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## Firm-level Innovation Activity, Employee Turnover and HRM Practices – Evidence from Chinese Firms

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# **Firm-level Innovation Activity, Employee Turnover and HRM Practices – Evidence from Chinese Firms**

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**Abstract:** This paper examines the relationship between employee turnover, HRM practices and innovation in Chinese firms in five high technology sectors. We estimate hurdle negative binomial models for count data on survey data allowing for analyses of the extensive as well as intensive margins of firms' innovation activities. Innovation is measured both by the number of ongoing projects and new commercialized products. The results show that higher R&D employee turnover is associated with a higher probability of being innovative, but decreases the intensity of innovation activities in innovating firms. Innovating firms are more likely to have adopted high performance HRM practices, and the impact of employee turnover varies with the number of HRM practices implemented by the firm.

**JEL Codes:** L22, M50, O31

**Keywords:** Innovation, HRM Practices, Employee Turnover

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## 1. Introduction

Employee turnover can be an important mechanism for innovation 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 innovation. 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 innovation activities of the firm. This paper examines the relationship between employee turnover, HRM practices and innovation activity in Chinese high technology sector firms.

In the current stage of China's economic development, innovation is considered as one of the 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 innovation activities based on firm-level data exists for China.<sup>1</sup> 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 innovation 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 variables in our analysis are the number of ongoing R&D projects and new commercialized products 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.

The empirical analysis shows that a higher turnover rate of R&D personnel is associated with a higher likelihood that a firm is innovating but a lower level of R&D effort and innovation

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<sup>1</sup>In fact, we are only aware of one article (written in English) by Wei, Liu and Herndon (2011) on this topic.

performance in innovating firms. Particularly important HRM practices for enhancing innovation are the use of job description manuals and training programs. Notably, employee turnover has larger impact on innovation performance for firms using more high performance HRM practices. Among the other drivers of innovation, 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 innovation is given. The third section describes the data and the econometric method used. The results are presented and discussed in sections four and five, respectively. Section six briefly 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 innovation.<sup>2</sup> Instead, the large innovation literature has mainly been concerned with firm size, product market competition, knowledge spillovers and R&D collaboration.

It is somewhat surprising that there is relatively little amount of work on HRM practices and innovation in view of the fact that the interest in new work practices emphasizing delegation of authority, empowerment of employees, information sharing and employee involvement, originated from the focus on the Japanese firms' organization of workplaces in which horizontal information flows play a key role. The interest in the Japanese work organization and job design was to a high extent due to the fact that they were largely considered as the main determinants of the high level of innovation and quality improvement that characterized Japanese firms; see e.g., Applebaum and Batt (1994).

The first two papers to look at the relationship between HRM practices and innovation were Michie and Sheehan (1999), (2003) in which the authors examined British firms' use of so-called high- and

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<sup>2</sup> 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).

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 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.<sup>3</sup> 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. Summarizing and concluding from the earlier empirical studies is difficult because these have not only made use of many different measures of innovation as the dependent variable but also included quite different measures of HRM practices. Moreover, it should be pointed out that the mechanisms behind the relationship are not well understood. A key candidate is that HRM practices promote learning processes of individuals as well as organizations (Cohen and Levinthal (1989), Shankar and Ghosh (2013)); for a systematic study of this mechanism for a developing country, see Santiago and Alcorta (2012).

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<sup>3</sup> 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.

Could we expect the relationship between HRM practices and innovation 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 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.<sup>4</sup> 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' innovation activities.<sup>5</sup> 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

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<sup>4</sup> 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).

<sup>5</sup> Two recent papers by Balsvik (2011) and Parrotta and Pozzoli (2012) examine the impact of between firm employee flows on firm productivity.

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 innovation activities within the firm. All in all, this implies that a too low turnover of personnel is associated with a low level of innovation activity.

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 innovation and creativity.

The alternative hypothesis states that in order to promote innovation a firm needs to employ and retain appropriate staff. As innovative 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 innovative firms should provide employment security as a means to get the employees involved in their firm as this is important for innovation. 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 innovation 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 of 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.<sup>6</sup> Kaiser et al. (2008) carry out a considerably more elaborated analysis in which

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<sup>6</sup> The direction of causality could in both cases go the other way.

they distinguish between R&D employees leaving and joining the firms. The innovation 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 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<sup>7</sup> 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 innovation 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’ innovation behavior 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. Decision rights typically lie with small informal groups, and so, to become a member takes time. Thus, in firms where these features still are present, a positive relationship between employee turnover and innovation could be weaker, and even negative.

### **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 targeted

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<sup>7</sup> 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.



firms in five industries: energy, electronic information, biotechnology, equipment manufacturing and environmental protection, all of which are considered as high tech industries in China (World Bank, 2011). 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, inputs and outputs 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 20% 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 median firm has 2,534 employees.

Next we turn to discuss the key variables used in our empirical analysis. The dependent variables are the firm's R&D efforts, which is measured by the number of ongoing R&D projects during year 2010, and innovation performance, which is measured by the number of new commercial products in 2010. The number of R&D projects is a direct measure of R&D effort and also highly relevant to outcomes of both product and process innovation; the number of new commercial products is a

typical measure for innovation performance.<sup>8</sup> They contain richer information than the binary indicators which are used in many earlier innovation studies. Together, these two variables provide a more detailed picture of the firm's innovation activity, not only of the innovation outcome, but also the intermediate role of R&D efforts, which are in the black box transforming the labor and management input into innovation outcomes.

On average, a sample firm has 56 ongoing R&D projects in 2010. The distribution is heavily skewed: 14.4 per cent of the firms have no R&D project at all; among firms with at least one R&D project, the median number is 30, which is only half of the average. 95% of the firms have 280 or fewer ongoing R&D projects, while the most R&D active firms have over 1,000 projects. The distribution of the number of new commercial products in 2010 is also skewed: 167 firms in our sample do not have commercialized any new product in 2010 and the median innovating firm has 15 new commercial products, while the average firm has 33.4. About 95% of the firms have 100 or less new commercial products.

INSERT TABLE 1 ABOUT HERE

One explanatory variable of interest is the voluntary turnover rate of technical employees. It is a proxy for the turnover of R&D employees, which is not available in our data set. This is measured by the number of technical employees who left the firm voluntarily<sup>9</sup> divided by the total number of technical employees. In general the voluntary turnover rate of technical employees is much lower than the turnover rate of all employees, which is not what is found in more advanced economies, such as the U.S., where the opposite pattern is strong (Shankar and Ghosh, 2013). Thus, 21.5 per cent of the firms did not experience any turnover of technical employees in 2010 and 95% of the firms had less than 6.5 per cent of their technical staff leaving voluntarily. On the other hand, the highest turnover levels observed in the sample exceed sixty per cent.

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<sup>8</sup> A weakness of this measure is that what constitutes a new product is a subjective assessment and that new products can also be developed by buying external resources rather than through internal innovation activities.

<sup>9</sup> This concept presents no ambiguities in the context of Chinese firms as this is part of the regular reporting of their HR offices.

The HRM practices used by the firm make up the other category of variables of special interest in the current study. First, in order to measure high performance practices, we include four binary variables indicating whether the firm uses: job rotation schemes, job description manuals, operation standard manuals, and training programs. In order to capture the degree of the usage of these high performance HRM practices, we construct a variable counting the number of these practices adopted by the firm. Moreover, we use a binary variable to track a special HRM practice that is often highlighted in Chinese context – whether there is a formal channel for employees' suggestions. Two of the HRM practices are measured as continuous variables: the proportion of base salary of an R&D employee's annual income, and the firm's training expenditures in 2010.

Table 1 contains some descriptive statistics. For two key variables, we also report the subsample statistics for top and bottom quintiles of their distributions. The technical employee turnover rate in the top (bottom) quintile with respect to the number of R&D projects is clearly below (above) average. The turnover rate in the top quintile with respect to new commercial products is almost twice as high as in the bottom quintile. The average number of the HRM practices examined in our study is 3.9. This number varies only little by quintiles of the number of R&D projects or new commercial products. The operation standards and job description manuals are adopted in almost all the high-tech firms in our sample.

There seems to be a negative relationship between R&D efforts and innovation outcomes and employee turnover, whereas there appears to be no systematic relation regarding the number of HRM practices adopted by the firms. Of course, a concern is that the measures of HRM practices or the technical employee turnover rate are proxying some other traits of the firm (like size or industry). To examine this we include observable controls in the more formal regression analysis presented below.

First of these firm characteristics we include is firm size, which is measured by two indicators - the total number of employees and firm output (sales) in 2010. A sizable literature has shown that large firms are more likely to innovate.<sup>10</sup> Another factor which has been extensively studied in the innovation literature is product market structure. We do not have access to measures of the degree of competition faced by the sample firms, but expect the dummy variables for industry affiliation to

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<sup>10</sup> Employee turnover has also been shown to be positively correlated with firm size, which is another reason for controlling for it.

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. We use two dummy variables, one for state owned enterprise (SOEs) and another for foreign owned firms. This is motivated by the fact that SOEs, for historical reasons, may differ from private firms in several respects, especially regarding management style, which may influence both innovation activity and employee turnover. Foreign 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 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 innovation activity.

As we are treating R&D as a production process, it is also necessary to control for R&D inputs. Here we enter the total number of technical employees and total investments in R&D and innovation activities in order to control for the scale factor which influences the technical employee turnover rate, R&D and innovation. Furthermore, we control for profitability, which is measured by the annual profits divided by the value of assets. Previous studies suggest that higher profits are associated with both more innovation activity and better management practices, and so it is important to control for this factor to mitigate omitted variables bias.

Finally, we include the turnover of non-technical employees as a proxy variable for unobserved time-invariant effects, such as management quality. Following Blundell et al. (2002), we enter the average number of R&D projects/new commercial products in previous years as a proxy for unobserved fixed effects such as the firm's knowledge capital.

### 3.2. Econometric Model

This paper utilizes a logit hurdle negative binomial model<sup>11</sup>, which assumes that the probability of observing no R&D projects or new commercial products in firm  $i$  during year 2010 is:

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

and the probability of observing a positive number of R&D projects or new commercial products is:

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

where  $Y_i$  denotes the positive number of R&D projects or the number of new products by firm  $i$  during 2010,  $Z_i$  and  $X_i$  denote firm characteristics, and  $g(\cdot)$  is a probability function following a negative binomial II model.

(1) is a logit model, which describes the binary process determining whether the firm carries out R&D projects (or has new commercial products) or not; equation (2) is a zero truncated negative binomial model, in which  $g(\cdot)$  describes the count process determining the intensity of R&D activity or new product commercialization. For further details of the model, see Appendix 1.

#### 3.2.1. Choice of Model

The reason for choosing this particular econometric model is as follows. First, as 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 processes generating zero outcomes and strictly positive outcomes differ. Since the factors influencing firm's 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

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<sup>11</sup> 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.

that the zeroes 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 the zero inflated models the zero outcomes can arise in two ways: as a consequence of strategic decisions (with probability  $w$ ) and incidentally (with probability  $1-w$ ), while the hurdle count model assumes that zeroes 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/new commercial products 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 the count part of the model, the marginal effects describe the influences on the expected number of R&D projects/new commercial products 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 and (ii) conditional marginal effects. The average marginal effects are calculated for all observations 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 groups of firms are calculated by inserting given values (e.g., median group values) into the marginal effects formula.

## 4. The Roles of Employee Turnover Rate and HRM practices

In the following presentation of the estimation results we will first report estimates from a specification with HRM practices measured as a count variable (Table 2) and next consider estimates of dummy variables for the individual HRM practices (Table 3). For the purpose of comparison, each table presents estimates of the same regressors on two dependent variables: the number of R&D projects and new commercialized products. This is followed by a discussion of other factors and the interaction of technical employee turnover and the HRM practices.

### 4.1 The Role of Technical Employee Turnover

From Table 2 it can be seen that the turnover rate of technical employees<sup>12</sup> is negatively and significantly correlated with both the number of R&D projects and the number of new commercialized products. For the median firm, a one percentage point increase in the technical employee turnover rate is associated with about 0.7 fewer R&D projects and 0.8 fewer new commercial products. Thus, firms with a higher technical employee turnover rate exert less R&D effort and have less innovation output.

INSERT TABLE 2 ABOUT HERE

On the other hand, the turnover rate of technical employees is positively and significantly associated with the probability of having at least one new commercialized product; on average, a one percentage point higher turnover rate is accompanied by about a one per cent increase in the probability of having a new commercial product. For the probability of having a R&D project, its impact is also positive, albeit imprecisely estimated.

In sum, while a higher technical employee turnover increases the probability of having at least one new commercial product on a yearly basis, it is negatively associated with the intensity of both R&D effort and innovation output. In other words, it takes a certain level of R&D labor mobility to bring in new

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<sup>12</sup> To reduce the problem of possible simultaneity bias, the employee turnover rate is entered with a one-year lag.

ideas that initiate R&D projects, but once firms cross the threshold and engage in innovation, their R&D efforts and innovation performance are discouraged by a higher technical employee turnover.

INSERT TABLE 3 ABOUT HERE

## 4.2. The Role of HRM Practices

The number of high performance HRM practices adopted by the firm is significantly and positively correlated with both the number of R&D projects and the number of new commercial products. For a median firm in our sample, one additional HRM practice is associated with three more R&D projects and 2.5 additional new commercial products per year; see Table 2.

As for the effects of the individual high performance HRM practices, shown in Table 3, many of the individual practices attach insignificant estimates. To some extent this may be due to collinearity among some of the more widely implement practices. Still, a few things are worth noting. First, introducing training programs in firms that are already innovating gives rise to a higher R&D and innovation intensity. Second, firms using job rotation schemes are more likely to have produced at least one new commercial product. This makes sense as job rotation facilitates communication and exchange of ideas which in turn activates innovation. Third, job description manuals exist in nearly all firms with R&D projects and consequently have no impact on the probability component. However, they are strongly and positively associated with the number of new commercial products. Finally, we may note that a higher share of performance pay (that is, a lower base salary share) increases the probability of having at least one new commercial new product in a given year. So, while higher incentive pay does not lead to more ongoing R&D projects, it seems to give rise to more commercialized products.



### 4.3. The Impact of Other Factors<sup>13</sup>

As for the control variables, a few results are also worth noting. In line with the earlier literature, the size of the firm is found to be positively related to its innovation activities. A firm with a higher output level is more likely to produce a new commercial product every year and an increase in the firm's employees increases both the number of R&D projects and commercialized new commercial products. Firms with more external cooperation partners have significantly more R&D projects. For the median firm it means that a one per cent increase in the number of cooperation partners gives rise to two additional R&D projects and three additional new commercial products. More profitable firms have a higher number of R&D projects. Of course, here it should be noticed that causality can go both ways.

The proxy for unobserved heterogeneity, the pre-2010 sample average of the dependent variable, turned out highly significant in all models. The estimated effect is not very large, however. The turnover rate of non-technical employees is negatively associated with probability of having at least one new commercial product.

### 4.4. The Interaction between Employee Turnover and HRM Practices

It seems plausible to assume that a firm's employee turnover rate is related to its HRM policies. Thus, we first experimented with excluding either the HRM practices variables or the technical employee turnover rate in the models in Tables 2 and 3. The estimates, which are not shown to save space, turned out to be quite insensitive to the inclusion of the exclusion of the abovementioned variables. This suggests that although the turnover rate of technical employees and HRM practices both influence the number of R&D projects and new commercial projects, their

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<sup>13</sup> As was noticed in Table 1, there is considerable variation in the key variables and hence a concern is that the estimates may be influenced by outliers. Therefore, we have estimated the models on shaved samples excluding the top 5 per cent observations on the number of R&D projects, new commercial products and firm size (number of employees). For the binary part the estimates are very robust whereas there are some changes and in the magnitudes (not sign and significance) for the count part estimates. Overall, the estimates for the saved samples do not differ much from those of the full sample. We also estimated the models separately for SOEs and non-SOEs. As the SOEs make up 46 per cent of the sample, this means the estimation samples are substantially smaller. In the R&D project models the coefficient estimates and conditional marginal effects for the technical employee turnover rate and the number of HRM practices are slightly larger in magnitude (and associated with higher significance levels) for the SOEs than for the full sample. For the models of new commercial products, employee turnover has a larger impact for SOEs and the number of HRM practices attaches a positive and significant estimate for non-SOEs.

influences seem to operate via different channels. Simple (unreported) Tobit model regressions also show that the HRM practices are only weakly correlated with differences in the technical employee turnover rate.

However, a closer inspection reveals that the technical employee turnover rate may have different influences depending on firms' use of different sets of HRM practices. This is shown in Table 4, which contains the conditional marginal effects. The firms are divided into subgroups according to the number of HRM practices adopted, and for each subgroup, the marginal effects are calculated by setting other values equal to their subsample median values.

For the number of R&D projects we find nonlinear relations for the number of HRM practices, the technical employee turnover rate and the number of new cooperating partners. One additional HRM practices has a larger marginal effect for firms with a few practices (three or less), but as the firm has implemented more than three practices, the marginal effect of adopting an additional practice decreases. The same pattern is observed for the number new cooperating partners. The negative effect of the turnover rate of technical employees is also first increasing in the number of HRM practices but is lower when the firm has more than three practices. For the other dependent variable, the number of new commercial products, the magnitudes of the marginal effects are increasing in the number of HRM practices implemented by the firm. Thus, for instance, is the negative effect of the turnover rate of technical employees almost three times larger for a firm having only one of the HRM practices examined than for a firm that has adopted five of the practices.

## 5. Discussion

We have found that the technical employee turnover rate is higher in innovating firms than in non-innovating firms and that for firms that are carrying out R&D projects and are producing new commercial products further increases in the turnover rate discourage the firm's R&D efforts and lower its innovation performance. These findings are in accordance with the inverted U-shaped relations between employee turnover and innovation which have also been documented by some previous studies; see e.g., Müller and Peters (2010). The theoretical reasons for a positive relationship – new ideas brought into the firm by new employees – are supported by our study, but

we also find that as the marginal benefits of employee turnover decreases while its costs increases, the impact of higher turnover eventually turns negative.

Thus, one of the key findings of the empirical analysis is that technical employee turnover in Chinese high-tech firms has a negative influence on both R&D effort and innovation performance. While, as discussed in Section 2, this is not necessarily inconsistent with theory, several distinguishing features of the Chinese innovation environment may also contribute to the differences observed with respect to studies for more developed economies.

First, despite significant improvements, the protection of intellectual property in China is still relatively poor. For a given level of employee mobility, Chinese firms face a higher risk of being copied by competitors and losing benefits of innovation 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 to innovation. So, again, firms facing high labor mobility have weaker incentives to innovate more because the high labor mobility creates leakages of the gains from innovation.

Third, the Chinese corporate culture is often considered to be 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 innovation (which is mainly brought by new employees joining the firm) is smaller, it is less likely that high labor mobility contributes to more R&D efforts activities or higher innovation performance.

Moreover, in Chinese firms it is usually relatively small informal groups which actually make the decisions. A newcomer's ideas are not be valued unless she is involved in one of these small groups or a member thereof speaks for her. As it takes time for small groups to accept newcomers, Chinese firms are slower in observing a newcomer's innovative ideas and in reaping the benefits thereof. Although Chinese firms are claimed to have spent large amounts of money on poaching high level technical employees, the overall impact on firm level innovation seems to be negative. Lastly, the general level of trust in China is lower (Wang et al., 2011), which means that the newcomers are less trusted and as a consequence their ideas are less valued. This is reinforced by the fact that as lack of trust is mutual, new employees do not commit themselves to innovate either.

Overall, there are a number of reasons for why the higher employee turnover among technical employees 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.

## **6. Concluding Remarks**

In this paper we have examined the empirical relationships between high-tech firms' technical employee turnover rates, HRM practices, R&D efforts and innovation performance using Chinese firm-level survey data from five high-tech industries. Unlike earlier studies, the analysis distinguishes between decisions whether or not to innovate and decisions of how much to innovate and therefore estimates logit hurdle negative binomial models.

A notable feature of the high-tech studied is that the turnover rate of technical employees is lower than that of the firm's overall workforce. We find that technical employee turnover is higher in innovating firms but that higher turnover in firms that are already innovating has negative effects on R&D effort as well as on innovation performance. As for high performance HRM practices, we find that they contribute both higher R&D effort and innovation performance. Moreover, the negative relationship between employee turnover and R&D effort and innovation performance is stronger in firms which have adopted more of the high performance HRM practices, which indicates that these practices increase the value of the employees to the firm for its innovation activities.

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## APPENDIX 1: The 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:

$$P(Y_i = 0 | \mathbf{Z}_i) = \frac{1}{1 + \exp(\mathbf{Z}_i' \boldsymbol{\gamma})} \quad (\text{A-1})$$

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:

$$P(Y_i = y_i | \mathbf{X}_i) = \frac{[1 - P(Y_i = 0 | \mathbf{X}_i)] g(Y_i = y_i | \mathbf{X}_i)}{1 - g(Y_i = 0 | \mathbf{X}_i)} \quad (\text{A-2})$$

Where  $g(\cdot)$  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:

$$\mu_i = E_{NB}(Y_i | \mathbf{X}_i, \epsilon_i) = \exp(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_p X_{ip} + \epsilon_i) \quad (\text{A-3})$$

The distribution of  $Y_i$  conditional on  $\mathbf{X}_i$  and  $\epsilon_i$  follows the Poisson form (Zaninotto and Falaschetti, 2011):

$$g(Y_i = y_i | \mathbf{X}_i, \epsilon_i) = \frac{e^{-\mu_i \exp(\epsilon_i)} \mu_i^{y_i}}{y_i!} \quad (\text{A-4})$$

The unconditional distribution  $g(Y_i = y_i | \mathbf{X}_i)$  is the expected value over  $\epsilon_i$  of  $g(Y_i = y_i | \mathbf{X}_i, \epsilon_i)$ :

$$g(Y_i = y_i | \mathbf{X}_i) = \int_0^\infty \frac{e^{-\mu_i \exp(\epsilon_i)} \mu_i^{y_i}}{y_i!} h(\exp(\epsilon_i)) d(\exp(\epsilon_i)) \quad (\text{A-5})$$

The choice of density  $h(\cdot)$  for  $\exp(\epsilon_i)$  defines the unconditional distribution. In the negative binomial II model,  $\exp(\epsilon_i)$  is assumed to be Gamma distributed with  $E[\exp(\epsilon_i)] = 1$ :



$$h(\exp(\epsilon_i)) = \frac{\theta^\theta}{\Gamma(\theta)} e^{-\theta \exp(\epsilon_i)} [\exp(\epsilon_i)]^{\theta-1} \quad (\text{A-6})$$

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

$$\lambda_i = \exp(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_p X_{ip}) \quad (\text{A-7})$$

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

$$g(Y_i = y_i | \mathbf{X}_i) = \frac{\Gamma(\theta + y_i)}{\Gamma(\theta) \Gamma(y_i + 1)} \left(\frac{\theta}{\theta + \lambda_i}\right)^\theta \left(\frac{\lambda_i}{\theta + \lambda_i}\right)^{y_i} \quad (\text{A-8})$$

and

$$g(Y_i = 0 | \mathbf{X}_i) = \left(\frac{\theta}{\theta + \lambda_i}\right)^\theta = (1 + \theta^{-1} \lambda_i)^{-\theta} \quad (\text{A-9})$$

Hence, the latent heterogeneity  $\epsilon_i$  induces over-dispersion:

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

while preserving the conditional mean:

$$E_{NB}(Y_i | \mathbf{X}_i) = \lambda_i = \exp(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_p X_{ip})$$

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

$$P(Y_i = y_i | \mathbf{X}_i, \mathbf{Y}_i > 0) = \frac{\exp(\mathbf{z}_i' \boldsymbol{\gamma}) \Gamma(\theta + y_i)}{[1 + \exp(\mathbf{z}_i' \boldsymbol{\gamma})] \Gamma(y_i + 1) \Gamma(\theta) [1 - (1 + \theta^{-1} \lambda_i)^{-\theta}]} \left(\frac{\theta}{\theta + \lambda_i}\right)^\theta \left(\frac{\lambda_i}{\theta + \lambda_i}\right)^{y_i}, \text{ for } y_i = 1, 2, 3 \dots \quad (\text{A-10})$$

Insert (A-7) into (A-10), then parameters  $\beta$ ,  $\gamma$ , and  $\theta$  can be estimated using Maximum Likelihood.

Firm  $i$ 's expected number of R&D projects, conditional on  $\mathbf{Y}_i > 0$  and  $\mathbf{X}_i$  is:

$$E(Y_i | \mathbf{Y}_i > 0, \mathbf{X}_i) = \frac{E_{NB}(Y_i | \mathbf{X}_i)}{1 - g(Y_i = 0 | \mathbf{X}_i)} = \frac{\exp(\mathbf{X}_i' \boldsymbol{\beta})}{1 - [1 + \theta^{-1} \exp(\mathbf{X}_i' \boldsymbol{\beta})]^{-\theta}} \quad (\text{A-11})$$

The expected number of R&D projects conditional on  $\mathbf{X}_i$  is:

$$E(Y_i | \mathbf{X}_i) = [1 - P(Y_i = 0 | \mathbf{X}_i)] E(Y_i | \mathbf{Y}_i > 0, \mathbf{X}_i) = \frac{\exp(\mathbf{Z}_i' \boldsymbol{\gamma} + \mathbf{X}_i' \boldsymbol{\beta})}{[1 + \exp(\mathbf{Z}_i' \boldsymbol{\gamma})] \{1 - [1 + \theta^{-1} \exp(\mathbf{X}_i' \boldsymbol{\beta})]^{-\theta}\}} \quad (\text{A-12})$$

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

$$\frac{\partial E(Y_i|Y_i>0, \mathbf{X}_i)}{\partial x_{ij}} \quad (\text{A-13})$$

which depends on all the values of regressors  $\mathbf{X}_i$ .

Since  $\frac{E(Y_i|\mathbf{X}_i, x_{ij}+\delta)}{E(Y_i|\mathbf{X}_i, x_{ij})} = e^{\beta_j \delta}$ , 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  $100 * \exp(\beta_j \delta) \%$ .

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

$$\frac{\partial P(Y_i=0|\mathbf{Z}_i)}{\partial z_{ik}} = - \frac{\gamma_k \exp(\mathbf{z}_i' \boldsymbol{\gamma})}{[1+\exp(\mathbf{z}_i' \boldsymbol{\gamma})]^2} \quad (\text{A-14})$$

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

$$\frac{\partial P(Y_i>0|\mathbf{Z}_i)}{\partial z_{ik}} = \frac{\gamma_k \exp(\mathbf{z}_i' \boldsymbol{\gamma})}{[1+\exp(\mathbf{z}_i' \boldsymbol{\gamma})]^2} \quad (\text{A-15})$$

which also depends on all the values of regressors in  $\mathbf{Z}_i$ .

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

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

$$\frac{\partial [P(Y_i>0|\mathbf{Z}_i)]}{\partial z_{ik}} E(Y_i|Y_i > 0, \mathbf{X}_i) + \frac{\partial E(Y_i|Y_i>0, \mathbf{X}_i)}{\partial x_{ij}} [1 - P(Y_i = 0|\mathbf{Z}_i)] \quad (\text{A-16})$$

which depends on all the values of regressors in  $\mathbf{X}_i$  and  $\mathbf{Z}_i$ .

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 a discrete variable  $z_{ik}$  is:

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

$$= P(Y_i = 0 | z_{ik} = 0, \mathbf{z}_{i,1,2,..,k-1,k+1,..,m}) - P(Y_i = 0 | z_{ik} = 1, \mathbf{x}_{1,2,..,j-1,j+1,..,n}, \mathbf{z}_{1,2,..,k-1,k+1,..,m}) \quad (\text{A-17})$$

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

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

$$E(Y_i | Y_i > 0, x_j = 1, \mathbf{x}_{1,2,..,j-1,j+1,..,n}) - E(Y_i | Y_i > 0, x_j = 0, \mathbf{x}_{1,2,..,j-1,j+1,..,n}) \quad (\text{A-18})$$

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

Table 1. Descriptive Statistics

Variables			Mean	Std. Dev.
Number of R&D Projects			55.98	126.25
Number of New Commercial Products			573	33.43
Voluntary Turnover Rate of Technical Employees			1.27	3.81
Technical Employees' Voluntary Turnover Rate in Subsamples	Number of R&D Projects	Zero	0.15	0.34
		Top 20% Firms	0.74	1.11
		Bottom 20% Firms	2.21	7.56
	Number of New Commercial Products	Zero	0.34	1.49
		Top 20% Firms	1.49	2.13
		Bottom 20% Firms	2.70	9.61
	Firms with 5 HRM Practices		0.59	1.43
	Firms with 2 or fewer HRM Practice		2.52	4.48
Number of HRM Practices			3.90	0.88
Number of HRM Practices in Subsamples	Number of R&D Projects	Zero	4.38	0.83
		Top 20% Firms	4.11	0.76
		Bottom 20% Firms	3.95	0.84
	Number of New Commercial Products	Zero	4.35	0.79
		Top 20% Firms	3.92	0.76
		Bottom 20% Firms	3.75	0.90
Training Programmes			0.71	0.45
Operation Standards Manuals			0.98	0.14
Job Description Manuals			0.90	0.30
Job Rotation Schemes			0.53	0.50
Base Salary Share of Total Pay			0.68	0.16
Training Expenses (10,000 Yuan)			8.80	32.70
New Cooperation Partners			40.91	130.34
State Owned Enterprise			0.46	0.50

Source: Survey of firms in five high-tech industries in China, 2011

Dependent Variable Independent Variable	Intensity Equation				Probability Equation			
	R&D Projects		New Commercial Products		R&D Projects		New Commercial Products	
	(1) Coefficient.	(2) CME <sup>1</sup>	(3) Coefficient	(4) CME <sup>1</sup>	(5) Coefficient.	(6) AME <sup>2</sup>	(7) Coefficient	(8) AME <sup>2</sup>
Technical Employee Turnover Rate	-0.029* (0.017)	-0.680* (0.411)	-0.036** (0.018)	-0.793* (0.421)	3.014 (2.543)	0.017 (0.014)	0.812** (0.412)	0.007** (0.003)
Number of HRM Practices	0.137** (0.061)	3.249** (1.464)	0.113* (0.060)	2.506* (1.332)	-1.030 (1.591)	-0.006 (0.009)	1.229 (1.428)	0.011 (0.012)
Formal Channel for Employee Suggestions	-0.231* (0.140)	-5.479 (3.462)	-0.037 (0.161)	-0.819 (3.613)	4.402 (2.729)	0.025 (0.016)	-1.753 (5.245)	-0.015 (0.045)
Base Salary Share of Total Pay	-0.304 (0.358)	-7.189 (8.376)	0.178 (0.408)	3.950 (9.132)	4.296 (3.981)	0.025 (0.023)	-12.476* (7.427)	-0.107* (0.060)
Training Expenses (10,000 Yuan)	-0.002 (0.002)	-0.051 (0.037)	-0.004*** (0.002)	-0.091** (0.037)	0.010 (0.039)	0.000 (0.000)	0.014 (0.019)	0.000 (0.000)
Log Number of New Cooperating Partners	0.110** (0.056)	2.595** (1.324)	0.156*** (0.052)	3.461*** (1.246)	-0.437 (1.542)	-0.003 (0.009)	3.070** (1.615)	0.026** (0.013)
Pre-Sample Average of Dependent Variable	0.006*** (0.001)	0.143*** (0.020)	0.009*** (0.001)	0.205*** (0.027)	4.882*** (1.548)	0.028*** (0.008)	12.185*** (3.711)	0.104*** (0.025)
Non-Tech Employee Turnover Rate	0.026 (0.029)	0.609 (0.697)	0.037 (0.039)	0.822 (0.886)	0.055 (1.522)	0.000 (0.009)	-6.475** (2.553)	-0.055*** (0.020)
Log Investments in Innovation	0.057 (0.054)	1.346 (1.313)	-0.036 (0.055)	-0.798 (1.207)	0.058 (0.881)	0.000 (0.005)	-1.626* (0.943)	-0.014* (0.008)
Profits to Asset Ratio	0.670* (0.399)	15.869* (9.568)	-0.108 (0.365)	-2.407 (8.130)	-16.260 (13.938)	-0.094 (0.082)	5.155 (7.762)	0.044 (0.066)
Log Number of Technical Employees	-0.091 (0.071)	-2.164 (1.700)	-0.102* (0.070)	-2.280 (1.601)	2.050 (3.200)	0.012 (0.018)	5.316** (2.492)	0.045** (0.020)
Log Number of Employees	0.251*** (0.073)	5.947*** (1.809)	0.245*** (0.071)	5.450*** (1.722)	-0.477 (3.314)	-0.003 (0.019)	-5.309** (2.361)	-0.045** (0.019)
Log Output	-0.015 (0.060)	-0.343 (1.409)	0.040 (0.059)	0.889 (1.315)	-1.064 (1.217)	-0.006 (0.007)	1.462* (0.876)	0.013* (0.007)
State Owned Enterprise	-0.076 (0.091)	-1.792 (2.273)	0.047 (0.091)	1.043 (1.955)	1.970 (1.952)	0.011 (0.011)	-1.153 (1.308)	-0.010 (0.011)
Foreign Owned Enterprise	-0.287 (0.255)	-6.798 (6.149)	0.231 (0.259)	5.139 (5.732)	---	---	-6.245 (379.169)	0.007** (0.003)

<b>Log likelihood</b>	-2226.44	-1594.83	-11.85	-16.57
<b>Number of Observations</b>	481	399	565	564
<b>LR (<math>\chi^2</math>)</b>	545.76	488.70	451.35	648.66
<b>Prob &gt; c(<math>\chi^2</math>)</b>	0.000	0.000	0.000	0.000
<b>Pseudo R<sup>2</sup></b>	0.109	0.133	0.950	0.951
<b>Alpha (<math>\chi^2</math>)</b>	0.706*** (0.050)	0.551*** (0.047)	---	---
Notes: 1. Conditional Marginal Effect, conditional on Median Values; 2. Average Marginal Effect				
***: Significant at 1%; **: significant at 5%; *: significant at 10%..				

\*The model included industry dummies which are not shown. They are jointly significantly different from zero in both intensity equations and in probability equation for new commercial products. The alpha is a test statistic for testing between the negative binomial model and the Poisson model. Data source: Survey of firms in five high-tech industries in China, 2011

Table 3. Estimates of Hurdle Negative Binomial Models with Individual HRM Practices\*

Dependent Variable Independent Variable	Intensity Equation				Probability Equation			
	R&D Projects		New Commercial Products		R&D Projects		New Commercial Products	
	Coeff.	CME <sup>1</sup>	Coefficient	CME <sup>1</sup>	Coefficient	AME <sup>2</sup>	Coefficient	AME <sup>2</sup>
Technical Employee Turnover Rate	-0.028* (0.017)	-0.735 (0.461)	-0.034* (0.018)	-0.759* (0.435)	3.120 (2.670)	0.017 (0.014)	0.994* (0.511)	0.008** (0.004)
Training programs	0.232* (0.121)	6.107* (3.365)	0.278** (0.121)	6.225** (3.016)	-0.381 (3.772)	-0.002 (0.020)	-3.270 (2.969)	-0.025 (0.022)
Job Rotation Schemes	0.149 (0.131)	3.913 (3.530)	0.024 (0.136)	0.533 (2.985)	-0.874 (4.342)	-0.005 (0.024)	4.821* (2.507)	0.037** (0.017)
Cross Functional Teams	0.076 (0.120)	2.009 (3.313)	-0.069 (0.107)	-1.544 (2.337)	-8.229 (6.175)	-0.045 (0.034)	5.793 (9.034)	0.044 (0.067)
Formal Channel for Employee Suggestions	-0.234 (0.145)	-6.169 (4.040)	0.020 (0.164)	0.454 (3.661)	6.329 (5.230)	0.034 (0.029)	0.271 (4.477)	0.002 (0.034)
Job Description Manuals	0.154 (0.161)	4.066 (4.317)	0.386** (0.157)	8.660** (4.231)	---	---	---	---
Base Salary Share of Total Pay	-0.353 (0.360)	-9.285 (9.320)	0.074 (0.407)	1.653 (9.177)	2.890 (4.161)	0.016 (0.022)	-14.522* (8.508)	-0.110* (0.059)
Training Expenses (10,000 Yuan)	-0.002 (0.002)	-0.056 (0.042)	-0.004** (0.001)	-0.081** (0.037)	0.013 (0.044)	0.000 (0.000)	-0.010 (0.021)	-0.000 (0.000)
Log (Number of New Cooperating Partners)	0.105* (0.058)	2.760* (1.516)	0.176*** (0.053)	3.953*** (1.443)	-1.319 (2.147)	-0.007 (0.012)	4.812* (2.658)	0.037* (0.019)
Pre-Sample Average of Dependent Variable	0.006*** (0.001)	0.160*** (0.024)	0.009*** (0.001)	0.200*** (0.039)	4.484*** (1.536)	0.024*** (0.007)	14.728*** (5.061)	0.112*** (0.028)
Non-Tech Employee Turnover Rate	0.022 (0.030)	0.572 (0.797)	0.036 (0.039)	0.810 (0.908)	0.504 (1.858)	0.003 (0.010)	-8.695** (3.713)	-0.066** (0.024)
Log (Investment in Innovation)	0.054 (0.056)	1.428 (1.487)	-0.031 (0.056)	-0.699 (1.250)	0.129 (0.992)	0.001 (0.005)	-1.714 (1.066)	-0.013 (0.007)
Profits to Assets Ratio	0.656*	17.261	-0.101	-2.254	-16.039	-0.087	14.650	0.111

	(0.398)	(10.637)	(0.366)	(8.199)	(15.276)	(0.083)	(11.751)	(0.088)
Log Number of Technical Employees	-0.090	-2.359	-0.109	-2.447	1.557	0.008	5.827**	0.044**
	(0.072)	(1.896)	(0.070)	(1.637)	(3.532)	(0.019)	(2.750)	(0.018)
Log Number of Employees	0.245***	6.457***	0.245***	5.497***	0.019	0.000	-5.742**	-0.044***
	(0.073)	(2.050)	(0.070)	(1.876)	(3.598)	(0.020)	(2.550)	(0.017)
Log Output	-0.021	-0.547	0.008	0.183	-1.042	-0.006	2.246**	0.017**
	(0.061)	(1.610)	(0.060)	(1.335)	(1.296)	(0.007)	(1.103)	(0.007)
State Owned Enterprise	-0.079	-2.073	0.050	1.129	1.009	0.006	-1.873	-0.014
	(0.091)	(2.557)	(0.090)	(1.953)	(2.201)	(0.012)	(1.580)	(0.012)
Foreign Owned Enterprise	-0.276	-7.262	0.237	5.310	---	---	---	---
	(0.254)	(6.868)	(0.256)	(5.736)				
Log likelihood	-2225.56		-1590.91		-10.91		-14.13	
Number of Observations	481		399		565		564	
LR ( $\chi^2$ )	547.53		496.53		453.24		653.54	
Prob > ( $\chi^2$ )	0.000		0.000		0.000		0.000	
Pseudo R <sup>2</sup>	0.110		0.135		0.954		0.959	
alpha( $\chi^2$ )	0.704*** (0.050)		0.538*** (0.046)		---		---	
Notes: .1. Conditional Marginal Effect, conditional on Median Values; 2. Average Marginal Effect								
***: Significant at 1%; **: significant at 5%; *: significant at 10%..								

\*The model included industry dummies which are not shown. They are jointly significantly different from zero in both intensity equations and in the probability equation for commercialized new products. The alpha is a statistic testing between the negative binomial model and the Poisson model. Data source: Survey of firms in five high-tech industries in China, 2011



**Table 4. Marginal Effects Across Firms with Different Number of High Performance HRM Practices**

	Number of R&D Projects					Number of New Commercial Products				
# HRM Practices	1	2	3	4	5	1	2	3	4	5
Turnover Rate of Technical Employees	-0.488* (0.295)	-0.574* (0.347)	-1.101* (0.661)	-0.691* (0.418)	-0.731 (0.449)	-0.318* (0.172)	-0.435* (0.231)	-0.664* (0.342)	-0.892* (0.475)	-0.956* (0.513)
Number of HRM Practices	2.334*** (0.755)	2.74*** (1.058)	5.262** (2.342)	3.303** (1.410)	3.495** (1.721)	1.005** (0.408)	1.376** (0.649)	2.099* (1.117)	2.820** (1.453)	3.023* (1.750)
Log (Number of New Cooperating Partners)	1.865* (0.977)	2.194* (1.127)	4.204* (2.227)	2.639** (1.348)	2.792** (1.421)	1.388*** (0.482)	1.901*** (0.645)	2.899*** (1.042)	3.894*** (1.420)	4.175*** (1.455)
***: Significant at 1%; **: significant at 5%; *: significant at 10%.										



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