Proximity to the best practice frontier and FDI spillovers on incumbent innovation and productivity.

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Abstract

Employing a comprehensive firm-level dataset, the paper attempts to examine the link between FDI influx and incumbent innovation activities in Indian manufacturing sector. While analysing the heterogeneity in the effects of FDI on innovation and productivity, the paper pays particular attention to the possible role of incumbents proximity/distance to best practice frontier in influencing the absorption of FDI spillovers. Alternately, we try to analyse whether the impact of FDI on incumbent innovation and productivity is conditional upon the location of incumbent vis-à-vis to the technology/efficiency frontier. The paper employs DEA (data envelopment analysis) technique to compute the incumbents' TFP and proximity/distance to the best practice frontier. Empirical results show that FDI entry incentivises the innovation in incumbents that lie close to frontier whereas incumbents located further behind the technology frontier are discouraged from innovating as a result of foreign firm entry.

1. Introduction

Foreign direct investment (FDI) is widely believed to be an ingredient of economic growth and welfare. FDI, through competition, productivity and knowledge spillovers, affect the productive efficiency and eventually the innovation activities of local firms in the host country. It may stimulate or impede the innovation incentives of incumbent firms depending on their proximity to or distance from the best practice frontier (Aghion et al. 2009). Alternatively, the incumbents' reaction to the FDI entry may vary, the relatively efficient incumbents located 'at or near' to the frontier will increase their innovation output than incumbents located away from the frontier. The theoretical explanation for this variation comes from Schumpeterian multi-sector models with escape-entry and discouragement effects. The twin effects emphasise that advanced entry induces innovation in sectors that are close to the technology frontier but impedes it in sectors that lie further behind the frontier. Incumbent firms close to the frontier have high technical efficiency than those away from the frontier. The former can escape and survive entry threat by innovating successfully since they react to the advanced entry by way of doing more R&D and coming up with new intensive innovations. This Schumpeterian escape-entry effect is similar to escape-competition effect developed by Aghion et al. (2001). In the case of incumbents lying further behind the frontier, the FDI entry discourages their innovation incentives by reducing the expected rents or payoffs from doing R&D. The laggard incumbents with a lower technical efficiency have no hope of winning against the entrants and hence cannot survive entry threat.

Based on this theoretical background, this study attempts to provide an empirical analysis of the variation of incumbents' response to the FDI entry while emphasising on their proximity to or distance from the best practice frontier. We analyse the patenting and productivity behaviour of the incumbent firms that lie close to and away from best practice frontier.

The study is conducted in the context of a catching-up Indian economy. The country, having low productivity and weaker domestic knowledge base, is believed to be further behind the world technology frontier. Since FDI is viewed to be one way of improving the knowledge base and closing the existing productivity gap between domestic firms and firms from advanced countries. Therefore, the question which arises is to what extent FDI has helped to overcome these problems. India, now being recognized as one of the top destinations of FDI, is a good candidate to study the impacts of FDI. The country opened up to global investment in the early 1990s with the massive LPG (liberalization, privatization, and globalization) programme and since then made huge strides in attracting foreign capital. Specifically, after 2000s' due to the removal of caps on various industries and streamlining of FDI policy, the country witnessed massive FDI inflows.

The remainder of the paper is structured as follows: The next section provides the literature review and highlights the role of incumbents' proximity to or distance from the frontier in FDI induced spillovers on innovation. Section 3 describes the data while as section 4 illustrate the empirical framework utilised in the analysis. Section 5 presents the empirical results and section 6 concludes the paper.

2. Literature Review

FDI affects incumbents' performance mainly through technology transfer and changes in competition. FDI entry brings about knowledge spillovers, triggers competition and induces a reallocation of inputs and outputs, thereby affecting the productivity and innovation incentives of incumbent firms. Gorg and Greenway (2004) and Navaretti and Venables (2004) provide a thorough overview of the theoretical background of the spillover effects from FDI. The existing theoretical literature on spillover effects is not free from ambiguity. It suggests that the net impact of FDI on incumbent performance is conditional upon so many factors most importantly on the characteristics of incumbents and the host country's environment. Depending on these characteristics, FDI spillovers on incumbent firms can be both negative and positive. Negative effects arise due to the increase in competition arising from the entry much advanced foreign firms into the host country market. The entry results into a drop in market shares of incumbents (specifically of laggards) as well as their exit from the industry. The positive effects, on the other hand, are the result of technology transfer, and managerial know-how associated with the FDI entry that spills over to local firms, hence helping them to improve their productive efficiency.

The more recent empirical research in this area claims that spillovers are more likely to materialise for incumbents residing close to the foreign firms but unlikely to occur if they lie away from the foreign firms (Aghion et. al 2005, 2009). It implies that in sectors where the productivity differential or technology gap between foreign entrants and incumbents is small, the benefits from entry are more than where this gap is huge. For instance, Glass and Saggi (1998) claim that technology gap between foreign firms and their domestic counterparts is related to absorptive capacity- the ability of an incumbent to recognize new information, adopt new technologies, assimilate and apply them to commercial ends. The lesser technology gap between foreign entrants and existing incumbents reflects the high absorptive capacity of the latter and hence their potential to absorb possible spillovers. This view is also backed by Schumpeterian competition models (for a thorough review of such theoretical studies see e.g. Aghion and Griffith, 2005). With respect to the technology gap, Kokko (1994) find that spillovers are smaller in Mexican industries with larger labour productivity gap between local and foreign firms. Kokko et al. (1996) find a similar result in Uruguayan manufacturing sectors; if the productivity gap is small, foreign technology appears to be more useful for domestic firms because they possess the necessary skills needed to learn and decode it. Pearce (1999) argues large technology gap reflects poor technical build-up and mimic capacity and hence lesser possibility for incumbents to learn from much advanced foreign firms. However, Findlay (1978) argues that relative backwardness of the host country firms indicates more scope for FDI spillovers to occur. The large technology difference between foreign firms and their domestic counterparts implies more pressure on latter and therefore, greater need for them to adopt new technologies. Using Indonesian manufacturing data, Sjohlom (1999) find evidence of spillovers to domestic firms only in a sub-sample with a large technology gap.

There is a plethora of empirical studies that analyse the impact of FDI on productivity- labour as well total factor productivity- of incumbents. However, extant empirical literature looking into the impact of FDI on innovativeness in developing, transition and catching-up countries is fewer. Particularly, the role of distance to the technology frontier in affecting the assimilation of FDI spillovers by incumbents has largely been ignored. Therefore, keeping in view, the dearth of empirical studies the present paper contributes in understanding the role of distance to the frontier in FDI-induced spillovers on incumbent innovation.

This study extents the existing spillover literature on many fronts. First, besides analysing the effects of FDI entry on incumbent productivity, it also examines the impact of FDI entry on incumbent innovation using a patent grant approach. The latter analysis is important for at least two reasons– (i) to find out whether the use of innovation output data and productivity data leads to similar conclusions about the existence of spillovers and, (ii) to capture the benefits that purely result from FDI driven technology transfer and know-how, other than imitation and reverse engineering by incumbents. The improvements in productivity may not purely reflect the FDI induced innovation activity. It could result from imitation by incumbents. It is also possible that productivity growth is driven by reallocation of resources between plants within incumbent establishments. Therefore a better way to explore the relation between FDI entry and innovation is to analyse it directly in the light of patent counts.

Second, while analysing the impact of FDI entry on incumbent innovation and TFP, the paper pays particular attention to the heterogeneity in the FDI spillover effects, i.e., whether these effects are conditioned by the incumbents' proximity to or distance from the best practice frontier. Since in the existent spillover literature, empirical evidence regarding dependency of FDI spillovers on incumbent characteristics is conflicting. While some of the empirical studies maintain that firm characteristics like higher technical efficiency and absorptive capacity are essential for spillovers to materialise. Others argue that for the spillovers to occur, there must a technological gap between foreign entrants and existing incumbents. Therefore, to clear the air about this ambiguity, there is a need for further empirical analysis of the spillover effects.

Third, the study employs a non-parametric approach by using data envelopment analysis (DEA) to estimate best practice frontier, total factor productivity of incumbents and their proximity to/distance from frontier. Unlike, stochastic frontier analysis, the non-parametric frontier approach is relatively new in this area of research (Kneller and Stevens; 2006).

3. Methods

3.1.1. Data

The study is conducted to investigate the impact of FDI on innovative and productivity performance of firms operating in Indian manufacturing sector. It covers a period of 14 years spanning from 2000 to 2013.

Econometric analysis is based on a balanced firm level dataset comprising 520 firms belonging to 17- three-digit manufacturing industries. The database for the study comes from various sources. For innovation analysis, we use data on patent grants compiled from the various issues of the patent office journal, the official journal of the Indian Patent Office (IPO) administered by the office of the Controller General of Patents, Designs & Trade Marks. The information on patent applications, patent grants, designs, and trademarks is made public in the form of quarterly publications. Other firm level data comes from comes from Prowess CMIE database. The database provides firm level data compiled from annual reports of the firms listed on the Bombay Stock Exchange. An important feature of the study is that it employs a series of input-output tables to work out the Intra- and inter-industry linkages. This is unlike the previous empirical studies that calculate such linkages using a fewer input-output tables. The national input-output tables are taken from World Input-Output Database (WIOD). The data on sector level FDI comes from India Stat and is crossed checked with other sources that maintain FDI data like RBI, DIPP, and SIA. Owing to huge discrepancy between FDI approvals and actual FDI We, unlike other studies, use actual FDI inflows instead FDI approvals. In India, not all FDI approvals are actually realised.

3.1.2. Estimating best practice frontier and Incumbent TFP Change through DEA approach

Frontier analysis evaluates the efficiency of a firm in terms of distance from the industry's efficient frontier. The efficient frontier is a function that indicates the maximum attainable level of output corresponding to a given quantity of inputs. It represents the maximum quantum of output(s) that is produced from a specific amount of input(s) (e.g., labour and capital). Each firm's relative efficiency, based on the distance between the firm's actual output and the estimated "best practice" frontier is expressed as the ratio of the firm's observed output relative to the fully efficient output.

The method for computing technical efficiency of firms and thereby generating a best practice frontier for any industry or sector through a mathematical optimization model goes under the descriptive title of Data Envelopment Analysis (DEA). It employs linear programming technique to construct a frontier over the observed data such that the constructed frontier envelops all the data points as tightly as possible. In other words, DEA frontier is a linear surface or "piecewise hyper-plane" extrapolated from all efficient firms in the sample such that the inefficient firms are "enveloped" by the frontier.

To get the flavour of DEA, in figure 1 we analyse the simplest case of a single-output and single-input model. We compute the technical efficiency scores under the output-oriented DEA approach.[1] The X-axis and Y-axis respectively measure input and output quantities. Figure 1 depicts DEA frontier as a line emanating from origin *o*, passing through point '*a*' which correspond to the highest ratio of output to input. The area below the frontier consists of feasible yet inefficient input–output combinations. The points (*b* to *g*) lying below frontier, therefore, symbolize inefficient producers/firms, while as *a* represent efficient producer/firm since it lies on the frontier.[2]

[1] In DEA, there are two approaches to compute the efficiency of a producer/firm. One input oriented approach and other output oriented approach. In the former the distance from the frontier is computed horizontally while as in latter it is computed vertically.

[2] We assume the production technology has constant returns-to-scale (CRS) which means that a proportional change in a firm's inputs should lead to the same proportional change in a firm's outputs.

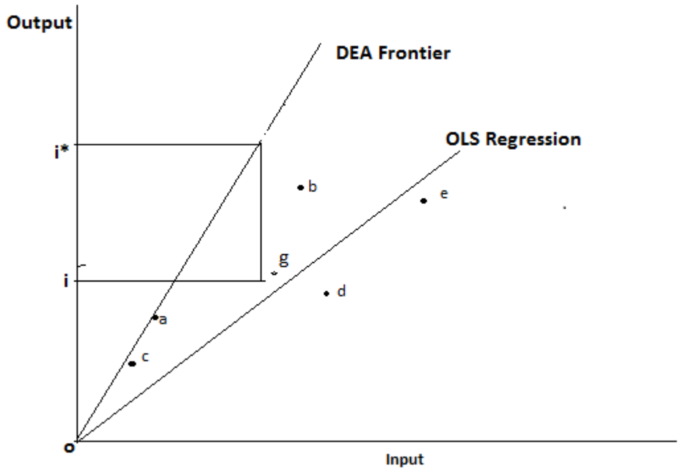


Figure 1. DEA Frontier

The OLS regression line with the intercept set at *o* is also drawn in Figure 1. OLS by not allowing for the inefficiency and assuming that deviations from the mean input-output correspondence are purely random would, therefore, underestimate the frontier.

The efficiency scores for firms *b* to *g* is measured by their distance to the frontier. For instance, the efficiency score for firm *g* is calculated as *oi* divided by oi^* which is the ratio of observed output level (what a firm produces) to the efficient output level (what it can produce). The value of the efficiency index for each firm ranges between 0 and 1, hence providing an indication of the degree of inefficiency of the firm. A value closer to 1 meaning more efficient while as a value closer to zero signifies the inefficiency of the firm. The value of unity indicates a firm is fully efficient and therefore located at the best frontier. The mathematical formulation of DEA is provided in appendix 1.

TFP change is computed by Malmquist productivity index (MPI). MPI measures the productivity changes along with time variations and can be decomposed into changes in efficiency and technology with DEA like nonparametric approach. Productivity decomposition into technical change and efficiency catch-up necessitates the use of a contemporaneous version of the data and the time variants of technology in the study period. Following Fare et al. (1994) the output oriented MPI[3] can be expressed as

$$MPI_O = \left[\left(\frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^t(x_t, y_t)} \right) \left(\frac{d_o^{t+1}(x_{t+1}, y_{t+1})}{d_o^{t+1}(x_t, y_t)} \right) \right]^{1/2}$$

Equation (3) is the geometric mean of two output oriented Malmquist TFP indices. One index uses period *t* technology and the other period *t+1* technology. It represents the productivity of a firm/producer with input-

[3] The subscript *o* in (5) denotes the orientation of MPI model. We use output oriented MPI, the input oriented MPI can be defined in a similar way as output oriented MPI presented here.

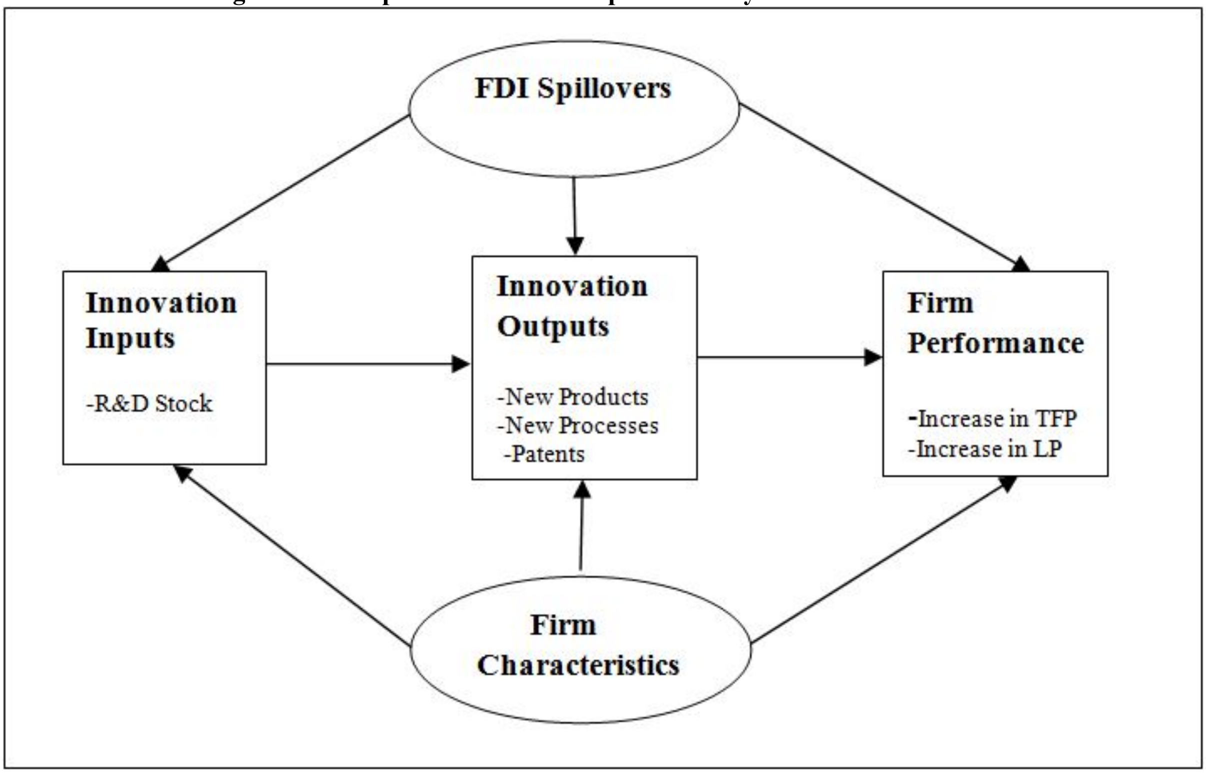
output combination (x_{t+1}, y_{t+1}) relative to the input-output combination (x_t, y_t). If the value of MPI turns out to be greater than one $(MPI_O > 1)$ it means a positive TFP growth of the firm from period *t* to *t+1*.

4. The Modelling Framework

The basic model is essentially an augmented version of Crepons' et al. (1998) model consisting of two different but related equations- the innovation equation and the productivity equation. In the former, we model innovation output (patenting) of a firm as a function of spillovers from different FDI types, distance to the frontier and their interactions. In the latter, innovation output along with other explanatory variables (spillovers from FDI, distance to the frontier and their interaction terms) enter as an exogenous variable to determine the changes in total factor productivity at the firm level. The purpose for inclusion of innovation output as an exogenous variable in productivity equation is to explicitly account for the fact innovation output influences the changes in productivity. Firms invest in research and development (R&D) to develop process and product innovations, which in turn contribute to their productivity. The model therefore encompasses two subsequently linked relationships: the innovation relation linking FDI spillovers to innovation output and the productivity relation linking innovation output and FDI spillovers to the changes in total factor productivity occurring at firm-level.

We, in fact, consider two versions of each of the equations– one where each of the dependent variables is modelled as a function of exogenous variables only and the other where along with exogenous variable; we include certain industry and firm specific controls that influence the variation in dependent variables.

Figure 1.Conceptual Model for Empirical Analysis



4.1.1. The innovation equation

We begin by establishing a functional relationship of innovation output with FDI spillover variables, distance to the frontier and their interaction terms. The firm-level innovation output is measured as the number of patent grants received by a firm over the period. The patent grant is essentially a count variable taking on non-negative integer values. The discrete non-negative nature of the patent counts makes linear regression models (LRMs) unable to provide the best fit of the count data, hence, such models are deemed to be inappropriate to handle count variables. The reason for ineptness to handle counts is the basic assumption of LRM such as normality of residuals and linear adjustment of the data that is no longer fulfilled. The usual way to deal with count data is to consider the Poisson regression model (Hausman et al. 1984).

Let p_{it} be the number of patent grants received by a firm in a year, and then p_{it} will have a Poisson distribution with parameter θ_{it} such that the probability to observe that a firm i receiving p_{it} patent grants conditional on exogenous variables (x_{it}) is given by:

$$P(p_{it}/x_{it}) = \frac{\theta_{it}^{p_{it}} e^{-\theta_{it}}}{p_{it}!}, \qquad p_{it} = 0,1,2,3,.... \qquad (1)$$

The parameter θ_{it} symbolizes the mean as well as the variance of the patent counts since for a Poisson model mean is always equal to the variance, i.e., $E(p_{it}) = Var(p_{it})$. The explanatory variables (x_{it}) enter the model by specifying a Poisson parameter θ_{it} such that $\theta_{it} = \exp(x_{it}\beta)$ where unknown parameter vector β is to be estimated. The conditional mean function of patent counts, given the exogenous variables, is therefore specified as:

$$E(p_{it}/x_{it}) = \exp(x_{it}\gamma) \qquad (2)$$

After incorporating the explanatory variables (2) can be written as:

$$E(p_{it}/fd_{jt}, prxm_{it}, ...) = \exp(\gamma + \gamma_1 \sum_{i}^{k} fd_{jt} + \gamma_2 prxm_{it} + \gamma_3 \sum_{i}^{m} fd_{jt} prxm_{it} + \lambda c_{ij} + \omega_t + \upsilon_i) \qquad (3)$$

In (3), the variables of interest include FDI entry variables $(\sum fd_{jt})$, proximity to the technology frontier $(prxm_{it})$, and their interactions $(\sum fd_{jt} prxm_{it})$. The term c_{ij} is a set of firm and industry specific controls, ω_t denotes year-specific effects and υ_i is for firm-specific effects. The subscripts i, j and t indicate incumbent firms, industries, and time respectively.

Although Poisson is a standard model for handling count data but the restrictive property of equidispersion, i.e., equality between first two moments makes it less applicable for practical purposes. In practice, the property of equidispersion rarely holds since patent counts show over dispersion (mean being greater than variance); thereby making the estimates obtained through Poisson regression biased (Gourieroux et al., 1984). The consequence of over-dispersion is the underestimation of standard errors which in turn results in inflated statistical significance. However, the Poisson estimates will still be asymptotically consistent. A further issue with Poisson modelling is that it does not allow for unobserved heterogeneity in the relationship between patent counts and explanatory variables. The negative binomial regression model (negbin) provides a better alternative to get around the issues associated with Poisson modelling for patent counts. The negative binomial estimator not only allows for the conditional mean to be different from conditional variance, but it also assumes that conditional mean is a product of a deterministic term and an error term that follows a gamma distribution.

The preponderance of zeros in our patent count sample raises yet another concern. The zero observations possibly result from two different data generating processes: firms that do not innovate at all and that attempt to innovate but fail to generate patents. The economic significance of the two types of zeros is quite different. Since our data set have excessive zeros, unusually more than would naturally be predicted by the standard count models such as Poisson and negbin (Lambert, 1992). Therefore, it is more appropriate to employ zero-inflated Poisson (ZIP) and zero-inflated negbin (ZINB) models for estimation purposes as they are better able to handle a large number of zero observations, thereby increasing the precision of estimates.

4.1.2. The productivity equation

The next equation in our model is a productivity function which measures the change in incumbent total factor productivity over the period. The productivity equation establishes that change in TFP of an incumbent is determined by FDI spillovers, distance to the frontier and their interactions. The productivity equation is related to the innovation equation in the sense that latter along with other exogenous variables enters as an independent variable in the former.

The empirical model closely follows the empirical model in Aghion et al. (2009). To establish that FDI entry affects incumbent productivity growth and that the extent of this effect depends on the location of the incumbent vis-a-vis to the technology frontier, the productivity equation takes the following functional form:

$$\Delta y_{it} = \beta + \beta_1 prxm_{it} + \beta_2 p_{it} + \beta_k \sum_{i}^{k} fd_{jt} + \beta_m \sum_{i}^{m} fd_{jt} prxm_{it} + \gamma c_{ij} + \omega_t + \upsilon_i \qquad (4)$$

The dependent variable Δy_{it} in (4) is the change in TFP at incumbent level computed through MPI. The right-hand side of (4) apart from including all exogenous and control variables that are in (3) also includes patent count as an explanatory variable.

4.1.3. Identification Strategy and Instruments

The key hypothesis to be tested is that FDI entry improves the innovative and productivity performance of incumbents located close to the technology frontier whereas it diminishes the innovation incentives and productivity of incumbents located further behind the technology frontier. However, before estimating the impacts of FDI on incumbent innovation and productivity, we need to look at the possible causal relation between FDI entry and incumbents innovative and productivity performance. There is a possibility that FDI may gravitate towards the incumbents/industries which have a history of coming up with innovations and are, therefore, branded as successful innovators. It is also possible that FDI entry may be inclined towards slowgrowing industries/sectors so as to gain a greater competitive advantage. In both the situations, FDI entry is likely to give rise to the problem of endogeneity, which if unaddressed, will lead to a bias in estimates. The paper employs the instrumental variable technique to tackle the issue of endogeneity.

We attempt to address the endogeneity issue by developing an alternative instrumental variable approach based on the starting business ratings of India compiled from various doing business reports published annually by the World Bank. The study, unlike others, comes up with the instruments for different categories of FDI. Earlier studies analyse the impact of aggregate FDI inflows on domestic productivity or innovation hence, a single instrument to address the endogeneity. However, the endeavour of this study is to examine the impact of different FDI types on incumbent innovation and productivity, therefore, the challenge is to come up with at least three different instruments each for three different FDI types. Horizontal FDI at the three-digit NIC-level is instrumented by starting business ratings which reflect the overall investment climate of a country. A better investment climate is likely to attract more global investment. The rationale behind instrumenting horizontal FDI by starting business ratings is that most of the horizontal FDI is market seeking. The driving force of market-seeking FDI, apart from market size, is how easy it is to establish a business in a host country. The starting business ratings based on components like- the number of procedures involved, associated time and cost, and the minimum capital requirements to start business-capture various aspects of business climate in a country. A better performance of hosts on these measures definitely makes them desirable destinations for foreign investment.

Most of the vertical FDI is efficiency seeking aimed at reducing production costs for MNCs. This type of FDI is mainly driven by relatively lower factor costs, i.e., locations with low-priced inputs or lower labour costs are believed to be favourite destinations for this category of investment. Based on this logic, vertical FDI is instrumented by hiring and firing index taken from various doing business reports. The index reflects costs associated with hiring and firing across destinations and hence can be viewed as a predictor of backward vertical FDI. In the case of forward vertical FDI, the foreign affiliates operating in a host country draw inputs from their parent companies, thus staying after the parent in the production chain. The process of drawing inputs from parents is likely to be influenced by the trading (import) costs across destinations. If trading costs are lower in a destination country, the likelihood of hosting more foreign companies' increases than if they are relatively higher. Keeping this in view, we instrument forward FDI by trading cost index. We expect a negative correlation between forward FDI and trading cost index implying countries with lower trading costs are favourite destinations for forward FDI.

4. Empirical Results

Before, we start discussing the main results; it is worth commenting on the mean values of patent grants, efficiency scores and malmquist TFP change provided in Table 1. The overall sample mean for patent grants is 1.20 implying that over the period each of the industry in our sample on an average has received a little more than one patent. However, there is a great deal of heterogeneity in the mean number of patent grants across the industries. The average is highest for basic metals with 4.53 grants followed by motor vehicles industry with 2.67 grants. The average grants for industries like fabricated metals, coke and petroleum, textiles, non-metallic minerals, leather and tobacco is well below the sample average. The average grants for fabricated metals is lowest with 0.05 grants followed by coke and petroleum with 0.08 grants.

As mentioned before, the output oriented DEA is employed to compute efficiency scores and malmquist TFP change for 17 industries comprising the sample. As the DEA methodology demands, a separate DEA model for each of the 17 industries is estimated under the assumptions of homogeneity.[4] The number of firms under analysis for each industry, the mean efficiency scores for each industry and the mean value for malmquist TFP change for each industry reported in Table 1 show a significant variation between the industries. The efficiency scores range between 0 and 1. Most of the industries under analysis show rates higher than 50% of the efficiency scores along the years of analysis. The highest score for technical efficiency is of the motor vehicle industry with an average score of 0.91 indicating that the industry is 9% inefficient. The score also indicates that the industry is 91% efficient. With the same level of resources, the industry can reach the best practice frontier by increasing its output level by 0.09 percentage points. The second highest efficiency score (0.85) is of other motor vehicle industry followed by basic metals. On the basis of the computed efficiency scores the lowest efficient industry is non-metallic minerals with an average efficiency score of 0.18, followed by coke and petroleum with an average efficiency score of 0.19. The average efficiency score for overall sample is 0.58 with 11 industries out of 17 (64.70%) having their average efficiency scores falling in the range of 0.58 - 0.91. The low averages of efficiency scores for some of the industries in the sample indicate the presence of inefficient firms in these industries.

The malmquist TFP depicting the change in TPF over a period has an overall sample average of 1.01 indicating an improvement in the overall TFP levels for the whole sample. However, average individual malmquist TFP scores exhibit variations between different industries reflecting heterogeneous changes in TFP levels over the years. The industry with highest improvement in TFP is electric equipment with the average malmquist TFP change of 1.14, followed by Chemicals and Chemical Products and motor vehicles each showing an average malmquist TFP of 1.13. On the contrary, the industry with lowest average malmquist TFP change is leather and related products with an average value of 0.79. The value of less than 1 for malmquist TFP change indicates deterioration in TFP levels while as a value greater than 1 signify improvements in TFP levels. In our sample most of the industries 10 out of 17 (58%) show an improvement in the TFP while as 7 out of 17 (42%) show a drop in the TFP levels over the study period.

[4] Three necessary conditions of homogeneity include; (a) the incumbents are engaged in the same process; (b) all incumbents are evaluated under the same measures of efficiency and; (c) all incumbents operate under the same conditions.

Table 1. Mean of Patent grants, efficiency scores and Malmquist TFP Change by Industry.

Industries	No. of firms	Patent Grants	Efficiency Score	Malmquist TFP Change
Motor Vehicles	17	2.67	0.91	1.13
Other Motor Equipment	28	1.12	0.85	1.03
Electric Equipment	37	1.61	0.72	1.18
Computer, Electronics and Optical Products	27	1.14	0.75	1.09
Machinery	48	1.45	0.61	0.85
Food Products	37	1.11	0.64	0.96
Chemicals and Chemical Products	94	1.15	0.58	1.14
Pharmaceuticals	63	1.04	0.66	0.97
Coke and Petro Products	10	0.08	0.19	1.01
Textiles	31	0.12	0.49	0.98
Fabricated Metal Products	14	0.05	0.23	1.04
Basic Metals	21	4.53	0.81	1.05
Non-Metallic Mineral Products	34	0.75	0.18	0.99
Rubber and Plastic Products	28	1.48	0.74	0.98
Leather and related Products	17	0.41	0.32	0.79
Paper	10	1.43	0.81	1.11
Tobacco	04	0.39	0.24	0.92
Total	520	1.20	0.58	1.01

4.1.1. FDI entry and Patenting

We start by considering the impact of FDI entry on incumbent innovation and then focus on how proximity to the best practice frontier affects conditions the FDI entry effects on innovation and TFP. The descriptive statistics of the variables included in the study is presented in Table 2. Before discussing the empirical estimates of patent grants presented in Table 6, a key identification issue that needs attention is the endogeneity of FDI entry. The endogeneity of the regressors of interest is confirmed by Durbin (score) and Wu-Hausman tests, where the null that entry variables are exogenous is rejected. The p-value of both the test statistics reported in Table 3 are highly significant, so we must continue to treat entry variables as endogenous. The first stage regression results with starting a business index, hiring index and trading cost index as instruments for horizontal, backward and forward FDI are reported in Table 4. From the regression coefficients, it appears that the instruments significantly determine the level of FDI types entering into the Indian manufacturing sector. The significance level in first stage results implies their strong relationship of instruments with FDI types, thereby rejecting any issues related to weak identification- a problem were estimators perform poorly since instruments are weakly correlated with endogenous regressors. The relevancy and validity of instruments is further confirmed by first stage regression summary statistics reported in Table 5. Although the significance of instruments is established through R^2 and F values, however, relying on R^2 and F statistic values is not sufficient. A better statistic to identify the relevance of instruments is partial R^2 and Shea Partial R^2 (Shea, 1997 and Baum et al., 2003). Both the statistics support the relevance of our instruments.

Table 2. Descriptive statistics of the variables.

Variable	Obs.	Mean	SD	Min	Max
Patent grants	7280	1.20	5.27	0.00	168.00
Total Factor Productivity (TFP)	6760	1.28	0.93	0.05	4.23
R&D Intensity	7280	0.91	0.76	0.01	4.41
Horizontal FDI	7280	0.29	0.11	0.01	0.59
Backward FDI	7280	0.41	0.43	0.05	0.49
Forward FDI	7280	0.16	0.21	0.02	0.37
Proximity to Frontier	7280	0.07	0.17	0.01	0.93
Export intensity	7280	13.03	18.62	0.00	101.41
Import intensity	7280	19.06	19.19	0.00	104.95
Firm size	7280	3.48	0.68	1.10	6.24
Firm age	7280	1.59	0.25	1.00	109.00

Table 3. Tests of endogeneity

Durbin (score) chi2 (3)	= 81.321 (p = 0.000)
Wu-Hausman F (3, 6873)	= 26.168 (p = 0.000)

Table 4. FDI Entry: First Stage Regression Results

Dep. Var.	*Horizontal FDI-$_1$ (l_1hfd)*	*Backward FDI-$_1$ (l_1bfd)*	*Forward FDI-$_1$(l_1ffd)*
Starting business ratings (SBR)^I	0.079***(0.024)		
Labour Hiring index (HI)^I		0.103***(0.039)	
Trading costs index (TCI)^I			0.067**(0.029)
Other exogenous variables	Yes	Yes	Yes
Time effects	Yes	Yes	Yes
Establishment effects	Yes	Yes	Yes

Robust Standard errors are in parentheses
****, **,*denote significance levels at 1, 5and 10 percent levels respectively.*
Super subscript I associated with SBR, HI and TCI indicates inverse of these variables.

Table 5. First-Stage Regression Statistics

Test Statistic	R-sq	Adjusted R-sq	Partial R-sq	Shea's Partial R-sq	F (3,6877)	Prob >F
l_1hfd	0.519	0.519	0.397	0.327	1487.384	0.000
l_1bfd	0.833	0.833	0.803	0.697	9568.528	0.000
l_1ffd	0.337	0.332	0.256	0.171	787.491	0.000

In Table 6 we present estimates obtained from ZIP and ZINB models. The empirical estimates of patent grants support the hypothesis that FDI stimulates the innovative performance of incumbents specifically when they are located near the best practice frontier. The impact is pronounced for incumbents operating in upstream sectors as well as for incumbents that operate in the same three-digit sector in which entry occurs. However, the impact seems to be insignificant for the firms operating in downstream sectors.

As is evident from the estimates reported in Columns 1 and 2 of Table 6 that sectoral FDI inflows positively affect the firm level patenting, suggesting that the rise in FDI inflows enhances the incumbents' propensity to patent. The estimated coefficients for *hfd* in columns 1 and 2 are significant at 5% level while as the coefficients on *bfd* appear significant at 1% level implying that innovative activities of firms in upstream sectors benefit more than those active in the same three-digit sector. The statistical significance of *bfd* suggests the existence of inter-industry effects in Indian manufacturing sector. It implies that backward FDI (linkages between foreign affiliates and their domestic suppliers) enhance the innovative performance of the firms working in the supplying sectors. One potential explanation for such a finding is that multinationals help local suppliers to enhance their production process by providing them necessary assistance in the form of employee training and technology. Our result corroborates with Javorcik (2004), and Blalock and Gentler (2008). The authors report the existence of spillovers from vertical FDI via backward linkages. In contrast to *bdf*, coefficients on Forward FDI *(ffd)* appear significant at 10% level in only one of the specifications; however the significance disappears upon the inclusion of controls in the regression (Row 3 of Table 6). This implies forward FDI hardly has any impact on the patenting activity of firms operating in downstream sectors.

To analyse the role of proximity to technology frontier in FDI induced spillovers on incumbent innovation we allow for the interaction between FDI types with proximity to the frontier and find it positively correlated with the incumbent patenting. The results suggest that spillovers on innovation materialise in case incumbents lie close to technology frontier and these incumbents happen to be ones with a higher technical efficiency. It indicates that technical efficiency of incumbents is a prerequisite for assimilating the technical know-how, marketing expertise and other benefits that accrue to the host country firms, as a result, of advanced foreign entry.

Table 6: Table 6: ZIP and ZINB estimates for patent counts.

Dep. Var. Patent grants	(1) ZIP	(2) ZIP	(3) ZIP	(4) ZINB	(5) ZINB	(6) ZINB
l_1hfd	0.997** (0.478)	1.123** (0.789)	1.876** (0.849)	0.819** (0.467)	1.643** (0.819)	1.449** (0.599)
l_1bfd	0.588*** (0.065)	0.547*** (0.114)	0.869*** (0.012)	0.584*** (0.068)	0.522** (0.121)	0.854*** (0.171)
l_1ffd	0.659 (0.912)	0.773 (0.786)	1.447* (0.656)	0.673 (0.901)	0.619 (0.961)	1.089 (0.982)
l_1prxm	-0.074** (0.046)	-0.078* (0.063)	-0.093* (0.071)	-0.047** (0.028)	-0.055** (0.029)	-0.071* (0.059)
l_1hfd*l_1prxm		0.091** (0.034)	0.097** (0.049)		0.126*** (0.059)	0.272*** (0.110)
l_1bfd*l_1prxm		0.087** (0.044)	0.048** (0.117)		0.138** (0.077)	0.089** (0.023)
l_1ffd*l_1prxm		0.510 (0.396)	0.286 (0.206)		0.201 (0.507)	0.156 (0.380)
Lnrd			0.577*** (0.129)			0.675*** (0.247)
Lns			0.128 (0.127)			0.174 (0.183)
Ep			0.009** (0.002)			0.013** (0.006)
Im			0.029 (0.026)			0.012 (0.013)
Lnag			0.074* (0.069)			0.086* (0.079)
Dpp			-0.061* (0.051)			-0.073* (0.064)
log pseudolikelihood	-2365.55	-2338.99	-2211.95	-1163.17	-1160.01	-1141.82
Wald Chi^2	466.48	582.18	730.53	534.71	583.58	876.34
Prob>chi^2	0.00	0.00	0.00	0.00	0.00	0.00
no. of obs.	7280	7280	7280	7280	7280	7280

Robust Standard errors are in parentheses
****, **,*denote significance levels at 1, 5and 10 percent levels respectively.*
The log- likelihood values for the ZIP and ZINB models include the log -likelihood of the probit model.
Firm fixed effects and time effects included.

In Table 7, we allow for the endogeneity of the FDI types, replacing them with their respective instruments. The IV estimates confirm that the effect of FDI entry on incumbents' innovation activities depends on incumbents' proximity to the technology frontier. The result holds for incumbents that operate in the same sector as MNC as well as for the incumbents that operate in upstream sectors and hence linked to MNCs through backward linkages. It entails that FDI spillovers on innovation exist only for the incumbents operating near to the frontier since they are able to assimilate the new knowledge and technology brought about by FDI. However, laggards operating away from the frontier fail to benefit from FDI. Owing low technical efficiency they are unable to absorb the technology shocks resulting from entry of foreign firms into the domestic market.

The coefficient estimates of control variables also need some attention. R&D intensity *(lrd)* is positive and significant across all the specifications, indicating a strong positive association between R&D and the number of patents received at the firm level. R&D efforts help firms to assimilate the foreign technologies by enhancing their absorptive capacity resulting into increase in effectiveness of external technology spillovers. The impact of export intensity on innovation is statistically significant, suggesting that exporting firms patent more relative to firms that serve only local markets. Our findings match with Banga and Wilmore (1991), for Brazil, Kumar, and Saqib (1996), for India, and Siedschlag and Zhang, (2014), for Ireland. The latter group of authors claims that exporting firms are more likely to implement product innovations. Age appears to have a meek positive impact on the patenting behaviour implying more experienced firms patent more than their younger counterparts. The estimated coefficients on import intensity and firm size are statistically insignificant, albeit positive.

We do not find results in support of the assumption that stronger patent laws induce greater patenting activity. The estimated coefficient on the dummy denoting introduction of product patents is negative but marginally significant, implying that stronger patent laws deter the patenting activity of firms operating in Indian manufacturing sector. The probable reason could be the restrictions on local imitation or reverse engineering due to enforcement of IPRs that seem to be at par with international standards.

Table 7: IV estimates of patent grants.

Dep. Var. Patent grants	(1) ZIP	(2) ZIP	(3) ZIP	(4) ZINB	(5) ZINB	(6) ZINB
l_1hfd	1.309** (0.728)	1.417** (0.704)	1.229** (0.752)	1.198*** (0.350)	1.515*** (0.521)	1.388*** (0.451)
l_1bfd	0.099*** (0.019)	0.066*** (0.014)	0.054*** (0.012)	0.039** (0.013)	0.044** (0.017)	0.037** (0.019)
l_1ffd	0.133 (0.120)	0.139 (0.126)	0.157 (0.123)	0.154 (0.132)	0.172 (0.161)	0.168 (0.157)
l_1prxm	-0.098** (0.055)	-0.107* (0.078)	-0.109* (0.086)	-0.044* (0.027)	-0.059* (0.035)	-0.051* (0.043)
*l_1hfd*l_1prxm*		0.194*** (0.069)	0.142*** (0.074)		0.166*** (0.099)	0.172*** (0.092)
*l_1bfd*l_1prxm*		0.127** (0.068)	0.133** (0.079)		0.153** (0.086)	0.139** (0.073)
*l_1ffd*l_1prxm*		0.198 (0.191)	0.176 (0.163)		0.212 (0.209)	0.201 (0.198)
lnrd			0.459*** (0.166)			0.475*** (0.147)
lns			0.199* (0.144)			0.174 (0.153)
ep			0.006* (0.003)			0.009** (0.003)
im			0.019 (0.016)			0.012 (0.013)
lnag			0.064** (0.043)			0.086** (0.049)
pv			-0.086 (0.081)			-0.092 (0.087)
log pseudolikelihood	-2424.48	-2391.71	-2225.09	-1166.08	-1161.59	-1139.81
Wald Chi^2	513.76	589.82	941.41	520.50	561.24	868.82
Prob>chi^2	0.00	0.00	0.00	0.00	0.00	0.00
no. of obs.	7280	7280	7280	7280	7280	7280

Robust Standard errors are in parentheses
****, **,*denote significance levels at 1, 5and 10 percent levels respectively.*
The log- likelihood values for the ZIP and ZINB models include the log -likelihood of the logit model.
Firm fixed effects and time effects included.

4.1.2. FDI entry and TFP growth

Next in Table 8, we describe the effect of FDI entry on incumbent TFP growth. Columns 1, 2 and 3 show OLS estimates of the variables of interest from standard FE model.[5] Columns 4, 5 and 6 report empirical estimates obtained from the IV-FE approach. The empirical results across all specifications reflect a positive and significant correlation of FDI entry with the subsequent TFP growth in incumbents. The estimated coefficients for both the horizontal FDI *(hfd)* and backward FDI *(bfd)* appear significant across all specifications. The IV estimates on *hfd* shows a marginal decrease in magnitude (columns 4, 5 and 6 in table 8) but the significance level remains same from FE specification to IV specification. The significance level for *bfd* remains constant at 1% throughout although with slight drop in the magnitude of estimates. This suggests that FDI entry not only spurs the productivity growth in the firms operating in upstream sectors but it also improves the productivity of the firms active in the same three-digit sector as MNC. The statistical significance of *hfd* and *bfd* suggests the existence of intra as well as inter-industry productivity spillovers in Indian manufacturing sector. In contrast to *bfd* and *hfd*, coefficients on Forward FDI *(ffd)* appear significant at 10% level in FE specification but the significance level altogether disappears in IV specification, suggesting a lack of productivity spillovers on firms operating in downstream sectors.

So far we assume that FDI entry affects all incumbents similarly. The assumption seems to be very strong since entry may not equally affect the productivity of incumbents. We now check the prediction from Aghion et al. (2009) that FDI effects on incumbent productivity vary depending on their proximity to/distance from the technology frontier. To check this prediction the FDI variants are interacted with the proximity to frontier variable. There appears to be a significant positive correlation between all the entry variables and productivity growth of incumbents that are located near to the frontier. Even after controlling for the endogeneity of entry variables, the results more or less remain same, supporting the view that FDI effects on incumbents are heterogeneous, with firms near the frontier benefiting more relative to ones away from the frontier. The evidence is not different from the findings of Aghion et al., (2009) based on the UK data. Our results also align with the views of Glass and Saggi (1998) that for local firms to benefit from FDI, they need to have achieved a certain threshold level of absorptive capacity.

[5] We have tested for random effect and fixed effect specifications. The value of the Hausman test static is 169.891 (p=0.000) reflecting that FE model is preferable.

Table 8. Change in TFP: FE and FE-IV Estimates.

Dep. Var. ΔTFP_{it}	(1) FE	(2) FE	(3) FE	(4) FE-IV	(5) FE-IV	(6) FE-IV
l_1hfd	2.970*** (1.254)	3.015*** (1.581)	3.678*** (1.621)	2.325*** (0.433)	2.550*** (0.666)	2.488*** (0.700)
l_1bfd	1.373*** (0.542)	1.526*** (0.554)	1.602*** (0.713)	1.117*** (0.128)	1.173*** (0.173)	1.224*** (0.208)
l_1ffd	0.398 (0.434)	0.705 (0.746)	0.767 (0.783)	0.279 (0.520)	0.272 (0.527)	0.294 (0.554)
l_1prxm	-0.081** (0.044)	-0.125* (0.068)	-0.129* (0.070)	-0.064* (0.040)	-0.052 (0.046)	-0.094* (0.051)
l_1hfd*l_1prxm		0.771*** (0.275)	0.748*** (0.277)		0.264*** (0.104)	0.266*** (0.109)
l_1bfd*l_1prxm		0.334*** (0.116)	0.355*** (0.119)		0.592*** (0.252)	0.602*** (0.257)
l_1ffd*l_1prxm		0.045 (0.063)	0.053 (0.050)		0.068 (0.059)	0.071 (0.058)
lnrd			0.204*** (0.097)			0.109*** (0.049)
lns			0.121 (0.129)			0.174 (0.153)
ep			0.007** (0.001)			0.009** (0.003)
im			0.011 (0.013)			0.012 (0.013)
lnag			0.091 (0.079)			0.086** (0.049)
pv			-0.011 (0.013)			-0.012 (0.037)
R^2	0.085	0.079	0.091	0.020	0.049	0.011
F-statistic/wald-chi^2	9.75	8.80	6.20	128.36	161.44	168.12
Prob>F/prob>chi^2	0.00	0.00	0.00	0.00	0.00	0.00
no. of obs.	6760	6760	6760	6760	6760	6760

Robust Standard errors are in parentheses

****, **,*denote significance levels at 1, 5and 10 percent levels respectively.*

Firm fixed effects and time effects included.

6. Conclusion and Policy Recommendations

The rationale of the study is to examine the impact of FDI spillovers on the innovative performance of firms operating in the Indian manufacturing sector. FDI can conceivably induce more innovation in the Indian manufacturing, or could undermine it. Using a panel data analysis, we employ a variety of parametric count data models to study the changes in the patenting activity of 942 incumbent firms operating in the manufacturing sector of India. The main determinants of patent production function appear to be horizontal FDI, backward FDI, firm size, firm age, R&D intensity and export intensity.

The econometric analysis uncovers the existence of intra-industry and inter-industry spillovers in Indian manufacturing sector. However, intra-industry innovation spillovers are relatively moderate than intra-industry spillovers on productivity. The existence of intra-industry spillovers suggests that benefits from horizontal FDI to the firms active in same sectors as the MNCs, occur through competition, demonstration and labour circulation. Conversely, inter-industry spillovers arising from backward FDI has a profound impact on the innovative activities of supplying firms in upstream sectors through backward linkages. Innovative performance of the firms' active in downstream sectors seems not to be affected by forward FDI indicating the absence of spillover effects to the firms' residing in downstream industries.

Based on the empirical findings an important policy implication the study offers is that FDI related public policies instead of aiming at attracting huge aggregate inflows should rather be tailored to promote and facilitate FDI projects with more vertical linkages (particularly backward linkages). This will enhance the interactive process between MNCs and domestic firms, thereby generating more inter-industry spillovers to domestic firms. This implies that policy makers should motivate MNCs to engage in local sourcing. Second, strict enforcement of property rights, on one hand may intensify competition thus helping domestic firms to assimilate spillovers through efficient use of available resources and technology. On the other hand, it may restrict the practice of imitation and reverse engineering the MNCs output, thereby depriving domestic firms to avail the full benefits of FDI. Therefore, policymakers need to devise such policy/policy-mix that while augmenting competition effect may not necessarily mitigate the imitation effects.

The study despite having a number of policy implications suffer from certain limitations that should be borne in mind while discussing its potential policy implications. The FDI-associated benefits accruing to firms operating in Indian manufacturing are realised through intra-industry and inter-industry effects. In intra-industry case, the FDI-related spillovers arise through a combination of competition effects, imitation/demonstration effects, and labour mobility. However, under the constraints of Indian data availability, it is not possible to unravel the different mechanisms underlying the observed spillovers. Second, the number of new products/processes introduced or new product sales are preferably better measures to gauge the innovative performance of firms than patent grants. There is always a possibility that some of the firms may not patent their new products/processes, therefore, evaluating the innovative performance on the basis of patent grants is a bit noisy.

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Table 6. Variable Description and Data Sources.

Variable	Measurement	Data Source
Innovation	Number of patents granted to a firm over the period.	IPO Publications
Total Factor Productivity change	Malmquist Productivity Index computed using DEA	-
Proximity to the Frontier	Inverse of the distance function calculated using DEA	-
R&D Intensity	Annual R&D spending of a firm in millions of rupees as a portion of total annual sales.	PROWESS
Horizontal FDI	Ratio of the output of foreign firms to industry output.	DIPP
Backward FDI	Share of the total output of an industry that is sold to foreign firms in downstream industries calculated using Input-Output tables.	WIOD
Forward FDI	Foreign share of total output of an industry that is sold to domestic firms in downstream industries calculated using Input-Output tables.	WIOD
Size	Log number of workers.	PROWESS
Age	Year of incorporation.	PROWESS
Export Intensity	Exports to sales turn-over.	PROWESS
Import Intensity	Imports to sales turn-over.	PROWESS