Firm-Level R&D Activity, Employee Turnover and HRM Practices: Evidence from China

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Abstract

With survey data from 582 Chinese firms across five high-tech industries, we examine the association between firm’s R&D activity, employee turnover rates and HRM practices. The analysis is performed using hurdle negative binomial model, which reveals both extensive and intensive margins of employee turnover rates and HRM practices on firms’ R&D activity. We find that turnover rate of technical employee is positively associated with the probability of having indoor R&D, but negatively associated with intensity of R&D activity among R&D-active firms. The adoption of high performance HRM practices like cross-functional team and channel for employee’s suggestion is associated with more indoor R&D, but its impact is independent of employee turnover. These results imply the possibility of encouraging indoor R&D activity by anchoring labor mobility at a suitable level – not too low to block idea exchange and not too high to risk the fruit of indoor R&D. Considering that firms may not have full control of employee turnover (at least not through the examined HRM practices), the government who is interested in facilitating R&D activity may consider using policy to adjust general labor mobility to a suitable level.

JEL Codes: L22, M50, O31

Keywords: R&D, HRM Practices, Employee Turnover

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1. Introduction

Employee turnover can be an important mechanism for R&D activities in firms. Persistent differences in turnover between two otherwise identical organizations will evolve very different tenure distributions, with implications for stability and organizational culture which in turn may have considerably different implications for R&D. The level of turnover can be a result of the human resources management (HRM) practices chosen by the firm, but the HRM practices can also have a direct effect on R&D activities of the firm. This paper examines the relationship between employee turnover, HRM practices and R&D activity in Chinese high technology sector firms.

In the current stage of China’s economic development, R&D and innovation are considered as key factors for continued increase in total factor productivity and hence sustaining high growth; see e.g., World Bank (2011). Very little systematic evidence of the drivers of R&D and innovation activities based on firm-level data exists for China. Empirical results from other (mostly advanced industrialized) countries, which are also rather scarce, do not necessarily generalize to the Chinese context, as labor markets in China are still relatively underdeveloped and protection of intellectual property rights remains weak. Moreover, Chinese firms also differ from Western firms with respect to corporate culture and a more important role for business groups and other networks.

For our empirical analysis we make use of data from a survey carried out by researchers at Renmin University (Beijing) in 2011. The sample consists of firms in China from five (high technology) industries: energy, electronic information, biotechnology, equipment manufacturing and environmental protection. In addition to standard controls in the analysis of R&D activities, the data set includes information about the firm’s HRM practices as well as measures of employee turnover for different categories, including technical personnel. The dependent variable in our analysis is the number of ongoing R&D projects during 2010. The econometric analysis is performed using a hurdle negative binomial model for count data. An advantage of this model is that it allows for analyses of both extensive and intensive margins.

In fact, we are only aware of one article (written in English) by Wei, Liu and Herndon (2011) on this topic.
The empirical analysis shows that a higher turnover rate of technical personnel is associated with a higher likelihood of having own R&D but a lower intensity of R&D activities in these firms. This relationship, which is also economically significant, is robust to inclusion of variables for HRM practices implemented by the firm. Particularly important HRM practices for enhancing R&D are the use of cross-functional teams and expenditures for employee training. Notably, the HRM practices are found to have an impact on R&D which is independent of employee turnover. Among the other drivers of R&D, external network cooperation attaches an especially large and positive marginal effect. This is perhaps not so surprising in view of the importance of networks and business groups in the Chinese corporate system.

The remainder of the paper unfolds as follows. Next, a brief review of the previous studies of the relationship between HRM practices, employee turnover and R&D is given. The third section describes the data and the econometric method used. The results are presented and discussed in section four. Section five concludes.

2. Previous Research

Since the mid-nineties a fairly large literature has built up dealing with HRM and firm performance. Performance is typically measured by productivity (surveyed in Bloom and van Reenen, 2011), while there is rather little (beyond case studies) on HRM and R&D. Instead, the large R&D and innovation literature has mainly been concerned with firm size, product market competition, knowledge spillovers and R&D collaboration.

The first two papers to look at the relationship between HRM practices and R&D were Michie and Sheehan (1999), (2003) in which the authors examined British firms’ use of so-called high- and low-road HRM practices and how these were related to firms’ R&D expenditures (the 1999 study) and process and product innovations during a three year period (the 2003 paper), respectively. They find that extensive use of modern (that is high-road) practices is positively correlated with investments in R&D and with process (but not

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5 Notable exceptions are Michie and Sheehan (2003), Laursen and Foss (2003), Jimenez-Jimenez and Sanz-Valle (2005) and Zoghi, Mohr and Meyer (2010). See also the recent survey by Foss and Laursen (2012).
product innovations. Laursen and Foss’s (2003) study investigates bundles of work practices and the degree of novelty in product innovation in Danish firms and finds a positive relationship. Jimenez-Jimenez and Sanz-Valle’s (2005) analysis of a relatively small sample of Spanish firms find that participative practices and promotion plans significantly increases the firm’s innovation orientation.

In a more recent study, Zoghi, Mohr and Meyer (2010) use Canadian longitudinal data to study how workplace organization is correlated with the adoption of process and product innovations. They find that decentralized decision-making, information sharing programs and (individual) incentive pay are associated with more innovations.\(^6\) Another recent study by Zhou, Dekker and Kleinknecht (2011) makes use of four waves of survey data from the Netherlands and finds that functional flexibility (measured by the rate at which people change their function or department within the firm) has a positive effect on the percentage of sales due to new products. Thus, this, as well as other studies, finds some evidence suggesting that internal labor mobility (functional flexibility, job rotation) is important for innovation activities.

Although there are a number of studies suggesting that especially the new, high involvement/performance work practices are implemented more frequently in innovative firms, the evidence is not very strong. Furthermore, existing empirical studies have made use of many different measures of innovation as the dependent variable, while few studies focus on the mechanism of R&D activity.

Could we expect the relationship between HRM practices and R&D activity to be different in the Chinese case? A central element in the modern work practices is delegation of decision rights to employees. This may not, however, function well in a Chinese context where keeping distance to superiors and showing respect to elders is deeply rooted in the culture. Participative decision making also presupposes a high level of trust between employees at different levels in the hierarchy, which is often said not to be present in Chinese workplaces; see Wang, Yeung and Zhang, (2011) for empirical evidence. Another cultural difference that

\(^6\)Notably, they also find, but do not discuss, that firms with a high vacancy rate (which is likely to be a sign of high employee turnover) are also more likely to innovate.
may weaken the effect of introducing modern HRM practices is that, in appraisals of performance, the employee’s attitude and behavior is traditionally considered more important than the results of her performance.\textsuperscript{7} There is to the best of our knowledge, only one earlier study, Wei et al. (2011), of the relationship between HRM practices and innovation in firms operating in China. The data used in that study was collected by a survey questionnaire sent to both CEOs and HR managers in firms in various industries (manufacturing accounts for only 24 of the respondents). Strategic HRM is measured using Huselid’s (1995) eight-item instrument and the firm’s product innovativeness (relative to industry average) is self-reported (that is, is assessed by the respondents). The results show a positive relationship between the strategic HRM measure and product innovation. The correlation is stronger for firms with flatter structure and developmental culture.

One particular aspect of firms’ internal labor markets that has attracted some attention recently (Møen, 2005; Kaiser et al., 2008; Müller and Peters, 2010) is the role of worker flows and employee turnover for firms’ R&D and innovation activities.\textsuperscript{8} As knowledge and competencies are embodied in people it is important to consider how these are transferred between firms. Two broad hypotheses have been put forward. The idea behind the first hypothesis is that with low employee turnover the result is likely to be result in too little experimentation and innovation. This is especially the case if the relevant employees are hired after graduation from college or university (or some vocational education) and therefore possess little professional experience from other firms or industries. As this brings few ideas from other companies, the firm itself becomes less capable of exploring new environments and adapting to changing technologies. Instead the focus will be on existing product performance – the improvements are typically small – and on efficiency within existing technology and product variety. As long as there is not sufficient flow of “new blood”, economic incentives, employee empowerment and involvement, cross-functional teams and adoption of new information technologies can do little to radically change the

\textsuperscript{7} Nevertheless, a number of studies have documented a positive relationship between the firm’s use of strategic HRM practices and its performance (typically measured by subjective ratings of the overall performance of the firm); see e.g., Björkman and Fan (2002), Chow, Huang and Liu (2008), Ngo, Lau and Foley (2008), and Wei, Liu, Zhang and Chiu (2008).

\textsuperscript{8} Two recent papers by Balsvik (2011) and Parrotta and Pozzoli (2012) examine the impact of between firm employee flows on firm productivity.
innovation activities within the firm. All in all, this implies that a too low turnover of personnel is associated with a low level of R&D.

The idea that employee turnover above a certain threshold is good for firm performance is related to the risky hires hypothesis put forward by Lazear (1995), according to which employees are thought of as real options and the firm’s choice is between a candidate with relatively predictable performance and one more risky. As long as firing costs are low, it may pay off for the employer to hire the risky candidate because s/he has an option value. Potential benefits are likely to be largest for positions where small differences in talent can have large impacts on performance outcomes (such as R&D and leadership positions). Hiring risky workers is likely to result in higher employee turnover, but may nevertheless give better performance in terms of R&D and creativity.

The alternative hypothesis states that in order to promote R&D activity a firm needs to employ and retain appropriate staff. As R&D employees need to undergo relatively much training, a lower rate of employee turnover is also typically associated with lower training costs. A related argument is that firms with own R&D should provide employment security as a means to get the employees involved in their firm as this is important for R&D activity. Another argument goes back to Jovanovic’s (1979) job-worker matching paper according which long job tenures reflect good matches between the job (or employer) and the employee.

All in all, whether the relationship between worker turnover and R&D activity is positive or negative is an empirical matter. However, the evidence is so far rather scant. An early paper by Ettlie (1985) examines (by means cross-tabulations) the role of new personnel and net manpower flows on process and product innovation in a small sample of food processing firms. He finds that “new blood” is good for major process innovations, whereas the opposite holds for product and minor process innovations. 9 Kaiser et al. (2008) carry out a considerably more elaborated analysis in which they distinguish between R&D employees leaving and joining the firms. The outcome is number of patents applied for. Their results indicate that the rate of R&D employees leaving the firm has, not surprisingly, a negative

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9 The direction of causality could in both cases go the other way.
impact on its patent activity, while an inflow of R&D employees affects patents positively. The net mobility effect is found to be positive. A recent paper by Müller and Peters (2010) makes use of the firm level churning rate\textsuperscript{10} of R&D employees as a measure of workforce turnover and their empirical analysis allows for non-linearities in the turnover-innovation relationship. They find that an increase in the churning rate, up to a certain threshold, is associated with a higher likelihood that the firm has innovated during the previous three years. Plausibly, the threshold is lower for process innovations than for product innovations.

There are two reasons for why the role of employee turnover for R&D activity is particularly interesting in a Chinese context. One is that after the removal of the lifelong employment ("iron rice bowl") system, employment security seems to have lost some of its importance. Hence, average turnover rates are reported to be quite high (annual rates of 20-40 percent have been mentioned); see Schmidt (2011). Another reason is that the new Labor Contracts Law which came into force in 2008 aims at providing more employment security by requiring formal employment contracts and introduces costs for employers in connection with employee displacements. Thus, evidence shedding light on whether and to which extent employee mobility enhances or decreases firms’ R&D activity is called for. It should be noted that a traditional feature of Chinese internal labor markets has been a relatively slow involvement of new employees in firms and organizations. This is because decision rights typically lie with small informal groups, to become membership of which takes time. Thus, in firms where these features still are present, a positive relationship between employee turnover and R&D activity could be weaker.\textsuperscript{11}

3. Data Description and Econometric Method

3.1. Data and Variables

The data used in this study comes from a survey collected by researchers at Department of Organization and Human Resources at Renmin University (Beijing) in 2011. The survey

\textsuperscript{10} The churning rate is the employee turnover rate at which employment is unchanged, that is, it is a measure of the extent of replacement hires during a given time period.

\textsuperscript{11} Japan is a country with similar traditions. A study by Aoshima (2009) finds a negative relationship between turnover of engineers and innovation in Japanese firms.
targeted firms in five industries: energy, electronic information, biotechnology, equipment manufacturing and environmental protection, all of which are considered as high tech industries in China. For each firm, the data set contains in addition to basic firm information such as total number of employees, establishment year, industry, etc., information about its overall performance outcomes, input and output of innovation activities, the number of total employees as well as of technical employees who voluntarily left the firm in each year during the period 2008-2010, detailed information about the innovation environment, organizational strategy and the use of HRM practices.

The sample comprises 582 companies. The five industries account for about twenty percent each. 45.7% of them are state-owned enterprises, private companies make up 26.6% and the rest have a mixed ownership structure. 89.4% are financed domestically, 2.2% are financed by foreign capital while 8.4% are joint ventures. The firm size ranges from 17 employees to 300,000 employees, though 95% of observations have fewer than 55,000 employees; the medium firm has 2,534 employees.

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<th>Table 1. Data Description</th>
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<tr>
<td>Variable</td>
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<tr>
<td>Number of R&amp;D Projects</td>
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<td>Number of Patents</td>
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<td>Channel for Suggestion</td>
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<td>Cross-Functional Team</td>
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<td>Share of R&amp;D Employees</td>
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<td>New Cooperating Partners</td>
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Next we turn to discuss the key variables used in our empirical analysis. The dependent variable is the firm’s R&D activity, which is measured by the number of ongoing R&D projects during year 2010. This is a direct measure of R&D activity and also highly relevant to outcomes of both product and process innovation. It is a broader measure than simple dummies for whether a firm has own R&D or not, as it accounts also for different levels of
effort spent on R&D activities.\textsuperscript{12} On average, a sample firm has 73 ongoing R&D projects in 2010. The distribution is heavily skewed: 84 firms have no R&D project at all; the median number of projects is 18, which is much lower than the average. 95 percent of the firms have 280 or fewer ongoing R&D projects, while the most R&D active firms have over 1,000 projects.

The first of two key explanatory variables is the voluntary turnover rate of technical employees. This is measured by the number of technical employees who left the firm voluntarily\textsuperscript{13} divided by the total number of technical employees. As the dependent variable in the regressions is ongoing R&D projects in 2010, we use a one-year lagged value of employee turnover rate to reduce the problem of simultaneity. In general, the voluntary turnover rate of technical employees is much lower than the overall worker turnover rate. Thus, 125 firms did not experience any turnover of technical employees in 2010; 95 per cent of the firms had less than 6.5 percent of their technical staff leaving voluntarily. On the other hand, the highest turnover levels observed are over sixty percent.

The HRM practices used by the firm make up the other category of variables of special interest in the current study. We have included three binary variables to measure the use of the following practices: whether the firm uses: (1) cross-functional teams, 2) job rotation schemes, and (3) special channels for employees’ suggestions. Two additional HRM practices are measured as continuous variables: (4) the proportion of base salary of an R&D employee’s annual income, and (5) the firm’s training expenditures in 2010. See Table 1 for further details.

In addition, we enter a number of conventional control variables into the regressions. These include firm size for which we use both the total number of employees and firm output

\textsuperscript{12} Two alternative measures utilized in earlier studies are number of patents and number of new products. Although both are included in the survey, we have chosen not to focus on them. Firstly, because existing patents are likely to be a noisy measure of current innovation activities, especially in the rapidly developing high-tech industries in China. Secondly, patents only reflect part of the between-firm variation in innovation, since not every innovation is patented. The other outcome variable, the number of new products, has the disadvantage that what constitutes a new product is rather subjective and new products can also be developed by buying external resources rather than through internal innovation activities.

\textsuperscript{13} This concept presents no ambiguities in the context of Chinese firms as this is part of the regular reporting of their HR offices.
(sales) in 2010. A sizable literature has shown that large firms are more likely to innovate.\textsuperscript{14} Another factor which has been extensively studied in the innovation literature is product market structure. We do not have access to measures of competition faced by the sample firms, but expect the dummy variables for industry affiliation to pick up the variation in competitive pressure across (but not within) industries. A third factor which potentially needs to be accounted for, especially in the Chinese context, is the ownership structure of the company. This is in part because state owned enterprises (SOEs) tend to pay their employees higher wages than corresponding firms with other forms of ownership and as a consequence, typically have a lower employee turnover rate. However, SOEs may also be more R&D active because they are more directly influenced by the government, which recently has exerted great efforts to stimulate innovation. Yet another dummy variable is included to indicate whether the capital is financed by a company registered abroad. This is motivated by the fact that multinational firms may choose to limit their R&D activities in their Chinese subsidiaries due to the relatively weak protection of intellectual property rights (Yang and Jiang, 2007).

Firm-level network expansion is measured by the number of new cooperating partners in 2010. Networks have been found to be related to R&D and innovation outcomes in earlier research (e.g., Rittera and Gemünden, 2004; Whittington et al., 2009; Huggins et al., 2012). It is also likely that employee mobility could be facilitated by inter-firm cooperation. Hence it is important to control this factor when examining the relation between the employee turnover rate and R&D activity.

As we are treating R&D as a production process, it is also necessary to control for R&D input. Here we control for total number of R&D employee, which represents the input of labor, and a proxy for the input of capital - the total cost of technical development – including the cost of in-house R&D, cost of introduction of new technology from other organizations, cost of technological improvements, costs of consultancy, etc. Moreover, we also include the total number of technical employees in order to control for the scale factor which

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\textsuperscript{14} Employee turnover has also been shown to be positively correlated with firm size, which is another reason for controlling for it.
influences both technical employee turnover rate and innovation activity. In the regressions reported below, we use the log value of all continuous independent variables.

3.2. Econometric Model

This paper utilizes a logit hurdle negative binomial model\(^{15}\), which assumes the probability of observing zero R&D project in firm \(i\) during a year is:

\[
P(Y_i = 0 | Z_i) = \frac{1}{1 + \exp(Z_i' \gamma)}
\]  

(1)

and the probability of observing a positive number \(y_i\) R&D projects is:

\[
P(Y_i = y_i | X_i) = \frac{[1 - P(Y_i = 0 | X_i)]g(y_i | y_i | X_i)}{1 - g(Y_i = 0 | X_i)}
\]  

(2)

where \(Y_i\) denotes the number of R&D projects, \(Z_i\) and \(X_i\) denote firm characteristics, and \(g(\cdot)\) is a probability function following negative binomial II model.

(1) is a logit model, which describes the binary process determining whether the firm carries out R&D projects or not; equation (2) is from a zero truncated negative binomial model, in which \(g(\cdot)\) describes the count process determining the intensity of R&D activity. (1) and (2) can be estimated jointly using maximize likelihood method. Further details of the model, see Appendix 1.

3.2.1. Choice of Model

The reason of choosing this particular econometric model is as follows. First, our dependent variable is of count data type, it can (and does) attach multiple values and has no upper bound. This implies we have to make a choice between two major categories of count data models: basic models including the Poisson model and the negative binomial model, and furthermore, between one and two parts models, that is, zero inflated models and hurdle models, respectively.

A key feature of the data set used in this paper is that the proportion of zero outcomes is large relative to the other count values. It is therefore important to check whether the

\(^{15}\) An alternative model for dependent variables that spread over a large range of positive values and cluster at zero is the Tobit model. This assumes variables are continuous and that the process generating zero outcomes is the same as the process generating the positive value outcomes. We have estimated our model using a Tobit specification and obtain largely similar results.
processes generating zero outcomes and strictly positive outcomes differ. Since the factors influencing firms’ decision regarding whether to innovate or not can be quite different from those influencing the decision concerning the intensity of innovation, it makes intuitively sense to relax the constraint assumption that the zeros are generated in the same way as positives. Furthermore, even if the same factors influence both the decision to innovate and the innovation intensity, their influences may exhibit different patterns.

The next choice is between hurdle count models and zero inflated models. The difference between them is that, in zero inflated models the zero outcomes can arise in two ways: as a consequence of strategic decisions and incidentally, while the hurdle count model assumes that zeros are exclusively the outcomes of strategic decisions (for details, see Lambert, 1992; Winkelmann, 2008). In the current case, it seems very unlikely that a firm that has adopted an innovation strategy would not have any ongoing R&D projects during the year. Consequently, we think the hurdle count model is a more natural specification to adopt in this context.

There is a further choice between a hurdle Poisson model and a hurdle negative binomial model. The former model nests in the latter: the Poisson model assumes that the variance equals the conditional expectation, while the hurdle negative binomial allows the variance to grow faster than the expectation (over-dispersion). The likelihood ratio test of over-dispersion factor alpha confirms that in our case over-dispersion is indeed present in the second part of model (see Table 2, below).

3.2.2. Marginal Effects

As the coefficient estimates from the hurdle negative binomial models are difficult to interpret, we have computed marginal effects implied by the estimated models. For binary part of the model, the marginal effects describe the influences on the probability of being an innovative firm; for count part of the model, the marginal effects describe the influences on the expected number of R&D projects among innovating firms. These computations and their relations to the model estimations are discussed in more detail in Appendix 1.

Subsequently, for each part of the model, two types of marginal effects will be reported: (i) average marginal effects across all observations and (ii) conditional marginal effects for certain types of firms. The average marginal effects across all observations are calculated by
first obtaining individual marginal effects by inserting the true values of the regressors into the marginal effect formula for each observation after which we compute the average of the individual marginal effects. The conditional marginal effects for certain types of firms are calculated by inserting given values (e.g., mean values) into the formula of marginal effect.

4. Results

4.1. The Roles of Employee Turnover Rate and HRM practices

Table 2 shows the estimates of the hurdle negative binomial model with full set of regressors. Columns (1)-(3) report the results of the count part, that is, the association of the regressors with the number of R&D projects for firms that have positive number of ongoing R&D projects during 2010. The results of the binary part, the determinants of the probability of having a positive number of R&D projects, are in columns (4)-(6). Columns (1) and (4) give the direct estimates of the parameters and columns (2) and (5) report the average marginal effects. Columns (3) and (6) contain the conditional marginal effects, which describe the situation for a domestically, non-state owned firm in the energy industry and with HRM practices of job rotation and cross functional team. Henceforth this will be referred to as our “example firm”.

Most regressors are found to influence the two processes differently. A one percentage point increase in employee turnover rate is associated with a decrease in the expected number of R&D projects by a factor of \( \exp(0.045 + 1) = 1.05 \); however, the same increase in employee turnover rate leads to an increase in the log value of relative probability of being an innovative firm by 1.21. The average marginal effects have a more direct interpretation: on average, a one percentage point increase in employee turnover rate is associated with three fewer R&D projects, but a 1.105 increase in the probability of having positive number R&D projects. For the example firm described above, a one percentage point increase in the employee turnover rate is associated with about one fewer R&D project, but a 0.158 increase in the probability of having a positive number of R&D projects. The coefficients as well as the marginal effects are significant at the five per cent level.
The three types of estimates all paint a similar picture: other things equal, R&D active firms tend to have a higher level of technical employee turnover rates than R&D inactive firms; but among firms that have crossed the hurdle and engaged in one or more R&D projects, employee turnover is negatively correlated with the intensity of R&D activity. A certain level of employee turnover seems to be necessary to bring new ideas that initiate R&D projects and to innovate. However, once firms start to carry out their own R&D projects, employee turnover begins to play a negative, albeit small, role so that firms with higher employee turnover are likely to have fewer R&D projects (other things being equal).

According to the estimates in Table 2, of the HRM practices examined, the negative coefficient to job rotation is significant at five per cent level in the binary part, while the positive estimates to cross-functional teams and training expenses are significant at five per cent level in the count part. Other things equal, introduction of cross-functional teams is associated with a higher number of R&D projects by a factor of $\exp(0.26) = 1.30$. For the example firm, the average number of R&D projects is predicted to increase by around six if the firm has implemented cross-functional teams.

Training expenditures are found to be positively and significantly associated with a firm’s R&D activities, which is not surprising. However, its influence is quite small: an increase of 10,000 RMB in the firm’s training expenditure is associated with an increase in expected number of R&D projects by 0.3 percent.

A potential problem is that the observed impact of employee turnover and HRM practices could be due to a “spurious” correlation. It is possible that, instead of employee turnover affecting R&D activity, both employee turnover and innovation are driven by an unobserved third factor. An example of such an unobserved factor is management quality. Firms with high management quality may have fewer employees voluntarily resigning and are more likely to adopt the high-performance HRM practices and to have more R&D projects. As a test of this spurious correlation, we have performed a “placebo” analysis, in which we replace the turnover rate for technical employees with that for non-technical employees. The idea is that if the observed association between technical employee turnover and R&D is actually driven by a third factor (such as management quality), a similar association should also be observed between the turnover of other types of employees and R&D - since general management quality is likely to influence the turnover of different types of
employees in a similar way. The results of the placebo analysis are shown in Table 3. Column (1) gives for comparison purposes the estimates for the turnover rate of the technical employees. Column (2) shows the estimates for turnover rate of non-technical employees, where we can see small and insignificant estimates which are quite different from those in column (1). These findings imply that a major part of the differences in innovation activity is due to the difference in technical employee turnover rates across firms, rather than a third unobserved factor such as management quality.

Another potential problem with our estimates of the impacts of employee turnover and HRM practices is that they may be biased because of endogeneity. Although placebo test does indicate that the observed association is not due to the third unobserved factor, the test does not exclude the potential bias caused by omitting variable that correlated with both turnover of technical employee and innovation activity. Since management quality is not directly observable in the data set, endogeneity bias cannot be ruled out. We know its direction, however, if the correlation directions among employee turnover, number of R&D projects and management quality can be assumed. Because it is likely that the voluntary employee turnover rate is negatively correlated with the number of R&D projects and management quality, while HRM practices and management quality are positively correlated with the number of R&D projects, the absolute values of unbiased estimates of employee turnover rate and HRM practices should both be smaller. As a check for possible bias caused by endogeneity, we include the turnover of non-technical employees into the regression as a proxy variable for unobserved factors. As shown in column (3) of Table 3, the inclusion of the proxy variable only leads to a tiny reduction in the magnitude of coefficient estimates in column (1), which supports our previous results and confirms our discussion about the direction of bias caused by unobserved factors.

As for the control variables, a few results are worth noting. For example, an increase in the number of external cooperation partners has a significant and positive effect on the number of R&D projects for the innovating firms. A one percent increase in the number of new co-operators is associated with around 0.4 percent increase in the number of R&D projects, which corresponds to six additional R&D projects in our example firm.

Firm size, as measured by the total number of employees, is associated with a higher intensity of R&D projects. Thus, a one per cent increase in the firm size is accompanied by a
0.3 per cent increase in ongoing projects in the R&D active firms. The size of the firm is, however, uncorrelated with the probability of being R&D active.

We observe no differences across the five industries in the probability of firms being innovative. But for the R&D active firms, there are some differences in the intensity of R&D activities. Firms in the energy industry have fewer ongoing projects than firms in the information, equipment manufacturing and environmental protection industries.

SOEs are more likely to carry out R&D projects, but among firms actively involved in R&D, SOEs have fewer projects. This indicates that SOEs may follow the government policy and start R&D projects, but are in reality exerting less effort in R&D than other R&D active firms. Finally, firms financed by foreign capital have, as expected, a lower number of ongoing R&D projects although it should be pointed out that the difference is not very precisely measured.
Table 2. Estimation Results of Hurdle Negative Binomial Model with Full Set of Regressors

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<td>Technical Employees’ Turnover Rate</td>
<td>-0.045***</td>
<td>-2.85</td>
<td>-3.205***</td>
<td>-2.78</td>
<td>-1.162**</td>
<td>-2.4</td>
<td>1.211***</td>
<td>2.67</td>
<td>0.105***</td>
<td>2.74</td>
<td>0.158**</td>
<td>2.15</td>
<td></td>
</tr>
<tr>
<td>Channel for Suggestions</td>
<td>0.07</td>
<td>0.36</td>
<td>4.795</td>
<td>0.35</td>
<td>1.761</td>
<td>0.35</td>
<td>-1.25</td>
<td>-1.04</td>
<td>-0.002</td>
<td>-0.06</td>
<td>-0.003</td>
<td>-0.06</td>
<td></td>
</tr>
<tr>
<td>Cross-Functional Teams</td>
<td>0.26*</td>
<td>1.73</td>
<td>17.564*</td>
<td>1.81</td>
<td>5.990*</td>
<td>1.77</td>
<td>-0.02</td>
<td>-0.06</td>
<td>-0.088</td>
<td>-1.4</td>
<td>-0.104</td>
<td>-1.17</td>
<td></td>
</tr>
<tr>
<td>Proportion: Base Salary</td>
<td>0.08</td>
<td>0.17</td>
<td>5.592</td>
<td>0.17</td>
<td>2.027</td>
<td>0.17</td>
<td>-0.40</td>
<td>-0.34</td>
<td>-0.034</td>
<td>-0.34</td>
<td>-0.052</td>
<td>-0.34</td>
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</tr>
<tr>
<td>Job Rotation</td>
<td>0.0027</td>
<td>0.02</td>
<td>0.190</td>
<td>0.02</td>
<td>0.069</td>
<td>0.02</td>
<td>-1.23**</td>
<td>-2.05</td>
<td>-0.113**</td>
<td>-2.01</td>
<td>-0.103</td>
<td>-1.15</td>
<td></td>
</tr>
<tr>
<td>Training Expenses</td>
<td>0.0030**</td>
<td>1.98</td>
<td>0.213*</td>
<td>1.9</td>
<td>0.077*</td>
<td>1.8</td>
<td>0.02</td>
<td>1.22</td>
<td>0.002</td>
<td>1.22</td>
<td>0.003</td>
<td>1.01</td>
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</tr>
<tr>
<td>Log Investment of Technical Development</td>
<td>0.06</td>
<td>0.96</td>
<td>4.617</td>
<td>0.96</td>
<td>1.673</td>
<td>0.93</td>
<td>0.11</td>
<td>0.42</td>
<td>0.010</td>
<td>0.42</td>
<td>0.015</td>
<td>0.41</td>
<td></td>
</tr>
<tr>
<td>Log #of R&amp;D Employees</td>
<td>0.22***</td>
<td>3.06</td>
<td>15.722***</td>
<td>2.95</td>
<td>5.697***</td>
<td>2.76</td>
<td>-0.74**</td>
<td>-2.22</td>
<td>-0.064</td>
<td>-2.29</td>
<td>-0.097</td>
<td>-1.43</td>
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</tr>
<tr>
<td>Log # of Technical Employees</td>
<td>-0.26**</td>
<td>-2.40</td>
<td>-18.283**</td>
<td>-2.33</td>
<td>-6.626**</td>
<td>-2.22</td>
<td>1.03</td>
<td>2.11</td>
<td>0.090**</td>
<td>2.16</td>
<td>0.135</td>
<td>1.47</td>
<td></td>
</tr>
<tr>
<td>Log # of New Cooperating Partners</td>
<td>0.36***</td>
<td>5.04</td>
<td>25.595***</td>
<td>4.6</td>
<td>9.275***</td>
<td>3.06</td>
<td>0.27</td>
<td>0.92</td>
<td>0.024</td>
<td>0.92</td>
<td>0.036</td>
<td>0.9</td>
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<tr>
<td>Log Output</td>
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<td>1.53</td>
<td>8.160</td>
<td>1.52</td>
<td>2.957</td>
<td>1.48</td>
<td>-0.04</td>
<td>-0.15</td>
<td>-0.004</td>
<td>-0.15</td>
<td>-0.006</td>
<td>-0.15</td>
<td></td>
</tr>
<tr>
<td>Log # of Employees</td>
<td>0.32***</td>
<td>3.57</td>
<td>22.858***</td>
<td>3.3</td>
<td>8.284***</td>
<td>2.88</td>
<td>-0.25</td>
<td>-0.63</td>
<td>-0.021</td>
<td>-0.63</td>
<td>-0.032</td>
<td>-0.63</td>
<td></td>
</tr>
<tr>
<td>Energy Industry</td>
<td>-0.20</td>
<td>-0.71</td>
<td>-13.111</td>
<td>-0.76</td>
<td>-5.628</td>
<td>-0.71</td>
<td>-15.24</td>
<td>-0.03</td>
<td>-0.541</td>
<td>-0.26</td>
<td>-0.154</td>
<td>-1.42</td>
<td></td>
</tr>
<tr>
<td>IT Industry</td>
<td>1.16***</td>
<td>4.83</td>
<td>117.933***</td>
<td>3.15</td>
<td>56.322***</td>
<td>2.09</td>
<td>-14.68</td>
<td>-0.02</td>
<td>-0.477</td>
<td>-0.38</td>
<td>-0.846***</td>
<td>-7.79</td>
<td></td>
</tr>
<tr>
<td>Equipment Manufacturing Industry</td>
<td>0.45**</td>
<td>2.10</td>
<td>37.034*</td>
<td>1.8</td>
<td>14.611*</td>
<td>1.66</td>
<td>-14.10</td>
<td>-0.02</td>
<td>-0.450</td>
<td>-0.41</td>
<td>-0.846***</td>
<td>-7.79</td>
<td></td>
</tr>
<tr>
<td>Environmental Protection Industry</td>
<td>1.08***</td>
<td>3.65</td>
<td>126.681**</td>
<td>2.29</td>
<td>50.127***</td>
<td>2.17</td>
<td>-15.09</td>
<td>-0.02</td>
<td>-0.623</td>
<td>-0.31</td>
<td>-0.846***</td>
<td>-7.79</td>
<td></td>
</tr>
<tr>
<td>Financed by Foreign Capital</td>
<td>-0.47</td>
<td>-1.46</td>
<td>-0.703</td>
<td>-0.09</td>
<td>-0.253</td>
<td>-0.09</td>
<td>18.38</td>
<td>0.00</td>
<td>0.000</td>
<td>---</td>
<td>0.000</td>
<td>---</td>
<td></td>
</tr>
<tr>
<td>SOE</td>
<td>-0.01</td>
<td>-0.09</td>
<td>-26.905*</td>
<td>-1.83</td>
<td>-9.675*</td>
<td>-1.7</td>
<td>0.46</td>
<td>1.29</td>
<td>0.040</td>
<td>1.3</td>
<td>0.051</td>
<td>1.01</td>
<td></td>
</tr>
</tbody>
</table>

Alpha: 1.1572, .0875

Likelihood-ratio test of alpha=0: chibar2(01) = 4.4e+04, Prob>=chibar2 = 0.000

AIC Statistic: 8.900

Wald Chi Z(18) = 65.68, Prob>chi2 = 0.0000

Log likelihood: -2481.93

Number of Observations: 562

Notes: .Conditional on firms in energy industry, with job rotation and cross functional team but no channel for employee suggestion and have mean values as to the continuous variables.

***: Significant at 1%; **: significant at 5%; *: significant at 10%.
<table>
<thead>
<tr>
<th>Variable of Interest</th>
<th>Turnover of Technical Employee</th>
<th>Turnover of Non-Technical Employee</th>
<th>Turnover of Technical Employee + Proxy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Logit ZTNB</td>
<td>Logit ZTNB</td>
<td>Logit ZTNB</td>
</tr>
<tr>
<td></td>
<td>Coeff z</td>
<td>Coeff z</td>
<td>Coeff z</td>
</tr>
<tr>
<td>Technical Employees' Turnover Rate</td>
<td>1.211*** 2.67</td>
<td>-0.045*** -2.85</td>
<td>1.183*** 2.61 -0.041** -2.28</td>
</tr>
<tr>
<td>Non-Technical Employees' Turnover Rate</td>
<td>-- --</td>
<td>-- --</td>
<td>-- --</td>
</tr>
<tr>
<td>Channel for Suggestions</td>
<td>-1.25 -1.04 0.07 0.36</td>
<td>-0.002 0.00 0.032 0.18</td>
<td>-0.042 -0.10 0.075 0.41</td>
</tr>
<tr>
<td>Cross-Functional Teams</td>
<td>-0.02 -0.06 0.26* 1.73</td>
<td>-1.181 -1.02 0.261* 1.69</td>
<td>-1.271 -1.06 0.258* 1.67</td>
</tr>
<tr>
<td>Proportion: Base Salary</td>
<td>-0.40 -0.34 0.08 0.17</td>
<td>-0.185 -0.16 0.187 0.39</td>
<td>-0.457 -0.39 0.088 0.18</td>
</tr>
<tr>
<td>Job Rotation</td>
<td>-1.23** -2.05 0.0027 0.02</td>
<td>-1.248** -2.04 -0.045 -0.27</td>
<td>-1.160* -1.89 -0.006 -0.03</td>
</tr>
<tr>
<td>Training Expenses</td>
<td>0.02 1.22 0.0030** 1.98</td>
<td>0.019 1.20 0.003** 2.00</td>
<td>0.018 1.13 0.003** 2.00</td>
</tr>
<tr>
<td>Ln alpha</td>
<td>0.146</td>
<td>0.154</td>
<td>0.146</td>
</tr>
<tr>
<td>AIC Statistic</td>
<td>8.900</td>
<td>8.932</td>
<td>8.902</td>
</tr>
<tr>
<td>Wald Chi2</td>
<td>65.68</td>
<td>63.65</td>
<td>66.09</td>
</tr>
<tr>
<td>Prob&gt; Chi2</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-2481.932</td>
<td>-2490.948</td>
<td>-2481.54</td>
</tr>
</tbody>
</table>

***: significant at 1%; **: significant at 5%; *: significant at 10%. 
4.2. The Interaction between Employee Turnover Rate and HRM Practices

Table 4 presents the average marginal effects from estimations of three different models. The first model includes employee turnover rate as the key independent variable, the second model only includes HRM practices variables, but not the employee turnover rate, and the third model includes the employee turnover rate as well as the HRM variables.

The magnitudes of statistically significant estimates are quite similar in all three models. Notably, the association between the employee turnover rate and R&D activity does not change much when the HRM practices are entered into the model. Nor does the inclusion of the employee turnover rate into the regression give rise to much change in the estimates of the HRM practices. These results suggest that although the turnover rate of technical employees and HRM practices both influence R&D activity, their influences seem to operate via different channels - as the influence of the turnover rate is not picking up the impact of HRM practices. In fact, simple OLS regressions\(^\text{16}\) show that the HRM practices are only weakly correlated with differences in the employee turnover rate.

A closer inspection reveals that the magnitude of the association between employee turnover rate and intensity of R&D activity varies among firms with different sets of HRM practices. This is shown in Table 5, which contains the conditional marginal effects of firms with different sets of HRM practices. Column (1) reports the marginal effects for firms which have no channels for employee suggestions, cross-functional teams, nor job rotation schemes; column (2) is for firms having cross-functional teams and job rotation schemes, but no channel for employee suggestions; column (3) shows marginal effects for firms which have adopted all the three above-mentioned HRM practices. To make the results comparable, the conditional marginal effects are calculated for our example firm, which is assumed to be in the energy industry, non-state owned, and has the sample mean values of the other firm characteristics.

\(^{16}\) Not shown, but available from the authors upon request.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Turnover Rate</th>
<th>HRM Practices</th>
<th>Turnover Rate + HRM Practices</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AME</td>
<td>Z</td>
<td>AME z</td>
</tr>
<tr>
<td>Technical Employees’ Turnover Rate</td>
<td>0.091***</td>
<td>-3.133***</td>
<td>-2.83</td>
</tr>
<tr>
<td>Channel for Suggestions</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Cross-Functional Teams</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Proportion: Base Salary</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Job Rotation</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Training Expenses</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Log Investment of Technical Development</td>
<td>0.016</td>
<td>0.79</td>
<td>8.470*</td>
</tr>
<tr>
<td>Log # of R&amp;D Employees</td>
<td>-0.0549*</td>
<td>-1.93</td>
<td>16.245***</td>
</tr>
<tr>
<td>Log # of Technical Employees</td>
<td>0.100**</td>
<td>2.33</td>
<td>-22.756***</td>
</tr>
<tr>
<td>Log # of New Cooperating Partners</td>
<td>0.017</td>
<td>0.71</td>
<td>24.946***</td>
</tr>
<tr>
<td>Log Output</td>
<td>-0.005</td>
<td>-0.21</td>
<td>7.679</td>
</tr>
<tr>
<td>Log # of Employees</td>
<td>-0.035</td>
<td>-0.99</td>
<td>25.664***</td>
</tr>
<tr>
<td>Energy Industry</td>
<td>-0.466</td>
<td>-0.02</td>
<td>-4.415</td>
</tr>
<tr>
<td>IT Industry</td>
<td>-0.388</td>
<td>-0.01</td>
<td>134.740***</td>
</tr>
<tr>
<td>Equipment Manufacturing Industry</td>
<td>-0.387</td>
<td>-0.02</td>
<td>48.289**</td>
</tr>
<tr>
<td>Environmental Protection Industry</td>
<td>-0.571</td>
<td>-0.02</td>
<td>153.286***</td>
</tr>
<tr>
<td>Ln alpha</td>
<td>0.1660</td>
<td>2.19</td>
<td></td>
</tr>
</tbody>
</table>

***: significant at 1%; **: significant at 5%; *: significant at 10%.
Table 5. Comparison of Marginal Effects Conditional on Different HRM Practices

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Logit</td>
<td>ZTNB</td>
<td>Logit</td>
</tr>
<tr>
<td>Technical Employees’ Turnover Rate</td>
<td>0.0180</td>
<td>-0.897**</td>
<td>0.158**</td>
</tr>
<tr>
<td>Channel for Suggestions</td>
<td>-0.0004</td>
<td>1.259</td>
<td>-0.003</td>
</tr>
<tr>
<td>Cross-Functional Teams</td>
<td>-0.036</td>
<td>5.138**</td>
<td>-0.104</td>
</tr>
<tr>
<td>Proportion: Base Salary</td>
<td>-0.006</td>
<td>1.595</td>
<td>-0.052</td>
</tr>
<tr>
<td>Job Rotation</td>
<td>-0.035</td>
<td>0.479</td>
<td>-0.103</td>
</tr>
<tr>
<td>Training Expenses</td>
<td>0.0003</td>
<td>0.0595*</td>
<td>0.003</td>
</tr>
<tr>
<td>Log Investment of Technical Development</td>
<td>0.002</td>
<td>1.279</td>
<td>0.015</td>
</tr>
<tr>
<td>Log # of R&amp;D Employees</td>
<td>-0.011</td>
<td>4.228***</td>
<td>-0.097</td>
</tr>
<tr>
<td>Log # of New Cooperating Partners</td>
<td>0.004</td>
<td>6.600***</td>
<td>0.036</td>
</tr>
<tr>
<td>Log output</td>
<td>-0.0007</td>
<td>2.188</td>
<td>-0.006</td>
</tr>
<tr>
<td>Log # of employees</td>
<td>-0.004</td>
<td>6.324***</td>
<td>-0.032</td>
</tr>
</tbody>
</table>

***: significant at 1%; **: significant at 5%; *: significant at 10%.

The estimates for the binary (that is, logit) part of model reveal little of interest, while there are more results worth of notice in the count (ZTNB) part of the model. Overall, for the example firm, the estimates of the employee turnover rate in all three columns are close to -1, indicating that a one percentage point increase in employee turnover is associated with one less R&D project.

Interestingly, the marginal effect of the employee turnover rate increases slightly with the number of HRM practices that the firm has adopted: for a firm without any of these three HRM practices, the marginal effect of the turnover rate is -.9; for a firm with cross-functional teams and job rotation, but no channel for employee suggestions, it is -1.2; for a firm with all three HRM practices, the marginal effect of the turnover rate is -1.3. It seems that R&D activity in firms with more innovative HRM practices is more “sensitive” to technical employee turnover. This could be because as a consequence of the use of these High Performance HRM Practices, the employees have become more valuable to the firm. Thus, as some of these employees leave the firm, they bring a marginally larger negative effect on firm’s R&D activity than in companies that have not implemented these practices.
5. Concluding Remarks

This paper has examined the empirical relationships between firms’ technical employee turnover rates, HRM practices and R&D activities. Using Chinese firm-level survey data and a logit hurdle negative binomial model, the study finds a significant negative association between technical employees’ voluntary turnover rate and intensity of R&D activities. Moreover, this relationship is robust to inclusion of HRM practices in the model. Likewise, the inclusion of the employee turnover rate does not give rise to noteworthy changes in the coefficients to the HRM practices. Thus, the technical employees turnover rate and HRM practices both influence firms’ R&D activities, but through different and independent channels.

The relatively high employee turnover rate is identified as another potential factor hampering R&D activities among Chinese firms and especially their decisions regarding how many in-house R&D projects to carry out. Unlike a few earlier studies that find positive influences of labor mobility on R&D and innovation, this paper observes a rather different situation in a developing economy like China. Several differences in the R&D environment may be part of an explanation of the differences observed.

First, in China, the protection of intellectual property is relatively poor. For a given level of employee mobility, Chinese firms face a higher risk of being copied by competitors and losing benefits of R&D due to the transmission of information via leavers. Second, due to the large population, the average number of job candidates for one position in China is very large, which results in higher recruitment cost and higher risk of mismatch. Both factors reduce the net benefit brought by newcomers. So, again, firms facing high labor mobility are reluctant to R&D because high labor mobility erodes its net benefits. Third, Chinese corporate culture is more conservative than Western culture. It is generally believed that the best strategy for new joiners is “shut the mouth and open the eyes and ears”, which limits the spillover of new ideas from new joiners. Since the positive effect of labor mobility on R&D (which is mainly brought by new employees joining the firm) is smaller, it is less likely that labor mobility facilitates R&D activities. Moreover, within a Chinese firm, it is usually small informal groups which actually make the decisions. A newcomer’s ideas are not be valued unless she is involved in a small group or a member thereof speaks for her. As it takes time for small groups to accept newcomers, Chinese firms are slower in observing newcomer’s innovative ideas and in reaping the benefits of having them. Lastly, the general level of
trust in China is lower (Wang et al., 2011), which means that the newcomers are less trusted and hence their ideas are less valued. On the other hand, lack of trust is mutual, and so, new employees do not commit themselves to R&D.

Thus, there are number of reasons for why the employee turnover is less likely to facilitate R&D activity in China. This list of characteristics specific to the internal labor markets of Chinese firms is of course mainly speculative. It should be noted, however, that Aoshima (2008) also finds a negative effect of the mobility of engineers on Japanese companies’ innovation performance. As China and Japan have many elements of a conservative corporate culture in common, this may explain why the labor mobility seems to influence innovation activity in China and Japan differently than in Western countries.

The employee turnover rate is not found to be reduced by the adoption of modern high performance HRM practices examined in this paper, such as cross-functional teams, job rotation schemes and channels for employees’ suggestions. On the other hand, we do find that firms that have introduced these HRM practices are more negatively affected by an increase in the employee turnover, suggesting that these practices are contributing to an increase in the value of the employees.

These results imply the possibility of encouraging indoor R&D activity by anchoring labor mobility at a suitable level – not too low to block idea exchange and not too high to risk the fruit of indoor R&D. Considering that firms may not have full control of employee turnover (at least not through the examined HRM practices), policy makers who is interested in facilitating R&D activity may consider using policy to adjust general labor mobility to a suitable level.
References


APPENDIX

Appendix 1: A Logit Hurdle Negative Binomial Model

Mullahy (1986) first offered solutions for how to deal with the situation when the zero outcomes of the data generating process differ from the positive ones within a hurdle model framework. Cameron and Trivedi (1986, 1998) further developed the model. Generally, hurdle models contain two parts: a binary probability model which determines whether the outcome is zero or not, and a truncated model which describes the positive outcomes.

This paper utilizes a logit hurdle negative binomial model. The first part of the model captures the probability of being non-innovative firm, which can be expressed as:

\[ P(Y_i = 0|Z_i) = \frac{1}{1+\exp(Z_i'y)} \quad (A-1) \]

The second part of the model captures the process generating positive outcomes, which follows negative binomial model. The probability of observing \( Y_i \) R&D projects can be expressed as:

\[ P(Y_i = y_i|X_i) = \frac{[1-P(Y_i=0|X_i)]g(Y_i=y_i|X_i)}{1-g(Y_i=0|X_i)} \quad (A-2) \]

Where \( g(.) \) is a probability function following the negative binomial II model.

The negative binomial model is obtained by generalizing the Poisson model by introducing an individual unobserved effect \( \epsilon_i \) into the conditional mean:

\[ \mu_i = E_NB(Y_i|X_i, \epsilon_i) = \exp(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \epsilon_i) \quad (A-3) \]

The distribution of \( Y_i \) conditional on \( X_i \) and \( \epsilon_i \) follows the Poisson form (Zaninotto and Falaschetti, 2011):

\[ g(Y_i = y_i|X_i, \epsilon_i) = \frac{e^{-\mu_i} \exp(\epsilon_i) \mu_i^{y_i}}{y_i!} \quad (A-4) \]

The unconditional distribution \( g(Y_i = y_i|X_i) \) is the expected value over \( \epsilon_i \) of \( g(Y_i = y_i|X_i, \epsilon_i) \):

\[ g(Y_i = y_i|X_i) = \int_0^\infty \frac{e^{-\mu_i} \exp(\epsilon_i) \mu_i^{y_i}}{y_i!} h(\exp(\epsilon_i)) \ d(\exp(\epsilon_i)) \quad (A-5) \]
The choice of density \( h(.) \) for \( \exp(\varepsilon_i) \) defines the unconditional distribution. In the negative binomial II model, \( \exp(\varepsilon_i) \) is assumed to have a gamma distribution with \( E[\exp(\varepsilon_i)]=1: \)

\[
h(\exp(\varepsilon_i)) = \frac{\theta^\theta}{\Gamma(\theta)} e^{-\theta \exp(\varepsilon_i)} [\exp(\varepsilon_i)]^{\theta-1}
\]

(\( A-6 \))

where \( \Gamma(\cdot) \) is the gamma function, such that \( \Gamma(s) = \int_0^\infty z^{s-1} e^{-z} \, dz \) for \( r>0 \) (Winkelmann, 2008).

Let

\[
\lambda_i = \exp(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip})
\]

(\( A-7 \))

Then, \( E(\mu_i) = E[\lambda_i \ast \exp(\varepsilon_i)] = E[\lambda_i] \ast E[\exp(\varepsilon_i)] = E[\lambda_i] = \lambda_i \), and the unconditional distribution \( (A-5) \) can be expressed as (Greene, 2012):

\[
g(Y_i = y_i | X_i) = \frac{\Gamma(\theta+y_i)}{\Gamma(\theta)\Gamma(\gamma+1)} \left( \frac{\theta}{\theta+\lambda_i} \right)^\theta \left( \frac{\lambda_i}{\theta+\lambda_i} \right)^{\gamma+y_i}
\]

(\( A-8 \))

and

\[
g(Y_i = 0 | X_i) = \left( \frac{\theta}{\theta+\lambda_i} \right)^\theta = (1 + \theta^{-1}\lambda_i)^{-\theta}
\]

(\( A-9 \))

Hence, the latent heterogeneity \( \varepsilon_i \) only induces over-dispersion:

\[ Var[Y_i | X_i] = \lambda_i \left[ 1 + \frac{1}{\theta} \lambda_i \right] = \lambda_i [1 + \kappa \lambda_i], \text{where } \kappa = \text{Var}[h_i], \]

while preserving the conditional mean:

\[ E_{NB}(Y_i | X_i) = \lambda_i = \exp(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip}) \]

Insert functions \((A-1), (A-8)\) and \((A-9)\) into \((A-2)\) and obtain the probability functions of the count part model:

\[
P(Y_i = y_i | X_i, Y_i > 0) = \frac{\exp(x_i'\gamma)\Gamma(\theta+y_i)}{[1+\exp(x_i'\gamma)]\Gamma(\gamma+1)\Gamma(\theta)[1-(1+\theta^{-1}\lambda_i)^{-\theta}]} \left( \frac{\lambda_i}{\theta+\lambda_i} \right)^{\gamma+y_i}, \text{ for } y_i = 1,2,3 \ldots
\]

(\( A-10 \))

Insert \((A-7)\) into \((A-10)\), then parameters \( \beta, \gamma, \) and \( \theta \) can be estimated using maximum likelihood method.

Firm \( i \)'s expected number of R&D projects, conditional on \( Y_i > 0 \) and \( X_i \) is:

\[
E(Y_i | Y_i > 0, X_i) = \frac{E_{NB}(Y_i | X_i)}{1-g(Y_i=0 | X_i)} = \frac{\exp(x_i'\beta)}{1-[1+\theta^{-1}\exp(x_i'\beta)]^{-\theta}}
\]

(\( A-11 \))

The expected number of R&D projects conditional on \( X_i \) is:
\[
E(Y_i | X_i) = (1 - P(Y_i = 0 | X_i))E(Y_i | Y_i > 0, X_i) = \frac{\exp(Z_i' \gamma + X_i' \beta)}{[1 + \exp(Z_i' \gamma)]\{1 - [1 + \theta^{-1} \exp(X_i' \beta)]}^{\theta}
\]

(A-12)

For a continuous variable \( x_{ij} \) that appears only in \( X_i \) (count part), its conditional marginal effect of the count part model is obtained by differentiating A-11 with respect to \( x_{ij} \):

\[
\frac{\partial E(Y_i | Y_i > 0, X_i)}{\partial x_{ij}}
\]

(A-13)

which depends on all the values of regressors \( X_i \).

Since \( \frac{E(Y_i | X_i, x_{ij} + \delta)}{E(Y_i | X_i, x_{ij})} = e^{\beta_j \delta} \), the interpretation of \( \beta_j \) is that: for a change of \( \delta \) in \( x_{ij} \), the expected number of R&D projects increases by a factor of \( \exp(\beta_j \delta) \), or by \( 100 \times \exp(\beta_j \delta) \)%.

For the continuous variable \( z_{ik} \) that appears only in \( Z_i \) (the binary part), its marginal effect is found by differentiating A-1 with respect to \( z_{ij} \):

\[
\frac{\partial P(Y_i = 0 | Z_i)}{\partial x_{ik}} = - \frac{y_k \exp(z_i' \gamma)}{[1 + \exp(z_i' \gamma)]^2}
\]

(A-14)

In the logit model, the reported marginal effect is calculated as:

\[
\frac{\partial P(Y_i > 0 | Z_i)}{\partial x_{ik}} = \frac{y_k \exp(z_i' \gamma)}{[1 + \exp(z_i' \gamma)]^2}
\]

(A-15)

which also depends on all the values of regressors in \( Z_i \).

Since the coefficient of the binary equation \( y_k = \partial \log[P(Y_i > 0 | Z_i)/P(Y_i = 0 | Z_i)]/\partial z_k \) [from (A-1)], it can also be interpreted directly as marginal change in the log value of relative probability of being innovative firm to non-innovative firm with respect to the change in \( z_k \).

For continuous variables that appear in both \( X_i \) and \( Z_i \) such that \( x_{ij} = z_{ik} \) for some \( j,k \), the overall marginal effect is obtained through differentiation of (A-12) with respect to \( x_{ij}(z_{ik}) \):

\[
\frac{\partial[P(Y_i > 0 | Z_i)]}{\partial x_{ik}}E(Y_i | Y_i > 0, X_i) + \frac{\partial E(Y_i | Y_i > 0, X_i)}{\partial x_{ij}}[1 - P(Y_i = 0 | Z_i)]
\]

(A-16)

which depends on all the values of regressors in \( X_i \) and \( Z_i \).

For a discrete variable, its partial effect is the difference in predicted values as the variable changes from 0 to 1 while all other variables are held constant at specified values.
For the binary part, the partial effect of discrete variable $z_{ik}$ is:

$$P(Y_i > 0 | z_{ik} = 1, z_{i,1,2..,k-1,1,k+1..m}) - P(Y_i > 0 | z_{ik} = 0, x_{1,2..,j-1,j+1..n}, z_{1,2..,k-1,1,k+1..m})$$

$$= P(Y_i = 0 | z_{ik} = 0, z_{i,1,2..,k-1,1,k+1..m}) - P(Y_i = 0 | z_{ik} = 1, x_{1,2..,j-1,j+1..n}, z_{1,2..,k-1,1,k+1..m})$$

(A-17)

which can be calculated using equation (A-1).

For the count part, the partial effect of discrete variable $x_{ij}$ is:

$$E(Y_i | Y_i > 0, x_j = 1, x_{1,2..,j-1,j+1..n}) - E(Y_i | Y_i > 0, x_j = 0, x_{1,2..,j-1,j+1..n})$$

(A-18)

which can be calculated using equation (A-11).