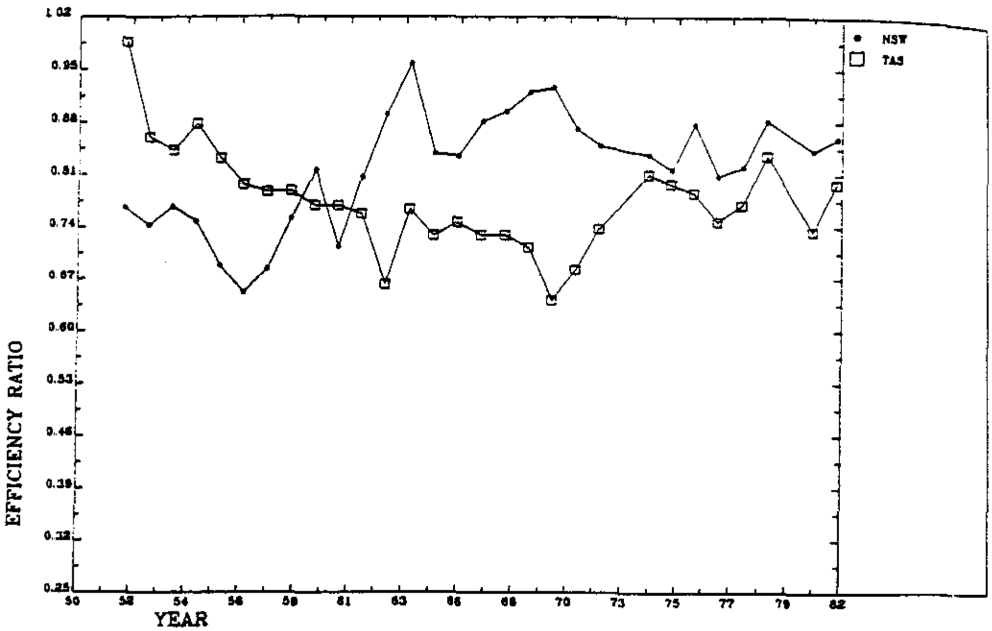


FIGURE 1B: E_1 STATE EFFICIENCIES (TRAIN-KM) FOR W A. AND S A.

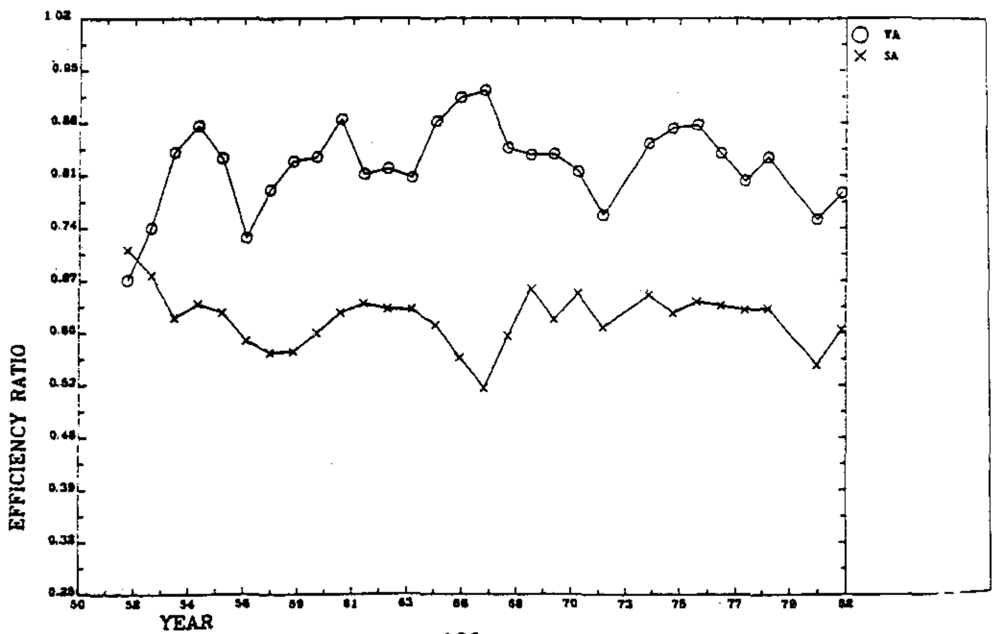


FIGURE IC: E_1 SIAIE EFFICIENCIES (TRAIN-KM) FOR VIC AND QLD

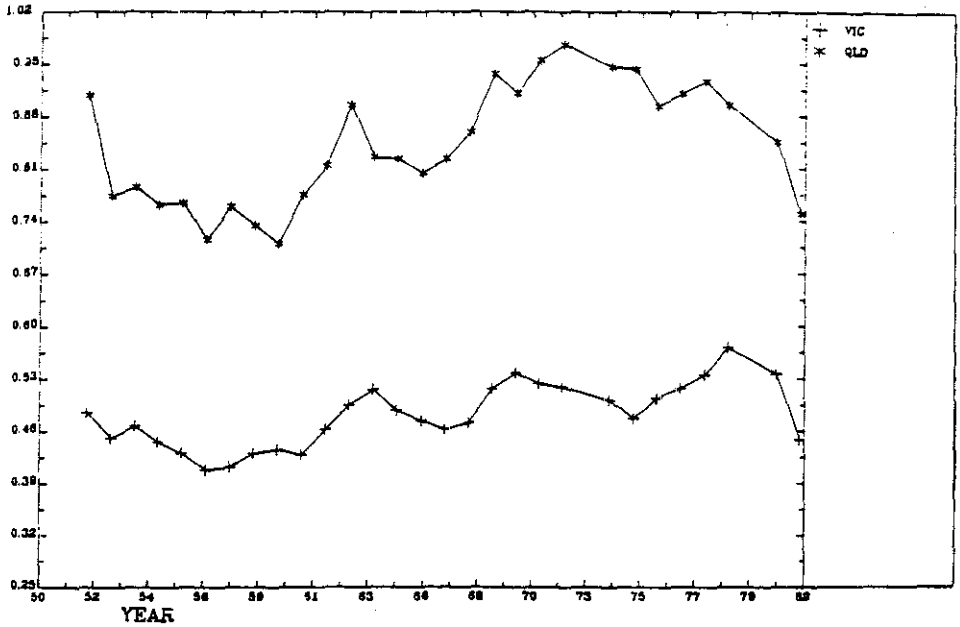


FIGURE ID: E_1 STATE EFFICIENCIES (NET TONNE-KM) FOR VIC AND QLD

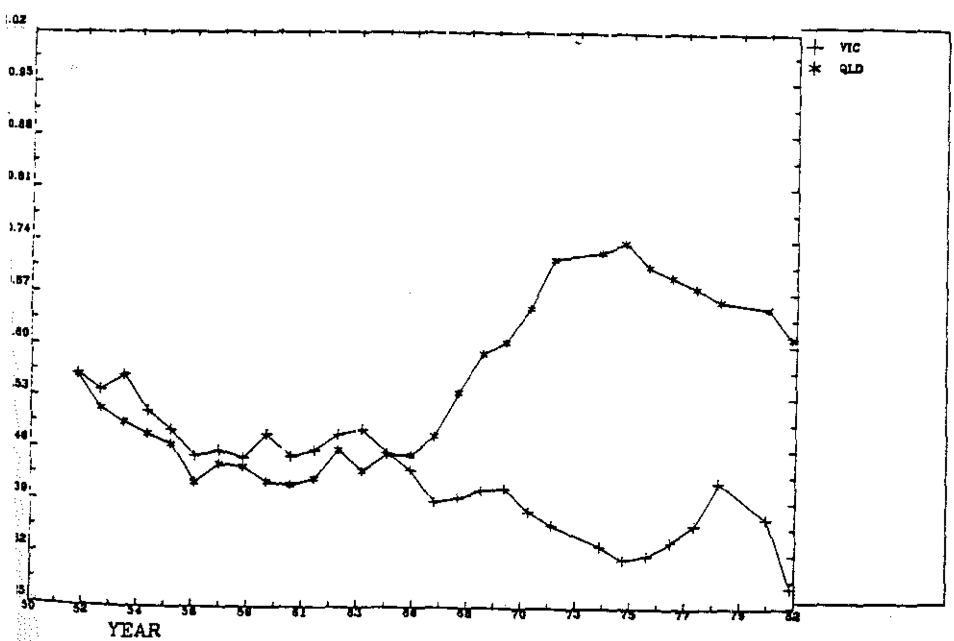


FIGURE 1E: E_1 STATE EFFICIENCIES (NET TONNE-KM) FOR NSW AND TAS

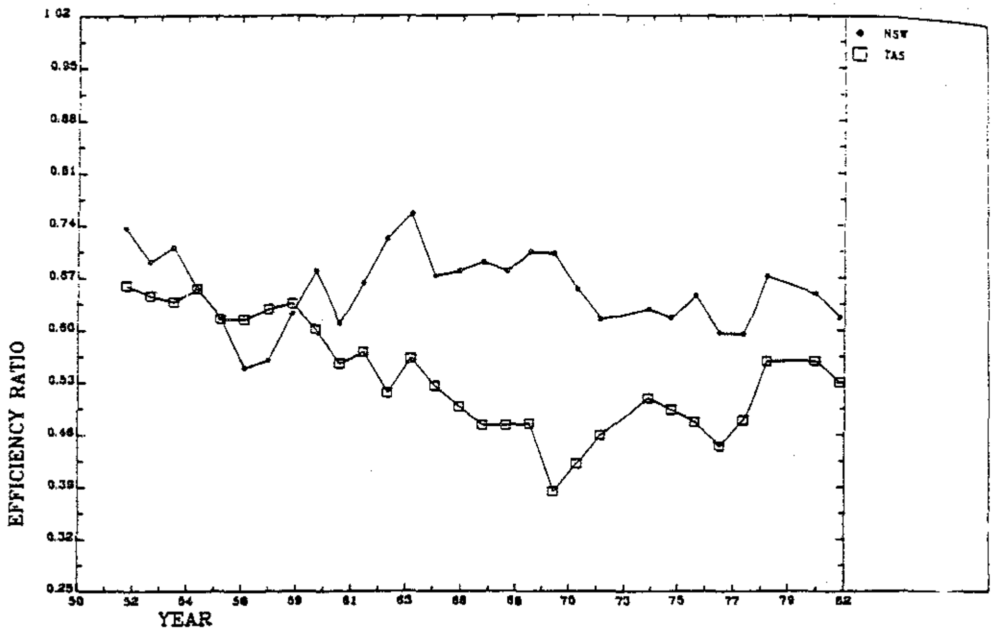
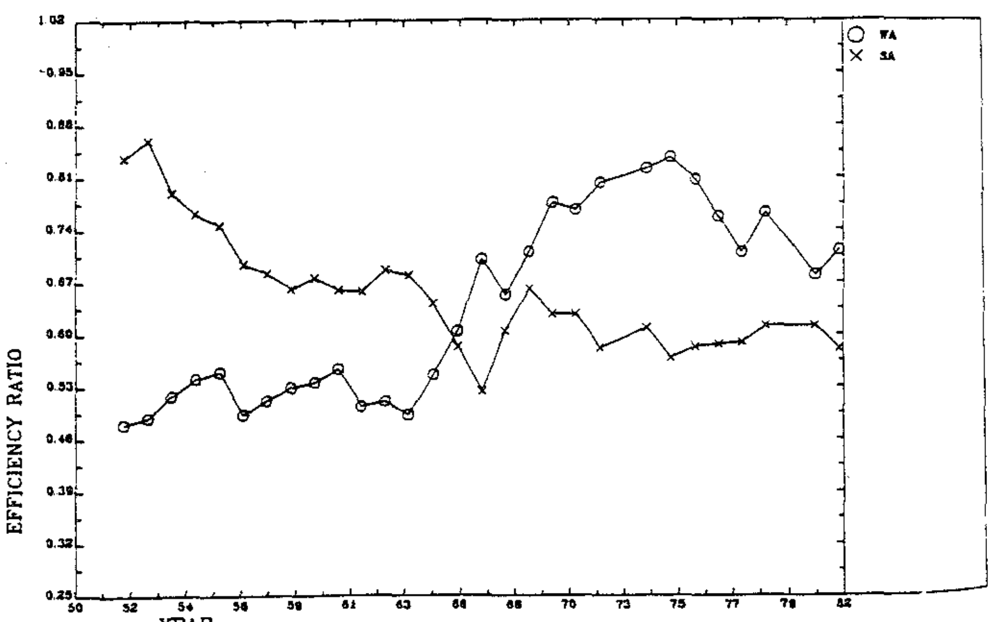


FIGURE 1E: E_1 STATE EFFICIENCIES (NET TONNE-KM) FOR W.A. AND S.A.



Western Australia shows a gradual increase in efficiency over time with its E_2 values increasing from 0 383 in 1952/53 to 0 641 in 1982/83 Similarly Queensland s E_2 values in table 2 have steadily increased from the 1952/53 E_2 values of 0.457 reaching a maximum in 1974/75 with an E_2 value of 0.662 and then decreasing steadily to an E2 value of 0.517 in 1982/83 Apart from these two states table 2 shows that generally government owned railways in New South Wales Victoria, South Australia and Tasmania have increasingly become more inefficient over time.

5 Conclusion

This paper set out to measure the technical efficiency of the freight divisions of government railways in Australia. It is beyond its scope to explain why the fluctuations in the efficiency indices from one year to the next do occur. Possible explanations could include factors like the incidence of transport workers union strikes across states from one year to the next The indices for the years 1979/80 and 1981/82 might have been distorted by the fact that these years are so close to the time the Road Maintenance (contribution) Act was repealed [in 1978/79] in most states, after the road-haulage operators strike which had the effect in the short run of diverting road traffic to rail systems. The results in 1979/80 and 1981/82 might have further been affected by the fact that Western Australia embarked on a program of transport deregulation starting from 1979/80 while Victoria started moving towards deregulating the transport industry in 1981 Further more there seems to be some relationship between the deregulation of road transport and the efficiency of government railways Firstly the state that has consistently experienced the highest level of technical efficiency as measured by E_2 is South Australia which is also the state where the land based transport services industry is most deregulated having completely deregulated road transport as far back as 1968. Victoria and Tasmania which have the most regulated transport industries in the sample period have also consistently the lowest indices of technical efficiency

Furthermore this paper has presented results on the nature of the production frontier in the freight divisions of six government owned railway systems. It is concluded that the properties of the frontier crucially depend on the output measure adopted In particular it seems that train-kilometres as a measure of output tends not only to understand the elasticity of output with respect to capital but also to exaggerate the efficiency of those states which are geographically large. Using efficiency indices based on net tonne-kilometres the preferred output measure, it was concluded that Victoria's was the most inefficient railway system while South Australia's was the most efficient. It was conjectured that the extent of transport deregulation may have an important role in motivating the appropriate choice of production functions and the associated optimal choice of factor combinations This conjecture itself can only be established by an empirical examination of related data

TABLE 3: THE OUTPUT INCREASING MEASURE OF EFFICIENCY, E_2 FOR GOVERNMENT RAILWAYS IN AUSTRALIA

YEAR	N S W	VIC	QLD	W A	S A	TAS
1982/83	0.531	0.180	0.517	0.641	0.491	0.436
1981/82	0.567	0.266	0.563	0.603	0.525	0.467
1979/80	0.594	0.313	0.572	0.702	0.525	0.466
1978/79	0.507	0.257	0.592	0.637	0.500	0.381
1977/78	0.509	0.235	0.609	0.694	0.497	0.346
1976/77	0.565	0.219	0.625	0.754	0.494	0.379
1975/76	0.530	0.213	0.662	0.791	0.477	0.396
1974/75	0.544	0.230	0.647	0.772	0.522	0.413
1972/73	0.529	0.256	0.636	0.749	0.491	0.361
1971/72	0.574	0.273	0.560	0.706	0.543	0.323
1970/71	0.629	0.303	0.509	0.717	0.543	0.286
1969/70	0.632	0.301	0.491	0.639	0.581	0.377
1968/69	0.602	0.291	0.434	0.572	0.518	0.374
1967/68	0.616	0.285	0.372	0.627	0.429	0.375
1966/67	0.603	0.327	0.346	0.518	0.494	0.401
1965/66	0.594	0.350	0.347	0.453	0.560	0.430
1964/65	0.692	0.382	0.324	0.396	0.603	0.470
1963/64	0.652	0.375	0.353	0.415	0.611	0.420
1962/63	0.584	0.353	0.313	0.408	0.578	0.480
1961/62	0.523	0.344	0.305	0.461	0.580	0.463
1960/61	0.603	0.375	0.309	0.442	0.599	0.513
1959/60	0.537	0.342	0.329	0.434	0.582	0.553
1958/59	0.468	0.352	0.333	0.416	0.606	0.544
1957/58	0.456	0.345	0.308	0.396	0.620	0.528
1956/57	0.532	0.381	0.359	0.457	0.682	0.529
1955/56	0.574	0.407	0.373	0.447	0.700	0.574
1954/55	0.639	0.459	0.389	0.423	0.731	0.555
1953/54	0.616	0.437	0.409	0.392	0.820	0.564
1952/53	0.670	0.461	0.457	0.383	0.792	0.580

REFERENCES

1 Afriat S.N (1972) 'Efficiency Estimation of Production Functions' International Economic Review 13 No 3 October pp 568-598

2 Aigner D.J and S.F. Chu (1968) 'On Estimating the Industry Production Function' American Economic Review 58 No 4 September pp 826-839

3 Aigner, D J., C.A.K Lovell and P J Schmidt (1977) 'Formulation and Estimation of Stochastic Frontier Production Function Models' Journal of Econometrics 6 No 1 July pp 21-37

4. Australian Bureau of Statistics Year Book Australia The Official Year of Australia ABS, Canberra, Australia; for the years 1973 to 1985

5 Australian Bureau of Statistics Transport and Communication Bulletin various years ABS Canberra Australia.

6 Caves, D.H., L R. Christensen and J.A Swanson (1981) 'Productivity Growth, Scale Economies and Capacity Utilization in U.S. Railroads, 1955-1974' American Economic Review, 71 December pp 994-1002

7 Commonwealth Bureau of Census and Statistics Official Year Book of the Commonwealth of Australia (up to 1972)

8. Färe R and C A.K. Lovell (1978) 'Measuring the Technical Efficiency of Production', Journal of Economic Theory 19 No 1 October pp 150-162

9 Farrell, M.J (1957) 'The Measurement of Productive Efficiency', Journal of the Royal Statistical Society A 120 Part 3 pp 253-281

10 Førsund F.R and L Hjalmarsson (1974) 'On Measurement of Productive Efficiency' Swedish Journal of Economics 76 No 2 June pp 141-154

11. Førsund F R. and L Hjalmarsson (1979), 'Frontier Production Functions and Technical Progress: A Study of General Milk Processing in Swedish Dairy Plants' Econometrica 47 No 4 July pp 883-900

12 Førsund, F R. and C S. Jansen (1977) 'On Estimating Average and Best Practice Homothetic Production Functions Via Cost Functions' International Economic Review 18 No 2 June pp 463-476

13. Førsund, F R., C.A.K. Lovell and P Schmidt (1980), 'A Survey of Frontier Production Functions and of their Relationship to Efficiency Measurement' Journal of Econometrics 13 pp 5-25

14. Greene W H (1980) Maximum Likelihood Estimation of Econometric Frontier Functions Journal of Econometrics 13 pp 27-56

15 Jondrow, J. C.A Lovell, I.S Materov and P Schmidt (1982), 'On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model' Journal of Econometrics Vol 19 pp 233-238

16 Kopal, Z (1961) Numerical Analysis 2nd Edition Chapman and Hall

17 Meeusen, W and J. Van den Broeck (1977) 'Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error', International Economic Review 18 No 2 June 435-444

18. Quandt, R E., (1983) Computational Problems and Methods' Ch. 12 pp. 699-764 in Z Griliches and M D Intriligator (Eds) Handbook of Econometrics Vol 1 North-Holland

19 Richmond, J (1974) Estimating the Efficiency of Production' International Economic Review 15 No 2 June 515-521

20 Schmidt P (1976) 'On the Statistical Estimation of Parameter Frontier Production Functions' Review of Economics and Statistics 58 No 2, May pp 238-239

21. Transport Economics Centre (1982), Estimation of Production Functions for Australian Railway Systems' Unpublished Interim Report. Transport Economics Centre. University of Tasmania

22 Wolfe, M.A. (1978) Numerical Methods for Unconstrained Optimisation Van Nostrand Reinhold.

APPENDIX: ESTIMATION PROCEDURES

The Empirical Model

To investigate the technical efficiency of the Australian railway transport sector we employ the Cobb-Douglas production function with the modification for non-zero technical progress Thus the production function is given by:

$$X_{it} = Ae^{mt} L_{it}^{\beta 1} K_{it}^{\beta 2} \quad (3.1)$$

In log linear form the full deterministic frontier production function is represented by:

$$\ln X_{it} = \alpha + \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + mt - \epsilon_{it} \quad (3.2)$$

where X_{it}, L_{it}, K_{it} are defined as in section 2.1; with t denoting time, i denoting the railway states. α [equal to ln(A)] β_1, β_2 and the parameter m representing the rate of technical progress growth are to be estimated. ϵ_{it} is the error term being strictly non-negative. The data to be used in (3 2) is as described in section 3 1.

To ensure that $\epsilon_{it} \geqslant o$, a gamma error distribution is assumed That is for $\epsilon \geqslant 0$ $\lambda > 0$ and $P > 2$.

$$f(\epsilon) = G(\lambda, P) = [\lambda^P / \Gamma(P)] \, \epsilon^{P-1} e^{-\lambda\epsilon}$$

where λ and P are parameters of the gamma distribution. The mean and variance of ϵ are given by P/λ and P/λ^2 respectively. The gamma function is:

$$\Gamma(P) = \int_o^{\infty} \epsilon^{P-1} \, e^{-\epsilon} \, d\epsilon$$

for real $P>0$ and if P is a positive integer $\Gamma(P) = (P-1)!$.

This distributional assumption satisfies the desirable properties that when $\epsilon_{it} = o$ the error distribution and its first derivative also equal zero. These requirements are desirable in the sense that if met, then all the classical regularity conditions will be satisfied ensuring that MLG the maximum likelihood estimator with a gamma error distribution will be consistent asymptotically efficient and asymptotically normally distributed.

The log-likelihood function of model (3 2) under the gamma error distribution assumption is:

$$L^{*} = TP \log \lambda - T \log \Gamma (P)$$

$$+ (P-1)\sum_{t\ i} \log (-x_{it} + \alpha + \beta_1 \ln L_{it} - \beta_2 \ln K_{it} - mt)$$

$$- \lambda \sum_{t\ i}(-x_{it} + \alpha - \beta_1 \ln L_{it} - \beta_2 \ln K_{it} - mt) \qquad (3\ 3)$$

where (t,i) denotes summation over all t years and i states and T represents the number of observations

In optimising (3 3) the derivation of consistent starting values for the numerical optimisation algorithms needs discussing The modified ordinary least squares (MOLS) technique described by Greene (1980) is employed Since the OLS estimates of the slope coefficients in (3 2) are consistent then total parameter consistency only warrants modifications to the intercept parameter "α". Effectively "α" is adjusted to ensure that $\epsilon_{it} \geq 0$, this involves identifying the smallest OLS residual and substracting it from the OLS "α" estimate. The new residuals which result from this modification also provide consistent starting values for the parameters P and λ. Specifically, denoting $\bar{e}$ and s^2 as the sample mean and sample variance of the MOLS residuals respectively implies that $\bar{e}^2/s^2$ and $\bar{e}/s^2$ are consistent estimates for P and λ respectively The MOLS estimates of (3 3) are then used as starting values in the iterative maximum likelihood estimation of (3 2) with a gamma distribution term The algorithms used to arrive at the MLG estimates are discussed in the Appendix at the end of the paper

Numerical optimisation of (3 3) was carried out using Quandt and Goldfeld's GQOPT4 FORTRAN subroutines. Four algorithms described in detail in Wolfe (1978) and Quandt (1983) were employed: two derivative methods GRADX (Goldfeld, Quandt and Trotter's quadratic hill climbing method) and DFP (the davidon-Fletcher-Powell algorithm); and two direct search methods POWELL (Powell's conjugate directions method) and MNSIMP (Nelder and Mead's simplex method) Analytical derivatives were employed for the derivative methods Following Greene (1980 pp 45-6) the

Gauss-Laguerre quadrate was employed to approximate Γ' and Γ , (the first and second derivatives of Γ(P)) to the 15th order (see Kopal (1961 pp 370-1, 564-7)) The gamma function Γ(P) was evaluated by the IMSL function DGAMMA All computations were done in double precision, maximum iterations set to 1 000 and accuracy in results set to six decimal places

In general, for both output measures the direct search algorithms out-performed the derivative methods when starting from MOLS estimates! For the train-kilometre output measure, POWELL reached the highest local optimum (L* = 31 70) closely followed by NMSIMP (31 39), DFP performed poorly by converging extremely slowly using all 1,000 iterations and only reaching (30 58) GRADX failed by continually straying into the forbidden $\epsilon_{it} < 0$ region For the net tonne-kilometre output measure POWELL reached the highest local optimum (L* = -27 63) closely followed by MNSIMP (-28 20) DFP converged only after 2 iterations to (-34 29) and GRADX again failed to converge Attempts were then made to restart allalgorithms from the local optima found by POWELL for both output measures Most algorithms immediately converged and hence no improvements found For both output measures GRADX failed due to excessive function deterioration after quadratic approximation

In a general econometric optimisation context the above conclusion that direct search methods performed better than derivative methods is surprising The explanations might lie in the fact that (3 3) does not behave like a quadratic function in the parameters For example squared and cross multiplied parameter terms are absent from (3.3) It is clear from Quandt (1983, pp 710-24), that GRADX and DFP (especially GRADX) are formally and intuitively justified as useful from the basis that a quadratic function is to be optimised; hence the quadratic approximation failure of GRADX On the other hand POWELL and NMSIMP only require that the function be continuous and hence perform independently of the function's concavity. We therefore hypothesize that the non-quadratic nature of (3 3) might explain the better performance of the direct search methods