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# Does R&D Outsourcing Drive Specialists Out of The Firm?

**Wenjing Wang**
Aarhus University
Department of Economics and Business
wwang@asb.dk

Abstract

Do specialists walk out of the firm when R&D outsourcing increases? This question is critical in understanding how open R&D strategy links to innovation performance - which is a black box rarely opened by previous studies. Based on a panel dataset consisting R&D and innovation activities of Danish firms during the period 2007-2010, this paper finds evidence for the link between R&D outsourcing and employment of R&D specialists - in terms of both absolute number and as a share of R&D total employment. Interestingly, the trajectory of impact diverges between two dimensions measuring R&D outsourcing: although the depth of R&D outsourcing (measured as the share of purchased R&D) is negatively linked with firm's internal employment of R&D specialists, the breadth of R&D outsourcing (measured by the types of purchasing partners) has the opposite effects.

Jelcodes:J21,M51

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**Keywords:** Open R&D, R&D Employment, Correlated Random Effect Models

**JEL Code**: J21, J31, M51, O32

## 1. Introduction

Although it is not a new idea to tap into external knowledge for technological advancement, recent years have seen an increasingly resort to external knowledge in firm's R&D and innovation process (Chesbrough, 2007; Davis & Harrison, 2001; van de Vrande et al., 2009). R&D partnership has been growing tenfold in the last three decades (Luca Berchicci, 2013, Hagedoorn, 2002), while stand-alone, internal corporate labs declines (W.W. Powell and E.Ginnella, 2010). Business models also advocate an open innovation paradigm, where "firms can and should use external ideas as well as internal ideas, and internal and external market, to advance technology" (Chesbrough, 2003). Following this trend, more firms begin to pursue openness "strategically" (G.Pertroni et al., 2012). Still, from long-term perspective, the trend of growing openness is "a sustainable development rather than a management fashion."(Ulrich Lichtenthaler, 2011).

This significant increase in the openness of firm's R&D and innovation process and the belief of its sustainability have attracted growing attention from various fields; so far, relevant literatures have contributed better understanding on this phenomenon, especially on its causes and consequences.

Generally speaking, firms outsource R&D with the hopes such as reducing cost (e.g. Bounfour, 1999; Caudy, 2001; Kumar and Snavely, 2004; Piachaud, 2002; Y-A Huang et al., 2009; Zhao and Calantone, 2003); focusing on their core activities which generate competitive advantage (e.g. S. M. Mudambi and S. Tallman, 2010; Venkatesan, 1992); accessing to talent and knowledge (e.g. Barthélemy and Quélin, 2006; C. Crimpe and U. Kaiser, 2010; De Sarbo et al., 2005; Kogut and Zander, 1992); and sharing the risk (e.g. W.W. Powell and E.Ginnella, 2010). Beyond firm-level decisions, spillover effect is identified as a major factor accounting for this phenomenon: "a discrepancy between the private value and social value of invention, while the private value of invention is too low for some firms to pursue a technology individually" (W.W. Powell and E. Ginnella, 2010).

Several impacts of resorting to external knowledge are found in previous studies. For example, Laursen and Salter (2006) and Luca Berchicci (2013) both find an inverted U shape relationship is between the openness and innovation performance, which is measured by fraction of the new products or patents; Xiaolan Fu (2012) have found an inverted U shape relationship of openness on innovation efficiency, which is measured by input-output ratio; Ulrich Kaiser and Johan M. Kuhn (2011) have found that participating programme that facilities public-private cooperation has significant impacts on annual patent applications. José Mata and Martin Woerter (2013) have found a positive impact of external R&D strategies on the firm's performance.

Despite the identification on the reasons and consequences of taping into external knowledge in R&D and innovation processes, the black box transforming innovation inputs into divergence outcomes has rarely opened up by systematic research. One important intermediate determining the trajectory of the transformation is the R&D employee, whose quality directly reflects firm's R&D ability, which in turn plays a major role in explaining the variances in performance indicators from different dimensions. Besides the role linking openness and performance, firm's R&D employment is worth to monitor as an important indicator by itself, because its evolvement has significant implication on the trajectory of R&D activity for both individual firm and the whole society. Peter Teirlinck, et al. (2010) has looked at the impact of outsourcing R&D on the R&D employment intensity; however, their study focuses on the size of R&D employment, which does not say anything about the employment evolvement inside R&D function.

This paper fills the gap by examining how the quality of R&D employment evolves with the opening of R&D process. Specifically, the impacts of two dimensions of openness - breadth and depth, on the firm's absolute and relative employment for R&D specialists are examined. The data is from Statistic Danmark's annual survey on R&D and innovation. So far, the estimation is based on around 4000 effective observations during the period 2007-2010. Three types of econometric models are used - correlated random effect tobit model, selection models and fraction response model. The first two are used to estimate the models for absolute change of R&D specialists' employment, while the third one is to estimate the models for the evolvement of the share of specialists within R&D function. The results show that the opening of R&D process has significant impacts on employment opportunity for firm's R&D specialists: while the share of purchased R&D reduces the employment of R&D specialists in both relative and absolute terms, collaborating with a broader variety of external organizations has the opposite effects.

The remainder of this paper unfolds as follows: section 2 discusses the related theories and previous studies, based on which two hypotheses are proposed; section 3 describes the empirical strategy to test the hypothesis; section 4 presents the estimation results.; section 5 concludes.

## 2. Theory and Hypothesis

How can outsourcing R&D have impact on firm's employment of R&D specialists? There is little theoretical analysis or empirical evidence for that. However, existing studies from three areas all provide some clue, based on which two general hypotheses can be established.

### 2.1. Theories and Hypothesis from Management Perspective

It is widely accepted that opening up the R&D and innovation process enables a firm to focus on core activities that generate competitive advantage (e.g. Barthélemy and Quélin, 2006; C. Crimpe and U. Kaiser, 2010; De Sarbo et al., 2005). Naturally, focusing on the core activity corresponds to adjustment in employment composition. Following this logic, the direction of change in R&D employment depends on where the firm re-anchors its core competency along the extended value chain when opening to external R&D resources. One scenario is that the firm still sees its core competency in cutting-edge R&D, so that its optimal choice is to enhance it by including more employees with higher-qualification (e.g. specialists) into the R&D team. The other possibility is that the firm no longer sees itself excel in original R&D compared with external agents; instead, it sees, for example, the ability of integrating resources as the major competency. In this case, firm may find employees with more general skills better serves its R&D strategy. Compare with the first scenario, the second one is supported by plenty of evidence in previous research, which make it the most accepted view about the employment implication of open innovation. These studies, which are mainly based on cases, find that in firms that open up the R&D and innovation process, skills for integrating knowledge become more important relative to skills for deepening of knowledge; the role of senior scientists is undermined whereas the role of engineers and the business innovation team has been highlighted (e.g. Girorgio Petroni, et al. 2013). Following this line, firms may tend to replace specialists or scientists with technical employees who have wider but shallower knowledge.

## 2.2. Theories and Hypothesis from Labor and Trade Perspective

Another way of analyzing the employment implication of open R&D and innovation strategy stems from the labor and trade theory explaining the wage polarization in US (Daron Acemoglu and David Autor, 2011). Just as trade has significant implication on domestic labor market, opening up firm's boundary for external R&D and innovation resources may also have important implications for internal R&D employment. For example, the existing labor theory predicts a decrease of medium-skilled worker's relative wage after outsourcing routine tasks, under the assumption that labor can not move across country border. Adapting it to firm's R&D outsourcing scenario, first we have to reverse the assumptions. Unlike a country, firms may have better control over the number of each type of employees compared with their wages, which are determined by the regional labor market, at least in the shorter term. In other words, it is more realistic to assume that for firms, the wage for each type of employee is fixed while the labor is mobile. Under this assumption, an parallel analysis with the one for country's outsourcing activity predicts that, accessing to cheaper external R&D resources substitutes away internal employment of R&D employee who perform corresponding tasks: the external high/medium/low-skill intensive R&D replaces internal demand and equilibrium number of high/medium/low-skill R&D employee. Again, when firm's R&D boundary is open, to outsource which part of R&D depends on firm's comparative advantage - thus we arrive to the similar prediction with the one from management perspective discussed in previous section.

## 2.3. Inference from Recent Empirical Study

The discussion above converges in that R&D outsourcing has impacts on the employment of R&D specialists, while the directions of the impacts depend on firm's comparative advantage and corresponding allocation of tasks to external resources. However, these explaining factors are not easy to be observed or proved empirically. Luckily, some inferences from recent empirical studies on the consequences of open R&D reveal a potential observable factor that may help to predict the direction to which the composition of R&D employment may evolve with R&D outsourcing.

Several recent empirical studies on R&D outsourcing arrive to a common observation that the influences of R&D outsourcing innovation performance depends on internal R&D and collaboration. For example, John Hagedoor and Ning Wang (2012) find external R&D facilitates enhance the efficiency of internal R&D when there is already a high-level of internal R&D, while the opposite is true for firms with low-level of internal R&D. C. Crimpe and U. Kaiser (2010) find a reverse-U shape relationship between purchased R&D and firm's innovation performance, and cooperation with other firms and internal R&D play a moderating role in this relationship. The underlying information from these studies is that, there are two different dimensions through which R&D outsourcing may link to performance: one is the combination between external and internal R&D (and the other is cooperation with external R&D partners. The first dimension can be captured by the share of outsourced R&D (depth of R&D outsourcing); the second dimension can be captured by the number of R&D partners (breadth of R&D outsourcing). On the other hand, traditional productivity theory links firm's performance directly to input of labor. In the specific case of R&D and innovation, where human resource is the key input, it is natural to infer that R&D and innovation performance varies with effective input of R&D labor, which can be reflected by the absolute number and share of R&D specialists. So it can be further inferred that outsourcing R&D and internal employment of R&D specialists are linked through similar pattern with the observed one between outsourcing R&D and innovation performance, if the inferred link exists. Still, it needs systematic evidence to establish the link between outsourcing R&D and internal employment of R&D specialists, so that their role as a key intermediate, which hides in the black box transforming the R&D outsourcing to innovation performance, can be identified.

To sum up, previous case studies from management perspective, labor and trade theory, as well as inference from existing relevant empirical evidence converge to the following predictions:

**H1**: The depth of R&D outsourcing has negative impact on R&D specialists' employment, in both absolute term and as a share of the total R&D employment;

**H2**: The breath of R&D outsourcing has positive impact on R&D specialists' employment, in both absolute term and as a share of the total R&D employment.

## 3. Empirical Analysis

This section discusses the empirical strategy that tests the above two hypothesizes.

### 3.1. Data and Variables

#### 3.1.1. Data

The dataset is constructed by merging survey data on firm's R&D and Innovation (FoU) activity with firm's basic information (FIRE). FoU survey is conducted annually by Statistics Danmark since 1990s, which targets at enterprises with at least # employees. Considering the availability and consistency of the variables of interest, only the surveys conducted during 2007-2010 are used. Each year's survey contains around 4000 firms; however, only a proportion of them have R&D related activity. FIRE data provides firm's basic information, such as location, industry, total number of employee, profit, etc. Only firms that appear in both datasets are used. For the purpose of this analysis, the sample (so that the population of interest) is further restricted to firms with positive R&D expenditure. Because firm may not participate the survey or have positive R&D expenditure each year, the panel data is unbalanced. In total, the dataset contains 3974 observations from 2285 different firms, which means each firm is observed 1.7 times on average.

### 3.1.2. Variables

#### *3.1.2.1. Dependent Variables*

The first dependent variable is FTE of researchers and other specialists employed by a firm, which is a direct measure of the employment opportunity for R&D specialists.

Another dependent variable is the share of R&D specialists within the firm, which reflects the composition within firm's R&D function.

Together, these two dependent variables reveal the position where a firm anchors itself on the R&D and innovation value chain from different perspectives.

#### *3.1.2.2. Main Explanatory Variables*

The degree of "openness" of R&D activity is measured via two aspects: depth and breath.

The depth of openness is measured by the purchased R&D expenditure divided by total R&D expenditure.

The broadness of openness here mainly refers to the broadness of R&D collaboration. This is measured by counting the number of types of external sources from which the firm purchase R&D. In the survey 2007 and 2008, firms are asked to fill out the expenditure for purchased R&D from each of the following eight mutual exclusive sources: There are two extra subordinating types of external R&D sources listed in the survey since 2009, which are regrouped in order to keep consistency across different years.

#### *3.1.2.3 . Control Variables*

Several factors that may influence R&D specialists' employment are controlled for:

Total R&D expenditure. It is a very close proxy for firm's effort/strategy on R&D, which relates to both openness of R&D and R&D specialists' employment.

Profit per employee. This is a proxy capturing a group of unobservable factors that may influence the capability and efficiency of hiring R&D specialists and managing external collaboration.

Industry. Previous research has pointed out that, persistent industry variations - especially in terms of technological opportunities and social institutions, result marked differences in collective invention (W.W. Powell and E.Ginnella, 2010). Thus it is important to control for the industry differences when examining the influence of collaboration in R&D and innovation. To balance between precise industry classification and consumption of degree of freedom, the first digit of Nace classification is used as industry indicator, which classifies the firms into seven different industries.

Location. Differences in social institutions and labor supply may influence firm's choice on R&D employment and cooperation. These differences are controlled by a location indicator "Kommune nr.", which specifies the region that the firm locates. In total, the sample covers eight different locations.

Asset and number of employee. They are used to control for firm size, which may relate to R&D employment and collaboration. Log values are used.

R&D department. It is a binary variable indicating whether a firm has R&D department or not. It reflects the importance that a firm places on R&D activity, which may relate to the employment of R&D specialists and external cooperation.

## 3.2. Econometric Models

To identify the impact on employment of R&D specialists, a correlated random effect (CRE) Tobit model is estimated; then the estimates are compared with three sample selection models, which use fixed effects (FE), CRE and pooled OLS specification for the second stage estimation respectively.

### 3.2.1. CRE Tobit Model

The Tobit model allowing for unobserved heterogeneity assumes an underlying equation determining the employment of R&D specialists:

$$y_{it}^{*} = \mathbf{x_{it}}\boldsymbol{\beta} + \mathrm{c_i} + \mathrm{u_{it}} \tag{3-1}$$

$$y_{it} = \begin{cases} y_{it}^{*}, & if\ y_{it}^{*} > 0 \\ 0, & if\ y_{it}^{*} \leq 0 \end{cases} \tag{3-2}$$

where $y_{it}^{*}$ and $y_{it}$ are latent and observed number of R&D specialists, respectively; $\mathbf{x_{it}}$ is a vector of explanatory variables, $\mathrm{c_i}$ is firm specific unobserved heterogeneity, and $\mathrm{u_{it}}$ is an idiosyncratic error.

The CRE approach, which dates back to Mundlak (1978), allows correlation between $\mathrm{c_i}$ and $\mathbf{x_i}$ , thus loosens the assumption of traditional random effect (RE) method and makes RE is a special case for CRE. Following Wooldridge (2010a), this paper models the conditional distribution of heterogeneity as:

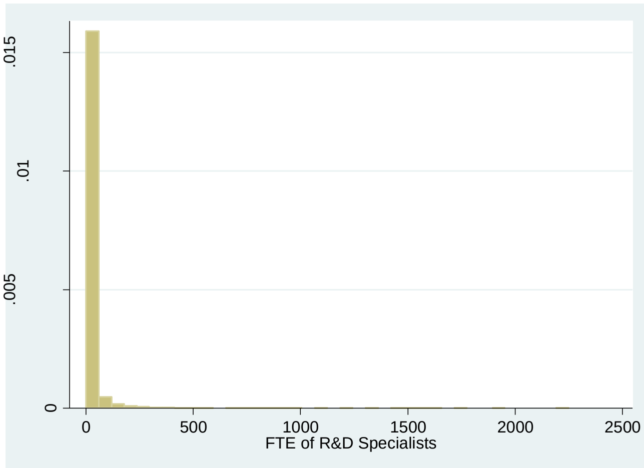
$$\mathrm{c_i} \mid \mathbf{x_i} \sim Normal\ (\psi + \bar{\mathbf{x}}_{\mathbf{i}}\boldsymbol{\xi}, \sigma_a^2) \tag{3-3}$$

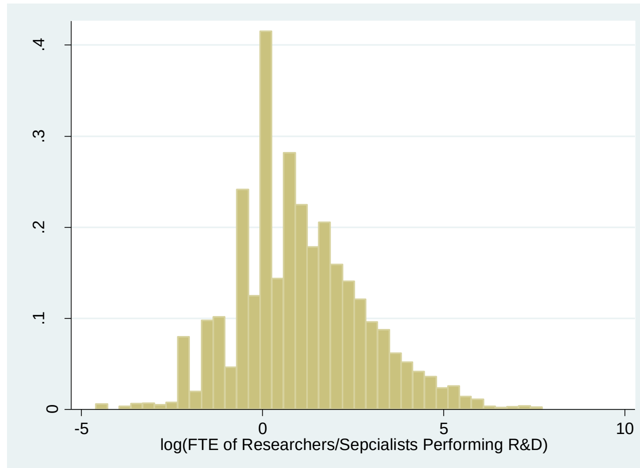
, and then equation (3-1) becomes:

$$\mathrm{y_{it}} = \max(0, \psi + \mathbf{x_{it}}\boldsymbol{\beta} + \bar{\mathbf{x}}_{\mathbf{i}}\boldsymbol{\xi} + \mathrm{a_i} + \mathrm{u_{it}}) \tag{3-4}$$

where we now have $\mathrm{a_i}|\mathbf{x_i} \sim Normal\ (0, \sigma_a^2)$ and $\mathrm{u_{it}}|\mathbf{x_i} \sim Normal\ (0, \sigma_u^2)$ - so that (3-4) can be estimated by joint maximum likelihood estimation (conditional on $\mathbf{x_i}$).

The suitability of Tobit model is evident in the data. Graph 1 shows the distribution of the major dependent variable – number of specialists performing R&D, highlighting a group of observations near zero (see graph 1); graph 2 shows the distribution of log value of R&D specialists, which resembles a truncated normal distribution with truncated point near -2. Tobit model. Both graphs indicate the existence of truncation, for which Tobit model fits well.




### 3.2.2. Selection Models

Though CRE Tobit model is more promising than traditional Tobit model in the context of this paper, CRE Tobit may still be too restrictive in the sense that it assumes the variables and the signs of marginal effects are the same between the decision process on whether or not hiring R&D specialists (participation decision) and that on how many R&D specialists to hire (intensity decision). To distinguish these two processes, a group of previous literatures make use of hurdle models (e.g.). Still, hurdle models are special cases for a more general group of model – selection model. To check whether the participation decision process differs from intensity decision process, this paper makes use of CRE sample selection model following Wooldridge (2010b). Generally, selection model also uses equation (3-1) to describe the intensity decision, which captures the expectation of dependent variable conditioning on that is positive. Besides, it introduces a selection equation (3-5) to replace condition equation (3-2):

$$\mathrm{s}_{\mathrm{it}} = 1\ [s_{it}^{*} > 0] = 1[\mathbf{x}_{\mathbf{it2}}\boldsymbol{\delta}_{\boldsymbol{t}} + \mathrm{c}_{\mathrm{i2}} + \mathrm{u}_{\mathrm{it2}} > 0] \tag{3-5}$$

Then observing condition equation (2) becomes:

$$y_{it} = \begin{cases} y_{it}^{*}, & if\ \mathrm{s}_{\mathrm{it}} = 1 \\ 0, & if\ \mathrm{s}_{\mathrm{it}} = 0 \end{cases} \tag{3-6}$$

where $\mathrm{s}_{\mathrm{it}}$ and $s_{it}^{*}$ are observed and latent selection indicators respectively; $\mathbf{x}_{\mathbf{it2}}$ is a vector of variables explaining participation; $\mathrm{c}_{\mathrm{i2}}$ is firm specific unobserved heterogeneity. Both $\mathbf{x}_{\mathbf{it2}}$ and $\mathrm{c}_{\mathrm{i2}}$ in equation (3-5) can be different from $\mathbf{x}_{\mathbf{it}}$ and $\mathrm{c}_{\mathrm{i}}$ in equation (3-1). In this way, the participation decision is allowed to differ from the intensity decision. Equations (3-1), (3-5) and (3-6) form the basic framework for selection models.

Following Wooldridge (2010b), the selection models are estimated with two-step procedure, with each step incorporated with CRE device from Mundlak (1978). The first step is to estimate the selection equation (3-5): $\mathrm{c}_{\mathrm{i2}}$ is assumed to relate to $\mathbf{x}_{\mathbf{i2}}$ only through the time averages of explanatory variables, while $\mathrm{a}_{\mathrm{i2}}$ is independent of $\mathbf{x}_{\mathbf{i2}}$:

$$\mathrm{c}_{\mathrm{i2}} = \overline{\mathbf{x}_{\mathbf{i2}}}\boldsymbol{\pi} + \mathrm{a}_{\mathrm{i2}} \tag{3-7}$$

$$\mathrm{a}_{\mathrm{i}2}|\mathbf{x}_{\mathbf{i}2} \sim Normal\ (0, \sigma_{a2}^2) \tag{3-8}$$

Then equation (3-5) becomes:

$$\mathrm{s}_{\mathrm{it}} = 1\ [s_{it}^* > 0] = 1[\mathbf{x}_{\mathbf{it2}}\boldsymbol{\delta}_{\boldsymbol{t}} + \overline{\mathbf{x}_{\mathbf{i2}}}\pi_t + \mathrm{v}_{\mathrm{it2}} > 0] \tag{3-9}$$

where $\mathrm{v}_{\mathrm{i}2} = \mathrm{a}_{\mathrm{i}2} + \mathrm{u}_{\mathrm{it}2}$ and $\mathrm{v}_{\mathrm{i}2}|\mathbf{x}_{\mathbf{i}} \sim Normal\ (0, 1 + \sigma_{a2}^2)$. Then equation (3-9) can be estimated with Probit model for each time period and inverse mill ratio for each observation $\hat{\lambda}_{\mathrm{it}}$ can be obtained.

One feature of selection model is that it allows the correlation between participation equation and intensity equation through error terms and unobserved factors. The correlation between error terms is assumed to be linear:

$$\mathrm{E}(\mathrm{u}_{\mathrm{it}}|\mathbf{x}_{\mathbf{i}}, \mathrm{c}_{\mathrm{i}}, \mathrm{v}_{\mathrm{it2}}) = \mathrm{E}(\mathrm{u}_{\mathrm{it}}|\mathrm{v}_{\mathrm{it2}}) = \rho_t \mathrm{v}_{\mathrm{it2}},\ \ t = 1, \dots, T. \tag{3-10}$$

Further assuming that

$$\mathrm{E}(\mathrm{c}_{\mathrm{i}}|\mathbf{x}_{\mathbf{i}}, \mathrm{v}_{\mathrm{it2}}) = \bar{\mathbf{x}}_{\mathbf{i}}\boldsymbol{\xi} + \psi_t \mathrm{v}_{\mathrm{it2}} + \mathrm{a}_{\mathrm{i1}} \tag{3-11}$$

Take expectation of (3-1) conditional on $\mathbf{x}_{\mathbf{i}}, \mathrm{v}_{\mathrm{it2}}$ and replace $E(\mathrm{u}_{\mathrm{it}}|\mathbf{x}_{\mathbf{i}}, \mathrm{v}_{\mathrm{it2}})$ and $\mathrm{E}(\mathrm{c}_{\mathrm{i}}|\ \mathbf{x}_{\mathbf{i}}, \mathrm{v}_{\mathrm{it2}})$ using (3-10) and (3-11), we have

$$\mathrm{E}(\mathrm{y}_{\mathrm{it}}|\mathbf{x}_{\mathbf{i}}, \mathrm{v}_{\mathrm{it2}}) = \mathbf{x}_{\mathbf{it}}\boldsymbol{\beta} + \bar{\mathbf{x}}_{\mathbf{i}}\boldsymbol{\xi} + \gamma_t \mathrm{v}_{\mathrm{it2}} + \mathrm{a}_{\mathrm{i1}} \tag{3-12}$$

where $\gamma_t = \rho_t + \psi_t$.

Conditioning on $\mathrm{s}_{\mathrm{it}} = 1$, we have:

$$\mathrm{E}(\mathrm{y}_{\mathrm{it}}|\mathbf{x}_{\mathbf{i}}, \mathrm{s}_{\mathrm{it}} = 1) = \mathbf{x}_{\mathbf{it}}\boldsymbol{\beta} + \bar{\mathbf{x}}_{\mathbf{i}}\boldsymbol{\xi} + \gamma_t \lambda_{it}(\mathbf{x}_{\mathbf{it2}}\boldsymbol{\delta}_{\boldsymbol{t}}^{\boldsymbol{a}} + \bar{\mathbf{x}}_{\mathbf{i2}}\pi_t^a) + \mathrm{a}_{\mathrm{i1}}$$

So that the equation for $\mathrm{s}_{\mathrm{it}} = 1$ is:

$$\mathrm{y}_{\mathrm{it}} = \mathbf{x}_{\mathbf{it}}\boldsymbol{\beta} + \bar{\mathbf{x}}_{\mathbf{i}}\boldsymbol{\xi} + \gamma_t \lambda_{it}(\mathbf{x}_{\mathbf{it2}}\boldsymbol{\delta}_{\boldsymbol{t}}^{\boldsymbol{a}} + \bar{\mathbf{x}}_{\mathbf{i2}}\pi_t^a) + \mathrm{a}_{\mathrm{i1}} + \mathrm{e}_{\mathrm{it1}} \tag{3-13}$$

where $\lambda_{it}(\cdot)$ is inverse Mills ratio, $\delta_t^a = \delta_t/\sqrt{1+\sigma_{a2}^2}$, $\pi_t^a = \pi_t/\sqrt{1+\sigma_{a2}^2}$, which can be estimated by probit regression of $\mathrm{y}_{\mathrm{it}}$ on 1, $\mathbf{x}_{\mathbf{it2}}$, $\bar{\mathbf{x}}_{\mathbf{i2}}$, $t = 1, \dots, T.$ in the first step.

The second step estimates the final equation (3-13) by using either FE, CRE, or pooled OLS after substituting $\lambda_{it}$ by $\widehat{\lambda_{it}}$. The consistency of the estimators depends on different assumptions; the major differences among these three models are: for $t = 1, 2, \dots, T$, OLS requires $\mathrm{E}[\mathrm{x}_{it}'(\mathrm{a}_{\mathrm{i1}} + \mathrm{e}_{\mathrm{it1}})] = 0$, which practically means that $\mathrm{E}[\mathrm{x}_{it}'\mathrm{e}_{\mathrm{it1}}] = 0$ and $\mathrm{E}[\mathrm{x}_{it}'\mathrm{a}_{\mathrm{i1}}] = 0$; both CRE and FE require $\mathrm{E}\ [\mathrm{e}_{\mathrm{it1}}|\ \mathbf{x}_{\mathbf{i}},\ \mathrm{a}_{\mathrm{i1}}] = 0$; in addition, CRE requires that $\mathbf{x}_{\mathbf{it}}$ and $\mathrm{a}_{\mathrm{i1}}$ are not correlated: $\mathrm{E}\ [\mathrm{a}_{\mathrm{i1}}|\ \mathbf{x}_{\mathbf{i}}] = E(\mathrm{a}_{\mathrm{i1}}) = 0$, while FE permits that (Wooldridge, 2010a).

Following Wooldridge (2010b), the standard error is obtained through bootstrap procedure.

The impacts on relative wage of R&D staff are estimated by CRE FE model.

### 3.2.3. CRE Fractional Response Model

A fraction response model is used to analyze the impacts of openness on the percentage of specialists among all the R&D employees.

Following Papke and Wooldridge (2008), a fraction response $y_{it}$ can be modeled with the following function:

$$E(y_{it}|\mathbf{x_{it}}, \mathrm{c_i}) = G(\mathbf{x_{it}}\boldsymbol{\beta} + \mathrm{c_i}), t = 1, 2, \dots, T \tag{3-14}$$

where $G(\cdot)$ can have any function form as long as $G(\cdot) \in (0,1)$ for y in [0,1]; $\mathbf{x_{it}}$ is a vector of explanatory variables, $\mathrm{c_i}$ is firm specific unobserved heterogeneity, and $\mathrm{u_{it}}$ is an idiosyncratic error.

CRE approach with Chamberlain-Mundlak device allows for the correlation between $\mathrm{c_i}$ and $\mathbf{x_i}$, by further assuming that $\mathrm{c_i} = \psi + \bar{\mathbf{x}}_\mathbf{i}\boldsymbol{\xi} + \mathrm{a_i}$, where $\mathrm{a_i}|\mathbf{x_i} \sim Normal\ (0, \sigma_a^2)$. Then (3-14) can be written as:

$$E(y_{it}|\mathbf{x_{it}}, \mathrm{a_i}) = G(\mathbf{x_{it}}\boldsymbol{\beta} + \bar{\mathbf{x}}_\mathbf{i}\boldsymbol{\xi} + \mathrm{a_i}), t = 1, 2, \dots, T \tag{3-15}$$

This paper assumes that $G(\cdot)$ takes logit form and estimates (3-15) by traditional random effect method. The APEs are the same as in the logit model, except that these are partial effect on a mean response (Wooldridge 2010). The standard errors are estimated via bootstrap procedure.

## 4. Results

Table 4-1 reports the average marginal effects (AME) on absolute employment of R&D specialists, which are estimated from CRE tobit model and CRE selection models. Following Wooldridge (2010), CRE selection model is estimated by two-step procedure. In the first stage is estimated by probit regression, and the second stage is estimated by FE, CRE and pooled OLS respectively.

The estimates are roughly stable across the four models, especially in terms of the sign and significant level. The magnitudes of marginal effects may look different to some extent, but when they are interpreted with the units of variables, the differences actually are small:

The breadth of openness, which is measured by the number of types of R&D partners, has positive effect on the R&D specialists' employment. The estimates are significant in three models, and the magnitude of marginal effect goes from 2.82 to 3.47, depending on estimation methods. On average, increasing one type of R&D partner leads to an increase of around three full-time equivalent hires of R&D specialists, holding other factors constant.

On the contrary, the depth of openness, which is measured by the share of purchased R&D, has negative effect on R&D specialists' employment. Again, the estimates are significant in three models; the magnitude of marginal effect goes from -18.77 to -37.08, meaning that 5 percent point of increase in the share of purchased R&D leads to a reduction of around one to two full-time equivalent hires of R&D specialists, depending on the estimation method.

As for the controlled variables, firm size, which is measured by the number of employees, has significant positive impact of the employment R&D specialists. In other words, for two firms with similar characteristics including total assets and R&D total expenditure, the one with more employees also hire more R&D specialists.

The analysis above shows how the absolute employment of R&D specialists responses to opening up to external resources. Another facet reflecting the transition is the evolvement of employment composition within R&D function. An important question under this strand is: "Do firms reposition their internal R&D when resorting to external R&D resources?" The answers can be inferred by looking at how the share of specialists within R&D function changes with indicators for opening R&D.

In the selection models, the estimator lambdas are not significant - no matter which method is used for the second stage estimation. This indicates that there are no systematic difference in the way that the examined factors influencing between the decision on "hiring R&D specialists or not" and the decision on "how many specialists to hire". Thus the estimators from CRE Tobit model are trustworthy, which confirms the prediction in section 3.2.1 about the validity of Tobit model given the data feature.

As such, the following analysis assumes there is also no systematic differences the decisions between "hiring zero percent of specialists within R&D function" and "the proportion of R&D specialists to hire", so that selection model is waived.

Table 4-2 reports the AMEs on the share of specialists among total R&D employment, which are estimated from fractional response model. The estimates for the variables of interest have the following interpretations:

The breadth of openness has significant positive effects on the share of R&D specialists within R&D function. On average, establishing one extra type of R&D partner is associated with around 0.25 percentage point increase in the share of R&D specialists. Combining this with previous finding, it is confirmed that establishing more types of R&D partner is associated with firm's upgrading in internal R&D employment – not only the absolute number but also the share of specialists within R&D function increase.

Again, the opposite is found in the effect of the depth of openness. Increasing the reliance of purchased R&D reduces the share of specialists within R&D function. On average, one percentage point of increase in the share of purchased R&D may reduce the share of R&D specialists by around 0.16 percentage point. So in general, the reliance on purchased R&D undermines the role of internal R&D specialists – in terms of both absolute employment and relative intensity within R&D function.

**Table 4-1. Marginal Effects on R&D Specialist's Absolute Employment: Estimated from CRE Tobit and CRE Selection Models**

| Dependent Variable: Number of R&D Specialists | AMEs<br>CRE Tobit Model | Marginal Effects<br>Second Stage Estimation, CRE Selection Model | | |
|---|---|---|---|---|
| | | CRE Probit - FE | CRE Probit - CRE | CRE Probit-POLS |
| Variables of Interest | | | | |
| Number of Types of R&D Partner:<br>Breadth of Openness | 2.8151*** | 3.4319** | 3.470353* | 3.1808 |
| Share of Purchased R&D: Depth of Openness | -22.1565*** | -18.7660 | -26.20458** | -37.0777** |
| Control Variables | | | | |
| R&D Department | 0.6670 | -- | -- | -- |
| Total R&D Expenditure | 0.0000951*** | 0.001443 | 0.0001808 | 0.000225 |
| Profit per Employee | 0.0005 | 0.0017629 | 0.0007012 | -0.0000722 |
| Log(Number of Employee) | 2.8990** | 5.8270* | 6.4372** | 9.2658* |
| Log(asset) | -0.4078 | 1.0345 | 0.1226 | -1.9395 |
| Average Number of R&D Partners | 1.2494 | -- | 1.4654 | 1.2362 |
| Average Share of Purchased R&D | -13.8437*** | -- | -19.5805* | -23.2050* |
| Average R&D Department | 1.7093 | -- | -- | -- |
| Average Total R&D Expenditure | 0.0000565*** | -- | 0.0001646 | 0.0000488 |
| Average Profit per Employee | -0.0002 | -- | 0.001827 | 0.003795 |
| Average Log(Number of Employee) | -1.7132 | -- | -1.9439 | -2.536822 |
| Average Log(asset) | 2.2736** | -- | 2.4434 | 5.3444 |
| 6 Industry Dummies | | -- | | |
| 7 Location Dummies | | -- | | |
| 3 Year Dummies | | | | |
| Lambda | -- | 19.0990 | 13.5675 | 11.6874 |
| Lambda*3 Year Dummies | -- | | | |
| Observations | 3974 | | | |
| Wald Chi2 | 3889 .19 | | | |
| Prob. > Chi2 | 0.0000 | | | |
| Rho | 0.6487*** | | | |

***: Significant at 1%; **: Significant at 5%; *: Significant at 10%. Based on bootstrap standard errors.

**Table 4-2. AMEs on Share of Specialists within R&D Function: from CRE Fractional Response Model**

| Dependent Variable: Share of R&D Specialists | Average Marginal Effects |
|---|---|
| Variables of Interest | |
| Number of Types of R&D Partner: Breadth of Openness | 0.2462** |
| Share of Purchased R&D: Depth of Openness | -0.1582** |
| Control Variables | |
| R&D Department | -0.2245 |
| Total R&D Expenditure | 2.09e-06 |
| Profit per Employee | 2.63e-06 |
| Log(Number of Employee) | 0.0210 |
| Log(asset) | -0.0408** |
| Average Number of R&D Partners | 0.0071 |
| Average Share of Purchased R&D | 0.0191 |
| Average R&D Department | 0.1044*** |
| Average Total R&D Expenditure | -0.0000239 |
| Average Profit per Employee | -7.47e-07 |
| Average Log(Number of Employee) | -0.0459 |
| Average Log(asset) | 0.0805*** |
| 6 Industry Dummies | |
| 7 Location Dummies | |
| 3 Year Dummies | |
| Observations | 3634 |
| Wald Chi2 | 144.07 |
| Prob. > Chi2 | 0000 |
| Rho | 0.5389*** |

***: Significant at 1%; **: Significant at 5%; *: Significant at 10%.
Based on bootstrap standard errors

## 5. Conclusion

This study contributes to the existing literature in three aspects:

First, it opens up an important part of the black box that transforms R&D outsourcing strategy to innovation performance. Zooming in the link between R&D outsourcing and innovation performance found by previous empirical studies (e.g.), R&D specialist's employment is identified as a major intermediate in between. The pattern that R&D outsourcing influences R&D specialist's employment is consistent with that on innovation performance: while the depth of R&D outsourcing (which reflects the degree of dependence on certain external partner) plays a negative role on R&D specialist's employment, the breadth of R&D outsourcing (which reflects the extent of external cooperation) plays a positive role on employment of R&D specialists - in terms of both their absolute number and as a share of total R&D employees.

Second, it adapts the theoretical framework from the areas of international trade and labor economics to analyze employment composition within firms. Unlike countries, firms tend to face more mobile labor but less flexible wage level for each type of employees. Under these different assumptions, a revised theoretical analysis provides predictions on the employment change associated with R&D outsourcing, which are compatible with the analysis based on previous case studies and empirical evidence from related areas.

Third, the prediction from theoretical analysis is supported by systematic empirical evidence based on up-to-date firm-level longitudinal data and econometric tools. Compared with previous empirical approach used for R&D and innovation research, the recent econometric methods increase the validity of the new findings without scarifying efficiency. For example, the random effect Tobit model incorporated with the CRE framework, which allows for correlation between unobserved heterogeneity and independent variables, realizes a more valid estimation compared with traditional random effect Tobit model. For the studies on R&D and innovation activity, where the unobserved heterogeneity and independent variables are very likely to be correlated, the advantage of CRE framework becomes more significant. Moreover, the findings are further confirmed by CRE sample selection model, which has more relaxed assumption compared with the popular models in existing literature (e.g. sample selection model or hurdle models). Besides taking care of the possibility that the process deciding whether or not to hire R&D specialists differs from the process deciding how many R&D specialists to hire, the CRE sample selection model also allows for correlation between these two processes and between the observed explanatory variables and unobserved individual heterogeneity. In addition, the CRE fractional model makes use of the fractional nature of the dependent variable - the share of the R&D specialists, and the estimators and predictions fit the real situation better. This improvement is comparable to the advance from linear model to probit or logit model for binary response variable. Despite the suitability of these models for empirical studies on R&D and innovation activity, hardly any existing studies make use of them.

The findings have several implications for R&D specialists, firms and policy makers. For R&D specialists, it becomes clearer how their employment opportunity will likely to evolve when the firm adjusts R&D outsourcing behavior: while they have some reason to worry when the firm increases the purchase from a particular R&D partner that undermines internal work, they should not be as pessimistic when the firm establishes a new type of external R&D partner. Equipped with this finding, R&D specialists become better at foreseeing their future employment opportunity and preparing for the adjustment, so that reduce the efficiency loss by reducing the adjustment period. For firms, it is important to aware the consequences of outsourcing R&D on employment structure within R&D function. Despite that the nowadays labor market is relatively flexible, it is far easier to reduce the employment of R&D specialists than increase it. Sometimes, it is even irreversible - once destroyed, it takes greater effort to recover it; and during the turmoil, firm may lose important business opportunity or even risk its survival. As the employment internal R&D specialist determines firm's own R&D capability which is at the same time difficult to rebuild, firms should take the employment consequence into seriously consideration when making R&D outsourcing decisions. For example, one possible way of making use of external resources without transmitting the signal that drives away R&D specialists, is to extend the types of R&D partners – in other words, to explore R&D cooperation opportunity outside the box. For policy makers, the findings suggest at least one way to encourage R&D activity and to increase its quality within the whole society: to increase the demand for (also the equilibrium amount of) R&D specialists by facilitating R&D cooperation among different types of organizations.

Several issues are left for future research. First, another facet reflecting the quality R&D employees is their income level, which is worth for further exploration. Then, by combining the changes in both income level and number of R&D specialist's employment, it is possible to track employment upgrading or downgrading brought by open R&D strategy. Second, R&D collaboration should be also counted into R&D partnership. Though the variety of R&D outsourcing partners can represent the extent of R&D collaboration to some extent, other types of collaboration may also play a significant role on R&D specialist's employment and R&D/innovation outcomes. Third, besides the general picture on the breadth of R&D collaboration, a more detailed one mapping the allocation and combination of investment across different types of external R&D partners may also play a role on employment and performance, which would be interesting to look into in future research.

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