Indian Suppliers' R&D Experience and Innovation Success

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Abstract

This paper analyses the role of Indian suppliers' R&D experience in their innovative success using a representative sample of Indian suppliers for the period 2000-2013. Using count data models and within an innovation production function approach, we investigate the influence of Indian suppliers' R&D experience in the achievement of innovative results. To estimate R&D experience, partially unobserved, we estimate a duration model and use the obtained results and a non-parametric procedure to impute R&D experience when unobserved. We obtain that R&D effectiveness increases along the R&D history of the Indian supplier.

Keywords: innovation, accumulation of knowledge, R&D experience, duration models, count data models

1. Introduction

It may be broadly accepted that the acquisition of technological knowledge is a dynamic, cumulative learning process which relies, to a great extent, upon the continuity of the performance of R&D activities within the Indian suppliers. There is a growing literature on suppliers' innovative persistence that supports this view. For instance, according to Cefis and Orsenigo (2001), sustained innovative persistence needs to be supported by a systematic and continuous process of accumulation of resources and competencies, so that persistence in carrying out these activities might be even more important than the size of R&D expenditures. The importance of knowledge accumulation in explaining innovation has been developed by the approach of evolutionary theory (Nelson and Winter, 1982). In particular, by investing in R&D projects, suppliers develop abilities in the form of knowledge, both scientific and informal know how, that may be used to develop further innovations at consecutive times. According to this view, suppliers benefit from dynamic increasing returns in the form of learning-by-doing, learning-to-learn or scope economies in the production of innovations (Cohen and Levinthal, 1989). More recently, the idea of knowledge cumulativeness, which may be defined as the degree by which the generation of new knowledge builds upon current knowledge, has been described by Malerba (2005). Innovative success yields profits that can be reinvested in R&D, thereby increasing the probability to innovate again.

In this paper, we argue that the time dimension of the cumulative process of R&D knowledge goes beyond the effect of R&D capital stock. Our hypothesis is that R&D experience, measured as the number of years devoted to the performance of R&D activities is a driver in the innovation success. In particular, we consider that the effect of R&D

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in the achievement of innovations depends on R&D experience, that is, on the time that the Indian suppliers have been engaged in R&D activities. Although it may be broadly accepted that suppliers' experience in R&D activities is an important key determinant of their innovative success, there is a lack of empirical evidence that explicitly deals with this issue. One strand of the empirical literature has focused on the analysis of the relationship between suppliers' R&D input (measured as R&D capital stock, R&D expenditures, or as the ratio of R&D expenditures to sales or revenues) and innovative output (measured, e.g., in terms of patents or productivity). In particular, the relationship between innovation, R&D and patents has been surveyed by Griliches (1990), who reports a robust R&D-patents relationship at the supplier level. More recently, the availability of Community Innovation Surveys (CIS) surveys throughout the European Union and in Norway and Iceland has given rise to a number of empirical works that also analyse the innovative performance of suppliers by relating innovation inputs to innovation outputs. Some of these works are those of Klomp and van Leeuwen (2001) for the Netherlands, Sandven and Smith (2000) for Norway, Lööf and Heshmati (2001) for Sweden, or Mairesse and Mohnen (2005) and Kremp and Mairesse (2004) for France. However, these empirical studies do not explicitly take into account the possibility that the effectiveness of the innovation inputs changes as firms accumulate experience in the performance of their innovation activities. A more recent strand of the literature has been devoted to the analysis of innovation persistence, both in the achievement of innovations (see, e.g., Geroski et al., 1997, Malerba et al., 1997, Cefis, 2003) and in the performance of R&D activities (Máñez et al., 2005, 2006, Peters, 2006). These empirical studies, however, have not directly modelled the continuity in the performance of R&D activities as an additional driver of innovation success. The aim of this paper is to test the hypothesis that R&D experience matters, i.e., that, due to the cumulative nature of technological knowledge, the number of years devoted to the performance of R&D activities affects positively suppliers' innovation success (measured as patents and product innovations). We therefore argue that suppliers with a greater experience in performing R&D activities achieve a higher effectiveness of their R&D investments. We use for this purpose a representative sample of the population of Indian suppliers for the period 2000 to 2013. The dataset is drawn from the Indian Industry Survey, a survey carried out annually that provides detailed information at the supplier level. We first analyse suppliers R&D patterns in order to determine the duration of suppliers' R&D spells, i.e. periods of time during which suppliers perform R&D activities in a continuous way. To estimate such (left) censored R&D spells, we implement a three steps procedure. First, we estimate a duration model to identify suppliers and industry characteristics affecting R&D durations; secondly, and as a necessary intermediate step, we directly use the duration model results to predict expected durations for right censored spells (still in progress at the end of our sample observation window); thirdly, the information on complete spells and estimated right censored spells is used to non-parametrically impute durations to left-censored spells. Once we have estimated the R&D experience of Indian suppliers as described above, we proceed to estimate, within the framework of an innovation production function and using count data models, the influence of suppliers' accumulated R&D experience on their R&D innovative effectiveness. To the best of our knowledge, this paper is the first attempt to empirically address, in a direct and explicit way, this issue, and this is the main contribution of this paper to the existing literature. Our results indicate that, after controlling for R&D capital stock and other suppliers' individual heterogeneity, suppliers' R&D effectiveness rises with the R&D experience, that is, with the accumulation of technical skills and knowledge that emerge for as long as suppliers R&D investments continue over time. In addition to past R&D experience, the performance of informal innovation activities, and the technological intensity of the industry in which the supplier operates, have been found to be significant determinants in the achievement of innovations. These findings may contribute to a better understanding of the cumulative process of learning and the importance of R&D experience in the effectiveness of R&D investments, and may be a guide for policy makers in the design of policy measures to be implemented in order to stimulate the production of R&D knowledge. In particular, given that R&D experience matters for innovation, our results suggest the convenience of implementing measures aimed at inducing suppliers to engage in R&D activities in a continuous way. Among these measures, a technological policy planed within a medium run perspective, or measures designed with the aim of creating a stable institutional framework, could help suppliers to persistently perform innovative activities.

The rest of the paper is organised as follows. In section 2, we present the empirical model and the econometric procedure, where we outline the empirical framework we use throughout the paper. Section 3 presents the data. Section 4 is devoted to the estimation of suppliers' R&D experience, including the estimation of a duration model, the calculation of "out of sample" predictions for right censored spells, and non-parametric predictions for left and left-and-right censored spells. Section 5 describes the estimation of the innovation production function. Finally, section 6 concludes.

2. Empirical Model and Econometric Procedure

Our main hypothesis to be tested relies on the idea that the effectiveness of R&D activities may vary with the R&D experience of the supplier, that is, with the accumulation of knowledge that takes place along with the research effort that is undertaken. Technical skills and learning-by-doing accumulated with time may not be properly measured by the standard R&D inputs considered by the empirical literature that has tried to explain the factors underlying the achievement of innovation results. We try in this paper to measure the extent to which this R&D experience matters in determining the effectiveness of R&D activities. Our approach is based on the concept of an innovation production function that can, in a very general form, be expressed as follows

$$N_{it} = f(x_{it}, \beta) \qquad (1)$$

where N_{it} stands for any chosen indicator of innovation outcomes and x_{it} represents the vector of innovation inputs in the equation. In particular, the parameter vector β may be decomposed as

$$\beta = [\beta_1(E_{it}), \beta_2] \qquad (2)$$

where β_1 is the parameter that measures the "innovative effectiveness" of the R&D input, E_{it} stands for firms' experience, and β_2 stands for other inputs' parameters. Notice that we write $\beta_1(E_{it})$, so that the effect of R&D in the achievement of innovation outcomes depends on R&D experience, that is, the time the firm has been developing R&D activities. The econometric approach to estimate the parameters in (1) is conditioned by the kind of data used to measure technical success, that is, the output of the innovation process (N_{it}). By far, the measure used more frequently is the number of patents registered by the supplier. In the present work two alternative measures for innovation output will be used: the number of patents registered, and the number of product innovations introduced by the supplier during the period under analysis. These two measures share two common features: both of them are event counts (non-negative integers) for unit i during the time period t, and in any given year many suppliers do not register patents or do not introduce innovations. The Poisson distribution is often a reasonable description for such count data. The basic Poisson probability specification is

$$\Pr(N_{it} = n_{it}) = f(n_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{n_{it}}}{n_{it}!} \quad (3)$$

We may model the single parameter of the Poisson distribution function, λ, as a function of our explanatory variables, x, and parameters, β, in the standard fashion

$$\lambda_{it} = \exp(x_{it}\beta) \quad (4)$$

It is easily shown that

$$E[N_{it} | x_{it}] = Var[N_{it} | x_{it}] = \lambda_{it} = \exp(x_{it}\beta) \quad (5)$$

so that λ_{it} represents the arrival rate of innovations per firm per year and also the expected number of discoveries per firm per year. Taking logs in (5) we get

$$\log E[N_{it} | x_{it}] = \log \lambda_{it} = x_{it}\beta \quad (6)$$

If the explanatory variables are used in logs, the estimated β are the elasticities of the expected number of innovations with respect to these variables. We will consider $x_{it} = (R_{it}, E_{it}, z_{it})$ where R_{it} is knowledge capital (derived from the flow of real R&D investments), E_{it} is the suppliers R&D experience, and z_{it} stands for an index of other inputs and, possibly, some control variables to be included in estimation. In our case, expression (5) will take the form

$$\lambda_{it} = A(t) R_{it}^{\beta_1(E_{it})} \exp(z_{it}\beta_2) \quad (7)$$

that is, the estimated function has a direct proportionate relationship between the R&D capital and innovation counts mediated by a multiplicative set of variables hypothesized to shift the distribution of expected innovation results. We now give a specific functional form to the relationship $\beta_1(E_{it})$ as follows

$$\beta_1(E_{it}) = \alpha_0 + \alpha_1 E_{it} + \alpha_2 E_{it}^2 \quad (8)$$

that is, a second order polynomial on E to allow for non lineal effects, which leads to the following expression for (7)

$$\lambda_{it} = A(t) R_{it}^{(\alpha_0 + \alpha_1 E_{it} + \alpha_2 E_{it}^2)} \exp(z_{it}\beta_2) \quad (9)$$

and, taking logs,

$$\begin{aligned} \log \lambda_{it} &= \log A(t) + (\alpha_0 + \alpha_1 E_{it} + \alpha_2 E_{it}^2) \log R_{it} + z_{it}\beta_2 = \\ &\log A(t) + \alpha_0 \log R_{it} + \alpha_1 E_{it} \log R_{it} + \alpha_2 E_{it}^2 \log R_{it} + z_{it}\beta_2 \quad (10) \end{aligned}$$

As long as α_1 and α_2 are different from zero, we will be confirming our hypothesis that R&D experience matters in determining the effectiveness of the R&D capital. In order to proceed further we need to solve a problem for the R&D experience variable. To see the problem more clearly we can have a first look at Figure 1 (that will be explained in more detail in section 4.1). In this figure, the horizontal axis shows the passage of time, and the length of each horizontal line shows the time spent on R&D activities. If the year 2000 represents the first year a supplier is observed, and the supplier reports R&D investment for this year, we do not know for how long it has been doing so, which implies a great limitation to our possibility of measuring the R&D experience for this type of suppliers. This made us to think on a procedure to estimate such (left) censored R&D experiences.

3. Data

The data are drawn from the Indian Industry Survey, a representative annual survey of Indian suppliers carried out since 2000. In the base year, 2000, suppliers were chosen using a selective sampling scheme with different participation rates depending on supplier size. All suppliers with more than 200 employees (large suppliers) were requested to participate and the participation rate reached approximately 70% of the number of suppliers in the population. Suppliers that employed between 10 and 200 (small suppliers) were randomly sampled by industry and size strata, holding around 5% of the population. The sample used in this paper covers the period 2000 - 2013. We are endowed with a sample of 6,627 observations, corresponding to 671 suppliers.

4. The Estimation of R&D Experience

4.1. R&D Duration Model

The unit of observation in this section is the R&D spell, defined as the number of uninterrupted years a supplier invests in R&D. Figure 1 presents our observation window (period of time for which we follow suppliers R&D patterns), corresponding to the period 2000 - 2013. Furthermore, it provides visual and simplified information about the sample distribution, number and types of R&D spells. The total number of spells in our sample is of 985 spells.

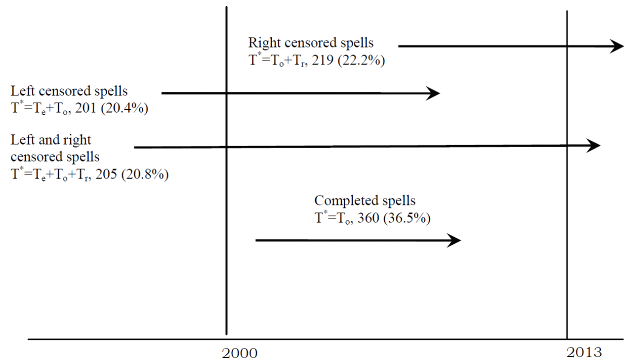

Figure 1. Sample distribution, number and types of R&D spells

We denote with T_e (elapsed duration) the length of time from the beginning of the spell still in progress at the time the supplier is incorporated to the survey, to this year of incorporation. We denote with T_o (observed duration) the observed spell duration over the observation window, and T_r (remaining duration) the length of time from 2013 to the end of the R&D spell. In Figure 1, each line represents a different R&D spell that suppliers may experience. The actual duration of the spell T* is measured by the length of the line. We start up for estimation with 579 spells (1666 observations). After deleting observations for which some of the relevant variables in the duration model were missing, we end up with 1653 observations corresponding to 569 spells. The specification of the model includes a number of variables that are considered to be relevant in determining the continuity of the performance of R&D activities. In addition, given that the duration model is a first step in order to obtain the parameter estimates that will be used for prediction purposes in the next sections, we have avoided the inclusion of highly time varying variables and/or variables with a clearly increasing or decreasing trend.

Table 1. Maximum likelihood estimates for the discrete time proportional hazard model

cloglog with Gamma individual unobserved heterogeneity and Weibull type duration dependence		
	Coefficients	p-value
Ln(t)	0.305	0.72
Food and tobacco	-1.189	0.23
Beverages	-1.673	0.15
Textiles	-1.385	0.21
Leather and shoes	-2.747*	0.08
Wood	-2.579	0.11
Paper	-1.739	0.16
Printing	-0.395	0.70
Chemical products	-1.983	0.11
Rubber and plastic	-1.876	0.19
Non metallic miner	-1.618	0.17
Metallurgy	-0.077	0.94
Metallic products	-0.858	0.38
Machin. and mech. eq.	-1.376	0.23
Office machines	-1.026	0.57
Electronic	-2.137	0.12
Motors and cars	-2.244*	0.09
Other transp. material	-0.756	0.51
Furniture	-1.789	0.20
Other manufact. goods	-1.580	0.30
International market	-0.383*	0.06
Age 5-10	-1.076**	0.03
Age 10-20	-1.012**	0.05
Age 20-30	-1.732**	0.03
Age 30-40	-1.865**	0.03
Age 40-50	-2.882**	0.04
Age > 50	-1.631*	0.06
Size 100-200	-0.763*	0.10
Size 200	-0.989***	0.01
No Corporate	0.636*	0.09
Med/High R&D intens.	-0.714***	0.01
R&D workers ratio	-4.860**	0.04
Regional spillovers	-1.571**	0.05
Local spillovers	-0.235	0.61
Intercept	3.666	0.11
Log likelihood	-717.008	
N. of observations	1653	
N. of spells	569	
Test for unobserved individual heterogeneity	LR test of Gamma variance=0 Chibar2(01)=2.152 p-value =0.07	

Table 1 shows the estimation results for the discrete time proportional hazard cloglog model. We find evidence of unobserved individual heterogeneity given that the hypothesis of the unobserved heterogeneity variance component (σ^2) being equal to zero is rejected at a 7% significance level. Furthermore, once controlling for unobserved individual heterogeneity, the duration dependence parameter is not significantly different from zero. According to our results, there are only two suppliers, (Leather and shoes and Motors and cars), showing a differential longer R&D spell duration. Suppliers selling also in international markets experience longer R&D spells. Suppliers' age increases the probability of experiencing longer R&D spells in a non linear manner. It is especially remarkable the effect on spell length for suppliers between 40 to 50 years old. For suppliers with more than 50 years the effect of age on duration decreases considerably and also the significance level with which this coefficient is estimated. In relation to the association between supplier's size and R&D investments, our results confirm that R&D spells of larger suppliers have lower chances of ending. Arguments related to superior supplier internal capabilities associated with size, such as exploitation of economies of scale and scope, larger market size, lower risk, higher appropriability conditions, financial means, etc., are the usual arguments to support a positive association between supplier size and innovative activities in general. Our results confirm that R&D spells of larger suppliers have lower chances of ending. However, the impact of supplier size on the length of the R&D spell is not linear, as the comparison of both coefficients suggests that R&D spells of suppliers with more than 200 employees (size 200) endure better survival prospects than suppliers between 100 and 200 employees. Suppliers that are not legally organized as a limited liability corporation have shorter R&D spells. In relation to R&D intensity and the nature of the R&D investments, we have included two different measures. The first is the yearly ratio of R&D

expenditure over sales and the second the yearly ratio of R&D employees over total number of employees in the supplier. The greater these two ratios, the more the supplier are expected to perform R&D activities in a continuous way. According to our results, those firms in medium/high R&D intensity industries enjoy R&D spells with longer survival prospects; as compared to those suppliers in low R&D intensity industries (the coefficient for medium/high R&D intensity is negative and significant at 1% level). As regards the ratio of R&D specialized workforce, which may also capture technological opportunities, we find a very strong effect in decreasing the risk of ending an R&D spell, contributing then to explain longer spells duration. This variable has appeared to be the best one in capturing the internal nature of the R&D activities. Finally, the literature on R&D has stressed the importance of spillovers on the decision to innovate. We find evidence of regional spillovers increasing the R&D spell duration. Local spillovers do not seem to be relevant, and suppliers' spillovers cannot be separately identified in the estimation from the supplier dummies.

4.2 Out- of-sample Prediction for Right Censored Spells

Once the parameters from the duration model have been estimated, we are interested in computing the average duration of right censored R&D spells for suppliers with different characteristics. To do this, we need to know the shape of the survival function. In general,

$$E\left(T_i^*\right)=\sum_{k=1}^{J} S_i\left(k\right) \tag{11}$$

where is the maximum survival time. The corresponding discrete time survival function is

$$S_i\left(k\right)=\left[1-h_1\left(x_{i1}\right)\right]\cdot\left[1-h_2\left(x_{i2}\right)\right]...\left[1-h_k\left(x_{ik}\right)\right]= \exp\left\{\sum_{s=1}^{k}\ln\left[1-h_s\left(x_{is}\right)\right]\right\} \tag{12}$$

In our sample there are 219 right censored spells with observed durations from 1 to 13 years. The distribution of observed durations for these spells can be found in Table 2. For all these spells we are going to calculate the value of the survival function from survival time 1 to survival time 200 (survival time that guaranties that for all the right censored spells the survival function value reaches 0). For the observed survival periods, the value of that function is calculated with the parameter estimates in the duration model applied to the value of the explanatory variables of any given supplier in that survival time period. For the non-observed survival periods in the future, we fix the values of the explanatory variables at their values in the observed final year (2013 for all of them), with the exception of the variable log(t) (log of the survival time) that before taking logs it is increased by one each considered extra year of the spell. We tried to capture main characteristics of the suppliers without the inclusion of highly time varying variables and/or variables with a clearly increasing or decreasing trend.

Table 2. Distribution of observed durations (T_o) for right censored spells

T_o	Number of spells	%
1	61	27.85
2	31	14.16
3	19	8.68
4	20	9.13
5	18	8.22
6	12	5.48
7	13	5.94
8	10	4.57
9	7	3.20
10	10	4.57
11	5	2.28
12	11	5.02
13	2	0.91
Total	219	100

Finally, we imputed as the total spell duration for a right censored spell the already observed number or years plus the expected duration remaining afterwards. That is, for instance, for right censored spells which observed duration is of 13 years we apply the formula in (11) to get as expected spell duration

$$E\left(T_i^*\right)=T_o+\sum_{k=(T_o+1)}^{200} S_i\left(k\right)=13+\sum_{k=14}^{200} S_i\left(k\right) \tag{13}$$

The distribution of predicted durations for the right censored spells can be found in Table 3.

Table 3. Distribution of predicted durations $\left(E\left(T_i^*\right)\right)$ for right censored spells.

T_o	Number of spells	%
2	27	12.33
3	31	14.16
4	24	10.96
5	26	11.87
6	17	7.76
7	21	9.59
8	13	5.94
9	15	6.85
10	7	3.20
11	10	4.57
12	5	2.28
13	11	5.02
14	3	1.37
16	2	0.91
17	1	0.46
19	2	0.91
21	1	0.46
33	1	0.46
37	1	0.46
41	1	0.46
Total	219	100

4.3. Non-Parametric Prediction for Left and Left-and-Right Censored Spells

In order to impute predicted spell durations for those spells that are either left or both left-and-right censored we proceed as follows. The spell duration we are seeking will be a weighted average of other spells durations, with higher weights for spells that are close in terms of the value of β0 + xijβ, and lower weights for spells that are far in terms of this value. For left and both left-and-right censored spells, the conditional expectations $E\left(T_i^*\middle|x_i\hat{\beta}\right)$ are replaced by non-parametric estimators $\hat{E}\left(T_i^*\middle|x_i\hat{\beta}\right)$, such as kernel estimators. In our sample there are 402 left censored and both left-and-right censored spells. Of them, 197 are left censored and 205 both left-and-right censored. The distribution of observed durations for these spells can be found in Table 4.

As we have already stated, we use the information related to the total spell length of observed complete spells and the one predicted for right censored spells (a total of 569 spells, of which 350 are complete and 219 are right censored). The total durations' distribution for these spells can be found in Table 5. For the left and both left-and-right censored spells, which observed durations are denoted by $T_{o,i}$, we use for the implicit matching procedure in the non-parametric regression (kernel regression) those observed complete and predicted right censored spells with duration equal or higher than $T_{o,i}$. The corresponding number of matching spells with $T_j^* \geq T_{o,i}$ are included in the first column of Table 4. Finally, the distribution of predicted durations for the left and both left-and-right censored spells can be found in Table 6.

Table 4. Distribution of observed durations (T_o) for left and both left / right censored spells

T_o (Number of matching spells $(T_j^* \geq T_{o,i})$)[a]	Left and both left/right censored spells		Left censored spells		Both left/right censored spells	
	Number of spells	%	Number of spells	%	Number of spells	%
1 (569)	59	14.68	59	29.95		
2 (381)	40	9.95	35	17.77	5	2.44
3 (274)	100	24.88	33	16.75	67	32.68
4 (208)	30	7.46	25	12.69	5	2.44
5 (161)	16	3.98	16	8.12		
6 (121)	29	7.21	8	4.06	21	10.24
7 (100)	10	2.49	6	3.05	4	1.95
8 (75)	2	0.50	2	1.02		
9 (61)	6	1.49	4	2.03	2	0.98
10 (45)	5	1.24	4	2.03	1	0.49
11 (38)	4	1.00	4	2.03		
12 (28)	7	1.74	1	0.51	6	2.93
13 (23)	94	23.38			94	45.85
Total	402	100	197	100	205	100

[a] For left and both left-and-right censored spells, which observed durations are denoted by $T_{o,i}$, we use for the implicit matching procedure in the non-parametric regression (kernel regression) those observed complete and predicted right censored spells with duration equal or higher than $T_{o,i}$.

Table 5. Distribution of observed complete durations and predicted right censored durations

T_o	Number of spells	%
1	188	33.04
2	107	18.80
3	66	11.60
4	47	8.26
5	40	7.03
6	21	3.69
7	25	4.39
8	14	2.46
9	16	2.81
10	7	1.23
11	10	1.76
12	5	0.88
13	11	1.93
14	3	0.53
16	2	0.35
17	1	0.18
19	2	0.35
21	1	0.18
33	1	0.18
37	1	0.18
41	1	0.18
Total	569	100

Table 6. Distribution of predicted durations $(E(T_i^*))$ for left and both left/right censored spells

T_o	Number of spells	%
2	8	1.99
3	23	5.72
4	41	10.20
5	32	7.96
6	47	11.69
7	49	12.19
8	28	6.97
9	28	6.97
10	14	3.48
11	7	1.74
12	11	2.74
13	8	1.99
14	55	13.68
15	16	3.98
16	12	2.99
17	10	2.49
19	3	0.75
20	1	0.25
25	3	0.75
26	2	0.50
29	2	0.50
32	2	0.50
Total	402	100

5. Estimates of the Innovation Production Function

We now proceed, using the results of the previous section, to estimate the innovation production function. Recall from section 2 our estimating equation, which takes the form

$$\log\lambda_{it} = \log A(t) + (\alpha_0 + \alpha_1 E_{it} + \alpha_2 E_{it}^2)\log R_{it} + z_{it}\beta_2 =$$
$$\log A(t) + \alpha_0 \log R_{it} + \alpha_1 E_{it}\log R_{it} + \alpha_2 E_{it}^2 \log R_{it} + z_{it}\beta_2 \qquad (14)$$

We will investigate, and estimate, the model under three alternative scenarios: the existence of over-dispersion in the data, the existence of random supplier specific effects, and the existence of fixed supplier specific effects potentially correlated with the regressor. One way for the model to arise is as a modification of the Poisson model in which λ_{it} is re-specified as

$$\log\lambda_{it} = x_{it}\beta + \varepsilon_{it} \qquad (15)$$

where exp(ε_{it}) has a gamma distribution with mean 1 and variance α. This is a natural form of 'over-dispersion' in that the over-dispersion rate is given by

$$\frac{\mathrm{Var}[n_{it}]}{\mathrm{E}[n_{it}]} = 1 + \alpha \mathrm{E}[n_{it}] \qquad (16)$$

If the results render an estimate for α different from zero, we will be rejecting the Poisson model as opposed to the NB model. Apparently, these extensions mirror the panel data models for the linear regression model. For the fixed effects case the model takes the form

$$\log\lambda_{it} = \mu_{it} + x_{it}\beta \ \ (+\varepsilon_{it} \text{ for the NB model}) \qquad (17)$$

Where µi is the coefficient of a binary variable indicating membership to the i-th group. Instead, a conditional maximum likelihood approach is used which removes µi from (17). The random effects model is

$$\log\lambda_{it} = x_{it}\beta + \upsilon_{it} \qquad (18)$$

Where v_i is a random effect for the i-th group such that e^{v_i} has gamma distribution with parameters (Θ,Θ). Before turning to the econometric results, we may have a look at some descriptive statistics presented in Table 7. This table provides descriptive statistics separately for two supplier size groups (suppliers with less or equal than 200 employees, and suppliers with more than 200 employees), according to the sample procedure of the survey. The first column displays intervals of years of R&D experience. For instance, the first interval "1-3 years" corresponds to suppliers that are either in their first, second or third year of R&D experience. This R&D experience is calculated for each observed period as the sum of past years with positive R&D spending, using the observed data of suppliers with no left censored R&D spells. Thus, what we show in this table are averages of the number of product innovations, the number of patents and the R&D-to-sales ratio that suppliers achieve each year when they are in their 1st to 3rd year of R&D experience, in their 4th to 6th year of R&D experience, and so on.

Table 7. Descriptive statistics on R&D experience and innovation results

	Suppliers with ≤ 200 employees				Suppliers with > 200 employees			
Intervals of R&D experience (years)	N. obs. (%)	Average number of product innovations in each year	Average number patents registered in each year	R&D / sales	N. obs. (%)	Average number product innovations in each year	Average number patents registered in each year	R&D / sales
1 – 3 years	381 (61.75%)	0.83	0.05	1.82	163 (48.95%)	0.73	0.51	0.95
4 – 6 years	149 (24.25%)	1.05	0.05	1.77	88 (26.43%)	0.76	0.69	1.39
7 – 9 years	68 (11.02%)	1.04	0.08	1.90	52 (15.62%)	1.11	0.34	1.44
10 – 13 years	19 (2.90%)	1.42	0.09	2.75	30 (9.0%)	1.68	0.60	1.76
Total	617				333			

A first comparison between the two size groups, suggests that large suppliers have, on average, longer R&D experience: the percentage of suppliers in the first interval is above 61% in the case of small suppliers, whereas this percentage is about 49% in the case of large suppliers. Consequently, the percentage of observations in the higher intervals is higher in the case of large suppliers. This could be indicating that the R&D experience is positively correlated with supplier size, which is consistent with the well established empirical finding of a positive correlation of supplier size with the probability of performing R&D activities. As regards to the average number of product innovations that suppliers achieve yearly, figures in Table 7 indicate that they rise with R&D experience. For the group of small (large) suppliers this average number ranges from 0.83 (0.73) in the first three years of R&D experience to 1.42 (1.68) in the highest observed interval of R&D experience (10th-13th years). In the case of the average number of patents, similar patterns are observed, although for the group of large suppliers there is a decline between the second and the third interval, which is recovered in the last interval. Thus, at a descriptive level, the data in our sample show that suppliers tend to achieve more innovative results as they accumulate years of R&D experience. Finally, the average R&D-to-sales ratio also shows a positive relationship with R&D experience. This ratio goes from 1.82 to 2.75 in the case of small firms, and from 0.95 to 1.76 in the case of large suppliers. Therefore, both the average number of our measures of innovative results and the R&D effort made by suppliers seem to increase with suppliers R&D experience. In order to test this last hypothesis, which is our main objective in this paper, we turn to the analysis of our econometric results. The econometric results from estimation for both product innovations and patents are reported in Tables 8 and 9, respectively. A first result in Table 8 is that the coefficients of both the R&D capital and the interaction of R&D capital with R&D experience are positive and statistically significant. Additionally, we observe that the coefficient of the interaction term with squared R&D experience is negative and also significant at conventional levels. These results arise regardless of the distributional assumptions we consider in the estimation, although the coefficients are somewhat lower in the panel estimation, that is, in columns (3) and (4). In our sample, for a value of 7 years undertaking R&D activities, corresponding approximately to the median of the sample distribution, the value of the elasticity would be of 0.084, that is, by about a 70% larger than the elasticity of a supplier that has been undertaking R&D for only one year. Moreover, the maximum value of the estimated elasticity, 0.094, corresponds to an R&D experience of about 13 years, and beyond that value the estimated elasticity decreases. This inverted-U shape of the R&D experience effectiveness could be related to a decrease in technological opportunities of the life cycle of the suppliers' product.

Table 8. Estimates of the Innovation Production Function

	Product Innovations			
	Poisson (pooled)	Neg. Bin. (pooled)	Neg. Bin. (random eff.)	Neg. Bin. (fixed eff.)
	(1)	(2)	(3)	(4)
log K	.064** (.003)	.064** (.016)	.047** (.011)	.043** (.011)
log K × E	.014** (.7e-03)	.010** (.003)	.007** (.002)	.008** (.002)
log K × E2	-.8e-03** (.4e-05)	-.6e-04** (.2e-04)	-.3e-04** (.1e-04)	-.3e-04** (.1e-04)
size 2	.805** (.023)	.470** (.117)	.015 (.091)	.036 (.098)
size 3	.576** (.027)	.489** (.150)	.013 (.115)	.008 (.125)
size 4	.259** (.028)	.240* (.141)	.221** (.109)	.188 (.120)
size 5	-.089** (.026)	-.021 (.124)	-.270** (.101)	-.325** (.112)
size 6	-.428** (.034)	.007** (.168)	-.035 (.129)	-.037 (.144)
cient./tecnic. services	.234** (.016)	.048 (.088)	.234** (.056)	.237** (.059)
quality control	-.731** (.015)	-.558** (.090)	.165** (.057)	.163** (.060)
imported tech.	.250** (.017)	.128 (.105)	.087 (.061)	.130** (.064)
marketing	.171** (.016)	.207** (.094)	.235** (.059)	.213** (.061)
design	.900** (.015)	.764** (.086)	.267** (.056)	.181** (.058)
other	-.001 (.049)	-.160 (.307)	.545** (.161)	.540** (.166)
med. tech. sectors	-.865** (.020)	-.619** (.095)	.207** (.072)	.194** (.077)
high tech. sectors	-.563** (.020)	-.309** (.110)	.455** (.081)	.481** (.087)
trend	-.082** (.008)	.059 (.047)	.024 (.029)	.028 (.030)
trend2	.003** (.5e-03)	-.003 (.003)	-.002 (.002)	-.003 (.002)
intercept	.459** (0.036)	.023 (.187)	-2.18** (.129)	-2.11** (.135)
N. obs (N.firms)	6464 (670)	6464 (670)	6464 (670)	5094 (510)
log likelihood	-53383.9	-10058.8	-8977.2	-6451.1
parameter ≠ 0 indicates over-dispersion		7.860** (0.209)	1.246** (0.112)	
LR test pooled vs. random effects			1965.57 p-value: 0.000	
Hausman test of correlated fixed effects				89.27 p-value: 0.000

Standard errors in parenthesis. ** significant at 1% level; * significant at 5% level

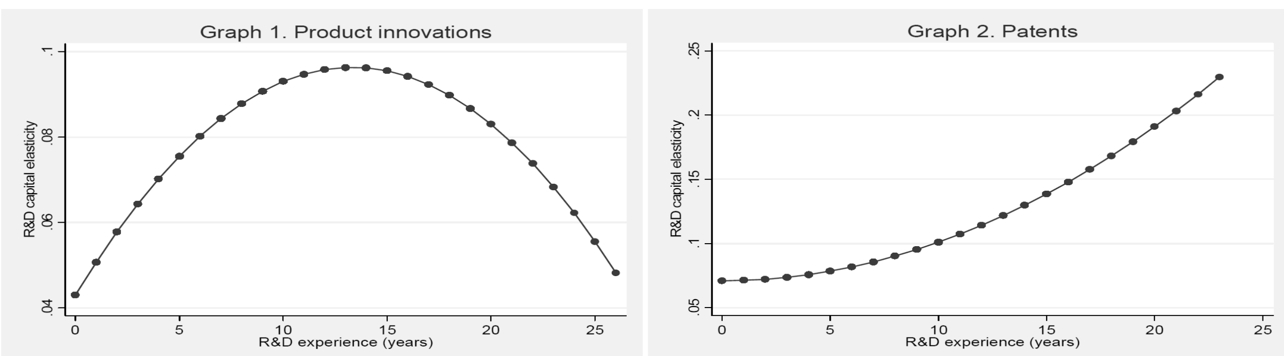

Figure 2. R&D capital elasticities

Figure 2 illustrates the R&D capital elasticities for product innovations and patents. The R&D capital elasticity for product innovations is represented in Graph 1. As already stated, our estimated elasticity gets its maximum value between the 12th and 13th year of R&D experience, and decreases for further years of R&D experience. However, as noticed previously, not all points depicted in Graph 1 are equally probable in our sample, and, in particular, 90% of the distribution is below 13 years of experience.

If we turn now to Table 9, we observe somewhat different results for the case of patents. Our preferred results are also those from the NB fixed effects estimation but, in this case, the coefficient of the interaction term of R&D capital with R&D experience is not statistically significant, whereas the coefficient of the interaction term of R&D capital with squared R&D experience turns out to be positive and statistically significant. This result is illustrated in Figure 2, Graph 2, where the (positive) slope of the curve rises with R&D experience. For a value of 8 years of R&D experience, which represents approximately the median of the sample distribution, the value of the elasticity is about 26.5 % higher than the elasticity of a supplier that has been undertaking R&D for only one year. We obtain that the longer the R&D experience, the higher the value of the elasticity, possibly indicating that it is required a lengthy R&D experience to benefit from dynamics economies of scale, but that, once accumulated the necessary knowledge, further R&D efforts pay more and more in terms of patents. Thus, our results indicate that the effectiveness of R&D capital changes along the R&D history of the supplier, and that the results may differ depending on the indicator of innovation results.

Table 9. Estimates of the Innovation Production Function

	Patents			
	Poisson (pooled)	Neg. Bin. (pooled)	Neg. Bin. (random eff.)	Neg. Bin. (fixed eff.)
	(1)	(2)	(3)	(4)
log K	.139** (.010)	.056** (.016)	.088** (.021)	.071** (.022)
log K × E	.005** (.001)	.008 (.005)	-.003 (.003)	-.003 (.003)
log K × E2	-.5e-05 (.5e-05)	-.1e-04** (.2e-04)	.3e-04* (.16e-04)	.3e-04**(.1e-04)
size 2	.693** (.106)	.550** (.211)	.151 (.202)	.019 (.232)
size 3	1.024** (.111)	1.096** (.260)	-.081 (.263)	-.202 (.300)
size 4	.599** (.110)	.853** (.238)	.300 (.232)	.078 (.268)
size 5	1.300** (.099)	1.455** (.213)	.266 (.213)	.017 (.250)
size 6	.674** (.109)	1.156** (.266)	.169 (.248)	-.080 (.284)
cient./tecnic. services	.573** (.039)	.298 (.161)	.361** (.111)	.348** (.118)
quality control	-.078* (.044)	-.160 (.145)	.258** (.113)	.286** (.121)
imported tech.	-.303** (.040)	-.288 (.176)	-.237** (.114)	-.215* (.119)
marketing	.364** (.038)	.525** (.155)	-.267** (.107)	-.352** (.111)
design	.363** (.037)	.929** (.138)	.371** (.104)	.224** (.109)
other	-.309* (.176)	-.525 (.510)	1.159** (.359)	1.35** (.381)
med. tech. sectors	-.199** (.051)	-.116 (.152)	.179 (.146)	.204 (.160)
high tech. sectors	.597** (.044)	.391** (.187)	.211 (.149)	.182 (.158)
trend	-.273** (.021)	-.235** (.078)	-.155** (.052)	-.134** (.053)
trend2	.011** (.001)	.011** (.005)	.006* (.003)	.004 (.003)
intercept	-2.75** (.123)	-2.44** (.321)	-1.98** (.261)	-1.579** (.185)
N. obs (N. suppliers)	6627 (671)	6627 (671)	6627 (671)	2261 (219)
log likelihood	-9415.49	-3437.0	-3007.4	-1870.4
parameter ≠ 0 indicates overdispersion		17.801** (0.946)	0.256** (0.029)	
LR test pooled vs. random effects			863.72 p-value: 0.000	
Hausman test of correlated fixed effects				82.27 p-value: 0.000

Standard errors in parenthesis. ** significant at 1% level; * significant at 5% level

Other complementary results in Tables 8 and 9 that deserve some attention are those related to informal innovation activities. In the case of product innovations, all kinds of informal activities contribute to the achievement of product innovations, whereas importing technology and marketing is negatively correlated with the number of patents obtained by the supplier. Informal innovation activities exhibit in our sample a positive correlation with formal R&D activities, raising the estimated R&D elasticity if they are excluded from the estimation. This point is remarkable in our sample because of two reasons. On the one hand, in the case of the Indian suppliers, with a considerable percentage of suppliers of small and medium size, these informal R&D activities may be important for their innovation effectiveness. On the other hand, empirical work in this area does not typically include this information in the R&D patents relationship, a point that, among others, may help to explain the lower obtained magnitude of our R&D elasticities.

6. Conclusion

In this paper we have tested the hypothesis that, due to knowledge cumulativeness, the period of time during which suppliers performs R&D activities, which we call R&D experience, is a key determinant of the number of innovations they may achieve. We have argued that the temporal dimension captured by R&D experience goes beyond the effect of R&D investments. In particular, we have tested the hypothesis that the effect of R&D capital stock in the achievement of innovations depends on R&D experience, that is, the number of years the supplier has been performing R&D activities. By doing so, this paper has been an attempt to contribute to a better understanding of the nature of the cumulative process of learning and the importance of experience in the achievement of innovations. We have investigated the role of suppliers R&D experience in the achievement of innovations, using a representative sample of Indian suppliers for the period 2000 - 2013. We first have analysed suppliers R&D patterns in order to determine the duration of suppliers' R&D spells. Once we have estimated the R&D experience of suppliers as described above, we have proceeded to estimate, within the framework of a knowledge production function and using count data models, the influence of suppliers' accumulated R&D experience on their R&D innovative effectiveness. Our empirical analysis has indicated that, after controlling for R&D capital stock and other suppliers' individual heterogeneity, suppliers' R&D effectiveness rises with the R&D experience, that is, with the accumulation of technical skills and knowledge that emerge for as long as suppliers R&D investments continue over time.

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