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ABSTRACT

This paper explores the horizontal and vertical technology spillover effect of foreign direct investment (FDI) across Indian manufacturing industries. On the basis of Pedroni cointegration tests, we find that technology spillovers can be transmitted via all kinds of intermediate factors. We find that the horizontal foreign presence and inter-industry foreign presence have exclusive penetration effect to spur labor productivity and technology spillover across Indian industries. Furthermore, intermediate factors like technology import intensity, inter-industry technology import intensity, R&D intensity and inter-industry R&D intensity promote technology spillover and labor productivity across Indian manufacturing industries.

Keywords: Foreign Direct Investment; Technology Spillover; Manufacturing; Panel Cointegration; Unit Root Tests.

JEL classification: O41, F43, E23, C22, C23

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1. INTRODUCTION

Foreign direct investment (FDI) is believed to bring positive spillovers to domestic firms of the host country. The advantage is that the presences of multinational corporations (MNCs), which are the most technological advanced firms, facilitate the transfer of technology and business know-how to affiliate and non-affiliated domestic firms of the recipient country. This transfer of technology may spread to the entire economy leading to productivity gains of domestic firms (Romer, 1993). These factors have motivated many countries to ease restrictions on FDI and even offer more favorable policy and business conditions to foreign investors in the domestic market. In India, after the economic reforms, the government has not only lifted most of the restrictions on foreign presence, but has been taking initiative to attract foreign investors as one of the key elements of economic policy. In order to attract foreign investors and to win the most prestigious project in the different regions of the country, India, like many other countries, is offering most generous tax incentives, subsidies, land acquisition in an attempt to overbid the rival countries.

FDI from MNCs being a non-debt source of development finance helps to provide funds for investment projects in the host economy. FDI increases the level of technological progress in the host country, which in turn can play a decisive role in the process of economic development. Technology transferred to the developing countries via FDI tends to be newer than that transferred via licensing (Findlay, 1978; Mansfield and Romeo, 1980). Apart from being the important source of development finance and a channel for technology transfer, FDI has a number of other proven attributes. It improves the managerial knowledge and skills, increases efficiency and productivity and provides a wide array of goods and services to the host economy. The underlying premise is that MNCs possess superior intangible assets including technology, managerial skills, export contacts, and, reputation and good will. Indeed, they are able to undertake competitive investment ventures abroad and compete more favorably than local firms. In addition, since MNCs possess these intangible assets and can transfer these to their subsidiaries located abroad and subsequently to local firms through the technology spillover effect, this effect is expected to increase productivity at the firm and at the sectoral levels.

It has been widely recognized that MNCs are among the most technologically advanced firms investing a significant part of their resource in R&D and technology up-gradation unlike purely domestic firms (Griffith, 1999). It is estimated that a substantial part of the world's R&D activities are carried out by companies operating in more than one country (Borensztein *et al.*, 1998), which translates into higher rates of innovations and patenting compared to firms not operating abroad (Criscuolo *et al.*, 2010). Technological superiority, better managerial practices, and ability to exploit economies of scale makes it possible for multinationals investing in previously unexplored countries to compete with local firms even though the latter are usually more familiar with local consumer preferences and business practices (Blomstrom and Sjoholm, 1999). If multinationals possess knowledge-based intangible assets which are not generally available in the host country firms, then it is reasonable to assume that at least some of their technological superiority may spillover to domestic firms via channels other than market transactions such as purchase of patents, licenses, etc.

FDI is now widely recognized as a catalyst for industrial development in developing countries in view of the fact that it brings new intermediate goods, additional capital for industrial projects, technology transfers and skills in the form of externalities and technology spillovers. The industrial sector in developing countries like India is now under pressure to speed up the modernization of its production process in order to survive and face the competition in the global competitive market. The process of economic reforms in India which started in the 1990s, was directed at a systematic shift towards an open economy along with privatization of a large segment of the economy. The removals of quantitative barriers in a phased manner, the lowering of tariff on imports, and the application of suitable tax policy and land acquisition policy, etc., have opened up the Indian economy to international market forces which has led to the rapid emergence of a highly competitive environment, especially in the industrial sector.[1] This has again emphasized the importance of continuous improvement in productivity, efficiency, and technology spillovers of the industrial sector in India.

Keeping these factors in mind the study examines whether FDI in a developing country like India precipitates positive externalities to local producers. To examine the technology spillover of the local producers/firms the study has selected twelve 2-digit level Indian manufacturing industries. The selected twelve 2-digit level manufacturing industries are food products, beverages and tobacco, textiles, cotton textiles, wood products, paper and paper products, leather products, chemicals, non-metallic mineral products, metal products, non-electrical machinery, and electrical machinery.[2] Furthermore, the study examines the FDI and intra-industry (horizontal) and inter-industry (vertical) technology spillover effect on domestic firms' labor productivity across Indian manufacturing industries.

The rest of this study has been organized as follows:

Section 2 gives an analytical description of the theoretical model and empirical framework for the study. Section 3 discusses the econometric techniques of panel unit root tests, panel cointegration, fully modified *OLS* (*FMOLS*), group fully modified *OLS* (*GFMOLS*) and

[1] For a recent literature survey, see Athreye and Kapur (2006); Ang (2009) and Madsen *et* al. (2010).

[2] See Appendix B, Table B.1, for the details of the selection.

dynamic *OLS* (*DOLS*) estimates. Section 4 interprets the empirical results of the study. Finally, Section 5 summarizes the findings of this study and gives some policy implications of this analysis.

2. EMPIRICAL FRAMEWORK

In the present analysis, we develop an empirical model to assess the technology spillover effect of FDI at the industry level. Following Romer's (1990) and Jones' (1998) R&D based endogenous technological change growth model, we consider that output of an industry can be produced by human capital, labor, industry-specific factor, and a continuum of the intermediate factors. Let us specify the production function for output of an *i*th industry at time t denoted by Y_{it} as being subject to the following functional relationship:

$$Y_{it} = A_{it}(H_{it}L_{it})^{\beta}\left(\int_0^N d(it)^{\theta}\,di + \int_0^{N^*} m(it^*)^{\theta}\,di^*\right)^{\frac{\alpha}{\theta}} \tag{1}$$

$$0 < \alpha < 1, \quad 0 < \theta < 1,$$

where H_{it} is human capital stock, L_{it} is labor, A_{it} is industry-specific factor of *i*th industry at time t, $d(it)$ and $m(it^*)$ are intermediate inputs of *i*th (own) industry and *j*th (other) industry, respectively. The intermediate inputs of the own and other industry range from 0 to maximum N and N^*, respectively. In addition, the varieties of intermediate inputs range are an index of the level of technology and technology transfer from one industry to other industry and increase through the level of R&D spending, technology import intensity (*TMI*), level of the foreign presence of own industry (*FP*) and foreign presence of other industry (*FPO*). The sum of the intermediate inputs of the own industry and intermediate inputs from the other industry is defined as follows:

$$\chi_{it}(\gamma) = \int_0^N d(i_t)^{\theta}\,di + \int_0^{N^*} m(i_t^*)^{\theta}\,di^* \tag{2}$$

where $\chi_{it}(\gamma)$,[3] is the total flow of intermediate inputs from its own sources and from other sources (industries), and, $\gamma \in \left[0, \bar{\gamma}_{it}\right]$. Maximization of an industry intermediate input tends to the maximization of the productivity of domestic firms. Thus, an industry which has a larger amount of intermediate inputs can improve the productivity of the domestic firms. Innovation in one sector by R&D spending can enhance the productivity of the other sector. Therefore, innovation results from R&D that uses technological knowledge from all other sources across the world by means of FDI. An industry's productivity can be increased by the variety of intermediate inputs which is the combination of own industry intermediate inputs and the intermediate inputs from other industries. More intermediate inputs can increase productivity and technology spillovers of an industry. The intuition in this model is that there is worldwide an advanced/leading edge technology which is the maximum level of technology that an industry can accomplish subject to the maximization of the varieties of intermediate inputs. The industry of a host country tries to reach to the world wide maximum leading edge technology (Eeckhout and Jovanovic, 2002). Therefore, at any point of time there is a worldwide leading edge technology, which has been created by the maximization of the number of variety of intermediate inputs used in the production (Howitt, 2000) and it can be defined as follows:

$$\chi_{it}^{\max}(\gamma) = \max\left\{\chi_{jt}(i) \mid i \in [0, N],\ j = 0,1,.................., N*\right\} \tag{3}$$

where *j* subscript denotes the variable specific to other industries. Each industry therefore tries to maximize the intermediate factors up to the worldwide leading edge technology.

[3] Our theoretical intuition in this model is closely linked by the theoretical framework of Keller (2002) and Romer (1990). Following Keller and Romer model, output of an industry can be produced by the continuation of the intermediate factors, human capital and labor. Furthermore, the total intermediate factors are the combination of intermediate factors from own industry and from other industries.

Suppose the Poison arrival rate (ϕ_t) of innovations in each industry can be defined as follows:

$$\phi_t = \lambda n_t;\ \lambda > 0 \tag{4}$$

where λ can be a parameter indicating the productivity of R&D, and n_t is the productivity adjusted by the quantity of final output devoted to R&D in each industry. An industry's total factor productivity excluding capital and labor that is represented by the sum of intermediate factors is considered to be the technological parameter. Let the industry average productivity parameter be χ_{it} which can grow as a result of the innovations. Now each industry tries to reach the worldwide leading edge productivity parameter, which replaces the preexisting average productivity parameter (Howitt, 2000). The rate of increase in the average equals the flow rate of innovations λn_t times the average increase in technology $\chi_{it}(i)$ resulting from each innovation. Since the innovations by technology up-gradation and R&D spending are uniformly distributed across all industries, these can be defined as follows:

$$\dot{\chi}_{it} = \lambda n_t \left(\chi_{it}^{\max} - \chi_{it}\right) \tag{5}$$

In the above equation, if the leading-edge technology parameter $\chi_{it}^{\max}$ remains unchanged, then each industry's average productivity level can converge to $\chi_{it}^{\max}$ as long as λn is positive. In fact, if the leading edge technology is constantly increasing then an industry which has a higher level of innovation by R&D spending can eventually have an average productivity level that is permanently closer to $\chi_{it}^{\max}$. Thus, an industry with higher level of innovations might have more up-gradation in technology, have more intermediate inputs, and finally can increase the productivity of domestic firms with higher technology spillover.

From Eqn. (2), $\chi_{it}(\gamma)$ is summation of the flow of intermediate inputs from its own industry and from other industries.[4] Therefore, output of ith industry at time t can be defined by including these discussed factors, and accordingly Eqn. (1) can be again written as follows:

$$Y_{it} = Ait(HitLit)^{\beta}\left(\int_{0}^{\bar{\gamma}_{it}} \chi_{it}(\gamma)^{\rho}\, d\gamma\right)^{\alpha/\rho} \tag{6}$$

where $0 < \rho < 1$.

From this production function $F(.)$, the number of different type of intermediate inputs used in this production function is $\chi_{it}(\gamma)$. Furthermore, we assume that $F(.)$ is smooth and constant returns to scale function and $\alpha \in [0, 1]$.[5] Now, the level of total output is determined by the quality adjusted effective labor and intermediate factors of production. In a symmetric equilibrium, where $\chi_{it}(\gamma) = \chi_{it}$, for all $\gamma \in [0, \bar{\gamma}_{it}]$, all firms producing intermediate goods or factors set the same price and sell the same quantity of each intermediate goods (Kwark and Shyn, 2006). This implies that the capital stock of an ith industry can be defined as the aggregate stock of the intermediate factors, which is given below.

$$K_{it} = \int_{0}^{\bar{\gamma}_{it}} (\chi_{it}(\gamma))d\gamma = \bar{\gamma}_{it}\chi_{it} \tag{7}$$

For empirical estimation and simplicity, the functional form is restricted to the Cobb-Douglas case and from the above discussion we get the following form of the production function:

$$Y_{it} = A_{it} H_{it}^{\beta} L_{it}^{\beta} \bar{\gamma}_{it}^{\sigma} K_{it}^{\alpha} \tag{8}$$

[4]The sum of the intermediate inputs from the own and other industries have been added into a single factor in the production function. Now aggregate output of an industry is produced by quality adjusted effective labor and intermediate factors in a Cobb-Douglas production function.

[5] In Eqn. (6) α, β and ρ represents the elasticity shares of capital, labor and intermediate factors, respectively.

From Eqn. (8), we interpret $\bar{\gamma}_{it}$ is the quality of intermediate input and it is governed by the flow of technology through R&D spending of own industry (*RDI*), other industries (*RDIO*), technology import intensity of own industry (*TMI*), and other industries (*TMIO*), respectively. The σ reflects the elasticity share of intermediate factors upon output and we assume that $0<\sigma<1$. However, in this case σ reflects the elasticity of intermediate factors specific to the R&D intensity of own industry (*RDI*), other industries (*RDIO*), technology import intensity of own industry (*TMI*), and other industries (*TMIO*) upon output. To empirically examine the horizontal (intra-industry) and vertical (inter-industry) spillover across Indian manufacturing industries, the simplest Cobb-Douglas form of the Model (8) has been developed and then after it has been extended to form the regression model for empirical estimation. From Eqn. (8), we can interpret that the output of an industry can be produced by the quality of labor (*QL*) in place of human capital (*H*), factor of intermediate inputs which has been incorporated with the capital stock, that is, R&D intensity of own and other industries, technology import intensity of own and other industries and industry-specific factor like foreign presence of own and other industries, respectively.

For empirical application and after adding the error term in the above Cobb-Douglas functional form, the production function in (8) can be written as:

$$Y_{it} = A_{it} H_{it}^{\beta} L_{it}^{\beta} \bar{\gamma}_{it}^{\sigma} K_{it}^{\alpha} e_{it} \tag{9}$$

Dividing both sides of the above equation by labor (*L*), we get the following equation, which is given below.

$$Y_{it} / L_{it} = A_{it} H_{it}^{\beta} \bar{\gamma}_{it}^{\sigma} \left(K_{it} \big/ L_{it} \right)^{1-\beta} K^{\alpha+\beta-1} e_{it} \tag{10}$$

Taking log in both sides of the Eqn. (10)

$$\ln\left(Y_{it}/L_{it}\right) = \ln\left(A_{it} H_{it}^{\beta}\ \bar{\gamma}_{it}^{\sigma} \right) + \beta_1 \ln K_{it} / L_{it} + \beta_2 \ln K_{it} + \varepsilon_{it} \tag{11}$$

Now if we define the logarithm of total factor productivity (*TFP*), which is as follows:

$$\ln TFP_{it} = \ln y_{it} - \beta_1 \ln K_{it} / L_{it} - \beta_2 \ln K_{it} \tag{12}$$

$$\ln TFP_{it} = Ln A_{it} + \sigma \ln \bar{\gamma}_{it} + \beta \ln H_{it} \tag{13}$$

$$LP_{it} = \ln TFP_{it} + \beta_1 (k_{it}/l_{it}) + \beta_2 k_{it} + \varepsilon_{it} \tag{14}$$

From, Eqn. (14), *LP* represents the log of labor productivity (output divided by the unit labor) or value added per worker of *i*th industry at time *t* and small letter symbol represents the natural log form, that is, (k_{it}/l_{it}) and k_{it} stand for $\ln(K_{it}/L_{it})$ and $\ln K_{it}$, respectively. However, in this study to empirically examine FDI and intra-industry and inter-industry technology spillover across twelve Indian manufacturing industries, we consider the labor productivity of domestic firms (*LPd*) of an industry is the endogenous variable. Note that there are constant returns to scale in labor and intermediate factors while there can be increasing returns to scale with respect to the labor, capital, human capital, foreign presence, R&D intensity, and *TMI* together. In addition, the capital stock has been exogenously added into the model because of the relaxation of constant returns to scale assumption. Now the total factor productivity (*TFP*) can be proxied by the inclusion of foreign presence of own industry, other industries (excluding the own) in place of *A*, R&D intensity of own industry and other industries, technology import intensity of own industry and other industries in place of γ, and quality of labor in place of *H*, respectively. Therefore, Eqn. (13) can again be written as follows:

$$\begin{aligned} TFP_{it} = {} & \beta_{0i} + \beta_4 FP_{it} + \beta_5 FPO_{it} + \beta_6 RDI_{it} + \beta_7 RDIO_{it} \\ & + \beta_8 TMI_{it} + \beta_9 TMIO_{it} + \beta_{10} QL_{it} + \varepsilon_{it} \end{aligned} \tag{15}$$

Furthermore, by substituting Eqn. (15) into Eqn. (14) we get the following extended model which is as follows:

$$\begin{aligned} LPd_{it} = {} & \beta_{0i} + \beta_1 k_{it} / l_{it} + \beta_2 k_{it} + \beta_3 X_{it} + \beta_4 FP_{it} + \beta_5 FPO_{it} + \beta_6 RDI_{it} \\ & + \beta_7 RDIO_{it} + \beta_8 TMI_{it} + \beta_9 TMIO_{it} + \beta_{10} QL_{it} + \varepsilon_{it} \end{aligned} \tag{16}$$

Apart from the above discussed exogenous variables, the industry-specific factor like market concentration index can be included in the set of exogenous variables in the specified Eqn. (16). Therefore, after including the market concentration index (*CON*) (in place of *X*) in the set of exogenous variables, the proposed empirical model for estimation can be extended to the following empirical model, which is as follows:

$$\begin{aligned} LPd_{it} &= \beta_{0i} + \beta_1 k_{it}/l_{it} + \beta_2 k_{it} + \beta_3 CON_{it} + \beta_4 FP_{it} + \beta_5 FPO_{it} \\ &+ \beta_6 RDI_{it} + \beta_7 RDIO_{it} + \beta_8 TMI_{it} + \beta_9 TMIO_{it} + \beta_{10} QL_{it} + \varepsilon_{it} \end{aligned} \tag{17}$$

3. ECONOMETRIC TECHNIQUES

From an econometric point of view, the present analysis follows three familiar steps. The first step is to investigate the stochastic process of the variables involved by means of panel unit root tests. To test the presence of stochastic trends, the present analysis employs a battery of panel unit root tests designed explicitly to address the assumption of cross-sectional dependence. The reason for applying several panel unit root tests is to check for the robustness of our results, as the testing strategies vary. Four different approaches of panel unit root test are proposed and used in the present analysis, namely Levin Lin and Chu (LLC); Breitung; Im, Pesaran and Shin (IPS); and Hadri.

The second step consists of testing for cointegration in order to assess the presence of a long-run relationship between the endogenous and exogenous variables in empirical models, which leads to technology spillovers across Indian manufacturing industries in the long-run. This is done by applying the test developed by Pedroni (1999; 2004) that arguably represents a significant advancement in addressing the low power of conventional single equation tests for a single time series by exploiting both the cross-section and time series information.

To measure the intensity of cointegration in our empirical models, we apply the Pedroni (1999, 2000 and 2004) cointegration tests (seven). If out of the seven statistics, at least four tests are in favour of cointegration, we conclude that cointegration exists in the model. If more than four tests support cointegration, we infer that there is strong cointegration in the model. Out of seven statistics, four tests are within-dimension statistics, and three are between dimension statistics. The four within-dimension statistics are based on pooling the autoregressive coefficients across the different cross-sectional (manufacturing industry in our estimation) units for the unit root tests on the estimated residuals. On the other hand, the three between dimension statistics are based on the estimators that simply average the individual estimated coefficients for each cross section. Among the within dimension category, three are non-parametric tests that correct for serial correlation: the first is a parametric variance ratio test, the second is a test analogous to the Philips and Peron rho-statistic and the third test is analogous to the Philips Peron t-statistic. The fourth one is the parametric test analogous to the ADF statistic (Harris and Solis, 2003). From the between dimension category, two are non-parametric tests analogous to the Philips and Peron rho, and t-statistic, respectively, and a parametric test similar to the ADF statistic (Harris and Solis, 2003).

These tests are based on the null hypothesis of no cointegration and heterogeneity is allowed under the alternative hypothesis. The main purpose of the panel cointegration is to pool information on the common long-run relationship but at the same time it allows for short-run dynamics and fixed effects to be heterogeneous across different members of the panel. To discuss the cointegration technique, the following system of equations has been considered:

$$\begin{aligned} &y_{it} = \alpha_{it} + x'_{it}\beta + \varepsilon_{it} \\ &x_{it} = \sigma_i x_{i,t-1} + \varepsilon_{it} \\ &i = 1,2,.......,N \;\; t = 1,2,......,T \end{aligned} \tag{18}$$

Furthermore, since the exact information on the number of supervisory workers at the firm/industry level is not available from the Center for Monitoring Indian Economy (*CMIE*) based data sets ‘Prowess’, the quality of labor (*QL*) variable has been dropped from the empirical Model (17). Now the empirical Model (17), which has been discussed in the empirical section can be specified for panel cointegration as given below:

$$\begin{aligned} LPd_{it} = \beta_{0i} + \beta_1 k_{it}/l_{it} + \beta_2 k_{it} + \beta_3 CON_{it} + \beta_4 FP_{it} + \beta_5 FPO_{it} \\ + \beta_6 RDI_{it} + \beta_7 RDIO_{it} + \beta_8 TMI_{it} + \beta_9 TMIO_{it} + \varepsilon_{it} \end{aligned} \tag{19}$$

where *i* stands for the cross-section (industry) unit of data, and it varies across twelve selected Indian manufacturing industries, *t* stands for time periods, and coverage of the data for different variables are from 1996 to 2008, i.e. 13 years. The detail discussion of the sources of the data and variables compilation has been given in the Appendix A.

Then, the third step is to obtain consistent parameter estimates from the above panel cointegration Model (19), for then a number of econometric procedures need to be adopted. Most of these arise because of the various possible nature of the error term ε_{it} in the model. If the error terms are independently and identically distributed and uncorrelated with input choices, then the ordinary least squares (*OLS*) estimates can be consistent but inefficient for non-stationary panel data. However, using the standard *OLS* techniques on non-stationary panel data may lead to false inferences in the regression model. Thus, in order to avoid this kind of inconsistency with *OLS* method, the present study employs the Pedroni (2000, 2001) fully modified *OLS* (*FMOLS*), group fully modified *OLS* (*GFMOLS*), and Stock and Watson (1993) dynamic OLS (*DOLS*) estimators to obtain consistent estimates of the cointegrated vectors (Kao and Chiang, 1999).

Pedroni (2000, 2001) *FMOLS* estimates can capture the heterogeneity across industries (slope and intercept heterogeneity) and permits short-run dynamics. According to Pedroni (2000, 2001), by applying *FMOLS*, inferences can be made regarding common long-run relationships which are asymptotically invariant to short-run heterogeneity (as theory suggests), that is prevalent in the dynamics typically associated with panels that are composed of aggregate data. The technique, therefore, deals with the endogeneity of the regressors and corrects for serial correlation which may lead to consistent estimates of β parameters in relatively small samples. Notice that, from Eqn. (18), the vector $\gamma_{it} = [\varepsilon_{it}\,\varepsilon'_{it}]$ is stationary and the covariance matrix is denoted by Ω_i. Then the *FMOLS* parameter estimate has the following form, which is given below:

$$\hat{\beta}_{FM} - \beta = \left(\sum_{i=1}^{N} \hat{\Omega}_{i22}^{-2} \sum_{t=1}^{T} (x_{it} - \bar{x})^2 \right)^{-1} \sum_{i=1}^{N} \hat{\Omega}_{i11}^{-1} \hat{\Omega}_{i22}^{-1} \left(\sum_{t=1}^{T} (x_{it} - \bar{x}) \varepsilon_{it}^{*} - T \hat{\gamma}_{it} \right) \quad (20)$$

where $\varepsilon_{it}^{*} = \varepsilon_{it} - \hat{\Omega}_{i22}^{-1} \hat{\Omega}_{i21}$

$$\hat{\gamma}_{it} = \hat{\Gamma}_{i21} + \hat{\Omega}_{i21}^{0} - \hat{\Omega}_{i22}^{-1} \hat{\Omega}_{i21} \left(\hat{\Gamma}_{i22} + \hat{\Omega}_{i22}^{0} \right) \quad (21)$$

Implicitly, the covariance matrix has been decomposed to $\Omega_i = \Omega_i^0 + \Gamma_i$, where, Ω_i is the contemporaneous covariance matrix and Γ_i is the weighted sum of autocovariances. Out of Pedroni's seven cointegration statistics, four are based on the within dimension (panel cointegration tests) and three are based on the between dimension (group mean panel cointegration tests). Both categories of tests are based on the null hypothesis of no cointegration, that is, $\sigma_i = 1 \forall i.$, σ_i is the autoregressive coefficient on estimated residuals under the alternative hypothesis.

The panel cointegration and group-mean panel cointegration tests differ as regards to the specification of the alternative hypothesis. For the panel cointegration statistics, the alternative hypothesis is $\sigma_i = \sigma < 1 \forall i$, while for the group-mean panel cointegration statistics, the alternative is given by $\sigma_i < 1 \forall i$. Hence, the group-mean statistics have the advantage that they allow for heterogeneous coefficients under the alternative hypothesis. For the second technique that has been employed refer to the work by Mark and Sul (2003), which is an extension of the single equation dynamic ordinary least squares (*DOLS*) method of Saikkonen (1991) and Stock and Watson (1993) for estimating and testing the hypothesis of cointegrating vectors to the panel data. The panel *DOLS* estimator correct for endogeneity and serial correlation by including leads and lags of the differenced I (1) regressors in the regression. Let us consider the following regression model:

$$y_{it} = \delta^{i} d_{it} + x'_{it} \beta + \varepsilon_{it} \tag{22}$$

Where, $\delta^{i} d_{it}$ represents the deterministic component, and x'_{it} terms are assumed to be I (1) and, not cointegrated. Let $u_{it} = \Delta x_{it} - E(\Delta x_{it})$ assumed to be correlated with ε_{it}. The estimator is based on the error decomposition, which is as follows:

$$u_{it} = \sum_{k=-\infty}^{\infty} \gamma'_{k} \Delta x_{i,t+k} + v_{it} \tag{23}$$

Where, v_{it} is orthogonal to all leads and lags of Δx_{it}. Inserting Eqn. (23) into regression Eqn. (22) give the following equation:

$$y_{it} = \beta' x_{it} + \sum_{k=-\infty}^{\infty} \gamma'_{k} \Delta x_{i,t+k} + v_{it} \tag{24}$$

From the above regression Eqn. (24), in practice the infinite sums are truncated at some small numbers of leads and lags (Mark and Sul, 2003). Westerlund (2005) considers data dependent choices of the truncation lags. Kao and Chiang (1999) show that in the homogenous case with $\Sigma_i = \Sigma$ and individual specific intercepts the limiting distribution of the DOLS estimator $\hat{\beta}_{DOLS}$ is given by

$$T\sqrt{N}\left(\hat{\beta}_{DOLS} - \beta\right) \xrightarrow{d} \mathrm{N}\left(0, 6\, \sigma^{2}_{u/\varepsilon} \Sigma^{-1}_{\varepsilon\varepsilon}\right) \tag{25}$$

where $\sigma^{2}_{u/\varepsilon} = \sigma^{2} - \sigma'_{\varepsilon u} \Sigma^{-1}_{\varepsilon\varepsilon} \sigma_{\varepsilon u}$.

Furthermore, FMOLS estimator possesses the same asymptotic distribution as the DOLS estimator. In the heterogeneous case $\Sigma_{\varepsilon\varepsilon}$ and $\sigma^{2}_{u/\varepsilon}$ are replaced by $\overline{\Sigma}_{\varepsilon\varepsilon} = N^{-1} \Sigma^{N}_{i=1} \Sigma_{i,\varepsilon\varepsilon}$ and $\overline{\sigma}^{2}_{u/\varepsilon} = N^{-1} \Sigma^{N}_{i=1} \sigma^{2}_{i,u/\varepsilon}$, respectively (Phillips and Moon, 1999). The matrix Σ_i can be estimated consistently (for $T \to \infty$) buy using the nonparametric approach. However, before going to interpret the regression results the statistical summary of the variables has been given in the following Table 1.

[Table 1 about here]

4. ESTIMATION RESULTS

Table 2 shows the result of panel unit root tests for ten variables, which have been discussed in empirical Model (19). The study uses a battery of panel unit root tests, proposed by LLC, IPS, Breitung and Hadri to check the robustness of the variables and to check for stationarity of the model. The null hypothesis in each case except the Hadri test proposes that each series has a unit root and the alternative hypothesis allows for some but not all of the individual series to have unit roots. The Hadri based Lagrange Multiplier (LM) test is based on the proposition that the null hypothesis contains no unit root against the unit root in the panel data.

From the reported results in Table 2, it can be interpreted that most of the tests fail to reject the unit root null for variables in level form (with the exception of the IPS and LLC in four case), but the tests reject the null of a unit root in first difference form (Table 3). These tests show that the variables in the regression model go forward to non-stationary processes and the application of simple *OLS* to the stacked regression Model (19) leads to the result of biased and inconsistent estimates. Thus, it is necessary to turn to panel cointegration techniques in order to determine whether a long-run equilibrium relationship exists between the non-stationary variables in level form.

[Table 2 about here]

To determine whether a cointegrating relationship exists between the endogenous and exogenous variables, the methodology proposed by Pedroni (1999, 2000) has been employed here. Basically, it consists of using the residuals derived from the panel cointegration in empirical Model (19), and constructing four within-dimension and three between-dimension statistics to test the null hypothesis of no cointegration against the alternative of cointegration. The Pedroni panel cointegration result is reported in Table 4. The results are in favor of the alternative hypothesis for existence of cointegration among the cointegrating vectors. Empirical evaluation brings out that out of the seven statistics four statistics are in favor of the existence of cointegration. Moreover, when we exchange the regressors in Model (19), then in all cases out of the seven statistics four statistics are in favor of cointegration (rejecting the null hypothesis of no cointegration).

[Table 3 about here]

The null of rejection is determined by large positive values for Panel Variance statistics, and in the case of others six statistics it is determined by large negative values. Econometric theory tells us that panel cointegration takes care of the short-run heterogeneity and gives long-run estimates of the underlying relationship. Empirical findings suggest that there is clear evidence of the existence of cointegration between the cointegrating vectors in Model (19). Thus, we can infer a long-run relationship between the endogenous variable (labor productivity over domestic firms) and the set of exogenous variables. Furthermore, presence of cointegration in empirical Model (19) points to the existence of horizontal and vertical spillover across twelve Indian manufacturing industries.

[Table 4 about here]

Table 5 reports the panel individual *FMOLS* estimates of labor productivity regression over the period of 1996-2008 across twelve Indian manufacturing industries. The coefficients of foreign presence are found to be non-negative and statistically significant across most of the industries. Thus, empirical results reveal the presence of horizontal spillovers across most of the manufacturing industries. Furthermore, except for a few manufacturing industries like metal products and non-electrical machinery, in rest of the cases, the industries have a long-run relationship between labor productivity and its horizontal foreign presence (*FP*).

It is evident that, with a few exceptions, the vertical (inter-industry) foreign presence (*FPO*) coefficients are found to be positive and statistically significant across most of the manufacturing industries. The industries like cotton textiles, textiles, woods products, paper and paper products, leather products, chemicals, non-metallic mineral products, metal products, and electrical machinery are gaining from the vertical spillover effect from FDI. Thus, the results suggest that inter-industry foreign presence has a decisive role for the determination of technology spillovers across Indian manufacturing industries.

[Table 5 about here]

Turning to other parameters like capital and capital intensity, the coefficients are found to be wrong economic sign that is negative in some cases. Thus, we cannot ignore the presence of multicollinearity between capital and capital intensity variables. These variables are still retained because in some cases we cannot ignore the distinctive impact of the size and scale factors to productivity and technology spillovers of Indian industries. Furthermore, our main objective is to examine the horizontal and vertical spillovers across Indian manufacturing industries, and our key results are not significantly affected even after including the insignificant capital and capital intensity variables in some industries. However, in some cases these coefficients are non-negative and statistically significant, so we could interpret the positive coefficients are showing the favorable effects on the productivity and technology spillovers across Indian industries. In addition, the expected positive coefficients control for the long-run relationship between labor productivity with size and scale factors like capital and capital intensity in the regression model.

It is generally assumed that firms with higher R&D spending have more innovative activities, greater technology up-gradation and finally higher productivity with more technology spillovers. R&D intensity is the crucial conduit for firm's absorptive capacity and technology spillovers from the foreign firms. It may be the case that a certain level of R&D

intensity is needed before firms benefit from FDI-generated externalities (Girma, 2005). From the results we cannot ignore the crucial role of the R&D intensity of own industry and inter-industry R&D intensity for the determination of technology spillovers. It is evident from this empirical evaluation that R&D intensity (*RDI*) exercises a strong influence in lifting the productivity and generating technology spillover across Indian industries. Turning to the inter-industry R&D intensity (*RDIO*), the results are suggestive of strong spillovers in the industries like food products, beverages and tobacco, cotton textiles, textiles, woods products, leather products, and metal products. This is clear indication of inter-industry R&D intensity (*RDIO*) spillover, i.e., an industry being affected by other industries R&D activities. Moreover, domestic firms of a certain industry have to augment its R&D intensity in order to raise their absorptive capacity and to use the technology that is developed elsewhere effectively and to close the gap between its TFP and the more innovative technological leaders TFP. Thus, these results indicate that more R&D spending and more innovation have significant implications for a firms survival and success and to gain access to more frontier technology across the world.

With regard to the technology import intensity of an industry (*TMI*) and other industry/inter-industry technology import intensity (*TMIO*), the estimated coefficients are positive in most cases. Thus, the results suggest that they both promote productivity and technology spillovers across Indian industries. This is an important result because it shows that firms that are behind the technology frontier because of low level of technology and are willing to invest in R&D, thereby have technology up-gradation, then they can grow faster than their rival that are not investing in R&D and technology. This implies that firms investing in technology up-gradation can experience a stronger growth in spillovers, productivity, and profits than those that do not. Furthermore, from the results it is clearly indicated that inter-industry technology import intensity can have an impact for a domestic firm to raise their productivity and technology spillovers from the FDI-generated firms. Thus, these findings clearly signify that technology up-gradation and R&D spending is essential and crucial for industries. What are also needed are that technology up-gradation and more R&D spending keep pace with the increasing product varieties with cheapest cost available in the economy. Thus, higher R&D spending and more technology-upgrading firms can come across to the most advanced technologically acquainted firms such that they can narrow down the technological differences and gain technology spillovers from the FDI-generated externalities.

[Table 6 about here]

Table 6 reports the *GFMOLS* and *DOLS* estimates (industry as whole, group results) of the labor productivity regression of Eqn. (19) over the period of 1996-2008 of twelve Indian manufacturing industries. The coefficients of horizontal foreign presence (*FP*), inter-industry foreign presence (*FPO*), R&D intensity (*RDI*), other industry/inter-industry R&D intensity (*RDIO*), technology import intensity (*TMI*), and other industry/inter-industry technology import intensity (*TMIO*) are found to be positive and statistically significant. These results show the long-run relationship between labor productivity and exogenous variables and it is evident that this long-run relationship leads to the technology spillover across Indian industries. To shed more light on the results, both horizontal and inter-industry foreign presence spurs technology spillovers and labor productivity across industries. Therefore, on that note it is interesting to allusion that firms of an industry get significant benefits from the inter-industry (vertical) foreign presence.

The *DOLS* estimates correct for the endogeneity and serial correlation problem inside the model by including leads and lags of the differenced regressors. The findings based on *DOLS* indicate that most of the regressors have a positive and statistical significant effect on labor productivity. From discussion, we may say that the most pivotal cointegrating vectors for spillovers studies are based on horizontal type foreign presence (*FP*) and inter-industry type foreign presence (*FPO*). Furthermore, it is important to note that both variables promote labor productivity and technology spillover across Indian manufacturing industries. Thus, we can infer that these key variables act like a catalyst to stimulate technology spillovers and labor productivity across Indian industries. The overall finding from the analysis presented in this study is the occurrence of both intra-industry and inter-industry technology spillover effect of FDI across twelve Indian manufacturing industries. Furthermore, this study reveals that the intra-industry (horizontal) and inter-industry (vertical) spillover are relatively higher in industries like cotton textiles, paper and paper products, leather products, chemicals, and non-metallic mineral products.

5. CONCLUDING REMARKS

The study analyzed the significant role of intermediate factors in the production process which is integrated in diverse ways such that it can act as a catalyst to augment the labor productivity and technology spillover across Indian manufacturing industries. Pedroni panel cointegration approach has been used to find out the long-run relationship between endogenous and exogenous variables. By implementing Pedroni test the study analyzed whether technology spillover can be transmitted by the constructive role of the intermediate factors, as explained in the theoretical and empirical approach of the model. The results provided evidence in favor of the existence of technology spillover both in the short-run and long-run. We found that the pivotal cointegrating vectors should include intra-industry/horizontal foreign presence and other/inter-industry foreign presence, since these have exclusive penetration effect to spur labor productivity and technology spillover across Indian industries. Furthermore, technology import intensity, inter-industry technology import intensity, R&D intensity and inter-industry R&D intensity promote labor productivity and technology spillover. Moreover, the study underscores the significant function of R&D

intensity and inter-industry R&D intensity, in so far as both factors enhance absorptive capacity of localized firms and drive labor productivity and technology spillover.

The study examined the horizontal and vertical technology spillover effect of FDI across Indian manufacturing industries. The study found evidence for the occurrence of horizontal and vertical technology spillover in eight industries out of twelve manufacturing industries. Empirical findings reveal that industries like cotton textiles, textiles, woods products, paper and paper products, leather products, chemicals, non-metallic mineral products and electrical machinery experience both intra-industry and inter-industry technology spillover effect of FDI.

Finally, the findings of this paper have important implications for raising the labor productivity and technology spillovers across Indian manufacturing industries. FDI is now considered to be a key growth enhancing factor in investment receiving host country like India. FDI not only brings capital but it also introduces advanced technology to the host country firms. Furthermore, from the paper we examined that both horizontal and vertical foreign presence, R&D intensity, and technology import intensity have exclusive penetration effect to raise the productivity spillover and competitiveness of an industry.

The policy authority of Indian government can consider initiative policy to attract more foreign capital by adopting a suitable policy regime, land acquisition policy, and labor laws. The higher the inflow of foreign capital, the higher would be the application of advanced technology, which would minimize the technological gap between foreign and local firms and later on accelerate the absorptive capacity of localized firms. There must be proper coordination between government and private parties so that domestic firms can take the best advantage of the policy regime and therefore, it can easily learn and wherever necessary import most advanced technology developed elsewhere in the world from technological leaders firms. This advantage definitely brings new initiative to domestic firms and therefore, domestic firms are able to emulate foreign technology and raise their labor productivity and competitiveness through technology spillovers. In order to increase the R&D intensity at the firms/industries level, Government of India can consider to implement suitable monetary policy. So that banks credit can be easily flow to the firms of an industry and it can help to set up new R&D development projects and works.

APPENDIX A

Data and Variables

Data

The data in this study mainly comes from the Centre for Monitoring Indian Economy (CMIE) based corporate data base 'Prowess', Annual Survey of Industries (ASI) and National Accounts of Statistics (NAS). The time series data *t* varies from 1996 to 2008, and cross-section *i* stands for the twelve selected Indian manufacturing industries.

Variables

Labor productivity

LPd: The labor productivity at the firm level has been constructed by dividing the gross value added to the number of man-days (labor) of firm of an industry. The analytical estimation has been based on the industry level, so the labor productivity has been constructed to the industry-specific variable. To make labor productivity as an industry-specific variable and to get the spillover effect across Indian manufacturing industry we simply take average of the labor productivity over domestic firms in an industry for a specific period of time.

Capital (*k*)**:** For the present study, to construct the capital variable from the Prowess data set we followed the methodology, derived by Srivastava (1996) and Balakrishnan *et al.* (2000). They used the perpetual inventory method, which involves capital at its historic cost. Thus, the direct interpretation of the perpetual inventory method is not an easy task. Therefore, the capital stock has to be converted into an asset value at replacement cost. The capital stock is measured at its replacement cost for the base year 1993-94. Then, we followed the methodology of Balakrishnan et al. (2000) to arrive at a revaluation factor. The revaluation factors R^G and R^N for initial year's gross and net capital stock, respectively, have been obtained as follows:

The balance sheet values of the assets in an initial year have been scaled by the revaluation factors to obtain an estimate of the value of capital assets at replacement cost.[6] However, the replacement cost of capital = R^i * (value of capital stock at historic cost), where, i stands for either gross (G) or net (N) value. The formula for the revaluation factor for the gross fixed asset R^G and value of the capital stock at its historic cost GFA_t^h is given below:

$$GFA_t^h = P_t I_t \ * \left(\left(1+g\right)\left(1+\pi\right)/\left(1+g\right)\left(1+\pi\right)-1\right)$$

where P_t = Price of the capital stock; I_t = Investment at the time period t (t =1993); = the difference between the gross fixed assets across two years, that is, $I_t = GFA_t - GFA_{t-1}$; g stands for the growth rate of investment, that is, $g = \left(I_t / I_{t-1}\right) - 1$ and $\pi = \left(P_t / P_{t-1}\right) - 1$. The revaluation factor for the gross fixed asset is $R^G = (l+g)(l+\pi)-1/g(1+\pi)$. Here, l stands for the life of the machinery and equipment. Thus, the revaluation factor has been constructed by assuming that the life of machinery and equipment is 20 years and the growth of the investment is constant throughout the period. We assume that the price of the capital stock has been changed at a constant rate from the date of incorporation of the firm to the later period, i.e., up to 2007. The revaluation factor which has been obtained is used to convert the capital in the base year into the capital at replacement cost, at current prices. We then deflate these values to arrive at the values of the capital sock at constant prices for the base year. The deflator used for this purpose is obtained by constructing capital formation price indices from the series for gross capital formation from the NAS. Then, subsequent year's capital stock is arrived at by taking the sum of investments, using the perpetual inventory method.

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[6]See Srivastava (1996, 2000) for detailed discussion of the perpetual inventory method to compile the real gross capital stock from the CMIE based Prowess data set.

Labor **(*l*):** For the present study, our principal source of the data base is Prowess. Our analysis is based on the Prowess data set. However, the Prowess data base does not provide the exact information regarding labor per firm. Thus, we need to use this information on man-days per firm. Man-days at the firm level are obtained by dividing the salaries and wages of the firm to the average wage rate of an industry to which the firm belongs.[7] Thus, the man-days per firm are as given below:

Number of man-days per firm = salaries and wages/average wage rate

To get the average wage rate, we used the information from ASI data. ASI contains information on total emoluments and total man-days for the relevant industry groups. The average wage rate can be obtained by dividing the total emoluments to the total man-days for relevant industry groups.

Average wage rate = total emoluments/ total man-days

Capital Intensity **(*k/l*)**: Capital intensity at the firm level can be obtained by dividing the real gross capital to the labor of that firm. To get capital intensity as an industry-specific effect, we simply divide the summation over all firms' capital stock to the summation over all firms' labor of an industry.

Market Concentration **(*CON*):** For the present study to measure the market concentration, we take widely used proxies of Herfindahl-Hirschman index of concentration (*HHI*). The *HHI* of market concentration formula is given below:

[7]For the present analysis when we compiled the labor variable from CMIE based Prowess data set and from ASI sources, then information's for total man-days and total emoluments in ASI data were available up to 2004-05. Thus, from ASI data we extrapolating the data range from 2004-05 to 2008 to get the average wage rate of an industry.

$$HHI = \sum_{i} \left(s_{ij} \Big/ \sum s_{ij} \right)^2$$

where s_{ij} is a total sale of the *i*th firm in the *j*th industry.

Foreign Presence **(*FP*):** Foreign presence is measured by the output share of foreign firms to the total industry output. However, in some previous empirical studies, employment or capital shares have been used to measure the foreign presence. Taking foreign presence as an employment share tends to underestimate the actual role of foreign affiliates because MNEs affiliates tend to be more capital intensive than local non-affiliated firms. On the other hand, the capital share can be easily distorted by the presence of foreign ownership restrictions. Hence, output share is the preferred proxy (Kohpaiboon, 2006).

FPO: Foreign Presence of other industries(other than *i* but summing over *j*) is compiled by taking the output share of foreign firms of all other selected industries divided by the total output of the selected industries. Let us consider to compute the foreign presence of other industries (*FPO*) for the food products industry, then we calculate the output share of all foreign firms of the eleven industries (excluding foreign firms output of food product industry) out of twelve selected industries divided by the eleven industry output (excluding food product industry output).

R&D Intensity

RDI: The R&D intensity is measured by the share of R&D expenditure to the total sales. To calculate this variable as an industry-specific effect, we measure the total R&D expenditure by summing up the R&D expenditure over all firms of an industry for a specified period divided by the total sales of that industry by again summing over sales of each firm during that period of time.

RDIO: R&D intensity of the other industry (other than *i* but summing over *j*) has been compiled by taking the sum of all *j* industries R&D expenditure to the total sales of the other *j* industries rather than *i*. For instance, we want to measure the R&D intensity of other industries (*RDIO*) for the food products industry, then, we take the sum of R&D expenditure of all eleven industries (excluding the R&D spending of food products industry) out of twelve selected industries divided by the sum of total sales of the eleven industries (excluding sales of the food products industry).

Technology Import Intensity (*TMI*)

*TMI***:** The technology imports can be broadly classified into two categories as embodied technology consisting of imported capital goods and disembodied technology consisting of blue prints and license fees considered to be remittances on royalty and license fees. Hence, the technology imports intensity of a firm can be obtained by summing up the embodied and disembodied technology divided by the total sales of that firm. To make the technology import intensity as an industry-specific effect, we calculate by summing up the total disembodied and embodied technology across all firms of an industry in a specified period divided by the total sales of that industry which is again obtained by summing up the sales over each firm during that period of time.

*TMIO***:** Technology import intensity of other industry (other than *i* but summing over *j*)

To compile this variable, for instance we consider for the textiles industry; then taking the summation of both disembodied and embodied technology across the firms of all eleven industries (excluding the firms of textiles industry) out of twelve selected industries for a specified time period divided by the total sales of all eleven industries (excluding the sales of textiles industry).

APPENDIX B

Table B.1. Classification of firms across Indian manufacturing industries in 2007

NIC 1987 CODE	Industry Classification	Domestic Firms	Foreign Firms	Total Firms
20-21	Food Products	146	12	158
22	Beverages and Tobacco	85	4	89
23	Cotton Textiles	307	4	311
26	Textiles	245	13	258
27	Woods Products	20	1	21
28	Paper and Paper Products	40	5	45
29	Leather Products	14	1	15
30	Chemicals	410	77	487
32	Non-metallic Mineral Products	96	14	110
34	Metal Products	176	24	200
35	Non-Electrical Machinery	229	26	255
36	Electrical Machinery	226	21	247

Source: Based on own calculations from the CMIE data set 'Prowess'.

Note: 1. FDI firms (foreign firms) are those firms with foreign equity of 10 percentages or more than of 10 percentages.

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Table 1: *A Statistical Summary of the Key Variables*

Variables	*Mean*	*SD*	*Min*	*Max*
LPd	9.966	2.083	7.58	15.963
k/l	12.777	3.914	0.754	17.927
k	13.184	4.405	0.512	20.742
CON	0.137	0.167	0.009	0.845
FP	0.178	0.155	0.034	0.594
FPO	0.070	0.013	0.039	0.105
RDI	0.002	0.002	0	0.047
RDIO	0.002	0.0006	0.002	0.05
TMI	0.017	0.014	0.001	0.089
TMIO	0.026	0.049	0.005	0.367

Note: Mean = simple average; SD= standard deviation; Min = minimum; and Max= maximum. Estimates of *LPd*, , *k/l*, *k*, are logarithmic transformation of their value. The other variables are converted into logarithmic form as ln(1+x) where x is the variable. No. of observations, NT=156.

Table 2: *Four Different Panel Unit Root Tests (Variables in Levels)*

Variables	*LLC*	*Breitung*	*IPS*	*Hadri*
LPd	-5.672	0.034	-3.827*	4.396*
k	-7.843*	-6.324	-5.395*	-1.278*
k/l	-8.076	0.085	-4.047	5.500*
CON	3.587	-1.682	5.394	6.628*
FP	0.017	-0.279	0.498	4.244*
FPO	4.973	-0.854	7.333	8.115*
RDI	-2.894	-2.499	-2.198	2.793*
RDIO	-4.022	-3.608	-2.435	3.206*
TMI	-6.110	-0.164	-3.378	0.831*
TMIO	13.444	4.110	4.716*	2.723*

Notes: 1. Automatic selection of maximum lags. Automatic selection of maximum lags is based on SIC: 0 to 2.

2. Newey-West bandwidth selection using Bartlett and Kernel.

3. A * indicates the rejection of null hypothesis of non-stationary (LLC, Breitung, IPS) or stationary (Hadri) at the 5% level of significance. NT=156.

Table 3: *Four Different Panel Unit Root Tests (Variables in 1st Differences)*

Variables	*LLC*	*Breitung*	*IPS*	*Hadri*
LPd	-13.990*	-4.337*	-10.024*	2.121
k	-12.620*	-9.883*	-9.104*	7.584
k/l	-9.798*	-5.112*	-6.925*	1.988
CON	-9.391*	-4.650*	-7.208*	2.675
FP	-8.395*	-5.292*	-6.295*	-0.681
FPO	-4.594*	-2.005*	-3.663*	1.857
RDI	-12.467*	-4.299*	-8.391*	5.162
RDIO	-13.993*	-5.122*	-12.310*	-1.469
TMI	-8.603*	-1.669*	-6.735*	2.473
TMIO	18.967*	-3.928*	6.292*	4.399

Notes: 1. Automatic selection of maximum lags. Automatic selection of maximum lags is based on SIC: 0 to 2.

2. Newey-West bandwidth selection using Bartlett and Kernel.

3. A * indicates the rejection of null hypothesis of non-stationary (LLC, Breitung, IPS) or stationary (Hadri) at the 5% level of significance. NT=156.

Table 4: *Panel Cointegration Tests*

(Models for Labor Productivity over Domestic Firms (*LPd*))

Statistics	*1*	2	*3*	*4*
Panel V-Statistics	-2.299 (0.142)	-1.886 (0.458)	-1.907 (0.321)	-1.922 (0.458)
Panel Rho-Statistic	4.054 (0.458)	3.604 (0.456)	4.123 (0.342)	4.435 (0.652)
Panel PP-Statistic	-6.661 (0.101)	-11.934 (0.054)	-7.065 (0.052)	-5.130 (0.085)
Panel ADF-Statistic	-3.330 (0.095)	-6.314 (0.065)	-3.309 (0.102)	-2.169 (0.083)
Group Rho-Statistic	5.293 (0.587)	4.942 (0.789)	5.400 (0.123)	5.740 (0.123)
Group PP-Statistic	-8.894 (0.078)	-14.760 (0.032)	-8.834 (0.089)	-8.910 (0.078)
Group ADF-Statistic	-2.575 (0.102)	-6.067 (0.056)	-3.761 (0.098)	-3.366 (0.078)

Notes: 1.Endogenous variable: *LPd*.

2. An intercept but no trend is included in estimation. Numbers in round parenthesis are p-values.

3. Column 1 regressors are *RDI, TMI, FP, FPO, RDIO, TMIO and CON*.

4. Column 2 regressors are *k/l, k, TMI, TMIO, FP, FPO and CON.*

5. Column 3 regressors are *k/l, k, RDI, RDIO, FP, FPO and CON.*

6. Column 4 regressors are *k/l, k, RDI, RDIO, TMI, TMIO and CON.*

Table 5: *FMOLS* Labor Productivity Regressions over the Period 1996-2008 in Twelve Industries of Indian Manufacturing (Individual *FMOLS* Results). (Industry-Year Panels)
Dependent variable: *LPd*

variables Industries	*k*	*k/l*	*CON*	*FP*	*FPO*	*RDI*	*RDIO*	*TMI*	*TMIO*
Food products	2.02* (8.50)	0.50* (7.81)	5.69* (9.18)	1.76* (8.36)	-1.44 (-1.01)	0.11* (5.05)	6.49* (2.83)	-3.05 (-1.10)	0.08* (9.66)
Beverages And tobacco	7.06* (5.70)	0.73 * (6.40)	1.84** (1.59)	3.34** (1.70)	-8.35 (-9.66)	-1.48* (-4.26)	11.56* (5.52)	6.19* (7.46)	3.54* (6.47)
Cotton textiles	3.62 (0.75)	-0.43 (-1.29)	-5.76** (-1.76)	0.35* (6.71)	8.01* (2.84)	9.45* (2.74)	8.67* (5.04)	0.02 (0.48)	0.06* (8.69)
Textiles	2.23* (3.26)	-0.32* (-6.58)	-6.41 (1.06)	0.09* (3.36)	7.20* (12.28)	0.75 * (7.71)	8.92* (7.43)	0.34* (4.42)	0.24* (11.66)
Woods products	-0.36* (-2.75)	-0.12* (-3.24)	-1.00* (-3.16)	0.19** (1.48)	0.55* (3.73)	3.28* (8.20)	2.72* (11.34)	1.03* (8.56)	-0.04* (-7.65)
Paper and paper products	-1.67* (-3.65)	0.52* (2.91)	2.64* (7.08)	4.04* (6.32)	4.72* (3.49)	7.12* (8.25)	-1.82* (-3.63)	-2.22* (-7.31)	-0.17* (-9.81)
Leather products	-0.09** (-1.89)	0.14* (6.62)	8.00* (3.00)	3.79** (1.77)	3.52* (2.96)	2.57** (1.50)	1.64* (4.53)	0.28* (2.17)	0.06* (1.94)
Chemicals	2.32* (8.48)	0.03* (5.14)	-0.81 (-0.80)	5.19* (6.41)	0.57* (2.13)	-0.41 (-0.69)	0.36 (1.20)	0.14 (0.57)	0.01 (0.14)
Non-metallic mineral Products	-9.44 (-1.79)	-0.10 (-0.14)	2.97* (1.90)	1.84* (2.65)	9.79* (2.58)	0.88 (0.98)	-2.03* (-1.87)	2.15 (0.95)	-0.10* (-1.95)
Metal products	0.61* (4.99)	-0.16** (-1.42)	-1.00* (-1.53)	-0.28* (-6.71)	6.73* (9.26)	0.72* (2.29)	0.87** (1.57)	0.55* (3.19)	0.01 (1.29)
Non-electrical machinery	1.65 (1.12)	-0.12 (-1.18)	3.44 (0.89)	-0.10 (-0.23)	1.08 (0.64)	0.85 (-0.30)	-1.30 (-0.33)	-0.77** (-1.59)	0.01 (0.00)
Electrical machinery	1.20* (2.99)	0.02* (1.78)	-0.26* (-9.72)	0.14* (5.51)	3.02* (6.82)	-0.84* (-6.72)	-0.19** (-1.57)	0.02 (0.91)	-0.00* (-4.78)

Notes: 1. Coefficients are long-run estimates of the labor productivity over domestic firms with respect to the regressors in the empirical Model 19.
2. A * denotes statistical significance at least at the 5% level, while ** represents this at the 10% level.
3. t-statistics are in the parenthesis. NT=156.

Table 6: *Panel GFMOLS and DOLS Results*

Dependent variable: LPd (Industry-Year panels)

Variables	*GFMOLS*	*DOLS*
k	0.31 (3.27)*	0.261 (0.75)
k/l	-0.22 (-2.02)*	0.27 (0.95)
CON	0.30 (0.60)	0.92 (2.38)*
FP	0.23 (1.47)**	0.11 (0.77)
FPO	4.72 (2.108)*	2.10 (2.87)*
RDI	1.03 (1.35)**	2.45 (4.10)*
RDIO	-5.28 (-1.33)	5.15 (5.06)*
TMI	0.15 (0.49)	0.05 (2.10)*
TMIO	0.09 (2.04)*	2.55 (6.67)*

Notes: 1. Coefficients are long-run estimates of the labor productivity over domestic firms with respect to the regressors in the empirical Model 19.

2. GFMOLS stands for the Group Fully Modified OLS estimates, and DOLS stands for the Dynamic OLS estimates. The DOLS regressions include one lead and one lag for the differenced regressors. AR Lags in Computing is S (0) 1.

3. A * denotes statistical significance at least at the 5% level, while ** represents this at the 10% level.

4. Absolute t-statistics are in the parenthesis. NT=156.