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R & D spillover and productivity growth: Evidence from Indian private firms

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Abstract

We test the R & D spillover hypothesis of the endogenous growth literature using panel data for a sample of private manufacturing firms in India over the period 1975–1986. We estimate an extended production function that includes the firm's own R & D capital stock and the spillover effect of the industry-wide R & D capital stock as inputs, as well as physical capital and labor hours. We specify models which eliminate three sources of estimation bias and flawed hypothesis tests: serially correlated errors, unobserved heterogeneity due to omitted factors of production, and endogenous determination of value-added and input levels. Several specification tests are used to select a well-behaved model. The final parameter estimates show evidence for the R & D spillover hypothesis in all industries.

JEL classification: O32; D24; L6

Keywords: R&D spillover; Firm level R&D; Firm level productivity

1. Introduction

Recent theoretical models of *endogenous growth* emphasize that R & D expenditures of individual firms contribute to sustained long-run growth of an economy through their industry-wide spillover effect (Grossman and Helpman, 1990a; Grossman and Helpman, 1990b; Romer, 1986). According to this view, individual firms invest in R & D to acquire private knowledge that enhances their productivity and profit. Private knowledge of individual firms then spills over to the rest of the

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industry and becomes social knowledge which acts as an external effect in enhancing the productivity of all firms. With the spillover effect of R&D, a constant or decreasing returns to scale aggregate production function may exhibit increasing returns to scale and thus may lead to sustained long-run growth (Romer, 1986), see Raut and Srinivasan (1993) for an exposition of the mechanism). However, one implication of this view would be that a less developed country can draw from the global technology pool at zero cost.

In contrast, Cohen and Levinthal (1989) among others argue that while knowledge from private R&D capital spills over to create social or public domain knowledge, a firm must invest in private R&D to acquire the technical capability needed to make use of the public domain knowledge to enhance its productivity. One implication of this latter view is that industry-wide knowledge will not contribute to private productivity gains unless the firm invests in R&D.

Thus while a firm in a less developed country can draw from the stock of international knowledge, the firm must spend resources to purchase technology from abroad, and then perform in-house R&D to understand and improve upon the foreign technology. Once a new technology has been adopted domestically by a firm or a group of firms, the associated technological knowledge could be used by other domestic firms at a negligible cost.

Empirical studies on spillover effects are very few. Following Griliches (1979), Jaffe (1986) provided some empirical evidence on spillover effects of R&D by using patent applications to construct a measure of 'similarity' of research activities among firms. Jaffe calculated the external R&D pool available to a firm by taking the weighted aggregate R&D expenditures of all other firms using the measure of research similarity as weights. He found that both external pooled R&D and in-house R&D efforts significantly influence the quantity of patent applications and the market value of the firm. While this estimate of the external R&D pool is attractive, it may provide a noisy measure. For instance, firms do not always apply for patents on new ideas and the value of a patent may vary greatly. More importantly, this measure of the external R&D pool cannot be constructed for most developing countries because the detailed patent information is not available.

Bernstein and Nadiri (1988) constructed a measure of the external R&D pool of a firm by taking unweighted aggregate R&D expenditures of other firms in the industry and found the spillover effect to be statistically significant in all industries. Romer (1987) found positive correlation between total factor productivity growth and growth in capital in aggregate data across countries and over time. He interpreted these findings as evidence for positive externalities in capital formation; to the extent that capital embodies technological knowledge, this positive correlation indicates the presence of spillovers in production of knowledge. However, Benhabib and Jovanovic (1991) pointed out that the positive relationship might be spurious due to endogeneity bias. They estimated a structural macro model using U.S. time series data to circumvent the endogeneity bias problem, and found no evidence of spillovers. However, no previous attempt has been made to estimate spillover effects of R&D expenditures in less developed countries.

The existing empirical literature on R&D activities of private Indian firms is limited. Using panel data on private manufacturing firms during 1975–1980, Raut (1988) estimated inter-relationships among different R&D input choices such as in-house R&D investment, import of technology from abroad, and purchase of technology from other domestic sources available to firms. In another study, Katrak (1989) used data on large enterprises to estimate the effect of import of technology on in-house R&D. [1] However, these studies did not relate R&D expenditures to productivity growth.

Studies on productivity growth of Indian firms have generally used three-digit industry level aggregate panel data (see, for instance, Ahluwalia (1985) and Goldar (1986)). Goldar, however, conducted an econometric analysis on firm level data to determine the effects of market concentration and effective rate of protection on total factor productivity growth of the textile industry. These studies do not, however, examine the relationship between R&D and productivity growth.

In this paper, we use panel data for a sample of Indian manufacturing private firms over the period 1975–1986 to estimate the productivity effects of a firm's own R&D, industry-wide R&D expenditures, as well as physical capital and labor inputs. Following the endogenous growth literature (see, for instance, Romer (1986), Lucas (1988), and Raut and Srinivasan (1993) for an exposition), we construct a measure of the R&D capital stock of an industry as the unweighted aggregate R&D expenditures of all firms in the industry. To examine the effects of in-house R&D and external R&D on productivity growth of individual firms, we estimate an extended Cobb–Douglas production function that includes in-house R&D capital and two-digit industry level R&D capital as inputs. In the context of production function estimation, the error term can be correlated with the right-hand variables due to serial correlation, unobserved heterogeneity caused by omitted variables or simultaneity in the determination of output and input levels. In the presence of correlation between the regressors and the error term, the parameter estimates are biased, inconsistent and the standard t and F-tests statistics cannot be used to test the significance of the parameter estimates. However, by using a balanced panel data set covering a 12-year period, we are able to correct for these sources of correlation between the error term and the regressors, and we apply various specification tests to choose the final set of parameter estimates from which our conclusions are drawn.

Section 2 discusses the expected relationships among private in-house R&D efforts, industry-wide R&D efforts, and the productivity growth rates of individual firms. Section 3 reports data sources, and summary statistics, and also outlines

[1] Other related studies in this area are Deolalikar and Evenson (1989), Ferrantino (1992), Katrak (1985), and Katrak (1990).

the procedures used to construct variables in this analysis. Section 4 considers the econometric issues, and the results of various specification tests, and then reports the final parameter estimates. Section 5 concludes the paper.

2. R&D and productivity growth of private firms

R&D investment decisions of a private firm depend on market structure, demand conditions and government policies regarding R&D investments and patent protection. In an oligopolistic industrial structure, a private firm may invest in R&D to survive industrial competition. For instance, a competitor might discover some cost-saving innovation or an improved product and thus reduce other firms' rates of profit and market shares or even drive a weaker firm out of the market. The profitability of investment in an R&D project will depend on future demand conditions both in domestic and international markets. Under the industrial policy of India, if a private firm established an R&D laboratory of a certain minimum size, then the firm was allowed to deduct its R&D expenditures from taxable income and to import R&D-related capital goods more easily. Even if all other conditions are conducive to investing in in-house R&D, a firm might not invest in such activities if patent laws do not assure the firm of a monopoly in the use of the technology that it has generated, at least for a sufficiently long period. If patent laws do not prohibit other firms from imitating the newly innovated technology of a firm, firms do not have incentives for investing their resources on risky innovation activities.

Whether investment in R&D of a private firm contributes to its productivity growth depends on the motive for investing in R&D. When a firm invests in R&D activities to take advantage of the tax shelters, R&D investments need not be positively related to productivity growth. On the other hand, if a firm invests in R&D because of competitive pressure, then own R&D investment and productivity will be positively related. Therefore, relationship between own R&D and productivity growth might differ from industry to industry depending on the industrial structure, changing market conditions, and appropriation conditions.

The output of R&D investment, namely technological knowledge, has been traditionally treated as a public good; once it is generated by a firm it can be copied almost without cost by any number of firms. Patent laws only temporarily protect a firm from others copying its new knowledge. But not all new knowledge is patented. Thus, part of new knowledge spills over to the rest of the firms in an industry either immediately or at least after the period of patent protection. Any firm can utilize the public domain knowledge to enhance its productivity. As mentioned briefly in the introduction, Cohen and Levinthal (1989) among others have argued against this view. We quote part of their argument from p. 570, "economists have assumed that technological knowledge which is in the public domain is a public good. Like a radio signal or smoke pollution, its effects are thought to be costlessly realized by all firms located within the neighborhood of the emission''. They suggest that the cost of utilizing public domain knowledge fruitfully is minimal for those firms which have accumulated technological capability or the stock of technological knowledge capital through considerable investments in R&D in the past. Thus, an implication of this view is that the effect of spillover R&D capital on productivity would be permeated mainly through the effect of own R&D capital.

An alternative channel through which spillover R&D can have positive effect on productivity of individual firms is in situations where a firm by its own isolated effort may not be able to innovate, whereas if others are also researching along similar lines, the firm might benefit from their research findings. The industry wide R&D could act as a catalyst to one's own R&D effort. Or in other words, new technological ideas are produced jointly with other firms. In such a situation, the firm will benefit not only from its own R&D efforts but also from the total R&D efforts in the industry. Furthermore, the effect of industry wide aggregate R&D will probably have larger effect on productivity than that of own R&D.

Modeling of R&D input choices for private firms and estimating such decision rules are carried out in Raut (1986) and Raut (1988). In this paper, we do not model the R&D investment decisions, nor do we estimate the importance of international spillover effects due to lack of appropriate data. Instead, we estimate the effects of individual R&D expenditures and industry-wide spillover R&D on the individual firm's productivity growth. Following Griliches (1979), we assume that like physical capital and labor, R&D capital of a firm which is the discounted sum of the past R&D investment streams, is a factor of production. We further assume that the industry level total R&D capital is also a factor of production.

Let Y_{ijt} be the level of value-added, R_{ijt} be the stock of R&D capital, K_{ijt} be the stock of physical capital and L_{ijt} be the number of work hours of firm i in industry j and period t, $i = 1,2,\dots,N_j$, $j = 1,2,\dots,J$ and $t = 1,2,\dots,T$. Let $N = \Sigma_{j=1}^{J} N_j$. Following the endogenous growth literature, we define the spillover R&D capital of a firm in industry j as $S_{jt} = \Sigma_{\tau=0}^{4} \lambda^{\tau} \Sigma_{i=1}^{N_j} RDEXP_{ijt-\tau}$, where λ is the discount factor that takes into account the depreciation of R&D capital. Following Griliches (1984), we choose the value of λ to be 0.85. Griliches found that the estimates of the parameters of production functions are not very sensitive to the choice of λ. He also suggested that the lags of three to four years are sufficient in constructing the value of in-house R&D capital stock. We follow his suggestions regarding the choice of the lag and the discount factor. However, it would be interesting to see the sensitivity of the estimates to the values of these two parameters. We assume the production function to be an extended Cobb–Douglas function similar to that of Griliches:

$$Y_{ijt} = A_{ijt} S_{jt}^{\alpha} R_{ijt}^{\beta} K_{ijt}^{\gamma} L_{ijt}^{\delta} \varepsilon_{ijt}. \tag{2.1}$$

In the above specification of a firm's production function, the factors other than own R&D capital and spillover capital which affect productivity and which are observed by the firm but not by econometricians are summarized in the constant term A_{ijt}; the term, ϵ_{ijt}, represents random disturbances. Denoting the log of a variable by the lower case with a hat over it and by $\hat{e}_{ijt} = \ln(\epsilon_{ijt})$, we have the following regression equation:

$$\hat{y}_{ijt} = \hat{a}_{ijt} + \alpha \hat{s}_{jt} + \beta \hat{r}_{ijt} + \gamma \hat{k}_{ijt} + \delta \hat{l}_{ijt} + \hat{e}_{ijt}. \tag{2.2}$$

In Section 4, we report parameter estimates under various assumptions about $\hat{a}_{ijt}$ and $\hat{e}_{ijt}$ and test some of these assumptions.

3. Data and variables

In 1973, the government of India introduced an incentive scheme to encourage private firms to establish their own in-house R&D laboratories. One of the objectives of this scheme was to provide firms of certain minimum size with easier access to imported laboratory equipments, components, and raw materials to carry out research work. Furthermore, the revenue or capital expenditure invested in scientific research by the in-house R&D units could be written off for income tax purposes. As a result of these policies, the number of in-house R&D laboratories in the private sector rose very rapidly. For instance, in 1984–1985 the total number of firms with in-house R&D laboratories was 602; 76% of these laboratories came into existence during the Fourth Five Year Plan period (1969–1970 to 1973–1974) or subsequently (Government of India, 1986, Table 2.1). R&D expenditures as a percentage of sales turnover for these firms gradually increased from 0.71 in 1976–1977 to 0.85 in 1979–1980, and then gradually dropped to 0.52 in 1984–1985 (Government of India, 1986, Table 2.3). These figures in India are, however, much lower than the corresponding figures in developed countries (which range from 2 to 3 percent).

While most of the 600 firms that are registered with the government's Department of Science and Technology report information related to their R&D activities to this department, departmental policy is not to release this data for academic research. Thus we are restricted to R&D-related information from the individual company reports for the firms which are registered with the government's Ministry of Company Affairs. These firms are required by law to report their R&D expenditures only if their R&D expenditures are higher than one percent of total sales. Thus, some of the firms in our sample incurred R&D expenditures but are not reported in our sample. Data on net sales, fixed assets, and total wages and salaries of the private manufacturing firms came from the Bombay Stock Exchange Directory for the firms which are registered with the Directory. After deleting firms that did not report data for some of the years, we obtain a balanced panel data set over the period 1975–1986 for 192 firms that were common to both sources of data.

The firms in our sample are given a three-digit Standard Industrial Code (SIC). We carry out our analysis for the overall industry as well as for the subgroups *Light, Petro-chemical, and Heavy* industries. These subgroups are constructed according to their technological homogeneity as used in Raut (1988) (also see the table in the appendix for the components of these three industries).

The measurement of variables raises a few problems. We consider the unobservable research capital as the sum of the distributed lag effects of the past in-house R&D expenditures, royalties and technical fees paid to foreigners and other domestic firms. The standard definition of R&D capital that is used in most studies of developed economies considers only the distributed lag values of in-house R&D expenditures. However, the sources of knowledge in less developed countries are presumably import of technology as well as in-house R&D investments (see Katrak (1989), and Raut (1988) on this). The R&D capital of firm i in industry j in period t is defined as $R_{ijt} = \Sigma_{\tau=0}^{4} \delta^{t} RDEXP_{ijt-\tau}$, where $RDEXP_{ijt}$ is the deflated real in-house R&D expenditure. We allow four lags in the definition of in-house R&D expenditure, because it has been argued in the literature that the effects of R&D investments persist for at most four periods (Griliches, 1979). We add 1 to $RDEXP_{ijt}$ for all ijt to ensure that firms with no R&D investments have non-zero R_{ijt} corresponding to non-zero output level in the above extended Cobb–Douglas specification. The same convention is used for the variable S_{jt}. δ is the rate of obsolescence which is taken to be 15% per year and declining geometrically. Griliches (1979) used different values of δ but found that his results were not sensitive to a particular choice of δ. We have used a decay rate of 0.15, since it has been used in most of the studies in this area. Similarly, the external industry level R&D capital is measured by $S_{jt} = \Sigma_{\tau=0}^{4} \delta^{\tau} \Sigma_{i=1}^{Nj} RDEXP_{ijt-\tau})$, where N_j is the number of both private and public firms in industry j in the whole economy. We use the Department of Science and Technology's two-digit industrial classification and their aggregate R&D expenditures data at the two-digit level.

We measure output by deflated net sales. The deflator is the wholesale price index available from the National Abstracts of India. There are two problems in using the wholesale price index rather than the industrial price deflator. First, the wholesale price index includes the sales taxes while the industrial price deflators include the excise duties, which are typically different. Second, the timing of the publications of the price indicators and of the Bombay Stock Exchange Directory do not coincide. However, utilizing the findings of Griliches and Mairesse (1987), we maintain that these discrepancies will not significantly change our final results. The value added of a firm could not be directly measured. We measure a firm's value added by multiplying the output with the ratio of value-added to output of the three-digit industry that the firm belongs to. Because the Indian firms do not report the number of work hours, we calculate it by dividing the total wages and salaries of a firm by the average wage rate of the three-digit industry that it belongs to. An ideal way to construct capital stock series is to compute $K_{t+1} = (1$

Table 1
Summary statistics by industry

Variables	Industry: Light	Petro-chemical	Heavy	Variable definition
LNCAP	4.679	4.572	4.050	log capital ($= k$)
	(1.116)	(1.625)	(1.437)	
LNWRKHRS	1.923	1.250	1.317	log work hours ($= l$)
	(1.031)	(1.449)	(1.371)	
LNRND	2.326	4.326	5.918	log R&D capital ($= r$)
	(3.52)	(4.16)	(4.29)	
LNSRDEXP	7.099	8.746	7.474	log spillover R&D ($= s$)
	(1.05)	(1.085)	(1.75)	capital
LNOUTPUT	4.338	4.112	4.080	log value-added ($= y$)
	(1.08)	(1.29)	(1.44)	
# firms	58	81	53	

$-\delta)K_t + I_t$, where K_{t+1} and K_t denote the stock of real capital in period t and $t+1$ respectively, δ is the depreciation rate of capital, and I_t is real investment in period t. However, we do not have the appropriate information to construct such a capital series. Bombay Stock Exchange reports the current value of the existing fixed assets of firms. We assume that the period t fixed assets in current prices that are reported in the Bombay Stock Exchange Directory is the same as $P_t K_t$, where P_t is the wholesale price index. Thus, we use deflated fixed assets as a measure of physical capital stock. Since we have used four-year lags to construct own R&D capital and spillover R&D capital, our effective sample period is $T = 8$ from now on. Table 1 provides the summary statistics of the variables used in our study.

4. Econometric specifications and empirical findings

In the R&D literature one generally [2] specifies a common time trend and intercept term for firms, and serially uncorrelated errors as follows:

$$\hat{a}_{ijt} = a + \mu t \tag{4.1}$$

and

$$\hat{e}'_{ijt}s \text{ are iid and independent of regressors in } (2.2). \tag{4.2}$$

In the above specification, a time trend μ denotes the rate of growth of

[2] See, for instance, the surveys of these models by Mairesse and Sassenou (1991) and Mohnen (1992).

Table 2
Parameter estimates of the model with common intercept and time trend [a]

Variables	Industry			
	Light	Petro-chemical	Heavy	Overall industry
Intercept	210.7	10.960	−1.810	53.757
	(7.45)	(0.48)	(7.77)	(3.56)
Time trend	−0.106	−0.004	0.002	−0.026
	(7.43)	(0.40)	(0.12)	(3.48)
LNCAP	0.549	0.295	0.245	0.324
	(16.7)	(14.4)	(8.64)	(21.5)
LNWRKHRS	0.307	0.515	0.712	0.534
	(9.06)	(22.7)	(23.3)	(33.2)
LNRND	−0.005	0.011	0.013	0.016
	(0.54)	(1.80)	(1.62)	(3.80)
LNSRDEXP	0.210	0.008	0.095	0.093
	(6.54)	(0.34)	(5.28)	(8.01)
adj. R^2	0.667	0.748	0.805	0.727
DW	1.049	0.887	0.595	0.794
1st order serial correlation	0.474	0.556	0.699	0.602
No. of observations	464	648	424	1536

[a] Absolute values of t-statistics are in parentheses.

disembodied (Hicks-neutral) technological change. Under assumptions (4.1) and (4.2), we can apply the ordinary least squares (OLS) procedure to obtain the best linear unbiased estimates of the parameters. These estimates are shown in Table 2.

Table 2 shows that the OLS estimates of the elasticities of labor and capital in all three industries are highly significant. The effect of spillover R&D is significant in all except petro-chemical industries. The effect of own R&D capital is significant around at the 10 percent level in all industries except for light industry; and spillover R&D is highly significant in all except petro-chemical industries.

The OLS assumption that the regressors are uncorrelated with disturbances is a serious one, violation of which leads to inconsistent and biased parameter estimates, and nonstandard distributions of the t and F statistics for the parameter estimates. In the present production function context, this assumption can be violated for three reasons: serial correlation of the error term, the presence of unobserved heterogeneity due to omitted variables, and simultaneity in the determination of value added in the left-hand side and some of the input variables in the right-hand side of Eq. (2.2). We address these problems in the rest of this section.

4.1. Serially correlated errors

A serious problem with the above OLS estimates is the assumption that errors are serially uncorrelated. There are several ways in which $\hat{e}_{ijt}$ can have serial correlation; for instance, the error term may include a serially correlated omitted factor of production, or the error term may include the residual of the approximation of the true production function by the assumed one, which could be serially correlated. Even if the omitted variables are constant over time, there is another important way serial correlation of the error term can arise. Suppose the above specification of the production function is correct. Suppose the trade unions or government policies do not allow firms to fire workers in the short run. Firms will respond to demand fluctuations arising mainly due to business cycle fluctuations by adjusting the capacity utilization. In such cases, to the extent that business cycles exhibit serial dependence, the error term in the above production function will be serially correlated and will be correlated with the regressors. More specifically, let us assume that $\hat{e}_{ijt}$ represents the productivity shocks of firm i in industry j in time period t, and let us assume that it follows a first-order autoregressive process:

$$\hat{e}_{ijt} = \rho \hat{e}_{ijt-1} + \hat{u}_{ijt}, \quad \hat{u}_{ijt} \sim \text{i.i.d.}\left(0, \sigma_u^2\right). \tag{4.3}$$

It is reasonable to assume that the optimal input levels, k_{ijt}, l_{ijt}, and r_{ijt} are not correlated with $\hat{u}_{ijt}$ since this is a shock to productivity this period which the firm may not have anticipated. But the last period's productivity shock $\hat{e}_{ijt-1}$, which is a component of this year's productivity shock is observable to the firm and will influence the input choices of the current period, and hence $\hat{e}_{ijt}$ will be correlated with the input levels of the current period.

Notice that the value of the Durbin–Watson statistic is well below 2 for every industry group. This indicates that the error term is serially correlated. [3] One advantage of having panel data is that we can estimate serial correlation coefficients of various orders and using those, transform the data (this transformation is known as Cochrane–Orcutt transform) to overcome this problem. The least squares estimates on the transformed data will produce the best linear unbiased estimates. To carry out Cochrane–Orcutt transformation, we need a consistent estimate of ρ. We estimate ρ by running OLS of $\hat{y}$ on the original regressors and one-year lag values of $\hat{y}$ and all original regressors and then take the coefficient of the lag dependent variable as an estimate of ρ. To detect the order of the serial correlation we use the residuals from this regression and run a regression on one-year lag values of the residuals without intercept. If the Durbin–Watson statistic of this regression is not around 2, then we reject the hypothesis of first-order autocorrelation of the errors and run a regression on two-year lag values

[3] The Durbin–Watson statistic is defined by $DW = \Sigma_{j=1}^{J} \Sigma_{i=1}^{Nj} \Sigma_{t=2}^{T} (\check{u}_{ijt} - \check{u}_{ijt-1})^2 / \Sigma_{j=1}^{J} \Sigma_{i=1}^{Nj} \Sigma_{t=1}^{T} \check{u}_{ijt}^2$ where, $\check{u}_{ijt}$ is the estimated residual of firm i in period t. However, the distribution of the statistic is not known in the panel data context. Thus the test criterion of no serial correlation if DW is around 2 could be misleading in this context. As a result, we independently estimated serial correlation to corroborate the Durbin–Watson statistic's inference regarding serial correlation.

Table 3
Parameter estimates of the model with common time trend and intercept using Cochrane–Orcutt transformed data [a]

Variables	Industry			
	Light	Petro-chemical	Heavy	Overall
Intercept	−0.473	0.042	−0.053	−0.068
	(6.28)	(0.79)	(1.48)	(2.37)
Time trend	0.001	0.001	0.001	0.001
	(4.37)	(6.26)	(6.57)	(11.4)
LNCAP	0.286	0.209	0.146	0.196
	(6.61)	(7.78)	(5.17)	(10.72)
LNWRKHRS	0.520	0.496	0.706	0.564
	(10.6)	(15.2)	(19.6)	(25.7)
LNRND	0.006	0.007	0.008	0.009
	(0.49)	(0.77)	(0.85)	(1.49)
LNSRDEXP	0.227	−0.023	0.093	0.055
	(4.25)	(0.52)	(2.63)	(2.58)
adj. R^2	0.739	0.675	0.780	0.741
DW	2.304	2.274	1.846	2.170

[a] Absolute value of t-statistics are in parentheses.

and compute the Durbin–Watson statistic again to see if it is around 2, and so on. Applying this criterion, we find that in all industry groups, the error term is first-order autocorrelated. Table 3 shows the OLS estimates of the model (2.2) on the Cochrane–Orcutt transformed data.

We find that the effects of disembodied technological change, own R&D and spillover R&D have been dramatically changed in sign and significance for quite a few industries. For instance, in the light industry, the significantly negative estimate of the time trend in Table 2 is now positively significant; the estimate of the effect of *LNRND* in Table 2 ceases to be significant in Table 3 for all industries. From the values of Durbin–Watson statistic, we find that there is no evidence of autocorrelation when (2.2) is estimated with Cochrane–Orcutt transformed data.

4.2. Unobserved heterogeneity

In the short run, the stock of physical capital and, to a great extent, the level of employment are fixed. However, during booms a firm utilizes extra labor effort and the maximum possible use of installed capacity, whereas during recessions these inputs remain idle. Thus a given combination of capital stock and employment level will produce higher levels of output during booms and lower levels of output during recessions. Not controlling for the effects of capacity utilization will bias the parameter estimates. To the extent business cycles are autocorrelated, correction for autocorrelation by Cochrane–Orcutt transformation will correct for such bias. We do not have detailed information about capacity utilization or business cycles for India. We assume that all firms face common business cycles and adjust capacity utilization in response to business cycles in similar manner; more specifically we assume that

$$\hat{a}_{ijt} = \hat{a}_{ij} + \mu t + \zeta_t \equiv \hat{a}_{ij} + \psi_t \tag{4.4}$$

where ζ_t in (4.4) captures the capacity utilization response of a firm due to the common business cycle effect in period t. Notice that in the above specification we can treat ψ_t as fixed time effect, which includes both a time trend and a common capacity utilization term. In the rest of the paper we assume specification (4.4) for $\hat{a}_{ijt}$ in (2.2).

For any hat variable $\hat{z}_{ijt}$, denoting by $\hat{z}_{.t} \equiv \sum_{j=1}^{J}\sum_{i=1}^{N_j} \hat{z}_{ijt}/N$ and by $z_{ijt} \equiv \hat{z}_{ijt} - \hat{z}_{.t}$, the production function (2.2) with the specifications (4.3) and (4.4) becomes

$$y_{ijt} = a_{ij} + \alpha s_{jt} + \beta r_{ijt} + \gamma k_{ijt} + \delta l_{ijt} + e_{ijt}. \tag{4.5}$$

Notice that (4.5) factors out the time effects ψ_t; for large N and under assumption (4.3) we have

$$e_{ijt} = \rho e_{ijt-1} + u_{ijt}, \quad u_{ijt} \sim \text{i.i.d.}\left(0, \sigma_u^2\right) \forall\, i,j,t. \tag{4.6}$$

In the rest of the paper we focus on the transformed model (4.5) and (4.6) unless explicitly mentioned otherwise.

Panel data are useful for correcting a crucial assumption generally made in the empirical production function literature, that a_{ij}'s are constant for all firms. There are factors other than the ones included in our empirical specification of the production function which affect output level, e.g., managerial ability and input quality. These factors are observable to the manager of the firm but not observable to the econometrician. There are no reasons why these omitted factors should take the same value for all firms. However, these omitted variables can have characteristics that make them vary across firms but remain constant over time, and thus could be represented as constant a_{ij} for the ith firm in the jth industry. This heterogeneity in the constant term should be taken into account in estimating the parameters, otherwise the OLS estimates will be biased.

4.2.1. Fixed effect model

The estimates of the parameters will crucially depend upon whether we assume a_{ij} to be fixed or random effect. Let us first consider the case when a_{ij}'s are assumed to be fixed effect. Denote the sample mean over t of a variable y_{ijt} by $\overline{y_{ij}}$. Notice that subtracting from (4.5) its time average, we can factor out the fixed effects as follows:

$$y_{ijt} - \overline{y_{ij}} = \alpha\left(s_{jt} - \overline{s_j}\right) + \beta\left(r_{ijt} - \overline{r_{ij}}\right) + \gamma\left(k_{ijt} - \overline{k_{ij}}\right) + \delta\left(l_{ijt} - \overline{l_{ij}}\right) + \eta_{ijt} \tag{4.7}$$

where $\eta_{ijt} = e_{ijt} - \overline{e_{ij}}$. If instead of (4.6) we assume that e_{ijt}'s are independently and identically distributed, then one can show the OLS estimate of $\mu = (\alpha\ \beta\ \gamma\ \delta)$ in (4.7) to be the best linear unbiased estimator (BLUE). The OLS estimator of (4.7) is also known as *covariance estimate, or fixed effect estimate or within estimate*. We denote it by μ_{cv}. Notice that μ_{cv} uses only the variations within firms, and does not utilize the variations between firms. Under the assumption of zero serial correlation, although the estimates of the fixed effect model are consistent for μ, they are not efficient. We estimated a fixed effect model and found that the errors in the estimated models were first-order autocorrelated. This supports our assumption (4.6), under which we have the following:

$$\begin{aligned} y_{ijt} - \rho y_{ijt-1} = {} & (1-\rho)a_{ij} + \alpha(s_{jt} - \rho s_{jt-1}) + \beta(r_{ijt} - \rho r_{ijt-1}) \\ & + \gamma(k_{ijt} - \rho k_{ijt-1}) + \delta(l_{ijt} - \rho l_{ijt-1}) + u_{ijt}, \qquad (4.8) \\ i = 1, \ldots N_j, \quad & j = 1, \ldots J, \quad t = 2,3,\ldots,T. \end{aligned}$$

If ρ were known we could treat Eq. (4.8) as a fixed effect model on the transformed variables and apply the above technique to get within estimates. Since ρ is unknown, we apply the procedure of Section 4.1 on the model (4.8) to get an estimate of ρ, and we use this ρ for Cochrane–Orcutt transformation of data. We then apply OLS on the Cochrane–Orcutt transformed data standardized to have mean zero for each firm. For this procedure, we implicitly assume that correlation between the standardized Cochrane–Orcutt transformed regressors and the standardized error term $u_{ijt} - \bar{u}_{ij}$ is negligible. The parameter estimates of the fixed effect model on Cochrane–Orcutt transformed data are reported in Table 4.

4.2.2. Random effect model

A large number of firm-specific factors that affect the output level, but are not included explicitly as regressors, can have the characteristics of a random variable similar in nature to the normal law of errors. In such a case, it is appropriate to assume the values of $(1-\rho)a_{ij}$'s as a realization of a random variable with mean $(1-\rho)a$ and variance σ_α^2; (4.8) then becomes

$$\begin{aligned} y_{ijt} - \rho y_{ijt-1} = {} & (1-\rho)a + \alpha(s_{jt} - \rho s_{jt-1}) + \beta(r_{ijt} - \rho r_{ijt-1}) \\ & + \gamma(k_{ijt} - \rho k_{ijt-1}) + \delta(l_{ijt} - \rho l_{ijt-1}) + \nu_{ijt}, \qquad (4.9) \\ \nu_{ijt} = {} & (1-\rho)(a_{ij} - a) + u_{ijt}, \\ i = {} & 1,2,\ldots,N_j, \\ j = {} & 1,2,\ldots,J, \\ t = {} & 2,3,\ldots,T. \end{aligned}$$

Denote by $x_{ijt} = (s_{jt} - \rho s_{jt-1}\ \ r_{ijt} - \rho r_{ijt-1}\ \ k_{ijt} - \rho k_{ijt-1}\ \ l_{ijt} - \rho l_{ijt-1})$ and the time average of the vector x_{ijt} by $\overline{x_{ij}}$. Following Hsiao (1986, Section 3.3), under the assumption that ρ, σ_α^2, *and* σ_u^2 are known, and using the special structure of

Table 4
Parameter estimates from the fixed effect and random effect models on Cochrane–Orcutt transformed data [a]

	Industries							
	Light		Petro-chemical		Heavy		Overall	
Variables	Fixed	Random	Fixed	Random	Fixed	Random	Fixed	Random
Intercept	-	0.001	-	−0.0002	-	0.0009	-	0.003
		(0.02)		(0.004)		(0.01)		(0.01)
LNCAP	0.035	0.243	0.082	0.151	0.142	0.158	0.089	0.151
	(0.88)	(7.01)	(3.12)	(6.24)	(4.98)	(5.63)	(5.09)	(9.12)
LNWRKHRS	0.712	0.546	0.630	0.627	0.782	0.792	0.698	0.684
	(13.4)	(13.2)	(15.3)	(19.57)	(22.1)	(23.8)	(29.3)	(33.2)
LNRND	0.012	0.014	0.004	0.007	0.002	0.003	0.007	0.010
	(1.16)	(1.56)	(0.52)	(1.01)	(0.354)	(0.34)	(1.54)	(2.07)
LNSRDEXP	0.357	0.311	−0.004	0.031	0.018	0.064	0.101	0.122
	(5.34)	(7.13)	(0.05)	(0.69)	(0.49)	(2.23)	(3.34)	(5.64)
adj. R^2	0.332	-	0.319	-	0.613	-	0.422	-
ψ	-	0.138	-	0.089	-	0.062	-	0.077
Fixed vs Random:								
F-statistic	-	20.278	-	6.268	-	1.404	-	13.30
Hausman statistic	-	81.11	-	25.07	-	5.62	-	53.19
Wu-test for simultaneity bias:								
F-statistic	76.9	-	5.512	-	0.591	-	35.435	-
	[0.0001]		[0.020]		[0.442]		[0.0001]	

[a] t-statistics are in parentheses, (), and prob > F in brackets, [].

V_{ij}^{-1} due to our specification in (4.9), one can derive the following form for the GLS estimator μ_{ran} of $\mu = (\alpha, \beta, \gamma, \delta)$ in (4.9):

$$\mu_{\text{ran}} = \Delta \mu_b + (I_4 - \Delta)\mu_{\text{cv}}, \tag{4.10}$$

where

$$\Delta = \psi(T-1)\left(\sum_{j=1,i=1}^{j=J,i=N_j} x'_{ij} Q x_{ij} + \psi(T-1) \sum_{j=1,i=1}^{j=J,i=N_j} \left(\overline{x_{ij}} - \bar{x}\right)\left(\overline{x_{ij}} - \bar{x}\right)'\right)^{-1}$$
$$\times \left(\sum_{j=1,i=1}^{j=J,i=N_j} \left(\overline{x_{ij}} - \bar{x}\right)\left(\overline{x_{ij}} - \bar{x}\right)'\right),$$

$$\mu_{\text{b}} = \left(\sum_{j=1,i=1}^{j=J,i=N_j} \left(\overline{x_{ij}} - \bar{x}\right)\left(\overline{x_{ij}} - \bar{x}\right)'\right)^{-1} \left(\sum_{j=1,i=1}^{j=J,i=N_j} \left(\overline{x_{ij}} - \bar{x}\right)\left(\overline{x_{ij}} - \bar{x}\right)'\right),$$

$$x_{ij} = \begin{pmatrix} x_{ij1} \\ \vdots \\ x_{ijT} \end{pmatrix},$$

$$\psi = \frac{\sigma_u^2}{\sigma_u^2 + (T-1)\sigma_\alpha^2}, \quad Q = \begin{pmatrix} 1-\frac{1}{T-1} & -\frac{1}{T-1} & \cdots & -\frac{1}{T-1} \\ & \vdots & & \\ -\frac{1}{T-1} & -\frac{1}{T-1} & \cdots & 1-\frac{1}{T-1} \end{pmatrix}_{(T-1)\times(T-1)}.$$

μ_{b} in the above formula is the OLS estimate of μ estimated using time averages of the dependent and independent variables. Thus, the estimator μ_{b} uses only the variations between firms, and as pointed out earlier, the estimator μ_{cv} uses only the variation within firms; the estimator μ_{ran}, on the other hand, uses both types of variations and the relative weights given to these two types of variations depend on the parameter ψ. If $\psi \to 0$, we have $\mu_{\mathrm{ran}} = \mu_{\mathrm{cv}}$ and if $\psi \to 1$, μ_{ran} coincides with OLS estimator with common intercept. This fact could be used to devise a specification testing of these models, but little has been published in the literature about this.

Since the parameters ρ, σ_α^2, *and* σ_u^2 are unknown in the above equations, we replace them by the following estimates:

$$\hat{\sigma}_u^2 = \frac{\sum_{j=1}^{J}\sum_{i=1}^{N_j}\sum_{t=2}^{T}\left[\left(y_{ijt} - \overline{y_{ij}}\right) - \mu_{\mathrm{cv}}'\left(x_{ijt} - \overline{x_{ij}}\right)\right]^2}{N(T-2)-4},$$

$$\hat{\sigma}_\alpha^2 = \frac{\sum_{j=1}^{J}\sum_{i=1}^{N_j}\left[\left(\overline{y_{ij}} - \bar{y}\right) - \mu_{\mathrm{b}}'\left(\overline{x_{ij}} - \bar{x}\right)\right]^2}{N-5} - \frac{\hat{\sigma}_u^2}{T-1}.$$

The estimate of ρ is obtained applying the procedure described in Section 4.1 on the model (4.5). In the above formulae, the μ_{cv} and μ_{b} are computed for the model (4.9) using Cochrane–Orcutt transformed data.

In Table 4 we report the estimates of ψ, and generalized least squares estimates from the random effect model. We find both the significance levels and magnitudes of the parameter estimates to be quite sensitive to the specification of the unobserved heterogeneity as a fixed effect or a random effect. Note that the estimated effect of *LNSRDEXP* is smaller in the random effect model than the estimate in the fixed effect model.

4.2.3. Fixed effect or random effect model?

Suppose $(1-\rho)a_{ij}$ could indeed be represented as a random effect. In that case μ_{ran} is the best linear unbiased estimator, while μ_{cv} is linear unbiased and consistent but not efficient. As in our study, most empirical studies find that these two models produce quite different parameter estimates (see, for instance, Hausman (1978)).

Perhaps the most serious problem with the variance component model is that GLS produces biased and inconsistent estimates (i.e., $\mathrm{E}\mu_{\mathrm{ran}} \neq \mu$ *and* $\mathrm{plim}_{N \to \infty} \mu_{\mathrm{ran}} \neq \mu$) if the random effect is correlated with the regressors. In our production function context, this is more likely to be the case, since $(1-\rho)a_{ij}$ represents the heterogeneity regarding the managerial ability of a firm which not only affects the output level, but also affects a firm's input choices. Thus, μ_{ran} will suffer from the endogeneity bias. However, panel data are again useful to test this. Following Mundlak (1978) approach, suppose $(1-\rho)a_{ij}$ and x_{ij} are related linearly as $(1-\rho)a_{ij} = \overline{x_{ij}^T}\theta + w_{ij}$, where w_{ij}'s are i.i.d. Substituting this in (4.9), and following Hsiao (1986, Section 3.4.2a), one can compute the GLS estimates for the parameters, and one can show that the μ_{ran} for this model is exactly the same as μ_{cv}. In this augmented model the null hypothesis of no correlation between $(1-\rho)a_{ij}$ and x_{ij} is equivalent to the null hypothesis H_0: $\theta = 0$. We can use the standard F-test statistic (see Hsiao, 1986, p. 48) for testing the null hypothesis H_0: $\theta = 0$ against the alternative H_1: $\theta \neq 0$. The F-test statistic in this case has central F-distribution with degrees of freedom 4 and $[N(T-1)-9]$ under the null. If the null hypothesis is rejected, then we use the fixed effect model; otherwise we use the random effect model. Since under the null hypothesis μ_{ran} is efficient, and under both null and alternative μ_{cv} is consistent, we can apply the Hausman specification test to select between these two models. The Hausman test statistic is given by $H = (\mu_{\mathrm{cv}} - \mu_{\mathrm{ran}})' V^{-1} (\mu_{\mathrm{cv}} - \mu_{\mathrm{ran}})$, where V is the difference between the variance–covariance matrix of μ_{cv} and the variance–covariance matrix of μ_{ran}. H is distributed as central chi-square with 4 degrees of freedom under the null hypothesis. These test statistics are also reported in Table 4.

Both the Hausman test and F-test reject the random effect model against the fixed effect model in all except the heavy industries.

4.3. Simultaneity bias and Wu-test

As mentioned earlier, in the context of production function estimation, most of the regressors in (2.2) are simultaneously determined with the value-added variable and thus the error term is expected to be correlated with the regressors. Controlling for unobserved heterogeneity and serial correlation in the estimates of the previous subsections has eliminated some of the correlation. We must, however, test if there still remains any correlation between the error term and the regressors due to simultaneity effect, which renders biased and inconsistent parameter estimates and invalid standard t and F distributions to conduct significance tests of the parameter estimates. In this section we conduct the Wu-test for the null hypothesis of no correlation between regressors and the error term, and provide alternative estimates of parameters in (2.2) whenever the Wu-test rejects the null hypothesis.

Wu (1973) and Wu (1974) proposed a series of tests in situations where instrumental variables exist for the regressors which are correlated with the error term, and he recommended the use of his T_2 test statistic whose performance seems to be better in small sample and Monte Carlo experiments. Wu's T_2 statistic is computationally complicated. It has been, however, shown (Nakamura and Nakamura, 1981) to be asymptotically equivalent to the simpler F-test suggested by Hausman (1978). We follow Hausman's approach as follows: the first step is to obtain the predicted values (or residuals) of the set of right-hand variables, k_{ijt}, l_{ijt}, r_{ijt}, which are presumably correlated with the error term in (4.8) by regressing them on a set of instrumental variables that includes regressors which are uncorrelated with the errors. The next step is to run a regression of the original regression equation augmenting the right-hand variables with these predicted values (or residuals) of the regressors. The Wu-test is equivalent to conducting the F-test of the null hypothesis that the regression coefficients of the predicted values (or residuals) are zero.

To construct instrumental variables for the Wu test and also to provide alternative estimates that are free from endogeneity bias in industries where the Wu test rejects the null hypothesis, we embed Eq. (2.2) in a system of factor demand functions. We assume that in the short run, the stocks of physical capital and R&D capital are fixed and producers minimize a short-run cost function. Let $\hat{w}_{ijt}$ be the natural log of real wage rate per unit of labor hour of firm i in industry j and period t; using Shephard's lemma, conditional factor demand for labor for our Cobb–Douglas production function can be derived as

$$\hat{l}_{ijt} = \hat{y}_{ijt} - \hat{w}_{ijt} + \ln\delta.$$

Substituting the above in (2.2) and utilizing specifications (4.3) and (4.4), we can find the following system of 'semi' reduced form equations:

$$\hat{y}_{ijt} = \frac{1}{1-\delta} \cdot \left[\breve{a}_{ij} + \psi_t + \alpha\hat{s}_{jt} + \beta\hat{r}_{ijt} + \gamma\hat{k}_{ijt} - \delta\hat{w}_{ijt} + \hat{e}_{ijt}\right], \tag{4.11}$$

$$\hat{l}_{ijt} = \frac{1}{1-\delta} \cdot \left[\tilde{a}_{ij} + \psi_t + \alpha\hat{s}_{jt} + \beta\hat{r}_{ijt} + \gamma\hat{k}_{ijt} - \hat{w}_{ijt} + \hat{e}_{ijt}\right], \tag{4.12}$$

where $\breve{a}_{ij} = \hat{a}_{ij} + \delta\ln\delta$ and $\tilde{a}_{ij} = \hat{a}_{ij} + \ln\delta$. The above is a system of equations with fixed time effects and fixed cross-section effects, and serially correlated errors. If there are measurement errors in wage rates or if there are errors in the functional approximation, or optimization, which could be considered fixed across firms or fixed over time, we can add those to $\breve{a}_{ij}$, $\tilde{a}_{ij}$ and ψ_t. In the literature of panel data, not much statistical theory has been developed for such a system. In our set-up, however, we are able to utilize the special structure imposed by the assumption of cost minimization to carry out statistical inference as described below.

First we use the same transformations of the hat variables as we did to arrive at the model in (4.5) without the hat variables; this factors out the fixed time effects ψ_t of the system of equations (4.11) and (4.12). Using the same notation as in Eq. (4.5), we arrive at the following system of equations:

$$y_{ijt} = a_{ij}/(1-\delta) + \alpha/(1-\delta) s_{jt} + \beta/(1-\delta) r_{ijt} + \gamma/(1-\delta) k_{ijt} - \delta/(1-\delta) w_{ijt} + u_{ijt}, \tag{4.11$'$}$$

$$l_{ijt} = a_{ij}/(1-\delta) + \alpha/(1-\delta) s_{jt} + \beta/(1-\delta) r_{ijt} + \gamma/(1-\delta) k_{ijt} - 1/(1-\delta) w_{ijt} + u_{ijt}. \tag{4.12$'$}$$

Let $\tilde{z}_{ijt}$ denote the transformed variable $z_{ijt} - \rho z_{ijt-1}$, being standardized to have mean zero for all i,j. The above system of equations, (4.11$'$) and (4.12$'$) reduces to the following system:

$$\tilde{y}_{ijt} = \alpha/(1-\delta) \tilde{s}_{jt} + \beta/(1-\delta) \tilde{r}_{ijt} + \gamma/(1-\delta) \tilde{k}_{ijt} - \delta/(1-\delta) \tilde{w}_{ijt} + u^*_{ijt}, \tag{4.13}$$

$$\tilde{l}_{ijt} = \alpha/(1-\delta) \tilde{s}_{jt} + \beta/(1-\delta) \tilde{r}_{ijt} + \gamma/(1-\delta) \tilde{k}_{ijt} - 1/(1-\delta) \tilde{w}_{ijt} + u^*_{ijt}, \tag{4.14}$$

where $u^*_{ijt} \equiv (u_{ijt} - \bar{u}_{ij})/(1-\delta)$. Under the assumption that the correlation between u^*_{ijt} and the regressors is negligible, we estimated the above system of SUR (seemingly unrelated regression) equations with cross-equation restrictions to get the predicted value of $\hat{l}_{ijt}$ for the purpose of the Wu-test as mentioned above and also to provide the alternative parameter estimates for industries for which the Wu-test rejected the null hypothesis of no simultaneity bias. For the Wu-test we estimated the above system without imposing cross-equation restrictions. The F values for Wu-test are shown in the last two rows of Table 4. The test rejected the null hypothesis of no simultaneity bias for the light and overall industries at the 1% level. For these two industries, we estimated the above system of equations (4.13) and (4.14), imposing cross-equation restrictions, but without restricting the parameters to be non-negative. The estimated models are as follows: (asymptotic t-values are shown below the parameter estimates):

Light industry:

$$\underset{(1.56)}{\alpha = 0.112}, \quad \underset{(1.51)}{\beta = -0.017}, \quad \underset{(5.87)}{\gamma = 0.362}, \quad \underset{(1.67)}{\delta = -0.275};$$

Overall industry:

$$\underset{(5.17)}{\alpha = 0.221}, \quad \underset{(3.31)}{\beta = 0.022}, \quad \underset{(6.51)}{\gamma = 0.260}, \quad \underset{(1.28)}{\delta = -0.194}.$$

Since the estimates of δ were negative for both industries, we estimated the system restricting the parameters to be non-negative, and we found the following parameter estimates:

Light industry:

$$\underset{(2.607)}{\alpha = 0.143}, \quad \beta = 0, \quad \underset{(9.37)}{\gamma = 0.281}, \quad \delta = 0;$$

Overall industry:

$$\underset{(6.123)}{\alpha = 0.197}, \quad \underset{(3.649)}{\beta = 0.018}, \quad \underset{(12.51)}{\gamma = 0.216}, \quad \delta = 0.$$

Notice that for overall industry both estimates are comparable in magnitude and significance; for the light industry, however, two estimates differ significantly. We also estimated the system of equations (4.13) and (4.14) without imposing the constraints and we found the parameter estimates of overall industry to be comparable to the above estimates in magnitude and significance but not for light industry. It is important to mention that the above system of equations with cross-equation restrictions is derived under the assumption of short-run cost minimization and Cobb–Douglas production function both of which might be wrong especially in the Indian context where strong labor unions and a plethora of government regulations exist. One needs to build up a more appropriate model of labor demand equations taking into account these regulatory factors. Thus we might base our inference about spillover effect of R&D by using the fixed effect model for all except the heavy industry and by using the random effect model for the heavy industry. These estimates are reproduced in Table 5.

4.4. *The final models and the main findings*

From the parameter estimates in Table 5, it is clear that spillover R&D is a highly significant determinant of productivity growth in all industries except

Table 5
Final models selected from fixed effect, random effect and 3SLS models [a]

	Industry			
Variables	Light	Petro-chemical	Heavy	Overall industry
	(Fixed effect)	(Fixed effect)	(Random)	(Fixed effect)
LNCAP	0.035	0.082	0.158	0.089
	(0.88)	(3.12)	(5.63)	(5.09)
LNWRKHRS	0.712	0.630	0.792	0.698
	(13.4)	(15.3)	(23.8)	(29.3)
LNRND	0.012	0.004	0.003	0.007
	(1.16)	(0.52)	(0.34)	(1.54)
LNSRDEXP	0.357	-0.004	0.064	0.101
	(5.34)	(0.05)	(2.23)	(3.34)

[a] *t*-statistics in parentheses.

petro-chemical, with its elasticity with respect to value added ranging from 0.064 in the heavy industry, 0.357 in the light industry and 0.101 in the overall industry. The effect of own R&D is significant only in the overall industry and in the rest of the industries own R&D capital is not significant.

The strongly significant effect of spillover R&D and the insignificant effect of own R&D capital for the light and petro-chemical industries might be due to the non-reporting problem we mentioned earlier, i.e., some of the firms with R&D expenditures less than one percent of total sales may not have reported their R&D expenditures in their annual reports and were thus not included in *LNRND* but they did report to the Department of Science and Technology and were thus included in *LNSRDEXP*. For the light and heavy industries in Table 5, the strongly significant effect of industry level R&D and the insignificant effect of in-house R&D might be due to the non-reporting problem mentioned earlier. This, however, needs to be checked with more appropriate firm level data on R&D. It was pointed out to me by Pierre Mohnen that it is often found in the literature that the rates of returns to R&D increase when capital and labor are corrected for R&D double counting. This could be a reason why elasticity of own R&D is insignificant or low (see Mohnen (1992) on this).

To gain more insight about the effect of private R&D on productivity growth, we note that the ratio of private sector R&D as a percentage of industrial (i.e., total of private and public sectors) R&D expenditures is 80% in the light, 44% in the petro-chemical, 48% in the heavy industries, and about 46% in the overall industry excluding the defense industry. Thus, from the estimates of the selected models, one could say that if all private firms increase their R&D expenditures by one percent, the percentage increase in the long-run output of each firm (including those which are not doing R&D) will be roughly $\eta\phi$, where ϕ is the proportion of private R&D expenditure to total industrial R&D expenditure and η is the sum of the significant estimates of the coefficients of *LNSRDEXP* and *LNRND*. These long-run effects for the light, heavy and overall industries are respectively 0.286, 0.031, and 0.050.

5. Conclusions

In this paper we have examined the contribution of in-house R&D capital and industry-wide external R&D capital, in combination with physical capital and labor hours to the productivity growth of private firms in India. We have used panel data on value added, work hours, physical capital, and in-house R&D investment of a sample of private manufacturing firms over the period 1976–1986 to estimate an extended Cobb–Douglas production function. Our sample covered a wide range of industries. We grouped the firms into light, petro-chemical and heavy industries to examine how these relationships vary across these industries. One often obtains inconsistent and biased estimates of the production function by running OLS and ignoring the possible correlation of the error term with the regressors due to serially correlated error terms, unobserved heterogeneity across firms arising from omitted variables, and simultaneity in the determination of value-added and inputs. We found parameter estimates to be very sensitive to the above types of assumptions on the error terms. We conducted the Hausman test, F test and Wu test to detect the sources of correlation and then selected parameter estimates that are more efficient, consistent and unbiased for drawing our conclusions.

On the basis of the selected models in each industry, we find evidence for the R & D spillover hypothesis of the growth literature. More specifically, we find that the firms gain significantly from the aggregate industry level spillover R&D capital in all except petro-chemical industries. The public policies that encourage faster rate of growth in industry wide spillover R&D capital would be conducive to generate higher productivity growths of private firms. The specific nature of these public policies will, however, depend on whether the observed significant positive spillover effect is due to weaker patent protection and very low cost in the utilization of globally or locally available public domain knowledge, or due to complementarities in the research efforts of individual firms in an industry. Future research along these lines will be very useful.

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Appendix A

Light	Manufacture of wood and wood products, paper and paper products, food products, beverages, tobacco products, textiles
Petro-chemical	Manufacture of rubber, plastics, petroleum, coal and coal products, chemicals and chemical products, pharmaceutical and non-metallic minerals
Heavy	Manufacture of machinery, machine tools and parts, electrical machinery, electrical appliances and parts, basic metals, and metal products

$\chi_4^2(\alpha) = 9.488$ if $\alpha = 0.05$, and $= 13.28$ if $\alpha = 0.01$; $F_{4,n(T-1)-9}(\alpha) = 5.52$ for all n's in our sample, and for $\alpha = 0.01$, and the second degrees of freedom 15.

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