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IN THE INDIAN RAILWAYS?

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Abstract:

Our objective in this paper is to shed some empirical light on a claim often made by critics of affirmative action policies: that increasing the representation of members of marginalized communities in jobs – and especially in relatively skilled positions – comes at a cost of reduced efficiency. We undertake a systematic empirical analysis of productivity in the Indian Railways in order to determine whether increasing proportions of Scheduled Castes and Scheduled Tribes in railway employment – largely a consequence of India's affirmative action policies – have actually reduced productive efficiency in the railway system. We find no evidence that higher percentages of Scheduled Castes and Scheduled Tribes in the railway labour force have reduced productivity. Indeed, some of our results suggest that the opposite is true, providing tentative support for the claim that greater labour force diversity boosts productivity.

Keywords: affirmative action; labour force; productivity; Indian railways

JEL codes: J 78; L 92

1. Introduction

This study is motivated by a desire to examine in a rigorous manner the effect of affirmative action (AA) in the labour market on the productive efficiency of Indian enterprises that reserve jobs for members of marginalized communities. In the United States, where AA in hiring has been practiced in many industries since the 1960s, a variety of studies of this kind have been carried out.[1] In India, however, rigorous empirical assessments of AA are few. The only studies assessing the impact of AA focus either on electoral representation (Besley et al. 2004; Munshi & Rosenzweig 2008), or on higher education (Bertrand et al. 2008). There has not been yet, to our knowledge, any systematic quantitative study of the effect of AA in the labour market on enterprise efficiency. We have sought to overcome this gap by identifying an important Indian industry with a policy of AA in hiring and promotion, for which we could obtain sufficiently detailed data to carry out a quantitative analysis of productive efficiency that would allow us to measure the impact of changes in the representation of members of marginalized communities in employment.

In India, AA takes the form of "reservations" or quotas for the "Scheduled Castes" (SCs), former "untouchables," now often called Dalits, and the "Scheduled Tribes" (STs), indigenous tribes marginalized from mainstream Indian society and often called Adivasis.[2] Together 22.5 percent of all seats in government supported educational institutions and public sector jobs are reserved for these groups.[3] However, quotas for the most desirable positions are usually only partially filled, because of an insufficient number of eligible candidates who meet the minimum qualifications set for such positions.[4]

The most frequent complaint about reservation policies is that they conflict with considerations of merit because quotas entail the selection of less qualified candidates in place of more qualified candidates. Most critics argue that a poorer quality of government service, or poorer academic performance, is to be expected from the beneficiaries of reservations[5]. Some critics even suggest that the failure to allocate key jobs on a strictly meritocratic basis has

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[1] Some of the U.S. studies have estimated industry-level production or cost functions, augmented by information on the extent and/or way in which labour inputs were affected by affirmative action. Other studies have analyzed company-level financial data to determine whether and how stock prices have been affected by evidence of affirmative action. Yet others have compared supervisor performance ratings of individual employees in establishments that do and do not practice affirmative action. The most comprehensive survey of such studies in the United States concludes that "There is virtually no evidence of significantly weaker qualifications or performance among white women in establishments that practice affirmative action…" and that "There is some evidence of lower qualifications for minorities hired under affirmative action programs…" but "Evidence of lower performance among these minorities appears much less consistently or convincingly…" (Holzer & Neumark 2000).

[2] In 2001 the SC and ST constituted about 16 percent and 8 percent of the Indian population, respectively.

[3] See Weisskopf (2004), chapter 1, for a detailed discussion of affirmative action policies in India (with comparisons to AA in the United States).

[4] In addition to SCs and STs, a substantial share of the Indian population belonging to “Other Backward Classes” (OBCs) has long been eligible for reservations in public sector employment and in admissions to public higher educational institutions within most Indian states. In principle, OBCs encompass communities that are socially and economically relatively deprived; they are often also marginalized by caste discrimination – albeit to a lesser extent than Dalits. Since the early 1990s OBCs have become eligible for employment and educational reservations at the all-India level too. At this level OBCs – defined according to a set of economic and social criteria outlined by a Central Government commission – are currently eligible for reservations of 27% of available seats.

[5] See, for instance, Guha 1990a & 1990b, and Shah 1991.

resulted in serious harm as well as gross inefficiency.[6] It should be noted that these criticisms are purely speculative, not having been grounded on any empirical foundation[7].

One can easily find in public discourse just as many arguments in favor as against reservation policies.[8] The most frequently and passionately voiced argument is that of compensatory social justice for communities that have long been denied equal treatment and equal opportunity. To counter critics who warn that reservations in hiring will adversely affect efficiency in the Indian public sector, proponents of such reservations often reject the notion that hiring is otherwise truly meritocratic.[9] Indeed, in a study of modern urban Indian highly-skilled labour markets for private sector jobs, which are assumed to be completely meritocratic, Deshpande & Newman (2007) show how caste and religious affiliations of job applicants shape employers' beliefs about their intrinsic merit. This confirms the findings of other studies that uncover labour market discrimination and point out how social identities impact hiring and wage offers (for instance, Bertrand & Mullainathan 2004, Pager & Western 2005, Thorat & Attewell 2007, Siddique 2008, and Jodhka & Newman 2007).

The polemics around reservation policies in the Indian public sector labour market are unquestionably very heated. Our study is motivated by the surprising fact that there has hitherto been no careful empirical study of the actual consequences of such reservation policies in practice. We chose to study the effect of reservations in India's single largest public sector enterprise – the Indian Railways (IR) – not only because of its economic importance[10] but also because the IR systematically collects a great deal of data on all aspects of its operations,[11] and because the debate about AA in India has prominently featured claims that job reservations have adversely affected the performance of the Indian Railways.

Our data base for this study consists of a pooled set of data on productive inputs and outputs for eight regional IR zones over a time span of 23 years – from 1980 through 2002, producing a total of 184 zone-years of observations.[12] Our approach to analyzing the effect of

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6 For example, in "Job Reservation in Railways and Accidents," *Indian Express*, September 19, 1990 (cited by Kumar 1992: 301), it is charged that the frequency of Indian railway accidents would likely increase because reservation policies result in a larger proportion of less competent railway officials and lower overall staff morale.

7 At the time of writing, the Indian Railways are under attack in the media for a recent spate of serious accidents. However, responsibility is this time being placed on the Minister of Railways, whose lack of involvement is cited as having resulted in sloth and lack of accountability among Railways staff. Once again, the sources of inefficiency and the reasons for high accident rates have not been systematically explored.

8 See Weisskopf (2004), chapter 2, for an extensive discussion of arguments made in India – as well as the United States – for and against affirmative action policies.

9 Thus Sachchidananda (1990: 19) wrote that: "The erosion in the level of competence in government and public sector enterprises is due to corruption, nepotism, connections, etc…. and not reservations for SC and ST. It is well known that the relation between merit and selection is compounded by considerations of class, community and caste."

10 The IR is one of the most important industries of any kind in India: it is the dominant industry providing essential freight and passenger transport services to Indians throughout the country, and it employs 1.4 million workers – far more than any other Indian public sector enterprise.

11 Our research assistant, Smriti Sharma, provided invaluable assistance in gaining access to essential information and data from the IR.

12 The beginning year of our time span was 1980, because prior to that year some key data were unavailable at the zone level; the end year was set at 2002, because in 2003 the number of IR zones was increased and new boundaries

reservations on productivity in the IR is twofold. First, we estimate a multifactor production function for the operations of the IR; and we assess the impact of reservations on productivity either by (a) introducing into the basic regression equation additional independent variables that reflect the extent to which the labour force was made up of AA beneficiaries or by (b) correlating residuals from the regression equation with measures of the proportion of AA beneficiaries in the labour force.[13] Recognizing the simultaneity problem that can arise in production function regressions, such that the level of inputs can be influenced by fluctuations in output demand or productivity shocks, we re-estimate the production function correcting for this.

As an alternative to traditional production function analysis, our second approach makes use of the non-parametric Data Envelopment Analysis (DEA) technique, which requires no *a priori* assumptions about the functional form of production relations and which allows for more disaggregation of input and output variables than is possible in production function analysis. DEA generates estimates of annual rates of change of total factor productivity, which we then regress on (or correlate with) variables hypothesized to affect productivity growth, notably the proportion of AA beneficiaries in total employment.[14]

Our key findings may be summarized as follows. Our production-function and data-envelopment analyses provide no evidence in support of the claim by critics of AA that increasing the proportion of jobs filled by SCs and STs has an adverse effect on total factor productivity or its growth over time. Furthermore, some of the results of our analyses suggest that the proportion of professional and administrative jobs filled by AA beneficiaries is positively associated with productivity and productivity growth. This finding resonates very strongly with studies assessing the productivity impact of workforce diversity in the U.S., which have found either a positive or no effect of diversity on productivity, but no evidence of a negative effect (Barrington & Troske 2001).

It might be argued that there is a causal relationship running not only from the SCST percentage of IR employees to productivity, but also the other way round, which would compromise our empirical results. However, the latter direction of causation is simply inconsistent with the way in which IR employees are hired and promoted. It could also be argued that affirmative action is more likely to affect the quality than the quantity of railway output. But correlations between the accident rate – the only systematically available indicator of output quality – and the percentage of IR employees who are AA beneficiaries show a statistically significant negative relationship between the two.

The rest of the paper is organized as follows. In section 2, we briefly describe the Indian Railway system and discuss the way in which we have compiled the data available from the IR. In sections 3 and 4, we present our production-function and DEA analyses, respectively. In

came into effect. Throughout the period from 1980 to 2002 the IR was operating with nine zones; but we could include only eight of these zones in our analysis because insufficient data were available for one of them (the Northern Railway). No previous quantitative study of productivity in the IR, as far as we are aware, has been based on data disaggregated by zone.

[13] Estimation of production functions has been applied by economists to a great many industries in India (see Goldar 1997), and it lends itself to a relatively simple way of assessing quantitatively the impact of employment reservations.

[14] For a thorough explication of the DEA approach, see Ray (2004). We relied on Coelli (1996) as a guide to our use of the technique.

sections 5 and 6, we address possible critiques of our work based in turn on reverse causality and on output quality. The concluding section 7 offers a glimpse into mechanisms that could possibly explain our results.

2. An Overview of the Data

As noted above, the IR is divided for administrative convenience into regional zones[15]. The number of zones in the Indian Railways increased from six to eight in 1951, nine in 1952, and finally 16 in 2003. The 9 zones in effect during the period 1952-2002 were: Central Railway (CR), Eastern Railway (ER), Northern Railway (NR), North-Eastern Railway (NER), North-East Frontier Railway (NFR), Southern Railway (SR), South Central Railway (SCR), South Eastern Railway (SER) and Western Railway (WR).

The IR as a whole in recent years has been operating about 9000 passenger trains, which transport 18 million passengers daily; its freight operations involve the transport of bulk goods such as coal, cement, foodgrains and iron ore. The IR makes around 65% of its revenues, and most of its profits, from the freight service; a significant part of these freight profits are used to cross-subsidize passenger service, enabling it to charge lower fares to consumers. During the period from 1980 to 2002, IR gross receipts (earned from passenger and freight traffic) grew consistently from 26 to 411 trillion rupees at current prices; this represents a fourfold increase at constant prices.

While total track kilometers in the Indian railway system increased modestly from 104,880 kms in 1980 to 109,221 in 2002, the percentage of electrified routes increased more rapidly, from just 7% to more than 20%. Coal had long been the main source of fuel for the IR; but by 2002 almost all IR's operations were fueled by more efficient (and less polluting) diesel or electric power. Since the 1980s there have also been significant technological improvements in the form of track modernization, gauge conversion, and upgrading of signaling and telecommunications equipment. And in the 1990s the IR switched from small freight consignments to larger container movement, which helped to speed up its freight operations.

In specifying the variables needed for our production-function and data-envelopment analyses, we sought as far as possible to make use of physical rather than value measures. We did so because the IR is not a profit-oriented enterprise. While it does seek to cover its costs, it has numerous politically-determined objectives – as reflected in the cross-subsidization of passenger by freight traffic – that make profitability a poor standard by which to evaluate IR performance, and that lead to pricing decisions that do not necessarily reflect the marginal cost or benefit of the commodity in question. In the following paragraphs, we describe in broad terms how we defined and measured the variables used in our analyses; further details, as well as sources of all the underlying data, are given in Appendix A.

Output variables. The output produced by the Indian Railways consists of passenger service and freight service, measured physically in terms of passenger-kilometers (PK) and net tonne-kilometers (NTK), respectively. For both passenger and freight service, the IR also provides data on revenues from each type of passenger rail service and each type of transported

[15] The information contained in the first three paragraphs of this section is based on Government of India, Ministry of Railways, Directorate of Economics and Statistics (2008), Key Statistics (1950-51 to 2006-07), and Government of India, Ministry of Railways (annual), Appropriation Accounts, Annexure G.

commodity. All of the data are available in annual time series for each zone as well as for all-India.

We first generated time series indices for total passenger output and total freight output from underlying time series for passenger and freight transport of different types. We then generated time series indices for total railway output by weighting the indices for total passenger output and total freight output according to their percentage of total railway revenue generated. The construction of the final zonal indices was done so as to reflect the scale differences between zones.

Although we believe that the above measures of railway output, based on physical measures, are superior to any value measures of railway output, we do recognize that industry outputs are most often measured in terms of gross revenue or value added. We therefore compiled data on railway revenue at current prices and deflated these data to obtain an alternative constant price time series for total railway revenue. We could not work with the value added variable since we did not have data on non-fuel material inputs.

Labour variables. The Indian Railways hire workers in four different labour categories: categories A and B include administrative officers and professional workers; category C includes semi-skilled and clerical staff; and category D includes relatively unskilled attendants, peons and cleaning staff. The total employment figures provided by the IR serve as raw measures of the overall volume of labour input, but they fail to reflect changes in the average quality of labour that result from changes in the category-composition of the labour force. We posit that the average quality of labour improves to the extent that the category-composition of jobs (the pattern of A+B, C and D employment) shifts in the direction of a greater proportion of higher-skilled jobs and a lesser proportion of lower-skilled jobs. In order to take account of the effects of changes in the average quality of labour over time, we constructed time series indices for a new variable measuring the volume of "effective labour" input for each zone (and for all-India).

In addition, we needed to work with labour input measures that distinguish AA beneficiaries from other employees. The IR provide data on the number of employees, in each category of employment, who declare themselves to belong to a Scheduled Caste or Tribe. Such a declaration is necessary for an SC or ST applicant to avail of reservations, and it is otherwise made only by some low-level employees.[16] The available data on SC+ST (SCST henceforth) employment in the high-skilled categories A and B are therefore accurate measures of the corresponding number of AA beneficiaries, because almost all SC or ST candidates who attain A and B positions owe their employment or promotion to the reservations policy.[17] On the other hand, the figures on SCST employment in the lower-skilled categories C and (especially) D over-estimate the number of AA beneficiaries, because many self-declared SCST employees would have been hired even in the absence of reservations.

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[16] An overwhelming percentage of the cleaning staff belongs to a formerly untouchable caste, whose traditional occupation has been cleaning. Given the stigma attached to being identified as an SC, those SC candidates who do not wish to avail of reservations typically do not declare themselves as SCs. However, cleaners are already stigmatized because of the "unclean" nature of their work, and thus many of them have no reluctance in identifying themselves as SC, irrespective of whether they occupy reserved seats. The IR provide figures separately for cleaners (part of Category D), and the percentage of those who declare themselves to be SC/ST is far higher than 22.5%.

[17] The difference between the cut-off scores required (in preliminary exams and in main papers) for applicants to qualify for reserved-category and for general-category A+B positions in the Indian Railways has been decreasing over time; so it is likely that over time the number of SC and ST candidates who succeed in occupying A+B positions without availing of reserved seats has slowly been increasing.

The ultimate objective of our quantitative analysis is to examine the effect of AA in the labour market on measures of productivity. Toward this end, in both the production-function and the data envelopment analyses, we worked with two measures of the SCST proportion: the first is the ratio of SCST employees to total employees in all labour categories (A, B, C, D), and the second is the ratio of SCST employees to total employees in labour categories A+B only. As discussed in the previous paragraph, the latter variable is more accurate in measuring the proportion of AA beneficiaries. When we examined graphs of each of the 8 zonal time series for the SCST proportions, however, we discovered that there were some distinctly outlying observations that appear to have been subject to measurement error. We, therefore, generated a second set of pooled time series with roughly a dozen questionable observations dropped from the full set of 184 observations.

Capital variables. The IR distinguishes between three types of capital stock – structural engineering, rolling stock, and machinery & equipment – and makes available annual current-price data on book value and gross investment for each type of capital, going back to 1966 for each zone and to 1952 for all-India. We chose to work with estimates of gross rather than net capital stock, because measures of net capital stock decline in value as the number of its productive future years decline, whereas measures of gross capital stock tend to be proportional to the capital value actually consumed during a given year. Book value data on capital stock are notoriously poor measures of the value of capital inputs, because they aggregate annual additions to capital stock that are valued at different prices every year; so we made use of the perpetual inventory method (Christensen and Jorgenson, 1969) to generate time series of constant-price gross capital stock of each type.

Constant-price gross capital stock measures that are calculated as in the previous paragraph do have one important shortcoming, in that they fail to reflect the extent to which embodied-in-capital technological progress increases the productive potential of a piece of constant-price capital stock from year to year. Just as we sought to adjust a raw measure of labour input (employment) to take account of changes in labour quality associated with the category-composition of labour in generating a better measure (volume of effective labour), so we found it desirable to adjust our raw measure of capital input (constant-price gross capital stock) to take account of changes in capital quality associated with the age structure of capital to generate a better measure that we call "effective capital input." We based these calculations on the assumption that a unit of constant price gross investment loses 1% of its productive value for each year elapsed since it was created.[18]

Material input variables. The main material input used by a railway system is fuel. Using standard conversion factors to convert all the measures of fuel in physical terms into their equivalent in coal-tonnes, we compiled time series of total coal-tonnes of fuel input for each zone and for all-India from 1980 through 2002.

In the case of fuel input, as with capital and labour inputs, we saw reason to generate a second, more nuanced variable to take account of changes in fuel quality associated with changes in the proportions of different kinds of fuel utilized by the IR. In particular, diesel- and electricity-powered locomotion is significantly more efficient than locomotion powered by other fuels, because it enables greater acceleration, allows for easier maintenance, and generates less

[18] We also repeated the estimation with a 2 percent capital obsolescence fraction, and that did not change our basic results.

pollution.[19] We sought therefore to construct an index of "effective fuel" that would take account of the extent to which locomotion is powered by the more efficient fuels.

3. Production Function Analysis

Although 22.5 percent of jobs in the IR are reserved in principle for SCST members, the actual percentage of SCST employees varies a lot by type of job, by zone and by year, because of the failure to fulfill quotas (in the case of high-level jobs) and the higher percentage of SCs in low-level jobs, as explained in the previous section. The variation in SCST employee proportions facilitates econometric estimation of the impact of SCST employees on productivity.

Using the variables described earlier,[20] we estimated log-linear Cobb-Douglas production functions of the following form.[21]

$$\ln(\text{output}) = \beta_0 + \beta_1 \ln(\text{capital stock}) + \beta_2 \ln(\text{labour}) + \beta_3 \ln(\text{fuel}) + \beta_4 \text{ time} + u$$

where time was introduced to capture the effect of technical change and u is the composite error term that captures both zone-specific and random effects. Our panel is a balanced macro panel, with the number of zones (N) = 8 being less than the number of time periods (T) = 23. We used fixed effects (FE) estimation, in order to account for zone-specific unobservable factors.[22] As a robustness check, we also ran the Prais-Winsten estimation procedure to correct for autocorrelation, heteroskedasticity and cross-sectional dependence; the results reported in Appendix B, Tables B-2a and B-2b support our main conclusions about the effect of the percentage of SCST employees on productivity.

We carried out a variety of different regression runs, which varied in terms of the variables included in the specification of the production function and/or the ways in which those variable were measured. Our runs varied along the following dimensions:

1. Which dependent variable we include in the regression: a physical measure, total output (q), or a value measure, total revenue (r). We believe that 'q' is the more reliable measure, because 'r' is dependent on pricing decisions and the IR, as a quasi-monopoly, does not set prices competitively.

2. Which measure of the three inputs we use as independent variables in the regression: the adjusted measures of effective labour (el), effective capital stock (ek), and effective fuel (ef); or the raw measures of total employment (l), unadjusted capital stock (k), and unadjusted fuel (f) –

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[19] Pollution from coal, coke and wood used in steam engines has adverse effects on railway employees and passengers as well as on the countryside.

[20] The underlying data on which the figures are based are described in Appendix A; both the all-India and the zonal time series data are available from the authors on request.

[21] We also estimated a translog production, but the estimates indicated a poor fit: most of the coefficients were not significant; the coefficients associated with the inputs did not satisfy monotonicity, and the estimated equation displayed high multicollinearity. We estimated the function using the actual values of the variables as well as the normalised values (around the mean), and both specifications displayed similar problems.

[22] The Hausman test in our case was inconclusive, but we ran the random effects GLS specification, with correction for autocorrelation, cross-sectional dependence and heteroskedasticity, to confirm that our FE results are not overturned. These runs are not reported in the paper but are available from the authors upon request.

which in our view are considerably less accurate, because they fail to take account of differences in quality between different subcategories of each input.

3. Whether we include or exclude a variable representing the percentage of SCST employees among all employees ("%SC_ALL"), or alternatively the percentage of SCST among category A+B employees ("%SC_AB"), as an independent variable in the regression equation. If such a variable is excluded, we correlate '%SC_ALL' or '%SC_AB' with residuals from the regression.

4. Whether to include all 184 zone-year observations that we compiled, or to exclude zone-years in which the figures we had for the variable representing an SCST percentage of employees were highly questionable We found 15 observations of '%SC_ALL' that were highly questionable, and 12 observations of '%SC_AB' that were highly questionable (mostly for different zone-years in the two cases). We believe that the regressions and correlations in which the questionable zone-years are excluded provide more reliable results.

Thus we estimated the following specifications:

Specification 1: ln q on ln ek, ln el, ln ef, t
Specification 2: ln q on ln k, ln l, ln f, t
Specification 3: ln r on ln ek, ln el, ln ef and t
Specification 4: ln r on ln k, ln l, ln f and t
Specification 5a: ln q on ln ek, ln el, ln ef, %SC_ALL, and t
Specification 5b: ln q on ln ek, ln el, ln ef, %SC_AB and t

In the case of specifications 1-4, the regression residuals were correlated first with '%SC_ALL' and %SC_AB' (including all zone-year observations) and then with '%SC_ALLx' and '%SC_ABx' (excluding the questionable zone-year observations). In the case of specifications 5a and 5b, the regressions were run first with all zone-year observations included and then with the questionable zone-years excluded; the latter runs were labeled 5ax and 5bx.

For the reasons given under points #1, #2 and #4 above, we believe that our most reliable specifications are 1, 5ax and 5bx. Nonetheless, to assure readers of the robustness of our findings, we report the results of all specifications of our FE regression runs in Appendix B, Table B1. One can see that the coefficients on the independent variables fluctuate within a fairly narrow band when the dependent variable is ln q, and they do the same when the dependent variable is ln r. For specifications 1 through 4, the residuals were correlated with the four alternative measures of SCST percentages, as discussed above. None of these correlations were found to be significant. In the case of specification 5bx, '%SC_ABx' (included as a separate independent variable) was found to have a positive and significant impact on total output.

The Simultaneity or Endogeneity Problem

In our production function analysis up to this point, we have estimated a technological relationship in which outputs are a function of inputs, ignoring possible variation in the demand for inputs resulting from productivity shocks associated with fluctuation in the demand for output. This approach fails to take account of possible correlation between input levels and productivity due to the fact that firms generally respond to changes in productivity by changing their usage of factor inputs. Because input levels may be correlated with unobserved productivity shocks, our independent variables may be correlated with the error term, which would result in biased OLS estimates of the production function. This is known as the simultaneity problem or the endogeneity problem in production function estimation.

Many alternatives to OLS have been proposed to address this problem; for instance, Olley & Pakes (1996) have derived conditions under which use of an investment proxy variable eliminates variation in the error term that could be related to unobserved productivity shocks. Levinson & Petrin (2003) (Lev-Pet henceforth) modify this approach by using intermediate inputs rather than investment as a proxy, since this has some advantages over the Olley & Pakes method. In particular, it is less costly to adjust material inputs than investment in response to productivity shocks and, unlike investment, material inputs are always non-zero. Intermediate inputs are thus considerably more sensitive to productivity changes, and their use as a proxy is more likely to control for variation in the error term due to unobserved productivity shocks.

A detailed exposition of the Lev-Pet method can be found in their paper; here we summarize the essence of their method. Their estimation method takes account of unobserved productivity shocks by treating the error term of a standard production function regression equation as the sum of two components – a transmitted productivity component and an error term uncorrelated with input choices. They show that, under the reasonable assumption that the demand function for an intermediate input is monotonically increasing in the unobserved productivity component, that demand function can be inverted. This allows one to model the unobserved productivity component as a function of an intermediate input variable and a state variable such as capital stock.

The residual that emerge from a Lev-Pet regression represents the error component of output, after accounting for all independent variables as well as time. Thus we can correlate the residuals from such regressions with SCST percentages of the labour force, in the same ways that we did for our FE regressions, in order to analyze the effect of varying percentages of SCST labour on productivity levels.

Table B-3 in Appendix B shows the entire set of results of our Lev-Pet estimations. This table reveals that in specifications 2-4 and 5ax there is a coefficient of exactly 1 on capital, and in specification 5bx there is a coefficient of exactly 1 on fuel. The literature on Lev-Pet indicates that specifications where the coefficients of capital and fuel turn out to be exactly 1 should be discarded. We therefore have three usable specifications – those numbered 1, 5a and 5b. Specification 1 gives us a statistically significant positive correlation between the regression residuals and %SC_ABx – our best SCST variable. Specification 5a gives us a negative but insignificant coefficient on %SC_ALL – our least reliable SCST variable; and specification 5b gives us a positive but insignificant coefficient on %SC_AB – our second-best SCST variable. The results from the usable specifications give no support for a negative effect of SCST employment on productivity, and some support for a positive productivity effect of the SCST percentage of workers in A+B jobs.

In Table 1 [NEAR HERE] we bring together the results from the three usable specifications of our Lev-Pet regression, which correct for simultaneity bias as well as the results from the three most reliable specifications of our FE regressions, which account for zone-specific unobservable factors. Table 1 illustrates our findings succinctly. ***All of our production function results, taken together, clearly reject the hypothesis that higher proportions of SC&ST employees in A and B jobs contribute negatively to productivity levels in the Indian Railways. Indeed, they provide some evidence that higher proportions of SC&ST employees in A and B jobs – predominantly beneficiaries of affirmative action -- contribute positively to Indian Railway productivity.***

Table 1: Production Function Estimates

	Lev-Pet (1)	**Lev-Pet (5a)**	**Lev-Pet (5b)**	**FE (1)**	**FE (5ax)**	**FE (5bx)**
Constant				-4.49	-4.50	-2.63
				(10.31)	(0.07)	(10.42)
ln ek	**0.88**	**0.93**	**0.79**	.074	0.11	0.003
	(0.37)	(0.39)	(0.44)	(0.50)	(0.44)	(0.47)
ln el	0.18	0.18	0.22	0.41	0.35	0.39
	(0.56)	(0.46)	(0.46)	(0.31)	(0.26)	(0.29)
ln ef	3.04E-38	4.37E-30	5.18E-35	0.021	0.016	-0.005
	(0.41)	(0.438)	(0.42)	(0.12)	(0.13)	(0.11)
time				**0.05**	**0.04**	0.04
				(0.02)	(0.02)	(0.19)
%SC_ALL		-0.19				
		(0.94)				
%SC_ALLx					-0.46	
					(0.54)	
%SC_AB			0.32			
			(0.93)			
%SC_ABx						**0.87**
						(0.32)
corr %SC_ALL	-0.02			-0.01		
corr %SC_ALLx	-0.05			-0.04		
corr %SC_AB	0.12			-0.07		
corr %SC_ABx	**0.19**			0		

Note: The full definition of each variable and the specifications of each regression are listed on p.8. In the case of the Lev-Pet estimation method, the constant term and the time variable are incorporated into an earlier stage of the analysis and thus do not appear in the production function regression.

Standard errors are in parentheses. Figures in bold are significant at 5%.

4. Data Envelopment Analysis

As explained in section 2, we also tried an alternative approach to investigate the impact of AA on productivity in the Indian Railways: a two-stage procedure in which the first stage was the use of the non-parametric method called Data Envelopment Analysis (DEA) of productivity changes and the second stage was an econometric analysis of factors potentially influencing those productivity changes. DEA allows one to analyze productivity in the context of a pooled data set of time series data on inputs and outputs for multiple production units within a given industry. It does not require specification of any particular functional relationship between input and output variables; and it allows one to work with more than one output variable as well as multiple input variables. Essentially, it fits a frontier, representing technical efficiency, enveloping the outermost data points. Because the frontier is generated from the data, it is not based on stochastic processes and therefore does not produce any measures of the statistical significance of the results obtained.

For the first stage of our alternative approach we tried two different variants. In Variant One, we initially used DEA to estimate annual changes in total factor productivity ("ΔTFP, henceforth") from 1980-81 to 2001-2002 in each railway zone, taking into account two output variables (passenger transport and freight transport) and eight input variables (employment in each of the four labour categories A, B, C, and D; constant-price gross capital stock of each type – structural engineering, rolling stock, machinery & equipment; and total fuel input (in coal-tonnes). Then for the second stage we sought to explain our estimated ΔTFP values (for each zone and pair of years) in terms of several variables that appeared likely to influence annual total factor productivity change. The independent variables consisted of three that were designed to capture the quality of the three types of inputs (labour, capital, and fuel) and one to reflect the scale of production. For labour quality we used %SC_AB or %SC_ABx, since our primary focus is on the impact of SCST as opposed to other labour on productivity;[23] for capital we used the average vintage of gross capital stock (of all types); and for fuel we used fuel quality (the share of coal-tonnes of fuel accounted for by diesel oil and electricity). For the scale of production, we used our aggregated measure of total railway output. We regressed the estimated values of ΔTFP (from year 't' to year 't+1') on the four independent variables (measured in year 't'), thus pooling 22 time series observations for each zone. Since we were dealing with panel data again, we conducted the tests for choosing between RE/FE and serial correlation; this time the tests indicated the use of FE estimation with no significant presence of serial correlation.

Subsequently we undertook a slightly different variant (Variant Two) of our alternative approach. For the first stage we did a new DEA run in which we used the “effective” measures of the capital stock and fuel input variables instead of the unadjusted "raw" measures of the first variant. In other words, we incorporated the 'quality" of the capital stock and fuel inputs into the first stage of the analysis, making it unnecessary to consider them in the second stage. For the second stage of this variant we simply correlated the estimated ΔTFP values (from year 't' to year 't+1') from the first stage with the various SCST variables (measured in year 't').[24]

For each of the variants of our two-stage DEA-based approach we undertook two separate analyses – one including observations for all eight zones, and the other including observations for seven zones, excluding the NFR zone. The reason for excluding this zone is that the figures for NFR constant-price gross rolling stock indicated a substantial and implausible decline throughout the period 1980-2002; in no other zone did we encounter such an implausible trend for any variable.[25] All of the first-stage and second-stage results we obtained for each DEA variant are available on request from the authors.

[23] Since DEA analysis permits us to use four separate labour input variables for the four different labour categories, there is no need to adjust for the category-composition of labour – as we had to do in our production-function analysis.

[24] Thus in the second variant we also dropped from consideration the possible effect of the scale of production, which had proven insignificant in the results for the first variant

[25] We chose not to exclude the NFR zone from our production-function analyses, because then we were using a single aggregate capital stock variable for capital input – and it showed substantial and plausible growth over the period from 1980 to 2002.

The key results of our DEA-based analyses are those that indicate the extent to which total factor productivity change (ΔTFP) is associated with the employment percentages of SCST employees – variously measured by the SCST percentage of total employment ("%SC_ALL") and the SCST percentage of A+B-category employment ("%SC_AB"), or the same measures when highly questionable observations have been excluded ("%SC_ALLx" and "%SC_ABx"). In the case of our first variant, using raw measures of capital stock and fuel inputs and undertaking a second-stage regression analysis of ΔTFP, the association is given by the estimated coefficient on the SCST variable. In the case of the second variant, using effective measures of capital stock and fuel inputs, the association is given by the correlation of ΔTFP with the SCST variable. The key results we obtained are given in Table 2.[26]

Table 2: Association of ΔTFP with SCST variables

	Variant #1		**Variant #2**	
	8 zones	**7 zones**	**8 zones**	**7 zones**
%SC_ALL	0.2	0.32	0.1	0.02
	(0.32)	(0.22)	(0.171)	(0.788)
%SC_ALLx	0.24	0.4	0.13	0.1
	(0.38)	(0.26)	(0.096)	(0.213)
%SC_AB	-0.03	0.12	0.13	**0.17**
	(0.3)	(0.18)	(0.079)	(0.028)
%SC_ABx	0.01	0.21	**0.15**	**0.24**
	(0.44)	(0.27)	(0.049)	(0.004)

Note: Figures in parentheses under variant #1 are standard errors; figures in parentheses under variant #2 are p-values. Figures in bold are significant at 5%.

Table 2 indicates that, under Variant One, the 2nd-stage regression runs to explain ΔTFP yielded positive coefficients on the SCST variables in all but one of the 8 cases, but no coefficient was even close to being significant at 5%. The correlations under Variant Two are all positive, though the in 5 of the 8 cases they were not significant at 5%. ***There is clearly no support here for the claim that higher proportions of SC&ST employees result in slower growth in total factor productivity.***

Under Variant Two, significant positive correlations with ΔTFP were obtained for %SC_ABx in the 8-zone case and for both %SC_AB and %SC_ABx in the 7-zone case. In particular, the correlation in the case of %SC_ABx in the 7-zone case is 24% and the p-value just .4%, reflecting a remarkably high level of significance. This is especially noteworthy because *we have every reason to believe that the results of 7-zone runs are more reliable than the results of 8-zone runs, and that the %SC_ABx tests are more reliable than the %SC_AB tests, because

[26] The results for variant #1 are based on 2nd-stage regressions excluding the scale of production variable, whose estimated coefficient value proved to be quite insignificant under most specifications.

in these cases we are excluding highly questionable observations in the underlying data.[27] ***Thus here we find evidence in support of the claim that higher proportions of SC&ST employees in A and B jobs contributes to more rapid total factor productivity growth, reinforcing our conclusion from the previous section that affirmative action has if anything improved productivity in the Indian Railways.***

5. Possible Reverse Causality

We have been assuming thus far that, if there is any relationship between the SCST percentage of employees and residual productivity (after controlling for factor inputs and technological change), the direction of causality runs from the former to the latter. We must recognize, however, that the percentage of SCST workers might be endogenous and a function of productivity, in which case the direction of causality would run the other way.[28] Thus the management of any given unit of IR might be simultaneously balancing two goals: to hire or promote more SCST employees, in order to satisfy affirmative action requirements, and to produce output in an efficient manner. In this case managers' willingness to hire SCST employees would vary positively with the number of productive SCST workers available for hire and/or with the residual productivity of that IR unit. Any observed correlation between SCST percentage and residual productivity across IR units and years could be due to the fact that some units or years are characterized by a higher supply of qualified SCST candidates and/or higher overall productivity, while other units or years are characterized by a lower supply of qualified SCST candidates and/or lower overall productivity.

This suggested alternative direction of causation, however, is inconsistent with the way in which hiring and promotion of employees actually takes place within the Indian Railways. As it happens, hiring and promotion decisions are made not at the zonal level but at the all-India level; and SCST employees are distributed across zones according to set rules (a mechanical roster system) rather than zonal manager discretion.[29]

One could still argue that correlation across years of SCST percentage and residual productivity might be due to a tendency of both the availability of qualified SCST candidates and the level of residual productivity to rise over time. It is certainly true that qualified SCST candidates become more numerous with each passing year (thanks in part to India's policy of reservations in higher educational institutions); but technological progress over time is controlled for in our regression equations, so there is no *a priori* reason to expect that residual productivity will also be rising steadily from year to year. In any case, the results of our fixed-effect regressions show that the lion's share of the correlation between SCST percentage and residual productivity arises from interzonal rather than intertemporal variance.

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[27] We also examined 2nd-stage correlations of SCST variables with estimates of ΔTFP values generated from a 1st-stage DEA run in which raw measures – rather than effective measures – of capital stock and fuel inputs were used; this resulted in correlation results very similar to those shown under Variant #2 in Table 2.

[28] We are indebted to William R. Johnson for drawing our attention to this possibility.

[29] See the Indian Railways Establishment Manual,Volume I, 1989 (http://www.indianrailways.gov.in/railwayboard/uploads/codesmanual/IREM_VOL_1/main%20Page.htm).

6. Qualitative Aspects of Efficiency

Considering our econometric analysis of railway productivity, one might be concerned that the measures of output we use are mostly quantitative in nature and that such measures fail to take account of possible changes in the *quality* of railway output. Elements of railway output quality include timeliness of arrivals at destinations, passenger comfort, and overall safety (i.e., freedom from accidents). Conceivably growth in the proportion of SCST labour could lead to a diminution in the quality of railway services provided, even as the quantity of services was not adversely affected.

Responding to this concern, we note first that one of our output measures – railway revenue – does reflect quality as well as quantity, insofar as higher quality is reflected in higher prices charged for railway services. Moreover, our quantitative measure of railway passenger output also reflects an element of quality because we weight the growth of passenger output according to class of service – thus giving more weight to the higher classes that provide more comfortable service. Nonetheless, it would be desirable to incorporate more fully into our work various indicators of timeliness, comfort, and accident-free service. We were not able to find systematic data on such indicators for the years and the zones of our statistical analysis; but we do recommend further research along these lines.[30]

Railway accidents, though rare, are obviously an important source of poor railway performance; they generate adverse consequences that go far beyond the loss of damaged equipment and the failure to complete a planned passenger or freight trip. Moreover, as noted in the introductory section, critics of reservation policies have suggested that higher proportions of SCST labour might well result in higher frequencies of railway accidents. We therefore thought it useful to see if trends in Indian Railway accident rates could be related in any way to trends in SCST labour percentages.

Correlating the all-India yearly railway accident rate (the total number of accidents per million train kilometers) over the period of our study (1980-2002) with the corresponding all-India figures for the percentage of SCST employees in total employment, we found correlation coefficients of -.69 for all employees and -.93 (both correlations significant at 1%) for employees in the upper-level A and B categories[31]. The second, higher correlation is the most relevant, both because IR employees serving in management and professional positions are especially responsible for guarding against accidents and because the data on SCST employees in the C and D categories fail to count many SCST employees who do not declare themselves as such.

Our finding of a highly significant negative correlation between the all-India accident rate and the SCST percentage of A+B-category employment results from the fact that the former has been declining and the latter rising (both fairly steadily) over the last few decades. This is strong evidence that higher SCST employment proportions are not resulting in higher accident rates – unless, of course, there are other likely determinants of the accident rate that have also shown steady trends (and the appropriate sign) over the same period. The most plausible alternative explanations for decreasing accident rates are increasing electrification of signals, improvement

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[30] The Indian Railways have only recently started to maintain figures on punctuality of long-distance trains. From January 2009 the Railway Board is analyzing punctuality performance by means of an "Integrated Coaching Management System" – a computer-based on-line system for accurate reporting and analysis of the voluminous data of long-distance train operations. (See http://www.indianrailways.gov.in/deptts/yearbook/ANNUAL_REPORT_08 09/Railway_Annual_Report_English_08-09.pdf.)

[31] Source: GOI, Ministry of Railways, Annual Statistical Statements.

in track quality, and safer track crossings (including better-guarded level crossings and more bridges over tracks). There is indeed evidence of positive time trends in each of these alternative determinants (see GOI, Ministry of Railways, 2005-06 Yearbook, especially pp. 18-25). There is insufficiently detailed data, however, to include such variables in a multivariate regression analysis of accident rates. While such an analysis might well counter the notion that higher SCST employment proportions actually promote greater safety, it seems unlikely that it could undermine the conclusion that higher SCST employment proportions do no harm.

7. Concluding Observations

Analyzing an extensive data set on the operations of one of the largest employers in the public sector in India, the Indian Railways, we have found no evidence whatsoever to support the claim of critics of AA that increasing the proportion of SC&ST employees will adversely impact productivity or productivity growth. On the contrary, some of the results of our analysis suggest that the proportion of SC&ST employees in the upper (A+B) job categories is positively associated with productivity and productivity growth.

Our finding of such positive associations in the case of A and B jobs is especially relevant to debates about the effects of AA on behalf of members of SC and ST communities, for two reasons. First, the efficacy with which high-level managerial and decision-making jobs are carried out is likely to have a considerably bigger impact on overall productivity than the efficacy with which lower-level semi-skilled and unskilled jobs are fulfilled. Thus critics of reservations are likely to be much more concerned about the potentially adverse effects of favoring SC&ST candidates for A and B jobs than for C and D jobs. Second, it is precisely in the A and B jobs – far more than in C and D jobs – that reservations have been indispensable for raising the proportion of SC&ST employees. Even without reservations, one would expect substantial numbers of SC&ST applicants to be hired into C and D jobs; but without reservations very few SC&ST applicants would have been able to attain jobs at the A and B level.

The results that we have obtained from our analysis of productivity in the Indian Railways are consistent with the results from productivity studies in the United States, in that there is no statistically significant evidence that AA in the labour market has an adverse effect on productivity. Our results are stronger, however, in that we do find some suggestive evidence that AA in the labour market actually has a favorable effect – in particular, that the growing proportion of SC & ST employees hired into high-level A+B category railway jobs, largely through India's reservation policies, has contributed to greater overall railway productivity.

It is beyond the scope of our paper to explain just how and why AA in the labour market may have such a favorable effect. We believe, however, that the answer may be found in one or more of the following suggestions that others have advanced to explain such a finding. Individuals from marginalized groups may well display especially high levels of work motivation when they succeed in attaining decision-making and managerial positions, because of the fact that they have reached these positions in the face of claims that they are not sufficiently capable – in consequence of which they may have a strong desire to prove their detractors wrong. Or individuals from marginalized groups may simply believe that they have to work doubly hard to prove that they are just as good as their peers – and so they may actually work harder. Having greater numbers of SC & ST managers and professionals working in high-level A+B positions in the Indian Railways might also serve to increase productivity because their community backgrounds make them more effective in supervising and motivating SC & ST workers in C and D jobs.[32] Finally, improvements in organizational productivity may well result from the greater diversity of perspectives and talents made possible by the integration of members of previously marginalized groups into high-level decision-making teams.[33]

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[32] This recalls the arguments in favor of AA in U.S. educational institutions made to the Supreme Court by U.S. military officers, who want to avoid having just white men in charge of troops that are disproportionately of color (See Weisskopf 2004, preface.)

[33] Page (2007) shows convincingly how groups that display a wide range of perspectives outperform groups of like-minded experts.

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APPENDIX A

Data Sources and Variable Construction (details)

In this appendix we identify the sources and provide further details on the construction of the variables that were used in our estimation of production functions (in section 4) and in our data envelopment analyses (in section 5).

Output Variables

The output of the Indian Railways (IR) includes passenger and freight service. IR statistics distinguish four different kinds of passenger output:

- Suburban (all classes)
- Non-suburban, which is further divided into three types, as follows:
  - Upper class (all air conditioned classes + first class ordinary)
  - Mail (mail in first, sleeper and second classes)
  - Ordinary (ordinary in second and sleeper classes)

Physical output is measured in terms of passenger-kilometers (PKMS), defined as the number of passengers carried multiplied by the average distance traveled. The IR collects data on PKMS as well as on revenues received for each of the four kinds of service. The underlying data on PKMS and on revenues, by year and by zone for each type of service, were obtained from Statement 12 of GOI, Ministry of Railways, Statistical Statements (annual).

We generated time series indices of **total passenger output** in each zone from time series indices (with a value of 100 in the base year 1980) for each of the four service types, using a procedure that weights observations of the latter in each year according to the proportion of revenues contributed by that service type to total passenger service revenues in that year.,

IR statistics distinguish nine different types of freight output, according to the type of commodity carried:

- Coal (for steel plants; washeries; thermal power houses; other uses)
- Raw materials for steel plants
- Pig Iron and Finished Steel Booked From Steel Plants
- Iron Ore for Export
- Cement
- Food grains
- Fertilizers
- Mineral oils
- Other commodities

Physical output is measured in terms of net tonne-kilometers (NTK), defined as the tonnes of freight carried multiplied by the average distance traveled. The IR collects data on NTK as well as on revenues received for each of the nine commodity categories. The underlying data on NTK and on revenues, by year and by zone for each commodity category, were obtained from Statement 13 of GOI, Ministry of Railways, Statistical Statements (annual).

We generated a time series index of **total freight output** in each zone from time series indices (with a value of 100 in the base year 1980) for each of the nine transported commodity categories, weighting observations of the latter in each year according to the proportion of revenues contributed by that commodity category to total freight revenues in that year.

To calculate observations of the variable **total railway revenue** by zone-year, we simply aggregated all the revenues received for passenger service and for freight transport and then deflated the total by the corresponding (all-India) price deflator for transport services (obtained from GOI, Ministry of Industry, Central Statistical Organization, <u>Index Numbers of Wholesale Price Indices</u>.

To calculate zone-year observations of the variables measuring total passenger output, total freight output and total railway output in physical terms, we aggregated the underlying data for each kind of passenger service and each type of freight transport as follows (note that all index time series take the value of 100 in the base-year 1980):

(1) For each zone create a *PKMS index* time series for each kind of passenger service. Calculate a *total passenger output index* by multiplying each value in the *PKMS index* by the corresponding percentage of total passenger revenue and then summing the products.
(2) For each zone create an *NTK index* time series for each type of freight transport. Calculate a *total freight output index* by (a) multiplying each value in the *NTK index* by the corresponding percentage of total freight revenue and then (b) summing the products.
(3) For each zone calculate a *total railway output index* by (a) multiplying each value in the *total passenger output index* and in the *total freight output index* by the corresponding percentage of total railway revenue and then (b) summing the products.
(4) The resultant zonal *total passenger output*, *total freight output* and *total railway output indices* will all have the value of 100 in 1980. To account for the heterogeneity of zone sizes, compute for each zone the ratio of zonal passenger, freight and total railway revenues to the corresponding all-India revenues in 1980.
(5) Calculate for each zone scale-adjusted indices of **total passenger output**, **total freight output** and **total railway output** by multiplying all values in each of the three zonal *output indices* (obtained in step 3) by the corresponding ratio (obtained in step 4).

<u>Labour variables</u>

The Government of India has a standard classification of employment categories for all its undertakings, and the Indian Railways are no exception. The employment categories are as follows:

- Groups A and B together (Engineers, Personnel Officers, Traffic Service Officers, Financial Advisors, Doctors)
- Group C:
  - Grade 1: Workshop and Artisan Staff (station masters, technicians, supervisors, nurses, pharmacists)
  - Grade 2: Running Staff (engine drivers, guards, train ticket examiners)
  - Grade 3: Other staff (clerical staff)
- Group D:
  - Grade 1: Workshop and Artisan Staff (gangmen, peons)
  - Grade 2: Running staff (train sweepers, train attendants)
  - Grade 3: Other staff (office peons, hospital attendants, sweepers)

Annual data on the total number of employees and on average wage per employee for each of the above seven distinct categories of labour, for all-India and in each zone, are provided in Statement 40-II of GOI, Ministry of Railways Statistical Statements (annual). We used the figures for total number of employees defined as the sum of total permanent and temporary employees.[34] We calculated the average wage per employee as the sum of the following components available from the source: pay and leave salary, running and overtime allowance, dearness allowance, traveling and compensatory allowance, provident fund contribution, gratuity, and pension benefits. In the case of employment, but not average wages, data are also available separately for total number of employees in Group A and in Group B.

Our time series data for the raw labour input variables **A-category employment**, **B-category employment**, **C-category employment**, **D-category employment** and **total employment** were compiled very easily from the disaggregated data on total number of employees described just above. As noted in the text of section 3, we posited that overall labour quality improves to the extent that the category-composition of employees shifts towards more higher-skilled employees and less lower-skilled employees. In order to take account of such changes in labour quality, as well as changes in the quantity of raw labour input from year to year, we created all-India and zonal time series for the quality of labour and the volume of effective labour as follows (all index time series take the value of 100 in the base-year 1980, unless otherwise noted):

(1) Using the disaggregated total employment data for each zone (and all-India), create an *employment index* time series for each labour category and a *total employment index* time series for labour of all categories taken together.
(2) For each zone (and all-India), calculate the wage bill for each labour category by multiplying employment in each category by the corresponding average wage, and calculate the total wage bill by summing the wage bills of each category..
(3) Calculate an *effective labour index* by (a) multiplying each value in the *employment index* for each labour category by the corresponding percentage of the total wage bill represented by that category and then (b) summing the products.
(4) Calculate the *labour quality index* by dividing the *effective labour index* by the corresponding *total employment index*; note that this index will be keyed to a value of 1.0 in 1980.
(5) The calculated zonal *effective labour indices* and *quality of labour indices* will all have the value of 100 in 1980. To account for the fact the category composition of labour – and hence the quality of labour – was not the same in 1980 for all zones, compute for each zone the zonal *base-year labour quality ratio* by calculating how the zonal category-composition of labour in 1980 compares to the all-India category-composition of labour in 1980. (This can be done by treating the zonal category-composition of labour in 1980 as if it were the all-India category-composition of labour in 1981, and then taking the resulting value of the all-India *labour quality index* in 1981 as the zonal *base-year labour quality ratio*.) Thus the category-composition of all jobs at the all-India level in 1980 serves as the standard that defines the 1.0 point of the labour quality scale.
(6) Calculate for each zone the final quality-adjusted indices of **labour quality** and **effective labour** by multiplying all values in each of the zonal *labour quality* and *effective labour indices* (obtained in step 3) by the corresponding zonal *base-year labour quality ratio* (obtained in step 5).

[34] Figures for temporary employees are given separately for the two subcategories of those with "less than three years of service" and those with "three years of service and over."

For the purposes of our analysis we needed to distinguish SCST labour from non-SCST labour. GOI, Ministry of Railways, General Managers' Annual Report provides data, for all-India and in each zone, on the number of Scheduled Caste & Tribe (SCST) employees in each of the four categories of labour (A, B, C, D). These data could easily be combined with the data on total employment to yield the **SCST percentage of total employment** first **in all labour categories** and then **in labour categories A+B** only.

Capital Variables

Data on capital investment and capital stock in the IR are reported in Annexure G of Government of India, Ministry of Railways Appropriation Accounts (annual). For each of three types of capital stock – structural engineering, rolling stock, and machinery & equipment – we obtained time series data on (1) gross investment during the year and (2) book value of capital stock at the end of the year, both valued at current prices. These data were available for all-India from 1952 through 2002, and for each of the 8 zones from 1966 through 2002.

In order to get the during-the-year constant-price gross investment figures for each type of capital, we deflated the current-price gross investment data using separate price indices for each type of capital. The appropriate indices are available in GOI, Ministry of Industry, Central Statistical Organization, Index Numbers of Wholesale Price Indices (annual). We then extrapolated zonal constant-price gross investment time series from 1966 back to 1952, under the assumption that, for each type of capital, the ratio of zonal constant-price gross investment in a given year to zonal constant-price book value of gross capital stock at the end of the year 1966 (obtained by deflating the corresponding current-price values with the 1966 price index for each type of capital) was the same as the corresponding ratio for all-India.

We used the perpetual inventory method to generate estimates of constant-price gross capital stock of each type, in each zone and for all-India, *at the beginning* of each year from 1980 through 2003. Based on information on the working lives of different kinds of railway capital provided in GOI, Ministry of Railways, Indian Railways Financial Code (1999 reprint), Vol. I, Chapter 2, Paragraph 219, we assumed that the lifetimes of the 3 types of capital are as follows: equipment and structures: 45 years; rolling stock: 30 years; machinery: 15 years. In other words, constant-price gross capital stock of each type at the beginning of year T is obtained by adding up constant-price investment for the years T-n through T-1, where 'n' is the average lifetime of that kind of capital. (Since we had investment figures going back only to 1952, the summing of past annual gross investments to get current beginning-of-year gross capital stock figures sometimes had to be truncated before going back the full 'n' years of capital lifetime. Thus in calculating gross rolling stock figures for the beginning of the years 1980 and 1981, we should have summed past gross investments back to 1950 and 1951; but we could only take these summations back to 1952; likewise, in calculating gross structural engineering stock figures for the beginning of the years 1980 through 1996, we should have summed past gross investments back to 1935 through 1951; but we could only take these summations back to 1952. Since annual investments in railway capital in the years prior to 1952 were surely much lower than in later years, we can be confident that the failure to account for investment in those pre-1952 years did not make a significant difference to our estimates of gross capital stocks from 1980 onwards.)

We then generated data for the average value of **constant-price gross structural engineering works, gross rolling stock,** and **gross machinery & equipment**, in each zone and for all-India, during a given year from 1980 to 2002 by averaging the corresponding values of constant-price gross capital stock at the beginning of that year and at the beginning of the next year. **Total**

constant-price gross capital stock for any zone (and for all-India) in each year from 1980 to 2002 was obtained simply as the sum of the estimates of constant-price gross capital stock of each type in that zone (or all-India) in the same year.

In order to calculate the average vintage of gross capital stock of each type, in each zone and for all-India in each year from 1980 to 2002, we needed to add together the average age of the gross capital stock at the beginning of the year and the number of years elapsed from the beginning of that year to the middle of the year 2002. The average age of gross capital stock of each type, at the beginning of any given year in any zone or for all-India, was obtained by summing the products of (1) each constant-price gross investment component of that constant-price gross capital stock and (2) the difference between the given year (of the capital stock) and the year in which the investment took place, and then dividing that sum of products by the constant-price gross capital stock (i.e., the sum of the constant-price gross investment component of the gross capital stock). We calculated **the average vintage of total gross capital stock of each type (and for all types** together), in each year, for each zone and for all-India, by taking an average of the vintages for each type of capital stock, weighted by the proportion of that type of capital in total constant-price gross capital stock.

To generate a capital obsolescence fraction corresponding to each estimate of the vintage of total gross capital stock, we assumed that a unit of constant-price gross investment loses 1% of its value as productive capital for each year elapsed since it was created. The capital obsolescence fraction (KOF) is thus related to the average vintage of gross capital stock (AVK) by the formula: KOF = e^(-.01*AVK). We could then calculate the value of **effective capital stock**, for each type of capital and for total capital stock, in each year, for each zone and for all-India, by multiplying the constant-price gross capital stock by the corresponding capital obsolescence fraction.

Material Input Variables

The main material input used by the IR is fuel, consumed (1) by locomotives and (2) for all other purposes – such as pumping stations, workshops, steamers, and electricity generating stations. Annual data on the amount and cost (at current prices) of fuel inputs, for all-India and in each zone, are provided in Statement 27(a) of GOI, Ministry of Railways, Statistical Statements (annual). This source lists seven kinds of materials used as fuel inputs, listed below with conversion factors used to convert physical measures of the materials into "coal-tonne equivalents" (CTE):

(1) Coal (1 tonne = 1 CTE)
(2) Firewood (2.5 tonnes = 1 CTE)
(3) Diesel oil – high speed (1.19775 kilolitres = 11 CTE)
(4) Diesel oil – light (1.19775 kilolitres = 11 CTE)
(5) Petrol (1.4094 kilolitres = 7.5 CTE)
(6) Kerosene oil (.70626 kilolitres = 1 CTE)
(7) Electric power (1000 KwH= 0.769231 CTE)

The conversion factors for items (2) through (6) are provided in the above-mentioned source. To obtain the conversion factor for electric power, we followed the method given in Manohar et al (1982): 1000 KwH= 1 mtcr (Metric Ton Coal Replacement) = 1/1.3 tonnes of coal = 0.769231 CTE. Using the above conversion factors, we converted physical measures of inputs of all of the fuel types into a single physical measure of total **fuel input** in CTE.

Because diesel- and electricity-powered locomotion is cleaner and more efficient than locomotion powered by other fuels, we wanted to work with a fuel input variable that would take account of the extent to which locomotion is powered by the more efficient fuels. We first calculated, for each zone and for all-India, annual values of a **fuel quality** variable defined as the percentage of total CTE of fuel accounted for by diesel oil and electricity. We then calculated the corresponding annual values of **effective fuel** input by multiplying the total CTE fuel input by (1 + .25*fq), where 'fq' is the value of fuel quality. Thus our measure of effective fuel gives diesel & electric fuel a weight of 125% as compared with 100% for other fuels, which appeared to us to be a reasonable estimate of the extent of to which the quality of the former is superior to that of the latter.

APPENDIX B

In this appendix, we report the detailed results that have been referred to in the main body of the paper at various points.

Table B-1: Fixed Effects Estimation Results

Specification:	**1**	**2**	**3**	**4**	**5a**	**5ax**	**5b**	**5bx**
Constant	-4.49	-4.45	-6.32	-2.03	-5.2	-4.5	-4.12	-2.63
	(10.31)	(9.89)	(14.02)	(8.18)	(9.7)	(9.07)	(10.67)	(10.42)
ln ek	0.074		-0.14		0.1	0.11	0.077	0.003
	(0.50)		(0.37)		(0.48)	(0.44)	(0.49)	(0.47)
ln el	0.41		0.65		0.43	0.35	0.37	0.39
	(0.31)		(0.61)		(0.30)	(0.26)	(0.30)	(0.286)
ln ef	0.021		-0.018		0.01	0.016	0.01	-0.005
	(0.12)		(0.09)		(0.48)	(0.131)	(0.12)	(0.106)
time	**0.05**	**0.05**	**0.06**	**0.06**	**0.04**	**0.04**	**0.04**	0.04
	(0.021)	(0.017)	(0.017)	(0.01)	(0.02)	(0.02)	(0.02)	(0.19)
%SC_ALL					-0.19			
					(0.28)			
%SC_ALLx						-0.46		
						(0.54)		
%SC_AB							0.14	
							(0.37)	
%SC_ABx								**0.87**
								(0.32)
ln l		0.46		**1.14**				
		(0.37)		(0.4)				
ln k		0.06		-0.01				
		(0.51)		(0.30)				
ln f		-0.01		-0.03				
		(0.07)		(0.07)				
corr %SC_ALL	-0.01	-0.01	0	0.04				
corr %SC_ALLx	-0.04	0.03	-0.03	0.02				
corr %SC_AB	-0.07	-0.06	-0.07	0.026				
corr %SC_ABx	0	0	0	0.11				

Note: For specifications 3 and 4 the dependent variable is ln r; for all other specifications it is ln q. Standard errors are in parentheses. Figures in bold are significant at 5%.

Table B-2a: Prais-Winsten Estimation Results with Panel-Specific AR (1)

Specification:	**1**	**2**	**3**	**4**	**5a**	**5ax**	**5b**	**5bx**
Constant	**-26.59**	**-27.4**	**-20.93**	**-21.81**	**-26.64**	**-27.04**	**-26.7**	**-26.97**
	(1.63)	(1.74)	(1.26)	(1.1)	(1.62)	(1.36)	(1.62)	(1.31)
ln ek	**0.95**		**1.1**		**0.96**	**1.04**	**0.99**	**1.05**
	(0.15)		(0.12)		(0.15)	(0.14)	(0.15)	(0.13)
ln el	**0.71**		**0.69**		**0.7**	**0.6**	**0.65**	**0.57**
	(0.16)		(0.13)		(0.16)	(0.16)	(0.15)	(0.14)
ln ef	0.12		**0.16**		0.12	0.12	0.13	**0.13**
	(0.07)		(0.06)		(0.07)	(0.07)	(0.07)	(0.06)
time	**0.01**	**0.02**	**0.01**	**0.03**	0.01	0.008	0.01	0.007
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	`
%SC_ALL					-0.17			
					(0.23)			
%SC_ALLx						-0.32		
						(0.34)		
%SC_AB							-0.17	
							(0.18)	
%SC_ABx								-0.09
								(0.297)
ln l		**0.82**		**0.83**				
		(0.18)		(0.13)				
Ln k		**0.94**		**1.08**				
		(0.17)		(0.11)				
Ln f		0.08		**0.1**				
		(0.06)		(0.05)				
corr %SC_ALL	0.03	0.06	0.05	0.08				
corr %SC_ALLx	-0.01	0.03	-0.02	0.04				
corr %SC_AB	**0.14**	**0.2**	0.09	**0.15**				
corr %SC_ABx	**0.2**	**0.27**	0.13	**0.19**				

Note: For specifications 3 and 4 the dependent variable is ln r; for all other specifications it is ln q. Standard errors are in parentheses. Figures in bold are significant at 5%.

Table B-2b: Prais-Winsten Estimation Results with Common AR (1)

Specification:	**1**	**2**	**3**	**4**	**5a**	**5ax**	**5b**	**5bx**
Constant	**-26.28**	**-27**	**-20.99**	**-21.88**	**-26.28**	**-26.65**	**-26.25**	**-26.71**
	(1.42)	(1.36)	(1.35)	(1.26)	(1.41)	(1.17)	(1.39)	(1.1)
ln ek	**1.01**		**1.21**		**1.01**	**1.05**	**1.01**	**1.04**
	(0.12)		(0.12)		(0.12)	(0.12)	(0.12)	(0.11)
ln el	**0.54**		**0.47**		**0.54**	**0.51**	**0.53**	**0.53**
	(0.11)		(0.11)		(0.11)	(0.12)	(0.11)	(0.13)
ln ef	**0.16**		**0.19**		**0.16**	**0.16**	**0.16**	**0.16**
	(0.07)		(0.06)		(0.07)	(0.06)	(0.07)	(0.06)
time	0.009	**0.02**	0.01	**0.03**	0.008	0.008	0.009	0.007
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)
%SC_ALL					-0.05			
					(0.28)			
%SC_ALLx						-0.37		
						(0.42)		
%SC_AB							-0.12	
							(0.2)	
%SC_ABx								0.1
								(0.33)
ln l		**0.61**		**0.57**				
		(0.11)		(0.11)				
ln k		**1.01**		**1.2**				
		(0.1)		(0.1)				
ln f		**0.12**		**0.14**				
		(0.06)		(0.05)				
corr %SC_ALL	0	0.03	0	0.03				
corr %SC_ALLx	-0.06	-0.03	-0.08	-0.03				
corr %SC_AB	0.09	0.13	0.01	0.06				
corr %SC_ABx	**0.15**	**0.19**	0.03	0.09				
AR(1) coeff	0.75	0.74	0.74	0.72	0.75	0.72	0.75	0.74

Note: For specifications 3 and 4 the dependent variable is ln r; for all other specifications it is ln q. Standard errors are in parentheses. Figures in bold are significant at 5%.

Table B-3: Lev-Pet Regressions

Specification:	**1**	**2**	**3**	**4**	**5a**	**5ax**	**5b**	**5bx**
ln ek	**0.881**		**1**		**0.93**	**1**	**0.79**	0.405
	(0.37)		(0.43)		(0.39)	(0.41)	(0.435)	(0.39)
ln el	0.183		0.0604		0.177	0.079	0.216	0.34
	(0.56)		(0.32)		(0.46)	(0.51)	(0.46)	(0.55)
ln ef	3.04E-38		2.41e-0.8		4.37E-30	6.50E-10	5.18E-35	1
	(0.41)		(0.34)		(0.438)	(0.45)	(0.42)	(0.35)
%SC_ALL					-0.185			
					(0.94)			
%SC_ALLx						-1.02		
						(1.32)		
%SC_AB							0.318	
							(0.93)	
%SC_ABx								1.365
								(0.97)
ln l		0.0105		-0.1498				
		(0.47)		(0.5)				
ln k		**1**		**1**				
		(0.39)		(0.35)				
ln f		8.44E-28		5.78E-38				
		(0.4)		(0.41)				
corr %SC_ALL	-0.02	-0.04	0.002	-0.01				
corr %SC_ALLx	-0.05	-0.05	-0.02	-0.02				
corr %SC_AB	0.12	0.12	0.07	0.08				
corr %SC_ABx	**0.19**	**0.19**	0.13	0.13				

Note: For specifications 3 and 4 the dependent variable is ln r; for all other specifications it is ln q. Standard errors are in parentheses. Figures in bold are significant at 5%.