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The Innovation-R&D Nexus: Evidence from the Indian Manufacturing Sector

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Abstract

While there is consensus that innovation is a prime motive force in the process of modern economic growth, there continues to be lack of clarity about how best to capture this process of innovation. Although it is relatively clear that research and development expenditure constitutes an important, perhaps even the most important, input into the innovation process, its relationship with the output of this process remains enigmatic. A sizeable literature considers this relationship in the developed country context, though primarily the US, and sheds light on a number of aspects. Evidence for developing countries, in contrast, is sparse.

This study intends to fill this gap by exploring the innovation-R&D relationship as exemplified by the influence of knowledge capital on patents, in the context of the emerging economy of India. Using a relatively large sample of 380 manufacturing firms spanning 22 industries over the recent period 2001-2010, we find weak evidence at best for this relationship. A one unit (dollar or rupee) increase in the knowledge capital stock is likely to raise the expected patent count by only about 0.7%, which given the current average patent count per firm per year, is only a marginal change. In addition, we also find that patent experience and the firm's access to resources are both strongly significant factors explaining changes in expected patent counts, although their magnitudes are equally small. Our semi-elasticity estimate w.r.t knowledge capital translates to an elasticity of about 0.02 at the means, which is in line with that for enterprises in Spanish manufacturing. However, it is an order of magnitude smaller than the 0.1 to 0.2 reported for the Dutch pharmaceuticals sector, and the 0.3 to 0.6 for firms in the US manufacturing sector.

Given the many reasons why most firms appear not to patent even when they conduct some research, policy makers would have to address multiple issues to bring about a more effective conversion of research into formal intellectual property in the developing country context.

The Innovation-R&D Nexus: Evidence from the Indian Manufacturing Sector

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1. Introduction

While there is consensus that innovation is a prime motive force in the process of modern economic growth, there continues to be lack of clarity about how best to capture this process of innovation. Although it is relatively clear that research and development expenditure constitutes an important, perhaps even the most important, input into the innovation process, its relationship with the output of this process remains enigmatic. The reasons for this are multiple: Not all research and development expenditure fructifies into innovation, a lot of it may just go 'waste'.[1] Even when it does result in research output, doubling it may not add very much to the existing research output. R&D expenditure may result in new products or processes, but these may be refused protection via patents and copyrights. Alternatively, such expenditure may result in new products and processes which are in fact granted protection. R&D expenditure may have significant implications for firm sales, profit and market value even when the associated innovations are 'small'; on the other hand, it may have no such implications even when the associated innovations are supposedly significant insofar as they have been granted protection. These multitudinous possibilities demonstrate the difficulty in relating research and development expenditure with the resulting research output.

Nevertheless, given the importance of this association, we persist in exploring it in our specific context. For this purpose we shall use patent data in lieu of research output in this study, because patents "… are available, are … related to inventiveness, and are based on … an objective and slowly changing standard" (Griliches 1990). Thus, patent counts, i.e. the number of patents granted to a firm, are intrinsically related to the firm's inventiveness. Furthermore, insofar as patents are granted on the criteria of novelty and non-obviousness, they are supposedly conferred for creating something new and for something that involves an inventive step, which makes them suitable proxies for innovation.[2]

The extant literature considers this relationship mostly in the developed country context, and sheds light on a number of aspects. Pakes and Griliches (1984) were amongst the first to study the significance of lags in the patents-R&D relationship for US manufacturing firms. They found that the relationship was more or less contemporaneous, and although patents are a good indicator of differences in the inventiveness across firms, they are not equally effective in explaining such variations over time for a given firm. Hall, Griliches and Hausman (1986) reach much the same conclusion, using a more up-to-date and larger sample of US firms (see also Hausman, Hall and Griliches 1984). These studies improve upon Bound et al. (1984) who reported a strong patents-R&D relationship, but used cross-section data. Montalvo (1997), and Blundell et al. (2002) who allow for a linear feedback mechanism in the patents-R&D relationship, are broadly in sync with the earlier studies using US data. Crépon and Duguet (1997), using a large 1980s sample of French manufacturing firms, not only confirm the positive patents-R&D relationship, but also find that past patents exercise a small effect on current patents. Cincera (1997), using a small international sample of firms, is in agreement regarding the patents-R&D relationship or the so-called knowledge production function. These studies report elasticities of patents with respect to R&D that vary between about 0.3 and about 0.6 for the most part. Czarnitzki et al. (2009) showed in the context of Belgian firms, that using R&D expenditure as a whole rather than just ‘R’ may lead to an underestimation of research productivity, because it is mainly ‘R’ and not ‘D’ that leads to patents.

The bulk of the studies in this area evidently pertain to the US, with only a few for some other developed countries. Evidence for developing countries, in contrast, is sparse. Deolalikar and Roller (1989), using a small sample of 145 Indian manufacturing firms in the late-1970s, find that the probability of patenting is insignificantly explained by R&D expenditure, with a near zero elasticity. Chadha (2009), using a more recent sample of 65 firms in the Indian pharmaceuticals sector, finds instead a research elasticity of patenting ranging between 0.5 and 1.8.

This study intends to fill the gap in our understanding of the knowledge production function in the developing country context with low levels of R&D, and it contributes to the literature in a number of ways. It is based on a relatively large sample of 380 manufacturing firms in India, spanning 22 industries, over the recent period 2001-2010. The sample excludes firms with less than ten years of R&D data, in the belief that firms need to conduct research for a ‘long enough’ period to realistically produce any innovation; it appears too sanguine to use data for just one or a ‘small’ number of years per firm, as some studies do. Second, we take stock of the fact that our count data (namely, patents) exhibit the phenomenon of ‘excess zeros’ (Cameron and Trivedi 2010). Thus, a firm may report zero patents either because it does not file for patents (on grounds that its innovation is not good enough, or the patent is too costly, or if it wants to keep the innovation secret), or because it did file for patents but was turned down by the patent office. In this situation, the number of zeroes is said to be ‘inflated’, and two distinct processes are seen as generating the count data, one determining the zero counts and the other the nonzero counts. As explained in detail in section 2, we employ the zero-inflated negative binomial to address this criticism of earlier estimation procedures. Third, earlier estimates may be consistent only under the condition of strict exogeneity of the regressors, which may or may not hold in our case. We strive to correct for possible endogeneity using the linear feedback model proposed by Blundell et al. (1999), which slackens the exogeneity condition by approximating the fixed effects by the log of patent counts from a pre-sample period. Finally, the earlier literature does not allow for the non-technical knowledge stock of the firm, which also determines the success with which R&D transforms into patents (OECD 2011). Thus, R&D may lead to patents only when combined with appropriate managerial and organisational changes, and changes in 'firm culture'. Although this variable is difficult to measure, section 2.1 explores using a patent stock variable to reflect such experience, as a first approximation.

Using our specification, we find weak evidence at best for the presence of the knowledge production function in the Indian manufacturing sector. A one unit (dollar or rupee) increase in the knowledge capital stock is likely to raise the expected patent count by only about 4.3% at most. Given the current average patent count per firm per year of about 0.8, this is an insignificant change. We also find that patent experience is a strongly significant factor explaining changes in expected patent counts, although its magnitude is only slightly larger at about 1.3%. Further, we find that firms with greater access to resources are more likely to patent than the less fortunate, which has special implications in the developing country context where small firms and start-ups are starved of research funds. Finally, although knowledge spillovers are strongly significant in explaining expected patent counts, a unit increase in spillovers from other firms raises patenting by a mere 0.3%. The rest of the paper is organised as follows. Section 2 develops the estimation model, and discusses the model variables. Section 3 details the dataset. Section 4 presents the empirical results, and section 5 provides a brief conclusion.

2. Estimation Model

Following Pakes & Griliches (1984), we posit that changes in a firm's stock of economically useful knowledge ($\dot{K}$) occur on account of R&D expenditure (R) and other stochastic factors such as the inherent randomness of innovations (u), so that the knowledge production function may be expressed as:

$$\dot{K} = R + u \tag{1}$$

where the error term also picks up the non-formal R&D inputs which are taken to be uncorrelated with the R&D expenditure.

Patents (PAT) are a manifestation, albeit imperfect, of the changes in the stock of knowledge ($\dot{K}$), so that an indicator function may be taken to relate the two as

$$PAT = a\dot{K} + v \tag{2}$$

where v captures the noise in the relationship. Combining (1) and (2), we may express the patent production function (Hausman et al. 1984, Hall et al. 1986, Cincera 1997, Crépon and Duguet 1997, Blundell et al. 2002) as

$$PAT = aR + au + v \tag{3}$$

where u and v are uncorrelated.

The regressand in (3) is a count variable that can take only discrete, non-negative values with no upper bound. Further, the distribution of patents granted is highly skewed, with a very large number of firms granted no patents (so that the regressand is zero), and a very small number granted many patents. In addition, the patent grants of a firm may occur independently over time; and their variance, conditional on their covariates, may tend to increase with the covariates. As a first approximation, therefore, the regressand can be modelled as a Negative Binomial process. In that case, if PAT_{it} is the patent count of firm i in period t, the probability of having a patent count of p_{it}, given the covariate vector x_{it}, is

$$f(p_{it}|x_{it}) = \frac{\theta^{\theta}{\lambda_{it}}^{p_{it}} \quad \Gamma(\theta+p_{it})}{(\lambda_{it}+\theta)^{(p_{it}+\theta)}\Gamma(p_{it}+1)\Gamma(\theta)} \tag{4}$$

where $f(\cdot)$ is the Negative Binomial probability distribution function (having parameters θ and p_{it}) with conditional mean $E(PAT_{it}|x_{it}) = \lambda_{it}$, and conditional variance $V(PAT_{it}|x_{it}) = \lambda_{it} + \alpha\lambda_{it}^2$. We then hypothesize that

$$E(PAT_{it}|x_{it}) = \lambda_{it} = exp(x_{it}'\beta) \tag{5}$$

where β is the parameter vector.

This formulation, however, runs into the criticism that count data often display the phenomenon of ‘excess zeros’ (Cameron and Trivedi 2010). To understand this, we must ask what the reason could be for a firm to report a zero patent count. There could be two distinct possibilities here: If a firm does not file for patents it will end up with zero patents. This may happen if the firm does not consider the innovation good enough to merit a patent, or if it considers the patent to be too expensive to obtain, or if it does not want to disclose its innovation in the patent document. We shall refer to this group as the ‘certain zero’ group. Alternatively, if a firm does file for patents but is turned down by the patent office, it will again end up with zero patents.[3] In a sense, then, the number of zeroes is ‘inflated’ and the case of zero patents cannot be explained in the same manner as that of non-zero patents. In other words, there appear to be two distinct processes generating the count data, with one determining the zero counts and the other (Negative Binomial) the nonzero counts. Let the probability of the former be $\psi_{it}(z_{it}'\gamma)$ for observation i in time period t, where ψ(·) is the logit function, z_{it} the relevant covariates and γ the associated parameter vector. Then the probability of having a patent count of p_{it} is $g(p_{it}|x_{it}, z_{it}) = \{\psi_{it}(z'_{it}\gamma) + [1 - \psi_{it}(z'_{it}\gamma)]f(0|x_{it})\}$ if $p_{it} = 0$, and $[1 - \psi_{it}(z'_{it}\gamma)]f(p_{it}|x_{it})$ if $p_{it} > 0$. This composite model, referred to as the Zero-Inflated Negative Binomial model, has a conditional mean $E(PAT_{it}|x_{it}, z_{it}) = \lambda_{it}[1 - \psi_{it}]$, and conditional variance $V(PAT_{it}|x_{it}, z_{it}) = \lambda_{it}[1 - \psi_{it}] + \lambda_{it}^2[\alpha + \psi_{it}][1 - \psi_{it}]$. The former is then related to the set of covariates as in equation (5) above.

2.1. *The Regressors*

Evidently the most important regressor in our specification relates to research and development investment. Although many of the studies reviewed above, and both pertaining to India in particular, use annual research and development expenditure and its lags, the conclusion appears to be that the lag structure does not add much to explaining knowledge production. In fact, Hall, Griliches and Hausman (1986) observe that "… R and D and patents appear to be dominated by a contemporaneous relationship, rather than leads or lags". Additionally, given that we are not interested in the lag structure per se in this study, we propose to capture the influence of past R&D expenditure by computing a knowledge capital stock ($KNOWCAP$). This is done using the perpetual inventory relation $KNOWCAP_t = (1 - d)KNOWCAP_{(t-1)} + R_t$ for each firm i, where $KNOWCAP$ is the stock of knowledge capital, R is research and development expenditure, d is the rate of depreciation of knowledge capital, and t is the time subscript (Hall 1990). In functionalising this relationship we follow the literature in setting the depreciation rate at 15% per annum. To determine the value of the stock in the 'first' period, we employ the sample period R&D expenditure to compute a proxy for the pre-sample rate of growth of R&D. This ranges from 0.5% for metals to 2.7% for pharmaceuticals, and is considerably less than the 8% p.a. used by various studies including those for developing countries. Having computed the value of the stock in the first period, we then employ the perpetual inventory equation to derive the complete series, using R&D data deflated by the industry sales deflator.

Recent developments in the innovation literature (Beneito et al. 2014) argue that another important factor contributing to the 'success' of research investment is experience in this domain. Earlier research and development activity may or may not have resulted in success in terms of patents generated, but at least improves the firm's ability to approach a research problem – in accordance with the maxim '*uses promptos facit*' or its modern version 'practice makes perfect'. In other words, the firm benefits from what the literature calls learning-by-doing and learning-to-learn (Nelson and Winter 1982). However, we feel that these are precisely the kinds of knowledge that are implicitly captured in the knowledge capital stock variable discussed in the previous paragraph. In fact, representing R&D experience as "the number of years the firm has been carrying out R&D" as do Beneito et al (2014), would be inadequate because there is both a time as well as a magnitude dimension to learning – the longer you do something the better you become at it, but equally the *more* you do it the better you become. Thus, if two firms conduct R&D over the previous five years such that the second firm conducts twice as much R&D as the first, then one may be justified in conjecturing that the second firm accumulates more technical knowledge than the first. Further, the effect of earlier investments in this learning process is likely to fade over time, so that what the firm did five years back may be less important than what it did two years back. Both these aspects of the innovation process are well-integrated in the perpetual inventory method that we use to compute the knowledge capital stock of firms, as discussed in the previous paragraph.

We feel, however, that even the knowledge capital stock variable is incomplete in capturing the firm's learning experience, because technical knowledge is only part of the story, and non-technical knowledge is also important in determining the success with which R&D investment gets converted into patents (OECD 2011), something that the studies cited above do not consider. For instance, R&D may fructify into innovations and patents only when matched by suitable managerial changes, or organisational changes in the research team, or changes in the 'firm culture'. Since the knowledge capital stock measure is based on R&D investment only, it probably fails to pick up the accumulation of non-technical knowledge in a firm. While it is not immediately obvious how we can directly measure the non-technical knowledge stock of firms, we explore the use of a 'patent experience' variable ($PATEXP$) as an indirect measure. This measure, defined as the number of patents filed (and subsequently obtained) by the firm, say in the previous five years, should capture the effect of the firm's non-technical knowledge stock. Being a composite measure, however, it would also capture persistence effects (Sanyal and Vancauteren 2013) insofar as the firm's previous patenting experience familiarizes it with the procedure, cost, and subsequent benefits of patenting, and thereby influences its current proclivity to patent. To explore whether the effect of a firm's knowledge capital stock on its patenting behaviour is affected by its patent experience, we also include the interaction term $KNOWCAP * PATEXP$ in the set of regressors.

An important covariate included by many of the earlier studies is firm size, which is captured alternatively by a firm's physical assets, employment or sales. However, these studies do not precisely spell out what advantages large firms have over small(er) ones in the innovation context. On the one hand, large firms arguably have greater access to resources, both for conducting research and to pay for the patenting process, than do smaller ones. Deeper pockets also enable them to weather the uncertainty attaching to the process of innovation better. On the flip side, small firms may be relatively more dynamic and hence more innovative, at least in certain industries (Acs and Audretsch 1990). Further, firms that are large in a given milieu, such as small economies, may be considered small in the context of large economies. In other words, the variable firm size hides opposing forces vis-à-vis the innovativeness of firms, and ideally should not be represented by a single variable as the earlier studies have done. We feel that these opposing forces ought to be allowed for by including two separate variables instead of a single portmanteau variable such as firm size. We propose to capture a firm's access to resources in terms of its real profits ($PROFIT$), which is expected to have an unambiguous positive effect on its innovativeness. The second factor pertaining to a firm's dynamism is very difficult to define, and as a first approximation we use the observation that highly innovative firms generally possess an important patent or two from inception. However, none of our sample firms fitted this observation, and so we omit this variable from our analysis.

Another important covariate in our context pertains to the knowledge spillovers that a firm may benefit from. Research and development undertaken by firms in the economy produces non-rival knowledge that may stimulate technological innovation in a 'neighbouring' firm. Unlike earlier studies that attempt to capture this effect in terms of the total research and development investment of the 'rest of the economy' (i.e. by firms other than the firm in question), we prefer to first compute the stock of knowledge capital in the rest of the economy, using the perpetual inventory method outlined above. We then allow for the fact that the extent of the knowledge spillover for a given firm likely depends on the extent to which it is intertwined with the economy on the input side, which we proxy by the share of its material input expenditure (on raw materials and utilities) in the total economy-wide input expenditure in a specific year. Multiplying this ratio with the knowledge capital stock of the 'rest of the economy' gives us the spillover variable ($SPILLOVER$). None of the covariates in our study are 'confounders', and are included to improve estimation efficiency, since they can potentially influence the dependent variable but are not influenced by the (individual) firm's knowledge capital.

The period being analysed witnessed a considerable strengthening of intellectual property protection as India became fully TRIPS compliant during its designated implementation period. This period saw three amendment acts – the Patents Acts 1999, 2002 and 2005. Our sample period also saw a number of fiscal and monetary policy reforms (Nayak, Goldar and Agrawal 2010) that may have had substantial implications for firm competitiveness and hence their innovation strategies. Finally, there were substantial changes in the cost of patenting with effect from 2004 (Government of India 2003), with potential implications for the patenting behaviour of our sample firms. We propose to allow for these disparate policy changes scattered across different time points in our sample period, by including a full set of year dummies.

3. The Dataset

The data for this study were compiled from two different data sources. The bulk of the data were drawn from the 'Prowess' database, marketed by the Centre for Monitoring Indian Economy (CMIE 2014), and pertain to firms traded on the Bombay and National Stock Exchanges of India. Only firms with data for R&D and physical capital for the ten-year period 2001-2010 were retained.[4] Implicit in this criterion was the concern that firms would have to conduct research and development for a long enough time period to realistically expect any output in terms of innovation. While it is evidently unclear how long such a period should be, and 'theory' has little to contribute in this respect, at the same time it might be too optimistic to presume that even firms with just one or a 'few' year's R&D ought to be included in the sample, as do some of the studies cited above. Therefore, we err on the side of caution in choosing the period in question to be a substantial ten years.

This yielded data for 380 firms for the period 2001-2010, or 3800 observations. The firms straddled 22 manufacturing industries mostly at the broad 2-digit, and some at the 3-digit, levels of the National Industrial Classification (NIC). These industries are: auto ancillaries, automobiles, cement, chemicals, domestic appliances, drugs and pharmaceuticals, electrical machinery, electronics, food and agro-products, leather and leather products, metals and metal products, non-electrical machinery, personal care products, petroleum products, plastic and plastic products, rubber and rubber products, textiles and textile products, construction material, consumer goods, gems and jewellery, glass and glass products, paper and paper products.

Data on the patents (PAT) filed by each firm in a given year, patents that were subsequently granted, were extracted from the online database of the Indian Patent Office of the Government of India. These data also served for creating the patent experience variable. Patent data were extracted by the year of filing, because our interest lies in relating the research output with the research input. This purpose would not be served by using the date of grant, given the long lag between the filing and grant dates. For the sake of completeness, we note that the modal lag between patent filing and patent grant is about four years for our sample, which is why our sample period stops at 2010. Table 1 provides the basic descriptive statistics for the model variables.

Of the 380 firms in the sample, 267 (about 70%) did not obtain a single patent during the study period. The mean patent count or the average number of patents per firm per year for the overall sample is about 0.8, with a substantial standard deviation of 5.2. This variable has a rather low correlation of 0.2 with knowledge capital stock, a much higher correlation of 0.6 with the patent experience variable, a correlation of about 0.3 with the profit variable, and a mere 0.04 with the spillover variable. Moreover, none of the pairwise correlations between the model regressors are disturbingly high. Importantly, 'between variation' much exceeds 'within variation' for all the model variables except spillovers.

4. Empirical Results

4.1. *Random and 'Fixed Effects' Negative Binomial Specifications*

We begin by presenting the results of the negative binomial model with random effects, wherein the dispersion parameter is randomly determined across firms. From Table 2, we find that there is a weak relationship between the expected patent count of a firm and its stock of knowledge capital, the relationship being statistically insignificant even using a one-tail test. From the full model in column (5), we see that a one unit increase in the regressor would increase the expected patent count by a factor of $e^{0.006331} = 1.00635$, or by only 0.6% ceteris paribus. The interaction term is insignificant with a coefficient close to zero and is therefore ignored. Patent experience turns out to have a strongly statistically significant effect on the regressand, although this translates into a mere 0.5% change in the dependent variable for every one unit change in this regressor. Similar is the case of the resource access proxy or profit, which though strongly significant, appears to effect a mere 0.3% change in the regressand. The spillover variable is strongly significant in explaining variations in expected patent counts, albeit with a small 0.3% effect on the dependent variable for every unit increase in the regressor. The hypothesis that all the regressors are simultaneously zero is strongly rejected, with the p-value of the associated Wald statistic being 0.

We next discuss the estimation results of the conditional 'fixed effects' negative binomial specification, wherein the dispersion parameter can take on any value due to unobserved firm-specific factors, but drops out of estimation following differencing. Table 3 informs us that the results are in almost complete conformity with those of the random effects specification. Thus, from the full model in column (5), we find that the stock of knowledge capital exerts a zero influence on expected firm patent counts; and the same holds for the interaction term. However, the patent experience variable ($PATEXP$), the resource access variable ($PROFIT$), as well as the spillover variable ($SPILLOVER$) are all statistically significant in explaining variations in the dependent variable as before, with semi-elasticities that are roughly in the same ball-park as those for the random effects specification. It is not surprising that the significance levels and the semi-elasticities are lower in this case, for the fixed effects specification makes use of the within-variation only, which as we saw in Table 1 is less than the between-variation for all variables except spillovers. In particular, research and development expenditure tends to be highly correlated over time for a given firm, and this becomes even more pronounced when we compute the knowledge capital stock variable, seriously reducing the variation that is available for identifying variations in the expected patent count. The Hausman specification test is not able to reject the null hypothesis that there is no systematic difference in the random effects and 'fixed effects' coefficients.

4.2. *Unconditional Negative Binomial Specification with Industry Dummies*

Researchers point out that the random effects and 'fixed effects' specifications discussed above actually pertain to random and fixed effects in the dispersion parameter, and not the regressors. In this sense, the conditional 'fixed effects' negative binomial model does not really correct for the fixed effects (Allison 2009). This may be remedied by estimating an unconditional negative binomial model with panel dummies in lieu of the fixed effects. While in theory this produces inconsistent estimates on account of the incidental parameters problem (Green 2012), simulation studies yield good results and do not provide evidence of any incidental parameters bias in the coefficients (Allison and Waterman 2002). Further, the downward bias in the standard errors of the regression coefficients can be effectively corrected using the deviance statistic. Unfortunately, in our context, we appear to have too many panels for the STATA algorithm to converge, so that instead of including firm dummies in our specification, we use industry dummies.

The estimation results of the unconditional negative binomial model with industry dummies and appropriately scaled standard errors are reported in Table 4. The full model results of column (5) show that the knowledge capital variable is now mildly positively related to the dependent variable, with a one unit increase in the former being associated with a 4.3% increase in the expected patent count. As before, the patent experience and profit variables exercise a strong positive influence on the regressand, albeit with significantly larger semi-elasticities of 2.8% and 0.9%, respectively. Similarly, the knowledge spillover variable is also strongly significant, although the associated semi-elasticity is still small at about 0.3%. Although the interaction term between knowledge capital and patent experience turns out to be mildly significant with a counter-intuitive negative sign, we ignore this result because the magnitude of this regression coefficient and hence the associated semi-elasticity is zero for all practical purposes.

4.3. *Zero-Inflated Negative Binomial Specification with Industry Dummies*

As we argued in section 2, count data often display the phenomenon of 'excess zeros', to handle which we estimate the zero-inflated negative binomial specification. This specification results in two sets of regression coefficients, the first pertaining to the expected patent count for those firms which do file patents, and the second pertaining to the odds of belonging to the 'certain zero' group or the group of firms which do not file patents. From the estimation results reported in Table 5, it is evident that if a firm's stock of knowledge capital were to increase by one unit, the expected number of patents in a year would increase by merely 0.7%, ceteris paribus. Once again, the interaction term of knowledge capital with patent experience has a coefficient that is zero for all practical purposes. Patent experience, profit and spillovers all exert a strongly significant positive influence on the expected patent count of firms, with semi-elasticities of 1.3%, 0.6% and 0.3%, respectively.

From the lower panel of Table 5, we can read off the results pertaining to the probability of belonging to the 'certain zero' group. We find that if a firm's stock of knowledge capital were higher by one unit, the odds that it would file zero patents would be lower by a factor of $e^{-0.2060766} = 0.8138$ or decrease by about 18.6%, ceteris paribus. If a firm's patent experience were higher by one unit the odds that it would file zero patents would decrease by a factor of $e^{-2.357555} = 0.0947$ or decrease by about 90.5%. However, if a firm's real profit were larger by one unit the odds that it would file zero patents would decrease by a factor of $e^{-0.0122489} = 0.9878$ or decrease by about 1.2% only, holding other factors constant. While the first of these results vis-à-vis the knowledge capital regressor is statistically insignificant, the second pertaining to patent experience is strongly significant, whereas the last one relating to real profits is only mildly significant using a one-tail test.

4.4. *Linear Feedback Models*

A possible shortcoming of the above specifications is that the estimates may be consistent only under strict exogeneity of the regressors. While this may not be a huge concern given that few firms actually patent, we nevertheless attempt to correct for this using the linear feedback model suggested by Blundell et al. (1999) (see also Czarnitzki et al. 2009). This model weakens the exogeneity condition by approximating the fixed effects by the log of patent counts from a pre-sample period ($L\_PRE\_SAM\_PAT$). In our case, we arbitrarily take this period to be 1991-1995. Given that many firms are likely to have no patents in this period, a dummy ($NO\_PRE\_SAM\_PAT$) is additionally used to represent this 'missing' value. Table 7 reports the results from the linear feedback mechanism applied to both the negative binomial and zero-inflated negative binomial specifications. In spirit, the results are no different from those discussed in the previous two sections, and need not be presented here in detail. Note that the pre-sample mean of the patent count is only mildly significantly different from zero using a one-tail test, indicating that we are no worse off in staying with the earlier results from these specifications.

4.5. *The Results in Perspective*

Not only is the zero-inflated negative binomial model preferable to the negative binomial on various theoretical grounds emphasized in the discussion above, it appears to be preferable on the basis of various test criteria as well. Tables 6 and 7 inform us that both the Akaike and Bayesian information criteria rule in favour of the zero-inflated model (without and with the linear feedback mechanism). Further, so does the Vuong test, except that Desmarais and Harden (2013) point out that the traditional Vuong test is biased, and needs to be corrected to allow a proper test of zero inflation. However, corrections using the Akaike and Bayesian information criteria still strongly advise in favour of the zero-inflated model (without and with the linear feedback mechanism). The only criteria that support the negative binomial over its zero-inflated variant are the mean predictions from the two models. Thus, as against the observed zero patent count of 90.5% in the sample, the negative binomial predicts a zero patent count of 90.6% versus 90.8% by the zero-inflated model. Furthermore, the mean absolute difference between the observed and predicted patent counts from the negative binomial model is 0.001 in comparison with 0.002 for the zero-inflated variant. Note, however, that both these differences are miniscule, so that we must resort to the differences in the information criteria and the bias-corrected Vuong test to choose between the two specifications in question.

Either way the results are fairly consistent across the different specifications as to sign, significance and even magnitude. The coefficient of knowledge capital stock remains mostly insignificant, and has a magnitude of only about 0.7% in the preferred zero-inflated negative binomial (full) regression. This implies that a one unit (dollar or rupee) change in the knowledge capital stock is likely to result in a 0.7% increase in the expected patent count, which is very small given that on average firms file less than a single patent annually. Our semi-elasticity estimate translates into an elasticity of about 0.02 at the means, which facilitates comparison with earlier studies.[5] Our elasticity is much below even the lower end of the elasticity range of 0.5 to 1.8 reported by Chadha (2009), part of which may have to do with the fact that her study relates to the Indian drugs and pharmaceuticals industry only. Our estimate is, in fact, in about the same range as the insignificant research elasticity of patents of 0.01 reported by Deolalikar and Roller (1989) for a sample of Indian manufacturing industries. An elasticity of 0.02 implies that a doubling of the knowledge capital stock (which is a rather tall order in any short period) would leave the average annual number of patents filed by a firm virtually the same as the current 0.8.

Interestingly, our knowledge capital elasticity of patent counts of 0.02 is comparable to that reported by Beneito et al. (2014) who use recent Spanish data. Their study finds very low elasticities of 0.07 for large firms and 0.04 for small and medium enterprises in Spain. Further, while the elasticities reported by some studies for other developed countries are higher by an order of magnitude, they are not very high in absolute terms. Thus, using recent Dutch data for the pharmaceuticals industry, Sanyal and Vancauteren (2013) report elasticites ranging between 0.1 and 0.2 only. Using data on US manufacturing firms from the

1970s, Hall et al. (1986) and Hausman et al. (1984) report elasticities ranging between 0.1 and 0.3 for the most part, although Blundell et al. (2002) report an elasticity of about 0.5, using their preferred pre-sample mean estimator. An important factor that one must allow for in comparing our elasticity estimate with those from earlier studies is that in most of the earlier studies the regressor was research and development investment (with or without lags) and not knowledge capital. While the latter is preferable insofar as it discounts the effect of past R&D investment, we must be aware that computing the knowledge capital variable further reduces the already low variation in firm-level R&D investment.

In addition to the above results relating to expected patent counts, another advantage of using the zero-inflated negative binomial model is the added information that it provides on the probability of 'certain' zero patents. The results discussed in section 4.3 on this score are perfectly plausible, for indeed one would expect firms with more patent experience and higher knowledge capital (as also better access to resources) to have a smaller likelihood of not filing patents. These results, though, cannot benefit from comparison with other studies, because none of the earlier studies report similar evidence, even where they employ a zero-inflated negative binomial model.

5. Conclusion

This study set out to explore the innovation-R&D relationship as exemplified by the influence of knowledge capital on patents, in the context of the emerging economy of India. It contributes to the received literature in a number of ways. It employs the zero-inflated negative binomial model to address the problem of 'excess zeroes' in count data such as ours. The linear feedback mechanism proposed by Blundell et al. (1999) is then used to estimate the preferred specifications, which yields consistent estimators by weakening the strict exogeneity condition. Based on a relatively large sample of 380 manufacturing firms in India, spanning 22 industries, the sample includes only firms with ten years of R&D data, because firms would need to conduct research for a 'long enough' period to realistically have a change of producing an innovation; data for just one or a few years may be inadequate. Further, knowledge capital stocks are employed rather than R&D expenditure and its lags, which is preferable for a number of reasons discussed above, including the point that it implicitly captures 'R&D experience' as a determinant of innovation. Unlike the received literature, we also introduce the firm's non-technical knowledge stock as another factor of the success with which R&D transforms into patents.

We find weak evidence at best for the presence of the so-called knowledge production function. The reasons that most firms do not patent even when they conduct some research can be multiple. It may lie in the realisation that the resulting innovations are 'small' and not worthy of seeking formal protection. Alternatively, the cost of patenting may be considered too high. Relevant in this context may be the non-monetary costs of patenting in terms of the paperwork and bureaucracy, which may be beyond most small firms with no dedicated R&D departments. Further, it might be the case that firms are apprehensive about revealing their innovations in the patent documents, given the general perception of a corrupt bureaucracy. Finally, one should not discount the simple possibility that most firm managers in a very low education developing country setting are not even properly aware of the patent system, how it functions, and what potential advantages it may bestow on those who can negotiate it. One would have to address all these factors to bring about a more effective conversion of research into formal intellectual property in the developing country context.

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Table 1: Sample Characteristics

Variable	Level	Mean	Standard Deviation	Minimum	Maximum
$PATENTS$	$Overall$	0.75	5.16	0.00	100.00
	$Between$		4.32		
	$Within$		2.83		
$KNOWLEDGE\ CAPITAL$	$Overall$	2.15	10.30	0.00	283.28
	$Between$		8.67		
	$Within$		5.58		
$PATENT\ EXPERIENCE$	$Overall$	2.77	19.73	0.00	450.00
	$Between$		16.86		
	$Within$		10.28		
$PROFIT$	$Overall$	6.94	29.18	–121.14	506.92
	$Between$		25.42		
	$Within$		14.39		
$SPILLOVER$	$Overall$	4.02	34.85	0.002	1219.36
	$Between$		17.72		
	$Within$		30.02		

Correlation Matrix

	PAT	$KNOWCAP$	$PATEXP$	$PROFIT$	$SPILLOVER$
PAT	1.00				
$KNOWCAP$	0.20	1.00			
$PATEXP$	0.64	0.27	1.00		
$PROFIT$	0.26	0.30	0.32	1.00	
$SPILLOVER$	0.04	0.08	0.05	0.35	1.00

Note: PAT is patents (count); $KNOWCAP$ is knowledge capital stock (Rs. million) using 15% depreciation rate; $PATEXP$ is patent experience (count); $PROFIT$ is deflated profit (Rs. million), and $SPILLOVER$ is knowledge spillover (Rs. million) using 15% depreciation rate.

Table 2: Random Effects Negative Binomial Specification
Dependent Variable – $Log(PAT)$

Variable	(1)	(2)	(3)	(4)	(5)
$KNOWCAP$	$0.0038^{\dagger}$	0.0022	$0.0094^{\dagger}$	0.0074	0.0063
	(0.0030)	(0.0029)	(0.0073)	(0.0073)	(0.0077)
$PATEXP$		0.0046^{***}	0.0054^{***}	0.0048^{***}	0.0046^{***}
		(0.0009)	(0.0012)	(0.0012)	(0.0012)
$KNOWCAP * PATEXP$			–0.0001	–0.00004	–0.00004
			(0.0001)	(0.0001)	(0.0001)
$PROFIT$				0.0027^{***}	0.0028^{**}
				(0.0010)	(0.0011)
$SPILLOVER$					0.0033^{***}
					(0.0007)
$Intercept$	-0.5974^{***}	-0.6351^{***}	-0.6983^{***}	-0.7205^{***}	-0.6960^{***}
	(0.1934)	(0.1939)	(0.2015)	(0.2014)	(0.2029)
N	3800	3800	3800	3800	3800
$Year\ Dummies$	Yes	Yes	Yes	Yes	Yes
$P - value\ (all\ slopes\ 0)$	0.0000	0.0000	0.0000	0.0000	0.0000

Note: ***, **, * denote significance at the 1%, 5% and 10% levels using a two-tail test; and † denotes significance at the 10% using a one-tail test

Table 3: Conditional 'Fixed Effects' Negative Binomial Specification
Dependent Variable – $Log(PAT)$

Variable	(1)	(2)	(3)	(4)	(5)
$KNOWCAP$	0.0008	–0.0004	–0.0040	–0.0051	–0.0068
	(0.0036)	(0.0034)	(0.0072)	(0.0071)	(0.0073)
$PATEXP$		0.0039^{***}	0.0035^{***}	0.0031^{**}	0.0028^{**}
		(0.0010)	(0.0013)	(0.0013)	(0.0013)
$KNOWCAP * PATEXP$			0.00003	0.00004	0.0001
			(0.0001)	(0.0001)	(0.0001)
$PROFIT$				0.0020^{*}	0.0022^{*}
				(0.0011)	(0.0012)
$SPILLOVER$					0.0034^{***}
					(0.0007)
$Intercept$	$–0.5621^{***}$	$–0.5940^{***}$	$–0.5591^{***}$	$–0.5807^{***}$	$–0.5519^{***}$
	(0.1953)	(0.1954)	(0.2052)	(0.2049)	(0.2062)
N	1090	1090	1090	1090	1090
$Year\ Dummies$	Yes	Yes	Yes	Yes	Yes
$P - value\ (all\ slopes\ 0)$	0.0000	0.0000	0.0000	0.0000	0.0000
$P - value\ (Hausman)$					0.9928

Note: ***, **, * denote significance at the 1%, 5% and 10% levels using a two-tail test;
and † denotes significance at the 10% using a one-tail test.
The Hausman specification test compares column (5) Table 3 with column (5) Table 2.

Table 4: Unconditional Negative Binomial with Industry Dummies
Dependent Variable – $Log(PAT)$

Variable	(1)	(2)	(3)	(4)	(5)
$KNOWCAP$	0.0593†	0.0231*	0.0584**	0.0404**	0.0419**
	(0.0410)	(0.0122)	(0.0259)	(0.0187)	(0.0189)
$PATEXP$		0.0288***	0.0333***	0.0278***	0.0278***
		(0.0092)	(0.0088)	(0.0088)	(0.0084)
$KNOWCAP * PATEXP$			–0.0006**	–0.0004**	–0.0004**
			(0.0002)	(0.0002)	(0.0002)
$PROFIT$				0.0103***	0.0090***
				(0.0027)	(0.0030)
$SPILLOVER$					0.0028***
					(0.0011)
$Intercept$	–2.4768***	–2.0417***	–2.1065***	–1.9426***	–1.9627***
	(0.3885)	(0.3377)	(0.3309)	(0.3188)	(0.3173)
N	3800	3800	3800	3800	3800
$Year\ Dummies$	Yes	Yes	Yes	Yes	Yes
$P - value\ (all\ slopes\ 0)$	0.0000	0.0000	0.0000	0.0000	0.0000
$Robust\ S.E.$	Yes	Yes	Yes	Yes	Yes
$Corrected\ S.E.$	Yes	Yes	Yes	Yes	Yes

Note: ***, **, * denote significance at the 1%, 5% and 10% levels using a two-tail test; and † denotes significance at the 10% using a one-tail test.
Corrected S.E. refers to corrected standard errors using the deviance parameter.

Table 5: Zero-Inflated Negative Binomial with Industry Dummies

Variable	(1)	(2)	(3)	(4)	(5)
$\underline{\boldsymbol{Log(PAT)}}$					
$KNOWCAP$	0.0097*	0.0088*	0.0163*	0.0061	0.0072
	(0.0052)	(0.0047)	(0.0095)	(0.0093)	(0.0093)
$PATEXP$		0.0134**	0.0153**	0.0129***	0.0130***
		(0.0060)	(0.0066)	(0.0049)	(0.0047)
$KNOWCAP * PATEXP$			–0.0001	–0.00004	–0.00005
			(0.0001)	(0.0001)	(0.0001)
$PROFIT$				0.0082***	0.0060**
				(0.0022)	(0.0024)
$SPILLOVER$					0.0032***
					(0.0009)
$Intercept$	–0.6941	–0.5617	–0.5858	–0.3946	–0.4400
	(0.3953)	(0.3930)	(0.3989)	(0.3989)	(0.3879)
$\underline{\boldsymbol{Inflate}}$					
$KNOWCAP$	–0.2038	–0.2307	–0.2332	–0.2007	–0.2061
	(0.1638)	(0.2062)	(0.2297)	(0.1973)	(0.2010)
$PATEXP$	–2.0926***	–2.3590***	–2.3878***	–2.4293***	–2.3576***
	(0.7224)	(0.6440)	(0.6390)	(0.5823)	(0.5914)
$PROFIT$	–0.0103*	–0.0137*	–0.0141*	–0.0112†	–0.0176†
	(0.0061)	(0.0079)	(0.0080)	(0.0071)	(0.0013)
$Intercept$	2.3394***	2.6300***	2.2983***	2.2636***	2.2918***
	(0.2894)	(0.2324)	(0.3161)	(0.3138)	(0.3144)
α	2.5382***	2.4305***	2.4382***	2.2381***	2.1650***
	(0.4884)	(0.4237)	(0.4273)	(0.3619)	(0.3660)
N	3800	3800	3800	3800	3800
$Year\ Dummies$	Yes	Yes	Yes	Yes	Yes
$P-value\ (all\ slopes\ 0)$	0.0000	0.0000	0.0000	0.0000	0.0000
$Robust\ S.E.$	Yes	Yes	Yes	Yes	Yes

Note: ***, **, * denote significance at the 1%, 5% and 10% levels using a two-tail test; and † denotes significance at the 10% using a one-tail test

Table 6: Zero-Inflated Negative Binomial versus Negative Binomial

Model	AIC	BIC	Vuong	Vuong (with AIC correction)	Vuong (with BIC correction)	Mean Absolute Difference between Observed and Predicted Count
ZINB	3269.068	3525.021	8.079***	7.890***	7.299***	0.002
NB	4283.759	4508.498				0.001

Note: ***, **, * denote significance at the 1%, 5% and 10% levels using a two-tail test;

Table 7: Linear Feedback Models

Variable	(1)	(2)
	Negative Binomial	**Zero-Inflated Negative Binomial**
Log(PAT)		
$KNOWCAP$	0.0275^{**}	0.0061
	(0.0126)	(0.0095)
$PATEXP$	0.0205^{***}	0.0116^{***}
	(0.0061)	(0.0045)
$KNOWCAP * PATEXP$	-0.0003^{**}	–0.00003
	(0.0001)	(0.00008)
$PROFIT$	0.0079^{***}	0.0054^{***}
	(0.0025)	(0.0021)
$SPILLOVER$	0.0033^{***}	0.0035^{***}
	(0.0009)	(0.0009)
$L\_PRE\_SAM\_PAT$	$0.4757^{\dagger}$	$0.3985^{\dagger}$
	(0.3640)	(2523)
$NO\_PRE\_SAM\_PAT$	-0.8174^{*}	0.2193
	(0.4621)	(0.4803)
$Intercept$	-1.3020^{**}	$-0.7351^{\dagger}$
	(0.5304)	(0.5484)
Inflate		
$KNOWCAP$		–0.1928
		(0.2025)
$PATEXP$		-2.3294^{***}
		(0.5777)
$PROFIT$		-0.0132^{*}
		(0.0080)
$Intercept$		2.2805^{***}
		(0.3368)
α		2.1220^{***}
		(0.3813)
N	3800	3800
$Year\ Dummies$	Yes	Yes
$Industry\ Dummies$	Yes	Yes
$P - value\ (all\ slopes\ 0)$	0.0000	0.0000
$Robust\ S.E.$	Yes	Yes
AIC	4195.377	3269.427
BIC	4432.602	3537.866
$Vuong$		7.397^{***}
$Vuong\ (with\ AIC\ correction$		7.212^{***}
$Vuong\ (with\ BIC\ correction$		6.634^{***}
$Mean\ Absolute\ Difference\ between\ Observed\ and\ Predicted\ Count$	0.001	0.002

Note: ***, **, * denote significance at the 1%, 5% and 10% levels using a two-tail test; and † denotes significance at the 10% using a one-tail test

Endnotes

[1] What is ‘waste’ in this context is often not clear; there might be some ‘learning-by-doing’ from the expenditure made, even when no innovation results from it.

[2] This is not to imply that researchers are unaware of the limitations of patent counts as measures of innovation. First, not all innovations are patentable. Second, even when they are they may not be patented, either because patenting may be costly and/or because firms may be apprehensive about disclosing the innovation in the patent document (Horstman et al. 1985, Harter 1993). As a result, patent propensity (or the percentage of innovations that are patented) may vary across industries and firms, so that patent counts may over- or under-estimate innovation for a given sector. Third, to the extent that patents are used for strategic purposes, they may not reflect innovativeness per se (Hall and Ziedonis 2001, Blind et al. 2006). Fourth, not all patents are commercialized, which may be a drawback when the focus is on quantifying the impact of innovation on, for instance, productivity growth. Thus, patents are imperfect measure of innovation, but so also are the competing measures.

[3] To jump ahead momentarily, our data set does not provide information on the patents that were filed but were rejected by the patent office.

[4] For a small number of firms the R&D data were interpolated if the gap was for one or two years at most. Firms for which the gap was larger were not included in the sample.

[5] While the increase in the expected patent count as the result of a one unit increase in the knowledge capital stock would be much larger at 4.3% if we use the negative binomial results instead, in absolute terms even that would be a very small increase over the mean patent count for our sample. Moreover, the associated elasticity at the means is still small at 0.03, as compared to 0.02 for the zero-inflated model.