Chapter 2
Infrastructure, ICT and Firms' Productivity and Efficiency: An Application to the Indian Manufacturing

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Abstract This paper highlights the role of infrastructure and information and communication technology (ICT) in the context of total factor productivity (TFP) and technical efficiency (TE) of the Indian manufacturing sector for the period 1994–2008. We use advanced estimation techniques to overcome problems of non-stationary, omitted variables, endogeneity and reverse causality by applying fully modified OLS, panel co-integration and system GMM. Estimation results suggest that the impact of infrastructure and ICT is rather strong. Interestingly, sectors exposed relatively more to foreign competition (e.g. Transport Equipment, Textile, Chemicals, Metal and Metal Products) are more sensitive to infrastructure deficiencies. This finding implies that improving infrastructure and ICT would benefit these sectors to a large extent, thus contributing to India's competitiveness. This outcome is of particular importance in the context of infrastructure bottlenecks in India.

2.1 Introduction

Manufacturing is an important sector in the Indian economy, comprising about 30 % of the non-agricultural GDP and between 70 and 80 % of the Indian exports. This sector has gained strength in many ways over the past 20 years, as a consequence of the liberalization of industrial controls and a gradual integration with the

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world economy (Natarajan and Duraisamy 2008). Important industries (for instance automobile components, pharmaceuticals, special chemicals, and textiles) have recorded exceptional growth in terms of overall output and exports in the reform period (since 1991). The average output growth rate of the manufacturing sector has been around 7–8 % in the last decade and is targeted at 12–14 % over the medium term to make it an engine of growth for the economy. Furthermore, the new manufacturing policy aims at achieving 2–4 % growth differential over the medium term, which will enable the manufacturing sector to contribute at least 25 % of GDP by 2025 (from around 15 % during the 1990s and the 2000s, Planning Commission 2011). Despite these achievements, however, the manufacturing sector exhibited disappointing productive performance. TFP growth in particular declined from above 5 % in the 1980s, to less than 2 % in the 1990s (see Trivedi et al. 2000; Goldar 2004). Recent estimates found only a marginal improvement of TFP growth in the 2000s (Sharma and Sehgal 2010; Kathuria et al. 2010).

Infrastructure is considered as a crucial factor for enhancing productivity and economic growth, especially in developing economies (see World Bank 1994). Recognizing that the infrastructure inadequacy in both rural and urban areas is a major constraining factor, the government of India has increased its infrastructure expenditure from 4.6 % of GDP to around 8 % in the last year of the eleventh Plan period (2007–2012). Furthermore, during the twelfth Plan (2012–2017), investment in infrastructure is targeted to be massive at USD 1,025 billion, which constitutes 9.95 % of the GDP (Planning Commission 2011).

Despite these efforts, however, infrastructure inadequacies are still recognized as a major constraining factor for the productivity of the firms (see Pinto et al. 2006). The World Bank investment climate surveys also show that the limited and poor quality of infrastructure acts as a major impediment to business growth in the country (World Bank 2004; Ferrari 2009). A failure to respond to this demand is causing serious obstacles in achieving the country's growth objective (see Sharma and Bhanumurthy 2011). As a matter of fact, India ranks very low in several infrastructures, compared to China, Brazil and South Africa, which are India's main competitors in the world market (see Table 2.10 in Appendix 2). Despite the recent government spending increase, this is still far from China's efforts, which has invested between 15 and 20 % of its GDP for the development of infrastructure since the mid-1990s (Straub et al. 2008).

In the theoretical literature, public infrastructure appears as a key factor of productivity and efficiency enhancement through its complementary relationship with other factors of production and external economies (Lucas 1988; Barro and Sala-i-Martin 1995). Empirical findings on this issue, however, are inconsistent and often contrary to each other. Over the last two decades a large number of studies have focused on this issue. Most have noted that public infrastructure positively and sizably affects economic performance (Aschauer 1989; Munnel 1990). Some others, for example Evan and Karras (1994) and Holtz-Eakin (1994) have challenged these findings on methodological ground and showed insignificant or minimal impact of public infrastructure. Nevertheless, with improvement in empirical methodologies, some recent studies again estimated large effects (Stephan 2003; Kamps 2006). In the case of India, Mitra et al. (2002), Hulten et al. (2006) and Sharma and Sehgal (2010) found moderate to large impact of infrastructure on the manufacturing performance. The wide range of estimates makes, however, the findings difficult to be employed in policy formulation. This paper is an attempt to clarify this debate, in a context of limited resources of the government of India to achieve its growth and development objective.

As for ICT more specifically, it is widely shown that its adoption in the developed countries is associated with significant improvements in performance. The recent empirical research suggests however that there is a considerable variation across countries, with European economies experiencing far lower increases in productivity linked to ICT than in the USA, where the strong acceleration in productivity growth since the mid-1990s has been associated with improvements in both ICT producing and ICT using sectors (see Oliner and Sichel 2002; Jorgenson 2001; Bosworth and Triplett 2000). Although India has a quite successful story in area of ICT, the Indian case is widely ignored in the standard literature.

Against this background, this chapter aims at empirically quantifying the impact of infrastructure as well as ICT on the performance of manufacturing industries in India. In this process, we introduce five main novelties from the empirical standpoint. *First,* in most of the previous studies on India, information was mainly taken from the annual survey of industry (ASI) database. We utilize Prowess, a new manufacturing database on eight important industries, which allows us to extend the time horizon of the study up to 2008. This dataset is rich and provides heterogeneity in terms of variables and industries. *Second,* while some of the earlier studies on India mainly focused on the impact of infrastructure on output growth, we move a step forward by analysing the impact on two other crucial indicators of industrial performance, namely total factor productivity (TFP) and technical efficiency (TE). *Third*, the inclusion of too many infrastructure variables separately in a regression analysis may lead to multicollinearity problem. In order to avoid this problem, we construct two composite indicators—one relating to total infrastructure (G), another encompassing information and communication technology (ICT)—by applying the principal component analysis (PCA) methodology to our initial physical indicators. *Fourth*, since in the recent years the Indian ICT sector has grown at an unprecedented rate, we investigate its role on the performance of the manufacturing sector separately. *Fifth*, most earlier studies on India directly applied OLS and did not pay serious attention to the stationarity issue of the variables. As non-stationarity of data series causes various estimation problems, we utilize unit root test and co-integration techniques to evaluate the integration between the variables in the panel context. For the estimation, we use fully modified OLS (FMOLS) and System GMM, which are likely to produce better results than the traditional estimators by taking care of endogeneity problem. It also allows us to employ the variables in level rather than in first difference form. This is important because some information is lost when difference forms are applied.

The rest of this paper is organized as follows. The second section presents the data and its sources used in the empirical analysis. Section three discusses the methodological aspects linked to the computation of total factor productivity (TFP) and technical efficiency (TE) and provides the estimates of both the indicators. The fourth section describes our empirical models of investigation and the econometric issues related to estimation. The fifth section presents the results and illustrates the impact of infrastructure and ICT on TFP and TE. The last section concludes and presents some policy recommendations.

2.2 The Data on Infrastructure, ICT and the Manufacturing Sector

Data on two-digit industry groups in the Indian manufacturing sector have been gathered from the Prowess database provided by the centre for monitoring the Indian economy (CMIE). Annual financial statements of firms belonging to eight industries,[1] namely *Food* and *Beverages*, *Textiles*, *Chemicals*, *Non-metallic Minerals*, *Metal* and *Metal Products*, *Machinery*, *Transport Equipment* and *Miscellaneous Manufacturing*, have been used. Subsequently, the firm-level data have been transformed into industry-level data by aggregation. This has been done for each year over the sample period, 1994–2008. The reason for taking 1994 as the initial year is that the Indian economy witnessed structural reforms in the early 1990s, which have subsequently brought in vast changes in the manufacturing sector policy. Another practical reason lies in the fact that data on price indices and deflators for all variables are available from this year onwards.

We use gross value added of the industries as the measure of nominal output which is deflated by industry specific wholesale price indices (WPI) to obtain output in real terms.[2] The deflator is obtained from the office of the economic adviser (OEA), Ministry of Commerce and Industry, Government of India (http://eaindustry.nic.in/). The series on real capital stock is constructed using the perpetual inventory capital adjustment method. Specifically, we compute it as:

$$K_t = (1 - \delta)K_{t-1} + I_t \tag{2.1}$$

where, K is the capital stock, I is the deflated gross investment, δ is the rate of depreciation taken at 7 %, consistent with similar studies for India (Ghosh 2009)

[1]Prowess (CMIE) classified the Indian manufacturing in eight two digit industries. The prowess follows an internal product classification that is based on the Harmonized System and national industry classification (NIC) schedules. There are a total of 1,886 products linked to 108 four-digit NIC industries across the 22 manufacturing sectors (two-digit NIC codes) in the database. For analysis, we have covered all available industries in the database. Furthermore, these eight groups of industries cover a sizeable part of the total organized industrial production in India.

[2]We prefer gross value added as a measure of output in computing TFP, as it is widely used in the Indian manufacturing sector literature (Goldar 2004; Kumar 2006). There are many advantages of using gross value added over output. Firstly, it allows us a comparison between the firms that use different raw materials. Secondly, if gross output is used as a measure of output, it adds the necessity of including raw materials, which may obscure the role of labour and capital in the productivity growth (Kumar 2006).

and t indicates the year. The initial capital stock equals the net book value of capital stock for the year 1994. Data on other control variables such as trade (export and import) and R&D have also been extracted from the same database. A summary statistics of the variables is reported in Table 2.11 of Appendix 3.

In this study transportation (road, rail and air), information and communication technology (ICT) and energy sectors are considered as indicators of physical infrastructure (indicators are presented in Table 2.6 of Appendix 2). These data are taken from World Development Indicators (WDI 2011) online, and infrastructure publications of CMIE (2009). Instead of using all infrastructure variables separately, which is likely lead to multicollinearity problem (see correlation between infrastructure variables in Table 2.9 of Appendix 2), we construct a total (G) and an ICT infrastructure index for India by applying the principal component analysis (PCA) method to our original indicators.[3]

2.3 Measuring Total Factor Productivity (TFP) and Technical Efficiency (TE)

We start our empirical analysis by computing the TFP for the Indian manufacturing sector. First, we construct a panel of eight industries and estimate a basic production function in Cobb-Douglas form:

$$\ln(Q_{it}) = \alpha_1 \ln(K_{it}) + \alpha_2 \ln(N_{it}) + \alpha_3 (T_{it}) + \eta_t + u_{it} \tag{2.2}$$

where Q, K, and N are value added, capital and labour input, respectively, for industry i and period t. T_i is the time trend specified for each industry i. α_1 , α_2 and α_3 are the parameters to be estimated. The term η_t represents fixed time effects and *ln* the logarithm of the variables.

Equation (2.2) was estimated using panel fixed effect method.[4] We then calculate the TFP by industry as follows:

[3]The principal component analysis (PCA) method is a widely used aggregation technique because of the subjectivity attached to other ad hoc aggregation methods. PCA is designed to linearly transform a set of initial variables into a new set of uncorrelated components, which account for all of the variance in the original variables. Each component corresponds to a virtual axe on which the data are projected. The earlier component explains more of the variance of the series than do the later component. The number of components is proportional to the number of initial variables that are used in the PCA. Usually, only the first components are retained, because they explain most of the variance in the dataset. The proportion gives the explanatory power of each component. For more details on the aggregation method using principal component analysis (PCA), see Nagaraj et al. (2000) and Mitra et al. (2002).

[4]We choose fixed effect (FE) model because the test statistic suggests that the OLS and Random Effect models are rejected. The fixed effect suggests that the firm specific group effects are strong. Other alternative methods of estimating productivity include growth accounting technique, but that is inferior to econometric estimation.

$$\ln(TFP_{it}) = \ln(Q_{it}) - \widehat{\alpha_1}\ln(K_{it}) - \widehat{\alpha_2}\ln(N_{it}) \tag{2.3}$$

where $\hat{\alpha}_1$ and $\hat{\alpha}_2$ are the estimated parameters of capital and labour, respectively. Results of calculations are shown in Table 2.6 of Appendix 1.

To measure the technical efficiency (TE) of the Indian manufacturing sector, we utilize the maximum likelihood (ML) estimates of stochastic frontier production functions, developed by Battese and Coelli (1992) for panel data. In this model, industry effects are assumed to be distributed as a truncated normal variable, which allows it to vary systemically with time.[5] Specifically, we employ time-varying efficiency model in the stochastic frontier function framework, as developed by Battese and Coelli (1992). The model may be specified as:

$$Q_{it} = \alpha X_{it} + (V_{it} - \mu_{it}) \tag{2.4}$$

where and X_{it} are output and inputs in log-form of ith industry at time t.

Disturbance term is composed of two independent elements, V_{it} and μ_{it}. The former is assumed to be independently and identically distributed as $N(0, \sigma_v^2)$. The element μ_{it} is a nonnegative random variable associated with technical inefficiency in production, assumed to be independent and identically distributed with truncation (at zero) of the distribution $N(\mu_{it}, \sigma_\mu^2)$. The parameters α can be obtained by estimating the stochastic production function (2.4) using a ML technique.

Coelli (1996) utilizes the parameterization of Battese and Corra (1977) to replace σ_v^2 and σ_μ^2 with $\sigma^2 = \sigma_v^2 + \sigma_\mu^2$ and $\gamma = \frac{\sigma_\mu^2}{\sigma_v^2 + \sigma_\mu^2}$ in the context of ML estimation. The term γ lies between 0 and 1 and this range provides a good initial value for use in an iterative maximization process. Subsequently, the relative technical efficiencies (TEs) of each industry can be predicated from the production frontier as follows:

$$TE = \frac{Q_{it}}{\exp(f(X_{it};\alpha))} = \exp(-\mu_{it}) \tag{2.5}$$

Since μ_{it} is, by definition, a non-negative random variable, TE is bound between zero and unity, where unity indicates maximum efficiency. Our model measuring the efficiency is:

$$\ln Q_{i,t} = \alpha_0 + \alpha_1 \ln K_{i,t} + \alpha_2 \ln N_{i,t} + \sum_t \lambda_t D_t + (v_{it} - u_{it}) \tag{2.6}$$

where D_t is a dummy variable having a value of one for tth time period and zero otherwise and λ_ts are parameters to be estimated. The dummy variable is introduced in the model for the technical change; this is in line with the general index approach

[5]This methodology, initially used with firm-level data, has also been employed to estimate productivity at the aggregate level (see Kathuria et al. 2010). Our working hypothesis is that some industries operate more efficiently than others.

of Baltagi and Griffin (1988). The change in λ_t between successive periods becomes a measure of rate of technical change.

$$TC_{t,t+1} = \lambda_{t+1} - \lambda_t \tag{2.7}$$

This implies that the hypothesis of no technical change is: $\lambda_t = k \, \forall t$.

In order to compute TE, we utilize the same panel of data which we used for TFP calculations. A Cobb-Douglas production function is also postulated for the estimation of Eq. (2.6). As for TFP, the results of the estimation are used to calculate the TE of the industries (see Table 2.7 of Appendix 1).

Interestingly, results of TFP and TE calculations clearly indicate substantial differences across industries. In terms of relatively high productivity growth, *Chemical, Transport Equipment* and *Machinery* industries are better performers. The less productive ones are *Textile* and *Non Metal products.* On the other hand, as regards TE, *Transport Equipment* and *Chemical* industries are seen to be the most efficient ones, with a substantial rate of improvement in their efficiency over the study period.

2.4 The Empirical Models of Manufacturing Performance and Estimation Issues

After estimating the TFP and TE of the Indian industries, we turn to assess the impact of total infrastructure (G) and information and communication technology (ICT) on the manufacturing performance. For this purpose, we specify four empirical models, which are as follows:

$$\ln(TFP)_{it} = \alpha + \beta \ln(\mathrm{G})_{it} + \delta X_{it} + e_{it} \tag{2.8}$$

$$\ln(TFP)_{it} = \alpha + \beta \ln(\mathrm{ICT})_{it} + \delta X_{it} + e_{it} \tag{2.9}$$

$$\ln(TE)_{it} = \alpha + \beta \ln(\mathrm{G})_{it} + \delta X_{it} + e_{it} \tag{2.10}$$

$$\ln(TE)_{it} = \alpha + \beta \ln(\mathrm{ICT})_{it} + \delta X_{it} + e_{it} \tag{2.11}$$

where TFP, TE, G and ICT are estimated total factor productivity (TFP), technical efficiency (TE), total infrastructure (G) and information and communication technology (ICT) index of industry *i*at period *t*. We also include a set of additional control variables (*X*): i.e. research and development intensity (R&D),[6] trade

[6]It is well established, in the related literature, that Research and Development (R&D) is an important determinant of productivity and export performance of firms. The pioneering study of Griliches (1979) has shown in the 'R&D Capital Stock Model' that this factor has a direct effect on the performance of firms. Empirical evidence reported by Lichtenberg and Siegal (1989) and Hall and Mairesse (1995) also provides strong support to Griliches's view. To capture the R&D

intensity (Trade)[7] and the size of the industry (Size)[8] which may affect firms' productivity as well.

In the related literature, a number of issues arise relating to application of estimators. These include spurious correlation due to non-stationary data, omitted variables, endogeneity and reverse causality, of infrastructure variables in particular, which may lead to biased estimation of coefficients. Some researchers, for example Holtz-Eakin (1994), have used the fixed-effects (FE) estimator for the analysis. The advantage of the FE estimator is that it can handle the issue of omitted variables that may be correlated with infrastructure. The approach of fixed effects considers controlling for the unobserved industry-specific time invariant effects in the data. However, it fixes the possible correlation between these effects and some of the independent variables in the model, conditioning them out by considering deviations from time averaged sample means. The consequence of employing such a procedure is that the dependent variable is exposed to its long-run variation—an approach that may not be suitable for studying a dynamic concept. Therefore, the FE approach may not be suitable in alleviating the adverse consequences of endogeneity bias.

Another method which could be useful in the presence of heterogeneity and contemporaneous correlation is system GMM (henceforth Sys-GMM). This estimator uses appropriate lags of variables in level form as instruments for equations in first difference form and conversely for equations in level form, all of which are combined into a system of equations with options to treat any of the variables in the system as endogenous. Blundell and Bond (1998) proposed the use of extra moment conditions that rely on certain stationarity conditions of the initial observation, as suggested by Arellano and Bover (1995). When these conditions are satisfied, the resulting Sys-GMM estimator has been shown in Monte Carlo studies by Blundell and Bond (1998) and Blundell et al. (2000) to have much better finite sample properties in terms of bias and root mean squared error. Another option is to retain the long-run properties of the series, which is to follow Fedderke and Bogetić (2009), and Sharma and Sehgal (2010), which apply panel co-integration techniques and establish a long-run relation between infrastructure and industrial performance. We are, therefore, set to apply aforementioned methodologies in this study for checking consistency and robustness of the estimates.

(Footnote 6 continued)

intensity, this study considers the ratio of R&D expenditure to industry's total sales. This variable is expected to have a positive impact on industries' productivity and efficiency.

[7]Trade intensive firms benefit from technology transfers through exporting and importing output material and other inputs, which can potentially help firms to enhance their productivity (see Sachs and Warner 1995). In this study, Trade intensity is captured by the ratio of total export plus import to the value of total sales of the industry. It is expected to have a positive impact on industries' performance.

[8]Theoretically, because of economies of scale, a larger size and increasing output should have a positive influence on the productivity of industry. In our model, capital (K) is taken as a proxy of the size of the industry and it is expected to have a positive influence on productivity, as well as on efficiency.

A preliminary step in our approach involves the testing for the stationarity of the series used in Eqs. (2.8)–(2.11). This has been done using the cross-sectional Im–Pesaran–Shin (CIPS) panel unit-root test, which is based on the simple averages of the individual cross-sectional augmented Dickey–Fuller statistics. The main advantages of this approach are that it incorporates potential cross-sectional dependence and it does not pool directly the autoregressive parameter in the unit root regression; thus it allows for the possibility of heterogeneous coefficients of the autoregressive parameters under the alternative hypothesis that the process does not contain a unit root. The results of the unit root test are reported in Table 2.12 of Appendix 4. For all individual series the hypothesis of unit root cannot be rejected at the level form; however it is rejected convincingly in the first difference form.

If the data generating process for the variables is characterized by panel unit roots, it is crucial to test for co-integration in a panel perspective. We apply Pedroni's (1999) test, an extension of the Engle-Granger construction to test the existing co-integration relationship. Two types of tests have been suggested by Pedroni. The first is based on the 'within dimension' approach, which includes four statistics: panel *v*-statistic, panel statistic, panel PP-statistic, and panel ADF-statistic. These statistics pool the autoregressive coefficients across different members for the unit root tests on the estimated residuals. The second test is based on the 'between-dimension' approach, which includes three statistics: group-statistic, group PP-statistic, and group ADF-statistic. These statistics are based on estimators that simply average the individually estimated coefficients for each member. We calculate heterogeneous panel co-integration as well as heterogeneous group mean panel co-integration statistics and results are reported in Table 2.13 of the Appendix 4. The rows labelled 'within-dimension' approach contain the computed value of the statistics based on estimators that pool the autoregressive coefficient across different industries for the unit root tests on the estimated residuals. The rows labelled between-dimension report the computed value of the statistics based on estimators which average individually the estimated coefficients for each industry. Overall these results provide support for co-integrating relationship for all our models.

2.5 Estimating the Effects of Infrastructure and ICT on the Manufacturing Performance

Having established a linear combination between variables that keeps the pooled variables in proportion to one another in the long run, we set to generate individual long-run estimates for all the models. Considering that the OLS estimators are biased and inconsistent when applied to co-integrated panels, we utilize the "group-mean" panel fully modified OLS (FMOLS) estimator developed by Pedroni (1999, 2000).[9]

[9]We have applied 'group-mean FMOLS', because we have a small sample for the analysis. Pedroni (2000) has shown that the 'group-FMOLS' has relatively lower small sample distortions

Table 2.1 FMOLS result: effects of total infrastructure on ln (TFP), 1994–2008

Industry	ln (G)	ln (trade)	ln (R&D)	Size ln (K)
Chemical	−0.0787 (−0.572)	0.0018 (0.083)	0.0629** (3.825)	−0.0144 (−0.6395)
Food and beverage	0.2423** (3.259)	0.0413 (1.021)	0.006 (1.2705)	0.0056 (0.19668)
Machinery	0.1779** (2.049)	0.0402 (0.976)	0.0492** (2.055)	0.0219 (0.4401)
Metal and metal products	0.3291** (6.727)	0.1015** (4.467)	0.0045 (0.423)	−0.0931 (−3.003)
Non metallic mineral products	0.2622** (3.668)	0.0552** (2.725)	0.0058** (2.725)	0.0129 (0.5726)
Textile	0.3079** (11.382)	−0.0371 (−1.215)	0.0023** (0.629)	0.00432 (0.2081)
Transport equipment	0.6544** (11.478)	0.0913** (6.337)	−0.0114 (−1.547)	−0.1031** (−14.778)
Miscellaneous manufacturing	0.56603* (1.909)	−0.1239* (−1.744)	−0.0061 (−0.1531)	−0.0329 (−0.2839)
Overall	0.315** (14.108)	0.0214** (4.4727)	0.0142** (2.9503)	−0.0248** (−6.1121)

Source Authors' estimations
Notes ** and * denote significant at 5 and 10 % critical level respectively. T-statistics are in parentheses

We first estimate Eq. (2.8), in which the impact of total infrastructure (G) on TFP is tested for each of the eight industries. Results are reported in Table 2.1. Surprisingly, estimated coefficients of the total infrastructure variable are found to be sizably large in several sectors and for the overall manufacturing as well. Results indicate that total infrastructure explains 65 % of TFP growth in *Transport Equipment*, 32 % in *Metal* and *Metal Products* and 30 % in *Textile*. In other industries, it varies from being large to moderate (except in the case of *Chemical*, where it is found to be statistically insignificant[10]). On an average, results suggest that the impact on overall manufacturing is around 0.32, which means that 1 % increase in infrastructure leads to a 0.32 % TFP growth.

Results regarding other control variables are rather mixed. Trade intensity is found to be positive and significant in *Metal* and *Metal Products*, *Non Metallic Mineral Products*, and *Transport Equipment*, which are sectors relatively more exposed to foreign competition. The impact is estimated to be 5–10 % in these industries.[11] However, the effect on the overall manufacturing is found to be around 2 %, which is lower than expected. Furthermore, the R&D variable explains only 1.4 % of TFP growth, which is not very surprising as Indian manufacturing is known for its low R&D intensity. Nonetheless, in research intensive industries, such as *Chemical* and *Machinery*, the effect is found to be 6 and 5 % respectively, which is quite encouraging, knowing that these sectors are the most productive in

(Footnote 9 continued)

and more flexibility in terms of hypothesis testing than other three versions of FMOLS (see also Basher and Mohsin 2004).

[10]We will see that it is not the case anymore for TE.

[11]In *Miscellaneous Manufacturing* also, the variable is estimated to be statistically significant, however, the sign of the coefficient is negative.

Table 2.2 FMOLS result: effects of ICT on ln (TFP), 1994–2008

Industry	ln (ICT)	ln (trade)	ln (R&D)	ln (K)
Chemical	−0.0111 (−0.265)	−0.0067 (−0.346)	0.0678** (7.891)	0.0063 (0.348)
Food and beverage	0.0781** (1.7958)	0.0794* (1.7467)	0.0059 (0.989)	0.0515** (2.003)
Machinery	0.0095 (0.205)	0.065225* (1.777)	0.0708** (3.413)	0.051530 (1.060855)
Metal and metal products	0.1778** (4.014)	0.1341** (4.434)	0.0074 (0.4867)	−0.0832** (−1.9258)
Non metallic mineral products	0.05662** (1.7452)	0.1037** (7.069)	0.0031 (1.0361)	0.0372** (1.7921)
Textile	0.2237** (26.435)	0.0017 (0.1311)	0.0011 (0.60934)	−0.0008 (−0.087)
Transport equipment	0.2174** (3.603)	0.0681* (1.761)	0.0194 (1.252)	−0.0963** (−4.976)
Miscellaneous manufacturing	0.2032 (1.217)	−0.0759 (−1.112)	0.0209 (0.565)	0.0222* (0.189)
Overall	0.1244** (12.941)	0.0462** (5.431)	0.0245** (5.743)	−0.001482 (−0.584)

Source Authors' estimations
Notes ** and * denote significant at 5 and 10 % critical level respectively. T-statistics are in parentheses

our sample (see Sect. 2.4). As for the size, the impact is noticeable in *Food* and *Beverage* and *Non Metallic Mineral Products*, which are characterized by small firms with low productivity growth. This result implies that a policy of concentration would generate higher productivity gains in these sectors.

Keeping in mind the dramatic development of the ICT sector in the recent years in India, we separately examine its effect on TFP growth by estimating Eq. (2.9). Results indicate that ICT is closely linked to manufacturing productivity as well. Its impact in some of the industries is substantially large, although smaller than that of the total infrastructure index (see Table 2.2). This outcome is in line with the literature which highlights that the elasticity with respect to infrastructure indicators tends to decrease with the level of disaggregation (see Munnell 1992). In *Textile*, *Transport Equipment*, and *Metal* and *Metal Products* industry, ICT has a positive and statistically significant effect of 18–22 % on TFP. The effect on the overall manufacturing is also estimated to be positive and sizable (12 %). Results regarding other control variables are not found to be very different from that in Eq. (2.8).

Next, we shift to the impact of infrastructure on technical efficiency (TE). We first estimate Eq. (2.10) and test the effect of total infrastructure by industry (see Table 2.3). The overall results for TE are not very different from those for TFP. Interestingly, it is still *Transport Equipment* (which is also the most efficient industry of our sample, see Table 2.8 in Appendix 2), which appears more dependent on infrastructure endowment (elasticity of 0.40). In other industries the estimated elasticity varies from 0.13 in *Chemical* to 0.20 in *Textile* products.[12] The estimated effect regarding the overall manufacturing (0.17) also confirm that TE is closely related to total infrastructure. Results regarding other control variables suggest that

[12]It is noteworthy that *Chemical*, in which TFP and infrastructure are uncorrelated, is responsive to infrastructure in terms of TE.

Table 2.3 FMOLS result: effects of total infrastructure on ln (TE), 1994–2008

Industry	ln (G)	ln (trade)	ln (R&D)	Size ln (K)
Chemical	0.1974** (9.146)	0.0183** (5.1496)	−0.00216 (−0.8359)	0.0136 (0.0136)
Food and beverage	0.1518** (4.808)	0.0148 (0.863)	0.0002 (0.0912)	0.0471** (3.874)
Machinery	0.14989** (10.441)	0.0101 (1.491)	0.0111** (2.799)	0.0163** (1.979)
Metal and metal products	0.1514** (21.081)	0.0178** (5.341)	0.0025 (1.584)	0.0188** (4.149)
Non metallic mineral products	0.1391** (13.042)	0.02353** (7.686)	−0.0005 (−1.204)	0.0195** (5.799)
Textile	0.2033** (26.155)	0.0211** (2.406)	0.004** (3.687)	0.0162** (2.721)
Transport equipment	0.4056** (15.049)	−0.0183** (7.783)	−0.0183** (−6.841)	0.0191** (7.563)
Miscellaneous manufacturing	0.1673** (6.383)	0.0053 (1.0028)	0.0036 (1.226)	0.0331** (3.851)
Overall	0.1757** (37.514)	0.0189** (11.215)	0.00004 (0.179)	0.0231** (11.945)

Source Authors' estimations
Notes ** and * denote significant at 5 and 10 % critical level respectively. T-statistics are in parentheses

trade and research related activities do not have a really sizable impact on the efficiency of industries, contrary to the results for TFP,[13] while the variable size appears as a more constant factor of efficiency growth, especially in *Food* and *Beverage* and *Non Metallic Mineral Products*.

Next, we test the effect of ICT on TE by estimating Eq. (2.11). Estimation results suggest that ICT has a positive, statistically significant and sizable impact on all industries (see Table 2.4). The effect still varies among the sectors. It is again *Transport Equipment*, followed by *Textile*, which show the highest sensibility to ICT limitations (with an elasticity of 0.16 and 0.12 respectively). The overall elasticity is also estimated to be 0.08. As for the size, it still plays a role in the efficiency of the *Food Industry* in particular, as seen previously.[14]

On the whole, while the estimated coefficients vary, both in terms of magnitude and statistical significance, various constant effects are perceivable across industries. *Transport Equipment*, *Textile* and *Metal* and *Metal Products* are found to be highly associated with infrastructure provisions, including ICT, as far as their productive performance is concerned. This is also the case with *Chemical* industry in terms of TE (which is with *Transport, Machinery and Metal* and *Metal Products* among the most productive industries in term of TFP and/or TE). This may be due to the fact that these sectors are relatively more exposed to foreign competition and need a more supportive environment in terms of infrastructure to be able to compete efficiently. This fragility justifies that a special attention has to be paid when taking decisions on

[13]Trade intensity is now a factor of efficiency in the *Chemical* and *Textile* industry, in addition to *Non Metal and Metal* sectors as in the case of TFP, with much smaller elasticities however.

[14]Results regarding the other control variables are not found to be very different from the previous estimation.

Table 2.4 FMOLS result: effects of ICT on ln (TE), 1994–2008

Industry	ln (ICT)	ln (trade)	ln (R&D)	Size ln (K)
Chemical	0.0781** (4.106)	0.0161** (2.118)	0.0098** (2.944)	0.0176** (2.511)
Food and beverage	0.0662** (3.074)	0.0257 (1.143)	0.0004 (0.147)	0.0691** (5.603)
Machinery	0.0763** (5.484)	0.0115 (0.794)	0.0204** (3.289)	0.0115 (0.794)
Metal and metal products	0.0941** (9.287)	0.0301** (4.351)	0.0019 (0.568)	0.0223** (2.263)
Non metallic mineral products	0.0786** (15.769)	0.0364** (17.141)	−0.0016** (−3.712)	0.0192** (6.167)
Textile	0.1241** (10.789)	0.0547** (2.731)	0.0018 (0.722)	0.0189 (1.329)
Transport equipment	0.1641** (4.133)	0.0318** (1.935)	−0.0047 (−0.705)	0.0213** (2.557)
Miscellaneous manufacturing	0.0886** (6.439)	0.0166** (3.241)	0.0088** (3.1911)	0.0353** (4.012)
Overall	0.0827** (20.889)	0.0046** (2.278)	0.0289** (12.176)	0.0269** (8.923)

Source Authors' estimations
Notes ** and * denote significant at 5 and 10 % critical level respectively. T-statistics are in parentheses

the quality and availability of infrastructure needed by these sectors. This also means that the pay-off of an improvement of total infrastructure and ICT would be more substantial in these industries, which could play a lead role in the context of industrial development and export growth. This conclusion is all the more important in reference to infrastructure bottlenecks in the country. In the light of the results, this fragility may also explain why some industries (*Textile* and *Metal* and *Metal Products*) have registered less satisfying performance in terms of TFP and TE. This might also be the case of the more productive ones (*Chemical*, *Machinery*) in the future, if infrastructure is not adequately improved in the near future.

Our finding on the ICT is also significant as earlier studies, in general, failed to acknowledge its role in enhancing productivity gains. Hu and Plant (2001), for instance, found little evidence in favour of ICT contributing to productivity in the USA. Parham et al. (2001) showed that the adoption of ICT contributed to only a 1.1 % improvement in productivity surge in the 1990s in the case of Australia. In the recent years, it seems that the Indian manufacturing has gained considerably from ICT not only in terms of production of equipment but also because of the use of ICT in the production process. This has perhaps generated substantial technological advances for the Indian industry and it seems that this is widely reflected in our results. Finally, the elasticity of the total infrastructure, although it varies across industries, is very much in line with the results suggested in the literature (see Véganzonès 2000).

Robustness Check

Our findings relating to total infrastructure and ICT are estimated to be pretty large in magnitude and therefore, we intend to examine the consistency of the results by an alternative estimator of Sys-GMM of Blundell and Bond (1998) with a fixed-effect option. We prefer this estimator for two reasons. First, it allows us to

Table 2.5 Sys-GMM results: determinants of ln (TFP) and ln (TE), 1994–2008

Variables	Dependent variable-ln (TFP)		Dependent variable-ln (TE)	
	(1)	(2)	(3)	(4)
ln $(TFP)_{t-1}$	0.59927** (0.0709)	0.68144** (0.0699)		
ln $(TE)_{t-1}$			0.5881052** (0.05539)	0.74239** (0.0577)
ln (R&D intensity)	0.00971** (0.0028)	0.00927** (0.00771)	0.002621** (0.0008)	0.00195** (0.0008)
Size: ln (K)	−0.01885** (0.0074)	−0.01511** (0.00771)	0.00449** (0.0022)	0.0058 ** (0.0023)
ln (trade intensity)	0.00046** (0.01226)	0.0124523** (0.01245)	0.00641** (0.00314)	0.0121** (0.0031)
Total infra index: ln (G)	0.1778** (0.0333)		0.07478** (0.01468)	
ICT infra index: ln (ICT)		0.08963** (0.02209)		0.02006** (0.0098)
Constant	0.3899 (0.0938)	0.42987** (0.1055)	0.0064** (0.0735)	0.43261** (0.0862)
Sargan (P-value)	108.6914 (0.0363)	108.8529 (0.0355)	188.8037 (0.000)	189.9978 (0.000)
AR(2)	0.238	0.129	0.131	0.101

Source Authors' estimations
Notes 1 Standard errors are in parentheses. *2* *, ** indicate statistical significance at the 10 and 5 %, respectively. *3* Sargan is the Sargan (1958) test of over-identifying restrictions. *4* One lag of dependent variable included in the model. *5* AR(2) is Arellano-Bond test for AR(2) in first differences

take into account the unobserved time-invariant bilateral specific effects. Second, it can deal with the potential endogeneity arising from the inclusion of the lagged dependent variables and other potentially endogenous variables (see Sect. 2.5).

Results of the analysis using Sys-GMM are presented in Table 2.5. In column 1, findings pertaining to Eq. (2.8) validate that total infrastructure is an important source of TFP growth in the Indian manufacturing. The estimated elasticity (around 0.18) is substantially large, however, lower than in the case of the FMOLS estimate (0.32). Results for Eqs. (2.9), (2.10) and (2.11) show similarities in this respect (see columns 2, 3 and 4 of the table). The elasticity of TFP regarding ICT (0.09) is also found to be relatively lower than that provided by FMOLS (0.12). The elasticity of TE with respect to total and ICT infrastructure (0.07 and 0.02 respectively) is even below half the estimate of FMOLS (0.18 and 0.08). Results related to R&D and trade intensity effect on TFP and TE also show a smaller magnitude, below 1 %.

Our results advocate that the selection of estimator is crucial in the field of research, as the magnitude of elasticity varies from one estimator to another.

Keeping in mind the complications relating to the endogeneity of the infrastructure variable, this study, therefore, goes to considerable lengths to address identification and spurious correlation problems, by using FMOLS and Sys-GMM techniques.[15]

Our results still support the earlier findings of Mitra et al. (2002), Hulten et al. (2006) and Sharma and Sehgal (2010), which found that infrastructure is an important channel of productivity growth in the Indian manufacturing sector. Moreover, if we compare our outcomes with important international studies, it is by and large the same (see Véganzonès 2000).

In contrast, results regarding other control variables are rather more mitigated. It seems that increased globalization leading to higher levels of trade intensity has still not become an important source of productivity growth, except in a few sectors exposed to foreign competition. Perhaps the learning by trading process is relatively slow in India, due to a long phase of industrial protection in the past. Also, the size of the firms does not seem to be a significant source of productivity and efficiency in the Indian manufacturing sector, although concentration could play a certain role in some of the industries like *Food* and *Beverage*. As for R&D, low intensity remains a serious concern in India and requires the attention of the policy makers. With improved efforts productivity enhancement can be achieved as in the light of our results research intensive industries like *Chemical* and *Machinery* tend to be more productive than others.

2.6 Conclusion and Policy Recommendations

Using a recent dataset on the Indian manufacturing industry for 1994–2008, this chapter presents evidence on the impact of infrastructure (G) and information and communication technology (ICT) on the total factor productivity (TFP) and technical efficiency (TE) of eight manufacturing industries in India. Results clearly bring out the key role played by total infrastructure and ICT. Findings suggest the elasticity of TFP with respect to total infrastructure is around 0.32, which is pretty large. Our results relating to TE are smaller, at around 0.12, but still sizeable. The evidence also highlights that the dramatic growth of ICT in India had a significant effect on the manufacturing productive performance, both in terms of TFP and TE (elasticity of 0.18 and 0.08 respectively). This constitutes an interesting result which is still not acknowledged in the literature. Considering the fact that our estimates with respect

[15]The early findings by Aschauer (1989) and Munnell (1990) were widely criticized on three grounds. *First*, common trends in output and public infrastructure data are suspected to have led to spurious correlation. *Second*, it is argued that causation runs in the opposite direction, that is, from output to public capital. *Final*, it has also been observed that applying the OLS technique directly on non-stationary data of infrastructure and output, may be a reason of a large elasticity magnitude in these studies (see Aaron 1990; Tatom 1991; Garcia-Mila et al. 1996). Considering the FMOLS and Sys-GMM estimation in this study, it seems we have overcome these problems and therefore the probability of spurious finding is rather low.

to infrastructure are pretty large in magnitude, we have examined the consistency of the results through an alternative estimator, of Sys-GMM. The estimated elasticity using this estimator, although smaller, still turned out to be significant.

Our results also show that some of the industries, such as *Transport Equipment*, *Textile* and *Metal* and *Metal Products* in terms of TFP and TE and *Chemical* in terms of TE, display a higher sensitivity to infrastructure deficiencies than the others. Interestingly, these industries are somewhat more productive and more exposed to international competition as well. These results are of particular importance in the Indian context, given the infrastructure bottlenecks in many parts of the country. It means that improving infrastructure and ICT endowments would particularly help these sectors to face strong international competition and reinforce the industrial export capacity of the country. Since the Indian manufacturing sector is still not being integrated into the world economy and is not able to enhance its competitiveness in the world market, the policy implications of these findings are pertinent. Our results may also explain why some industries (*Textile* and *Metal* and *Metal Products*) have registered less satisfying productive performance.

In the analysis, we have also used three important control variables namely, trade and R&D intensity, as well as the size of the firms. The findings suggest a weak impact on performance. Low in-house R&D remains a serious concern in India and requires a special attention of the policy makers. *Chemical* and *Machinery* are the more research intensive industries, and the impact of R&D is noted to be sizeable. Interestingly, these two industries are also the most productive ones in our sample. As for trade intensity, our findings exhibit a higher sensitivity in sectors more exposed to international competition (*Textile*, *Transport*, and *Metal* and *Metal Products*, as well as *Chemical*). As for size, a policy of concentration of firms would be advisable in sectors like *Food* and *Beverage* and *Non Metallic Mineral Products* as they are characterised by lower levels of TFP.

Results of this study are somewhat in line with earlier findings of Mitra et al. (2002), Hulten et al. (2006) and Sharma and Sehgal (2010). They further support the argument that a lack of infrastructure can bring a halt to growth in developing economies, the concern expressed by the World Bank (1994). Enhancing total infrastructure and ICT, especially in the sectors more sensitive to infrastructure deficiency, can constitute a powerful engine of competitiveness and industrial growth. In fact, like other developing countries, India is also increasingly concerned about improving productivity as the country faces the intensifying pressure of globalization. In this context, infrastructure deficiencies have to be taken into consideration, if the country needs to further diversify its growth objective in terms of inter-industry and inter-spatial distribution.

Appendix 1

See Tables 2.6 and 2.7.

Table 2.6 Estimated TFP of the Indian manufacturing industries, 1994–2008

	Chemical	Food and beverage	Machinery	Metal and metal products	Non-metallic mineral products	Textile	Transport equipment	Miscellaneous manufacturing
1994	2.61	2.23	2.32	2.09	1.99	2.06	2.11	1.7
1995	2.64	2.21	2.31	2.13	1.95	2.04	2.23	1.72
1996	2.65	2.21	2.33	2.15	2	2.08	2.23	1.8
1997	2.67	2.2	2.36	2.12	1.96	2.14	2.25	1.72
1998	2.66	2.25	2.37	2.1	1.99	2.15	2.22	1.7
1999	2.7	2.26	2.4	2.11	2.02	2.16	2.19	1.67
2000	2.75	2.25	2.46	2.19	2.02	2.2	2.3	1.86
2001	2.73	2.29	2.44	2.24	2.04	2.24	2.26	1.92
2002	2.71	2.32	2.45	2.22	2.08	2.23	2.3	1.9
2003	2.74	2.35	2.47	2.29	2.1	2.24	2.42	1.93
2004	2.88	2.36	2.52	2.31	2.16	2.25	2.49	1.82
2005	2.91	2.41	2.56	2.37	2.15	2.28	2.53	1.78
2006	2.9	2.4	2.6	2.36	2.16	2.28	2.54	1.78
2007	2.93	2.39	2.69	2.44	2.18	2.29	2.57	1.88
2008	2.94	2.41	2.72	2.4	2.25	2.31	2.55	1.92
Average	2.76	2.3	2.47	2.23	2.07	2.2	2.35	1.81

Source Authors' calculations

Table 2.7 Estimated TE of the Indian manufacturing industries, 1994–2008

	Chemical	Food and beverage	Machinery	Metal and metal products	Non-metallic mineral products	Textile	Transport equipment	Miscellaneous manufacturing
1994	87.55	87.55	87.55	87.55	87.55	87.55	87.55	87.55
1995	88.68	88.73	88.42	88.23	88.74	88.91	88.37	88.79
1996	90.03	89.63	89.65	89.17	89.96	90.22	89.95	90.38
1997	90.95	89.96	90.33	89.82	90.75	90.86	91.38	91.1
1998	91.34	89.93	90.28	89.7	91	90.89	91.72	91.05
1999	91.98	90.61	90.62	90.03	91.41	91.24	92.81	91.55
2000	93.37	92.09	91.95	91.18	92.67	92.24	94.66	93.53
2001	93.81	92.47	92.33	91.47	93.08	92.55	94.89	94.01
2002	93.87	92.41	92.34	91.29	92.89	92.42	94.55	93.91
2003	94.7	93.73	93.39	92.13	93.78	93.35	95.17	94.73
2004	94.76	94.29	93.59	92.38	94.63	93.5	95.82	95.06
2005	95.38	94.77	93.98	92.94	95.1	94.04	96.34	95.92
2006	96.21	95.65	94.79	93.81	95.6	94.78	97.15	96.58
2007	96.99	96.66	95.46	94.46	96.13	96.17	98.78	97.29
2008	97.55	97.4	96.1	95.28	97	96.94	100	98.18

Source Authors' calculations

Appendix 2

See Tables 2.8, 2.9 and 2.10.

Appendix 3

See Table 2.11.

Table 2.8 Infrastructure and ICT variables: sources of data

Variable	Sector	Indicator	Data sources
Air	Transportation	Air transport, passengers carried	WDI
Electricity	Electricity	Electricity production (kWh/per-capita)	WDI
Internet	Information and Communication	Internet users (per 100 people)	WDI
Mobile	Information and Communication	Mobile cellular subscriptions (per 100 people)	WDI
Mobile-telecom	Information and Communication	Mobile and fixed-line telephone subscribers (per 100 people)	WDI
Port	Transportation	Port (commodity wise traffic, 000 tones)	CMIE
Rail-goods	Transportation	Railways, goods transported (million ton-km)	WDI
Rail-pass	Transportation	Railways, passengers carried (million passenger-km)	WDI
Roads	Transportation	Roads, total network (km/1000 people)	WDI
Tel	Information and Communication	Telephone lines (per 100 people)	WDI

Table 2.9 Correlation between infrastructure variables

Variable	Air	Internet	Rail-goods	Rail-pass	Roads	Electricity	Mobile-telecom	Port
Air	1.0000							
Internet	0.94436 (11.120)	1.0000						
Rail-goods	0.95490 (12.455)	0.98924 (26.195)	1.0000					
Rail-pass	0.92500 (9.4285)	0.97362 (16.526)	0.98821 (24.988)	1.0000				
Roads	0.44718 (1.9363)	0.59462 (2.864)	0.63232 (3.161)	0.71497 (3.9606)	1.0000			
Electricity	0.86329 (6.624)	0.91276 (8.654)	0.94132 (10.802)	0.96968 (15.367)	0.79114 (5.009)	1.0000		
Mobile-telecom	0.96660 (14.607)	0.96579 (14.424)	0.96958 (15.342)	0.94285 (10.958)	0.49967 (2.234)	0.84824 (6.203)	1.0000	
Port	0.84629 (6.1528)	0.92715 (9.5834)	0.94871 (11.622)	0.96885 (15.151)	0.77283 (4.716)	0.98565 (22.615)	0.85021 (6.254)	1.0000

Source Authors' calculations

Table 2.10 Relative infrastructure endowments in India[a]

Country/group	Fixed broadband Internet subscribers (per 100 people)	Internet users (per 100 people)	Mobile cellular subscriptions (per 100 people)	Quality of port infrastructure[b]	Roads, paved (% of total roads)	Secure Internet servers (per 1 million people)	Telephone lines (per 100 people)	Electric power consumption (kWh per capita)	Electric power transmission and distribution losses (% of output)
India	0.67	5.3	45.5	3.9	49.3	2.2	3.2	570.9	24.4
Brazil	7.52	39.3	90.0	2.9	NA	40.7	21.5	2206.2	17.2
China	7.78	28.8	56.1	4.3	53.5	1.9	23.6	2631.4	4.9
Russian Federation	9.09	42.1	162.5	3.7	80.1	20.4	31.6	6132.9	10.8
South Africa	0.98	8.9	94.2	4.8	NA	62.6	8.8	4532.0	9.8
South Asia	0.56	5.5	45.8	3.8	58.9	1.9	3.0	516.9	23.1
East Asia and Pacific	8.05	29.8	65.7	4.8	47.6	91.5	22.5	2797.4	5.2
Low-middle income	3.54	18.2	60.9	3.8	29.3	7.7	12.7	1527.0	11.1

Source World Development Indicators (2011)
[a]Years of comparison are 2010, 2009 and 2008.
[b]1 = extremely underdeveloped to 7 = well developed and efficient by international standards

Table 2.11 Summary statistics

	ICT infra index ln (ICT)	Total infra index ln (G)	ln (TE)	ln (K)	ln (R&D intensity)	ln (trade intensity)	ln (N)	ln (Q) (GVA)	ln (TFP)	ln (Q) (real output)	ln (M)	ln (F)
Mean	2.89	2.71	2.02	4.33	1.93	0.3	3.85	4.28	2.03	4.64	4.29	3.22
Median	2.94	2.74	2.02	4.23	1.81	0.27	3.94	4.25	2.03	4.65	4.30	3.16
Maximum	3.01	2.82	2.06	5.15	3.29	0.77	4.35	5.34	2.08	5.65	5.32	3.79
Minimum	2.15	2.23	2	3.58	0.69	0.14	3.02	3.35	1.99	3.76	3.43	2.64
Std. Dev.	0.21	0.14	0.01	0.35	0.65	0.11	0.29	0.41	0.02	0.39	0.04	0.35
Skewness	−2.96	−2.87	−0.02	0.56	0.25	1.76	−0.9	0.33	0.36	0.11	0.03	−1.52
Kurtosis	10.8	10.47	2.23	2.66	2.01	6.62	3.28	3.29	2.21	0.22	0.15	0.22

Source Authors' calculations

Appendix 4

See Tables 2.12 and 2.13.

Table 2.12 Test for panel unit root applying Im, pesaran and Shin W-statistics

Variables	At level	At 1st difference
Ln (TFP)	0.12202	−3.04503**
Ln (TE)	1.92950	−4.91739**
Ln (R&D intensity)	1.01247	−2.39198**
Size: ln (K)	−1.22424	−2.73512**
Ln (Trade intensity)	2.14169	−2.45611**
Total Infra Index: ln (G)	1.54134	−5.63417**
ICT Infra Index: ln (ICT)	4.44407	−5.10710**

Source Authors' estimations
Notes ** Denotes significance at 5 %

Table 2.13 Pedroni (1999) panel cointegration test results

Statistics	ln (TFP), ln (K), ln (Trade intensity), ln (R&D intensity), ln (G) (1)	ln (TFP), ln (K), ln (Trade intensity), ln (R&D intensity), ln (ICT) (2)	ln (TE), ln (K), ln (Trade intensity), ln (R&D intensity), ln(G) (3)	ln (TE), ln (K), ln (Trade intensity), ln (R&D intensity), ln (ICT) (4)
Within dimension				
Panel v	0.673340	1.028951	−275.3083	−578.5434
Panel ρ	−1.171354	−1.382245*	−2.636909**	−1.015245
Panel PP	−8.588976**	−6.646745**	−6.783835**	−4.528324**
Panel ADF	−10.96266**	−7.042465**	2.326346	1.720540
Between-dimension'				
Panel ρ	−0.100532	−0.360805	−1.722097**	−0.433731
Panel PP	−9.912829**	−7.565237**	−7.671325**	−5.287092**
Panel ADF	−11.99638**	−6.434163**	3.636288	2.135979

Source Authors' estimations

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