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Do specialists exit the firm outsourcing its R&D?

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Abstract

Do specialists exit the firm increasingly outsourcing its research and development (R&D) work? Although this question is critical in understanding how R&D outsourcing links to innovation performance, the answer is not yet clear. This paper proposes that the optimal level of firm's internal employment of R&D specialists decreases with the deepening of R&D outsourcing but increases with the broadening of R&D outsourcing. These relations can be inferred from previous empirical studies as well as our theoretical analysis, and are supported by the empirical evidence from estimations of correlated random effects (CRE) Tobit, CRE selection and CRE fractional response models on a panel dataset of Danish firms.

Keywords: Correlated random effect models, employment of R&D specialists, R&D strategy, R&D outsourcing breadth and depth

JEL Code: J21, M51, O32

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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 processes (e.g. Chesbrough, 2007; Davis and Harrison, 2001; Van de Vrande et al., 2009). R&D partnerships have been growing tenfold in the last three decades (Berchicci, 2013; Hagedoorn, 2002), while stand-alone, internal corporate labs declines (Powell and Ginnella, 2010). Following the growing focus on open innovation, which emphasizes external ideas and paths for advancing technology (Chesbrough et al, 2008), more firms have begun to pursue openness strategically (Pertroni et al., 2012). From long-term perspective, the trend of growing openness is a sustainable development rather than a management fashion (Lichtenthaler, 2011).

As an important form of utilizing external knowledge, R&D outsourcing has attracted a lot of attention from both academics and practitioners. It is a major dimension of open innovation, more convenient to measure and compare, and it has a more controversial and interesting role.

So far, existing research has contributed a better understanding towards the causes and performance-related consequences of resorting to external resources for R&D. Several motivations have been identified, including reduce cost (e.g. Bounfour, 1999; Y-A Huang et al., 2009; Zhao and Calantone, 2003), focus on core activities that generate competitive advantage (e.g. Mundambi and Tallman, 2010; Venkatesan, 1992), use external talent and knowledge to foster internal creativity, and speed up innovation projects (e.g. Crimpe and Kaiser, 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” (Powell and Ginnella, 2010).

Although drivers of resorting to external knowledge are similar, the impacts may differ. For example, Laursen and Salter (2006)/ Berchicci (2013) find an inverted U-shape relationship between innovative performance and openness of innovation/R&D; Crimpe and Kaiser (2010)/ Fu (2012) finds an inverted U-shape relationship between R&D outsourcing/openness and innovation performance/efficiency; while Mata and Woerter (2013) have found a positive impact of external R&D strategies on the firm’s general performance.

Why do firms with seemingly similar motivations choose different levels of R&D outsourcing and end up with different performance? Through which mechanism is R&D outsourcing associated with performance? Does R&D outsourcing have implications for a firm’s internal R&D competency? The answers to these questions are critical for justifying R&D outsourcing as an effective tool for improving innovation performance without compromising long-run competency; in addition, conducting R&D outsourcing in the correct way also requires a detailed road map connecting different dimensions of R&D outsourcing to various indicators beyond short-term performance. However, despite the identification for the possible causes and consequences of outsourcing R&D in previous studies, the process transforming the practice of R&D outsourcing into performance of different measures is still in the black box rarely opened by systematic research. Existing explanations for the curvilinear link between R&D outsourcing and performance are based on intuitive thinking about the pains and gains of outsourcing R&D. Although these explanations are inspiring and have been spread by a large body of later literature, systematic empirical evidence to fully establish its validity and significance is still lacking. Above all, some unknown important factor other than the known pains and gains may exist within the black box, which may actually occupy such a major part of the channel linking R&D outsourcing to performance that the space for the direct effect of R&D outsourcing as a practice or strategy by itself may turn out to be quite small. So, before regarding R&D outsourcing as an effective tool that may improve innovation performance, it is necessary to examine the black box more closely. Moreover, the identification of additional factor in the black box may also reveal some surrounding links, all of which may incubate further important implications for R&D and innovation strategies and policies.

Bringing light into the black box from the angle of labor economics, the employment of R&D specialists reveals itself as a potential key intermediary transforming R&D outsourcing into innovation performance. Examining R&D specialists' employment will not only contribute a better understanding R&D outsourcing relates to innovation performance, but also has practical implications such as R&D on competency and capacity for firms and policy-makers. Since employment of R&D specialists embodies R&D employment quality and R&D capacity, it is a key indicator for firm's core competency. Thus, tracking R&D specialists' employment relates to questions such as "what has happened to firm's core competency in the wave of opening R&D and innovation?", which is raised as one of the most important questions in the research on opening R&D and innovation (Christensen, 2008), probably due to concerns that R&D outsourcing may result in fewer internal employed R&D specialists and is thus weakening firm's R&D capability. The firm's employment of R&D specialists also influences the demand for and equilibrium quantity of R&D specialists in society, which determines its aggregate R&D capacity. In sum, the evolvement of R&D specialists' employment has significant implications on the trajectory of R&D activities for both individual firms and the whole society.

Compared with the profound meaning of tracking employment implications of R&D outsourcing, existing related literature is rather thin. So far, only one empirical study based on relatively a large data exists, which finds that internal R&D employment intensity decreases when firms decide to start, to increase, or to stop R&D outsourcing (Teirlinck, et al. 2010). However, that study focuses on the aggregate level of R&D employment rather than the evolvement of employment inside R&D function - especially R&D specialists' employment, thus it does not inform us about the quality aspect of R&D employment or the competency evolvement inside R&D function. As for implications for R&D specialists' employment, existing evidence is based on case studies. For example, one pioneering case study finds that, in some firms that adopt open innovation, the role of senior scientists is undermined whereas the role of engineers and the business innovation team has been highlighted (Petroni, et al. 2012). One of the aims of this study is to examine whether the trend observed in the above-mentioned case study actually is a common pattern experienced by a broader range of firms.

Another feature of this study is that, R&D outsourcing is measured through two dimensions – the breadth and depth. While the depth of R&D outsourcing reflects the degree of reliance on external resources (this is commonly used by previous literatures), the breadth of R&D outsourcing captures the variety of external resources utilized by the firm; the breadth is better at tracking knowledge integration, whereas the depth captures knowledge specialization. The two-dimension measurement means that the way of R&D outsourcing can be identified more precisely. In addition, by introducing another dimension of measurement, a larger set of economic tools become relevant, which produces a more detailed picture of open R&D strategy. As for empirical study, because the depth and breadth may be correlated and both may affect innovation performance, the effect of R&D outsourcing or openness found in previous studies using only one dimension may actually be a compound effect.

In short, this paper aim at filling the gaps by examining how the employment of R&D specialists evolves with the broadening and the deepening of R&D outsourcing respectively, and hence, shed light on the mechanism that transforms R&D outsourcing into innovation performance. In addition to the theoretical contribution, this study also has practical implications for both individual firms and industry. For the firm, there will be a detailed roadmap connecting the two dimensions of R&D outsourcing, the choice of R&D strategy, the evolvement of R&D specialists' internal employment and R&D capacity; for industry, some potential ways of increasing both the equilibrium level of R&D specialists' employment and aggregate innovation activity may emerge.

The implications of R&D outsourcing for R&D specialists' employment are first examined theoretically. Both the analysis based on management literatures and a model inspired by Lazear (2005)'s paper on entrepreneurship theories and the inference from existing relevant empirical studies yield a common prediction: R&D specialists' employment within the firm decreases with the deepening of R&D outsourcing but increases with the broadening of R&D outsourcing. In addition, the analysis also implies that, while the association between firm's internal employment of R&D specialists and depth of R&D outsourcing exists independent of firm's strategy, the co-evolvement with the breadth of R&D outsourcing has its roots in the firm's strategic choice between either acting as a specialist or acting as an integrator facing the emergence of cheaper complementary external R&D resources.

The predictions are next examined empirically, using panel data from Statistic Denmark's annual survey on R&D and innovation activities in over 2200 firms during 2007-2010. Three types of econometric models are used - correlated random effects (CRE) tobit models, CRE selection models and CRE fractional response models. The former two types explain the absolute number of R&D specialists, while the third type explains the share of specialists within R&D function. The empirical results support the predictions: the depth of R&D outsourcing significantly and negatively associates with firm's internal employment of specialists in both absolute and relative terms, whereas the breadth of R&D outsourcing has the opposite effects.

The remainder of this paper unfolds as follows: section 2 presents the related previous studies and theoretical analysis, based on which two hypotheses are proposed; section 3 describes the empirical strategy for testing the hypotheses; section 4 presents the estimation results; section 5 discusses the results and policy implications; section 6 concludes.

2. Theories and Hypotheses

How does the firm's internal employment of R&D specialists associate with R&D outsourcing strategy? Could broadening and deepening the outsourcing indicate different evolvement trajectories for internal employment? There is little direct theoretical analysis or empirical evidence existing for these questions. However, previous studies provide some clues, based on which two general hypotheses can be stated.

An important clue for analyzing the association between R&D outsourcing and employment stems from several empirical studies on how R&D outsourcing affects innovation performance. A common observation shown by these studies is that the direction of the influence of R&D outsourcing on innovation performance depends on internal R&D and collaboration. For example, Hagedoorn and Wang (2012) find that external R&D increases 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-levels of internal R&D. Crimpe and Kaiser (2010) find an inversed U shape relationship between purchased R&D and firm's innovation performance, in which both cooperation with other firms and internal R&D play a moderating role. The mainstream interpretation of these findings is that, it takes certain level of absorptive/integrative capacity for the firm to benefit from R&D outsourcing strategy, which is built upon internal R&D (e.g. Spithoven, 2010); while collaboration in R&D increases the variety of external knowledge that may be translated into firm-specific knowledge (Crimpe and Kaiser, 2010). Another angle of interpreting these findings (which provides clues for this paper) is that, there may exist two different dimensions of R&D outsourcing, which have different implications for innovation performance. One dimension is the depth of R&D outsourcing, reflected by the share of outsourced R&D; the other is the breadth of R&D outsourcing, reflected by the range of R&D outsourcing partners, which is also related to collaboration. From this angle, the findings from previous studies indicate two diverging directions that the two dimensions of R&D outsourcing may link to innovation performance. While the link between breadth of outsourcing and performance is positive, the link between depth of outsourcing and performance can be negative.

On the other hand, traditional production 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/efficiency varies with effective input of R&D labor, which can be reflected by the absolute number and the share of specialists within R&D function.

Combining the above two aspects together, it can be further inferred that R&D outsourcing and internal employment of R&D specialists are linked through similar pattern with those between R&D outsourcing and innovation performance. Still, it takes systematic evidence to establish the links. If the links are proved to exist, then the internal employment of R&D specialists, which previously hides in the black box transforming R&D outsourcing practice to innovation performance, can be highlighted as a key intermediary.

In addition to previous empirical studies, theories from management and personnel economics also provide some clues for the way that R&D outsourcing may link to employment of R&D specialists within the firm.

Related theories in management field have drawn a big picture about how the internal employment of specialists evolves with R&D outsourcing.

In previous studies, 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. Mudambi and Tallman, 2010; Crimpe and Kaiser, 2010). Naturally, focusing on the core activity corresponds to adjustment in the composition of employment. When cheaper external R&D resources become available, the value chain in which the firm locates also changes. The corresponding change in the employment of R&D specialists should depend on where the firm re-anchors its core competency along the transformed value chain.

One possibility is that the firm no longer considers itself as excel in original R&D compared to external agents. In this case, the firm may find the cost of direct purchase cheaper than internally produced R&D, so it increases the proportion of purchased R&D and the outsourcing deepens. Consequently, the firm will not need as many R&D specialists as before; instead, it will be better off by replacing specialists or scientists with technical employees who have wider but shallower knowledge which is enough to utilize purchased R&D. This kind of evolvement in R&D personnel's employment has been observed by several case studies, which find the demand for R&D specialists decreases with deepening outsourcing (e.g. Petroni, et al. 2012).

Another scenario is that the firm still sees its core competence in cutting-edge R&D, so that its optimal strategy is to use more of this advantage and to produce more knowledge internally. This scenario also means that, before cheaper external R&D becomes available, the firm is limited by its internal resources: the optimal amount of synthesized knowledge, which matches the need of other producing factors, is larger than that can be produced with only internal resources. When cheaper external complementary R&D resources become available, it pays off for the firm to adjust the composition of internal knowledge production to realize higher value from R&D. However, for this scenario, existing theories do not give direct predictions on the exact way that firm's internal employment of R&D specialists links to the two dimensions of outsourcing. To see the picture more clearly, further analysis is needed.

The following provides a theoretical analysis on how the internal employment of R&D specialists links to the breadth and depth of R&D outsourcing, for the firm that still has comparative advantage in at least one specific R&D area among the extended set of relevant organizations due to R&D outsourcing. The analysis is made through adapting the model analyzing individual's decision on becoming entrepreneur (Lazear, 2005) into a model for firm's decision on R&D outsourcing strategy and internal employment.

In order to produce more synthesized knowledge for innovation and to better utilize internal R&D by outsourcing, the firm may consider between two types of R&D strategies – specializing strategy and generalizing strategy.

Specializing R&D strategy means that the firm focuses only on its competitive advantage and creates value by using its strongest endowment directly and outsourcing all the other complementary knowledge components to external partners. The value of knowledge added internally depends on its strongest knowledge endowment:

$$\text{Value added by the specializing firm}$$
$$= \max\,[P_1(s_1,c_1), P_2(s_{2,}c_2), \dots, P_n(s_n,c_n)] - \textstyle\sum_{i=1}^{n} C_i(s_i,c_i) \qquad (2\text{-}1)$$

, where $i = 1,2,\dots,n$ denotes the i^{th} knowledge component; s_i denote the number of internal specialists who produce knowledge i, $P_i(s_i,c_i)$ denote the amount of knowledge i produced by s_i specialists and c_i denote other complementary resources such as external knowledge and capital; $C_i(s_i,c_i)$ is the cost function for producing the i^{th} knowledge; assume $P'_{s,c}(\mathrm{s,c}) > 0$, $P''_s(\mathrm{s,c}) < 0$, while $C'_{s,c}(\mathrm{s,c}) > 0$, $C''_s(\mathrm{s,c}) > 0$, which are consistent with the features of standard production function and cost function; because $\mathrm{s,c}$ are complementary in the knowledge production, $P''_{s,c}(\mathrm{s,c}) > 0$; further assume that marginal cost of internally employed specialists is independent of the marginal cost (price) of external complementary c, so that $C''_{s,c}(\mathrm{s,c}) = 0$.

Generalizing R&D strategy means that the firm acts as a generalist, whose advantage stems from integrating knowledge from different sources rather than producing a specific knowledge by itself. Internal knowledge is not used directly for innovation but as a base for utilizing external knowledge. The firm keeps a broader set of expertise internally so that it can create value by assembling external knowledge instead of producing a specific knowledge all by itself. In this case, the value that it creates is more likely to be limited by its weakest knowledge endowment:

$$\text{Value created by integrating firm}$$
$$= \lambda \min\left[P_1(s_1, c_1), P_2\left(s_{2,}c_2\right), \ldots, P_n(s_n, c_n)\right] - \textstyle\sum_{i=1}^{n} C_i(s_i, c_i) \qquad (2\text{-}2)$$

, where $\lambda > 1$ reflects the premium of knowledge integration; other denotations are the same as (2-1).

Facing the expanding set of necessary knowledge for innovation and relatively restricted R&D funding, the firm usually have to choose between world-leading position in one (or a few fields) or some (more superficial) level of knowledge in many areas (Christensen, 2008). In other words, there is a trade-off between the above two strategies, just like a budget line capping the two-dimensional coordinates with one axis representing the average strength of firm's R&D ability and the other axis representing the breadth of R&D ability. The firm's choice of R&D strategy should be along the budget line connecting pure specializing strategy and pure generalizing strategy; the dots along the segment represent mix strategies between the two extremes.

Let's start with looking at each end of the budget line – namely, what happens to firm's internal employment of R&D specialists if the firm follows pure specializing or pure generalizing strategy.

Define $P_s(s_s, c_s)$ to be the knowledge that the firm is endowed the largest amount, and $P_w(s_w, c_w)$ to be the knowledge that the firm is endowed the smallest amount.

A firm following specializing strategy is likely to specialize in producing knowledge s and will solve

$$\max_{\mathrm{s}} \{\mathrm{P_s}(\mathrm{s_s}, \mathrm{c_s}) - \textstyle\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{C_i}(\mathrm{s_i}, \mathrm{c_i})\} \tag{2-3}$$

with first order condition

$$\mathrm{P}_s'(s_s, c_s) = C_s'(s_s, c_s) \tag{2-4}$$

Thus the firm that specializes will only employ specialists who can produce knowledge s to the amount s_s that satisfies (2-4).

A firm following generalizing strategy choose s_w so that

$$\max_{\mathrm{s}} \{\lambda P_w(s_w, c_w) - \textstyle\sum_{i=1}^{n} C_i(s_i, c_i)\} \tag{2-5}$$

with s_w satisfying first order condition

$$\lambda P_w'(s_w, c_w) = C_w'(s_w, c_w) \tag{2-6}$$

Moreover, equation (2-2) requires minimum internal endowment of all the other kind of knowledge:

$$P_i(s_i, c_i) = P_w(s_w, c_w),\ \ i = 1, 2, \dots, w-1, w+1, \dots, n. \tag{2-7}$$

In the current scenario that we are discussing, when cheaper external R&D resources become available, firms can utilize it to increase its internally added value. Under previous assumptions $P'_{s,c}(\mathrm{s},\mathrm{c}) > 0$ and $P''_{s,c}(\mathrm{s},\mathrm{c}) > 0$, the marginal product of internally employed specialists will increase with complementary resources: $P'_i(s_i, \mathrm{c}'_i) > P'_i(s_i, c_i)$ if $\mathrm{c}'_i > c_i, i = 1,2,..,n$. In addition, previous assumption $C''_{s,c}(\mathrm{s},\mathrm{c}) = 0$ indicates $C'_{si}(s_i, \mathrm{c}'_i) = C'_{si}(s_i, c_i)$. Consequently, if s'_s, s'_w denote the new optimal number of internally employed specialists for specialized firm and generalized firm respectively, then $\mathrm{s}'_s > s_s$ and $\mathrm{s}'_w > s_w$, where s'_s satisfies

$$P'_s(s'_s, c'_s) = C'_s(\mathrm{s}'_s, \mathrm{c}'_s) \tag{2-8}$$

and s'_w satisfies

$$\lambda P'_w(\mathrm{s}'_w, \mathrm{c}'_w) = C'_w(\mathrm{s}'_w, \mathrm{c}'_w). \tag{2-9}$$

Condition (2-7) requires the firm following generalizing strategy to also increase the production of other type(s) of knowledge, in order to match the increased endowment of knowledge w. Thus, generalizing firm should not only increase s_w but also increase the employment of related specialists $s_i \; where \; i \neq w$, so that the total internal employment of R&D specialists for generalizing firm will be:

$$\text{Number of specialists in generalizing firm} = \mathrm{s}'_w + \textstyle\sum_i \mathrm{s}'_i, i = 1, 2, \ldots, w-1, w+1, \ldots, n \tag{2-10}$$

where $\sum_i \mathrm{s}'_i \geq \sum_i s_i > 0$ for $i = 1, 2, \ldots, w-1, w+1, \ldots, n$.

In contrary, for firms following specializing strategy, value maximizing conditions (2-3) and (2-4) show the optimal strategy is to only increase s_s to s_s' which satisfies (2-8). The total employment of internal R&D specialists for specializing firm will be:

$$\text{Number of specialists in specializing firm} = \mathrm{s}_s' \tag{2-11}$$

Which strategy will lead to larger increase in the number of internally employed R&D specialists? For simplicity and consistency with later econometric analysis, assume that the total required synthesized knowledge is the same between generalizing and specializing firm, and R&D specialists with different expertise have same wage (which is also likely in reality). Then $\lambda P_w(\mathrm{s}_w', \mathrm{c}_w') = P_s(\mathrm{s}_s', \mathrm{c}_s')$ and $\lambda P_w'(\mathrm{s}_w', \mathrm{c}_w') = P_s'(\mathrm{s}_s', \mathrm{c}_s') = wage\ per\ employee$, which is followed by $\mathrm{s}_w' = \mathrm{s}_s'$ if we assume $P_{s,w}'(\cdot)$ is linear. Applying same assumptions to the situation before the price reduction of complementary resources gives $s_w = s_s$. Comparing (2-10) and (2-11) indicates that generalizing firm employs more R&D specialists than specializing firm by the amount of $\sum_i^n s_i'$ where $i = 1, 2, \dots, w-1, w+1, \dots, n$, as resources complementary to internally employed specialists become cheaper. Thus, the price reduction for the complementary resources leads to a larger increase in the employment of internal specialists for the generalizing firm than for the specializing firm - by the amount of $\sum_i^n s_i'$, $\mathrm{i} = 1, 2, \dots \mathrm{w} - 1, \mathrm{w} + 1, \dots, \mathrm{n}$.

Meanwhile, for firms following generalizing strategy, it pays off to outsource a broader range of external R&D partners for complementary knowledge when it becomes cheaper. As discussed before, if $\mathrm{c}_w' > c_w$, knowledge production P_w also increases: $P_w'(s_w, \mathrm{c}_w') > P_w'(s_w, c_w)$ and $\mathrm{P}_w(s_w, \mathrm{c}_w') > \mathrm{P}_w(s_w, c_w)$, thus maximizing (2-2) requires the firm also increase the production of other type of knowledge P_i, $i \neq w$ which becomes the new restriction. Consequently, the firm has to not only increase outsourced component of c_w, but also seek new external sources for cheaper $c_i where\ i \neq w$, so that P_i can reach the new level that at least equivalent to P_w' and the internally generated value is maximized. While for firms following specializing strategy, the increase in knowledge production P_s due to cheaper (thus more) c_s is irrelevant to the outsourcing of all the other types of knowledge $c_i, i = 1, 2, \dots s-1, s+1, \dots n,$ because maximizing internally generated value only depends on the firm's strongest endowment. In sum, the outsourcing range for firms following generalizing strategy is more elastic than that for firms following specializing strategy.

The analysis above reveals that, as the resources complementary to internally employed R&D specialists become cheaper, firms following generalizing R&D strategy tend to employ more R&D specialists and introduce more types of outsourced knowledge than firms following specializing R&D strategy. In other words, the internal R&D specialists' employment evolves together with the breadth of R&D outsourcing, with firm's strategic choice underlying the observed link.

The link between the depth of outsourcing and internal employment of R&D specialists is more straightforward. Let $\mathrm{TC}(\mathrm{s}, \mathrm{c}) \geq 0$ denote total R&D cost function, $\mathrm{I}(\mathrm{s}, \mathrm{c}) \geq 0$ denote cost of internal R&D and $\mathrm{E}(\mathrm{c}) \geq 0$ denote cost of outsourced R&D, where s denotes employment of internal R&D specialists and c denotes other production factors, which are consistent with those in pervious equations. Assume $\mathrm{I}(\mathrm{s}, \mathrm{c})$ and $\mathrm{E}(\mathrm{c})$ follow the feature of normal cost function: $\mathrm{I}'_{\mathrm{s}}(\mathrm{s},\mathrm{c}) > 0$ and $\mathrm{E}'_{c}(\mathrm{c}) > 0$. Naturally, total R&D cost equals to the sum of internal R&D cost and external R&D cost:

$$\mathrm{TC}(\mathrm{s},\mathrm{c}) = \mathrm{I}(\mathrm{s},\mathrm{c}) + \mathrm{E}(\mathrm{c}) \tag{2-12}$$

, where s is chosen by the firm so that it satisfies the first order condition of (2-12):

$$\mathrm{TC}'_{\mathrm{s}}(\mathrm{s},\mathrm{c}) = \mathrm{I}'_{\mathrm{s}}(\mathrm{s},\mathrm{c}) \tag{2-13}$$

The depth of R&D outsourcing $\mathrm{d}\ (\mathrm{s},\mathrm{c})$ can be expressed as:

$$\mathrm{d}(\mathrm{s},\mathrm{c}) = 1 - \mathrm{I}(\mathrm{s},\mathrm{c})/\mathrm{TC}(\mathrm{s},\mathrm{c}) \tag{2-14}$$

The first partial differentiate of $\mathrm{d}(\mathrm{s},\mathrm{c})$ in (2-13) with respect to s gives:

$$\frac{\partial \mathrm{d}(\mathrm{s,c})}{\partial \mathrm{s}} = \frac{\mathrm{TC}'_{\mathrm{s}}(\mathrm{s,c})\times \mathrm{I}(\mathrm{s,c}) - \mathrm{I}'_{\mathrm{s}}(\mathrm{s,c})\times \mathrm{TC}(\mathrm{s,c})}{[\mathrm{TC}(\mathrm{s,c})]^2} \tag{2-15}$$

After replacing $T\mathrm{C}(\mathrm{s},\mathrm{c}) - \mathrm{I}(\mathrm{s},\mathrm{c})$ with $\mathrm{E}(\mathrm{c})$ according to (2-12) and replacing $TC'_{s}(s,c)$ with $I'_{s}(s,c)$ according to (2-13), (2-15) becomes:

$$\frac{\partial \mathrm{d}(\mathrm{s,c})}{\partial \mathrm{s}} = -\frac{\mathrm{I}'_{\mathrm{s}}(\mathrm{s,c}) * \mathrm{E}(\mathrm{c})}{[\mathrm{TC}(\mathrm{s,c})]^2} \tag{2-16}$$

, which is negative since $I'_{s}(\mathrm{s},\mathrm{c}) > 0$ and $\mathrm{E}(\mathrm{c}) \geq 0$ by previous assumptions. Thus internal employment of R&D specialists decreases as R&D outsourcing deepens, no matter the firm follows the specializing or integrating R&D strategy.

The analysis above serves as a simple example showing the mechanism through which the firm chooses the employment of specialists with the breadth/depth of R&D outsourcing. The analysis is based on the assumptions that neither individual firm nor specialist can manipulate the market price for the labor and that the marginal product function is linear decreasing. Further analysis based on looser assumptions is likely to produce the similar results.

What about the firm follows the mixed R&D strategy? This scenario corresponds to the internal segment of the “budget line” connecting pure specializing R&D strategy and pure generalizing R&D strategy. As for R&D outsourcing breadth and specialists’ employment, a simple generalization of the above analysis gives the answer: the more emphasis for generalizing R&D strategy and knowledge integration, the broader range of R&D outsourcing is, and the more R&D specialists are hired internally. As for R&D outsourcing depth and specialists’ employment, the negative relation naturally applies to firms with mixed R&D strategy, since this relation holds regardless of firm’s R&D strategy.

To sum up, the inference from existing relevant empirical evidence, as well as theoretical analysis based on related management studies and a model inspired by Lazear (2005), both converge to the following predictions:

Hypothesis 1: R&D specialists’ employment within the firm decreases with deepening R&D outsourcing;

Hypothesis 2: R&D specialists’ employment within the firm increases with broadening R&D outsourcing.

While hypothesis 1 holds regardless of firm’s R&D strategy, hypothesis 2 roots in firm’s R&D strategic choice between specialization and generalization when cheaper complementary external R&D resources become available.

3. Empirical Analysis

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

3.1. 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. Considering the availability and consistency of the variables of interest, this paper uses only the surveys conducted during 2007-2010. Each year's survey contains around 4000 firms; however, only a proportion of them have R&D related activity. FIRE data provides basic information of the firm, such as location, industry, total number of employees, profits, 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 expenditures every year, the panel data are unbalanced. In total, the dataset contains 3973 observations from 2285 different firms, which means each firm is observed 1.7 times on average.

3.2. Variables

3.2.1. Dependent Variables

The first dependent variable is the number of full-time-equivalent (FTE) researchers and other specialists who work on R&D within 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, which is measured by the number of R&D specialists divided by the number of all the employees within the firm's R&D function.

While the absolute number of R&D specialists embodies the capacity of internal R&D, the share of R&D specialists emphasizes the quality aspect of R&D employment. Together, these two dependent variables reflect R&D competency from the facet of labor input.

3.2.2. Main Explanatory Variables

R&D outsourcing activity is measured by two dimensions - depth and breadth:

The R&D outsourcing depth is measured by the expenditure on purchased R&D divided by total R&D expenditure.

The R&D outsourcing breadth mainly refers to the variety of R&D outsourcing partners, which is measured by the number of types of external sources from which the firm purchase R&D. In the survey, there is information about firm's expenditures on purchased R&D from each of the following eight mutual exclusive sources: firms from the same business category in Denmark, other firms in Denmark, firms from the same business category abroad, approved technological service institutes (ATS) in Denmark, universities and colleges in Denmark, other public research institutions in Denmark, other firms abroad, and other public research institutions abroad. Based on this information, eight binary variables with each indicating whether firm has purchased R&D from certain category are generated, and then a variable counting the total types of external R&D purchasing partners is constructed to measure the breadth of R&D outsourcing.

3.2.3. Control Variables

Several factors that may influence both R&D specialists' employment and R&D outsourcing breadth/depth are controlled for:

Total R&D expenditure. Recent research shows that firms with higher R&D expenditure are more likely to engage in open innovation (e.g. Mina A. et al, 2014). On the other hand, breadth and depth of R&D outsourcing may also highly relate to open innovation. Thus, R&D expenditure may correlate with R&D outsourcing breadth/depth through open innovation strategy. Meanwhile, R&D expenditure captures the scale of R&D, which directly links to R&D specialists' employment. Thus both R&D outsourcing breadth/depth and R&D specialists' employment may relate to total R&D expenditure, which is necessary to be controlled for to avoid omission bias.

For similar reasons, it is also necessary to control for:

Firm size. It is captured by the value of asset and the number of full-time-equivalent employees, which may relate to both R&D employment and outsourcing. Log values are used in the models.

R&D department. It is a binary variable indicating whether a firm has R&D department or not. It reflects the degree of importance that a firm attaches to R&D activities, which may relate to both the internal employment of R&D specialists and R&D outsourcing.

Profit per employee. This is a proxy capturing a group of unobservable factors that may influence both the capability and efficiency of hiring R&D specialists and R&D outsourcing depth and breadth.

Industry. Previous research has pointed out that, persistent differences across industries - especially in terms of technological opportunities and social institutions, result marked differences in collective invention (Powell and Ginnella, 2010). As collective inventions may relate to internal employment of R&D specialists and R&D outsourcing activities, they may both link back to the industry differences, which are thus necessary to control. To balance between precise industry classification and consumption of degree of freedom, the first digit of (NACE) industry classification is used, 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 outsourcing. 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.

3.3. Descriptive Statistics

Table I provides a brief descriptive statistics of the major variables. Among the firms investing in R&D, 75% of them hire R&D specialists. Compared with firms without R&D specialists, firms with R&D specialists are on average larger (in terms of asset value and number of employees), enjoying more profit per employee, investing more on R&D, outsourcing a smaller proportion of it but to a broader range of external agents. In the sample, the average outsourcing depth is 15% while the outsourcing breadth is 0.74; on average, a firm employs fifteen R&D specialists, who account for 55% of R&D employment.

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Table II provides a more detailed picture for R&D outsourcing depth and breadth, which are summarized across quintiles. Among the firms that outsource R&D, the average outsourcing depth in the medium quintile is 23%, and the average outsourcing breadth is two. Separately examining each quintile ladder of outsourcing breadth or depth, we can see that the average depth or breadth roughly doubles as moving to the next quintile. Cross examination on the quintiles between outsourcing breadth and depth reveals that, outsourcing breadth evolves along an inverted-U shape curve as outsourcing deepens: firms with medium level of outsourcing depth have two types of outsourcing partners on average, which is around 30% broader than the firms with outsourcing depth at the 1st quintile (1.52) or the 5th quintile (1.32).

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3.4. 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 in the second stage estimation respectively. Then CRE fraction model is used to analyze the impacts on the share of R&D specialists.

The CRE specification allows for correlation between unobserved heterogeneity and independent variables, and is a more reliable estimation compared with random effect (RE) models (e.g. RE Tobit model) which are often found in previous studies. For 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.

The comparison between CRE Tobit estimations and CRE sample selection estimations is also relatively new to literature. CRE sample selection models place even fewer restrictions and serves reality better than the popular models in existing literature such as 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 both the correlation between these two processes and the correlation 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, so that 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.

In sum, these recently developed models are good candidates for empirical studies on R&D and innovation activity, thus enhancing the validity of this study.

3.4.1. CRE Tobit Model

The Tobit model allowing for unobserved heterogeneity assumes an underlying equation determining the employment of R&D specialists as (3-1):

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

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

, where y_{it} and y_{it}^{*} are latent and observed outcome variable 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 c_i and $\mathbf{x_i}$, thus loosens the assumption for traditional random effect (RE) method and makes RE a special case of CRE. Following Wooldridge (2010), the conditional distribution of heterogeneity is modeled as:

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

Given (3-3), equation (3-1) and (3-2) can be summarized as:

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

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

3.4.2. Selection Models

Although CRE Tobit estimates are more reliable than traditional RE Tobit estimates, CRE Tobit model may still be rather restrictive - because it assumes the explanatory variables and the signs of marginal effects are the same between the two processes deciding whether or not to hire R&D specialists (participation decision) and how many R&D specialists to hire (intensity decision). To distinguish the two processes, a group of previous literatures make use of hurdle models. Still, hurdle models are a special case of a more general group of models – selection models. To check whether the participation decision process differs from intensity decision process, this paper makes use of CRE sample selection models following Semykina and Wooldridge (2010). Generally, selection models also use equation (3-1) to describe the intensity decision, which captures the expectation of dependent variable conditioning on positive outcomes; in addition, it introduces a selection equation (3-5) to relax condition equation (3-2):

$$\mathrm{s_{it}} = 1\,[s_{it}^{*} > 0] = 1[\mathbf{x_{it2}}\boldsymbol{\delta_t} + \mathrm{c_{i2}} + \mathrm{u_{it2}} > 0] \tag{3-5}$$

Then equation (3-2) becomes:

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

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

Following Semykina and Wooldridge (2010), the selection models are estimated with two-step procedure incorporated with CRE device from Mundlak (1978). The first step is to estimate the selection equation (3-5): $\mathrm{c_{i2}}$ is assumed to relate to $\mathbf{x_{i2}}$ only through its time averages $\overline{\boldsymbol{x_{\iota 2}}}$, so that $\mathrm{a_{i2}}$ is independent of $\mathbf{x_{i2}}$:

$$\mathrm{c_{i2}} = \overline{\boldsymbol{x_{\iota 2}}}\boldsymbol{\pi} + \mathrm{a_{i2}} \tag{3-7}$$

$$\mathrm{a_{i2}}|\mathbf{x_{i2}} \sim Normal\ (0, \sigma_{a2}^{2}) \tag{3-8}$$

Then equation (3-5) becomes:

$$\mathrm{s_{it}} = 1\,[s_{it}^{*} > 0] = 1[\mathbf{x_{it2}}\boldsymbol{\delta_t} + \overline{\boldsymbol{x_{\iota 2}}}\pi_t + \mathrm{v_{it2}} > 0] \tag{3-9}$$

where $\mathrm{v_{i2}} = \mathrm{a_{i2}} + \mathrm{u_{it2}}$ and $\mathrm{v_{i2}}|\mathbf{x_i} \sim Normal\,(0, 1+\sigma_{a2}^2)$. Then equation (3-9) can be estimated with Probit model for each time period and inverse Mill's ratio for each observation $\hat{\lambda}_{\mathrm{it}}$ can be obtained.

One advantage 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:

$$E(u_{it}|\boldsymbol{x_i}, c_i, v_{it2}) = E(u_{it}|v_{it2}) = \rho_t v_{it2},\ t = 1, \dots, T. \qquad (3\text{-}10)$$

Further assuming that

$$\mathrm{E(c_i|\mathbf{x_i}, v_{it2})} = \bar{\mathbf{x}}_\mathbf{i}\boldsymbol{\xi} + \psi_\mathrm{t}\mathrm{v_{it2}} + \mathrm{a_{i1}} \qquad (3\text{-}11)$$

Taking expectation of (3-1) conditional on $\mathbf{x_i}, \mathrm{v_{it2}}$ and replacing $E(\mathrm{u_{it}}|\mathbf{x_i}, \mathrm{v_{it2}})$ and $\mathrm{E(c_i|\, \mathbf{x_i}, v_{it2})}$ with (3-10) and (3-11) gives:

$$\mathrm{E(y_{it}|\mathbf{x_i}, v_{it2})} = \mathbf{x_{it}}\boldsymbol{\beta} + \bar{\mathbf{x}}_\mathbf{i}\boldsymbol{\xi} + \gamma_t \mathrm{v_{it2}} + \mathrm{a_{i1}} \qquad (3\text{-}12)$$

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

Conditioning on $\mathrm{s_{it}} = 1$, (3-12) becomes:

$$\mathrm{E(y_{it}|\mathbf{x_i}, s_{it} = 1)} = \mathbf{x_{it}}\boldsymbol{\beta} + \bar{\mathbf{x}}_\mathbf{i}\boldsymbol{\xi} + \gamma_t \lambda_{it}(\mathbf{x_{it2}}\boldsymbol{\delta_t^a} + \bar{\mathbf{x}}_\mathbf{i2}\pi_t^a) + \mathrm{a_{i1}}$$

, where λ_{it} (·) is the inverse Mills ratio obtained by previous estimation of equation (3-9).

Thus, the equation for $\mathrm{s_{it}} = 1$ is:

$$\mathrm{y_{it}} = \mathbf{x_{it}}\boldsymbol{\beta} + \bar{\mathbf{x}}_\mathbf{i}\boldsymbol{\xi} + \gamma_t \lambda_{it}(\mathbf{x_{it2}}\boldsymbol{\delta_t^a} + \bar{\mathbf{x}}_\mathbf{i2}\pi_t^a) + \mathrm{a_{i1}} + \mathrm{e_{it1}} \qquad (3\text{-}13)$$

, where $\delta_\mathrm{t}^\mathrm{a} = \delta_t/\sqrt{1+\sigma_{a2}^2}$, $\pi_t^a = \pi_t/\sqrt{1+\sigma_{a2}^2}$.

The second step estimates the final equation (3-13) by using either FE, CRE, or pooled OLS after substituting λ_{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 $\mathrm{E}[\mathrm{x}'_{it}\mathrm{a}_{\mathrm{i1}}] =$; both CRE and FE require $\mathrm{E}\,[\mathrm{e}_{\mathrm{it1}} | \,\mathbf{x_i},\, \mathrm{a}_{\mathrm{i1}}] = 0$; in addition, CRE requires that $\mathbf{x_{it}}$ and a_{i1} are not correlated: $\mathrm{E}[\mathrm{a}_{\mathrm{i1}} | \,\mathbf{x_i}] = E(\mathrm{a}_{\mathrm{i1}}) = 0$, while FE permits that (Semykina and Wooldridge, 2010).

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

3.4.3. CRE Fractional Response Model

A fraction response model is used to analyze the impacts of outsourcing 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:

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

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 average marginal effects are the same as in the logit model, except that these are partial effects on a mean response (Wooldridge 2010). The standard errors are estimated via bootstrap procedure.

4. Results

Table III reports the estimates from correlated random effect (CRE) Tobit model and CRE selection models. Following Wooldridge (2010), CRE selection models are estimated by a two-stage procedure. The first stage estimates selection function (3-9) by CRE probit model, while the second stage estimates intensity function (3-13) by fixed effects (FE), CRE and pooled OLS respectively. As discussed in section 3.4.2, these three second-stage methods require different assumptions on the association between independent variables, unobservable time-invariant and time-variant individual characteristics, and the choice among them faces a trade-off between efficiency and consistency: FE estimators tend to be the most consistent but the least efficient; pooled OLS estimators can be the least consistent but the most efficient; the CRE locates somewhere in between. As it is unknown which assumption best serves the reality, the second-stage estimates from all the three methods are reported. These results also serve as one of the first empirical examples that provide comparison across CRE models with different second-stage estimation methods.

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Although the econometric models are different, they all reveal a similar picture: the estimates are roughly stable across the four models, especially in terms of the signs and significant levels; the magnitudes of marginal effects exhibit some differences, but when they are interpreted together with the units of variables, the differences are actually small.

The breadth of outsourcing, which is measured by the number of types of R&D outsourcing partners, has positive effect on R&D specialists' employment. The estimates are significant in three models, and the magnitude of marginal effect goes from 2.81 to 3.35, depending on estimation method. On average, increasing one type of R&D outsourcing partner leads to about three more full-time- equivalent hires of R&D specialists, holding the other factors constant.

On the contrary, the depth of outsourcing, 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 -0.18 to -0.35, meaning that 5 percent increase in the share of purchased R&D leads to one to two fewer full-time-equivalent hires of R&D specialists, depending on the estimation method.

In the selection models, the estimators associated with the selection indicator lambda are only significant at 10% level at the most, regardless of the second-stage estimation method. This indicates only slightly difference exists in the impacts of the examined factors on the two processes determining “hiring R&D specialists or not” and “how many R&D specialists to hire”; this also explains why the estimates are roughly stable across CRE Tobit model and CRE selection models. In other words, the comparable estimates from the two different types of models not only further confirm the robustness of the positive/negative association between R&D outsourcing breadth/depth and R&D specialists’ employment, but also indicate that the decisions “hire or not” and “how many to hire” are influenced by the examined factors in similar ways.

The analysis above shows how the absolute number of R&D specialists evolves with R&D outsourcing. Because labor input directly links to the production scale, the absolute number of employment actually reflects the firm’s internal R&D ability through the facet of quantity.

Another facet reflecting firm’s internal R&D ability is employment quality. An important question under this strand is whether firms adjust their employment composition within R&D function 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 R&D outsourcing.

Table IV reports the estimates from CRE fractional response probit model for the share of specialists among total R&D employment.

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Generally speaking, the share of R&D specialists relates to the two dimensions of R&D outsourcing in the parallel way through which the absolute number of R&D specialists relates to R&D outsourcing.

On one hand, a significant and positive association is found between the share of R&D specialists within R&D function and the breadth of R&D outsourcing. On average, establishing one extra type of R&D outsourcing partner is associated with around 2.5 percent increase in the share of R&D specialists. Combining this with previous finding, it is confirmed that establishing more types of R&D outsourcing partner associates 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, which corresponds to an upgrade in internal R&D capacity and capability.

On the contrary, a significant and negative association is found between the share of R&D specialists within R&D function and the depth of R&D outsourcing. On average, one percent increase in the share of purchased R&D links to a reduction in the share of R&D specialists by around 0.16 percent. So in general, an increasing 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, which embodies deterioration in R&D capacity and capability.

As for control variables, several results are worth to notice. First, the scale indicators associate positively with the absolute number of R&D specialists but negatively with the share of R&D specialists: as firms acquire more assets or invest more on R&D, they employ more R&D specialists – which is not surprising; but at the same time, they also tend to fill even more supporting staff (non-specialists) into R&D function - which is somehow interesting. In addition, consistent with previous literatures which find that several aspects of innovation differ across industries, this paper also find industrial differences in firm's internal employment of R&D specialists, in terms of both absolute number and the share within R&D function.

5. Discussion

This paper identifies the employment of R&D specialists as a key intermediary inside the black box transforming R&D outsourcing practice into innovation performance. The link between outsourcing practice and performance found in previous studies can now be further explained by focusing on labor input: R&D outsourcing practices have significant implications for a firm's internal employment of R&D specialists, which directly determines firm's R&D and innovation performance.

In addition, examining the two dimensions of R&D outsourcing separately reveals diverging implications on the employment of R&D specialists: while broadening R&D outsourcing associates with more employment of R&D specialists, deepening R&D outsourcing implies the opposite.

Furthermore, the theoretical analysis of the firm's employment of R&D specialists and R&D outsourcing reveals that the observed link between R&D outsourcing breadth and R&D specialists' employment of may stem from the same root – the firm's strategic choice of acting either as a R&D specialist (who produces with its own strongest knowledge endowment), or as a generalist (who adds values by integrating different knowledge from external sources). For similar reasons, the causal interpretation of the link between the breadth of R&D outsourcing/cooperation and R&D/innovation performance found in previous studies is challenged. On the other hand, the link between R&D outsourcing depth and employment of R&D specialists exists regardless of the firm's strategy.

The study also has several practical implications for R&D specialists, firms and policy makers. For R&D specialists, it becomes clearer how their employment opportunities are likely to evolve when the firm adjusts its R&D outsourcing behavior: while specialists have some reason to worry when the firm increases the purchase from a particular R&D partner, they should not be as pessimistic when the firm establishes a new type of external R&D (outsourcing) partner. Equipped with this finding, R&D specialists are able to better foresee their future employment opportunities so that they can be prepared for the adjustment. The friction (efficiency loss) can be reduced due to their preparation and corresponding shorter adjustment period.

For firms, a more detailed roadmap becomes available, which connects the internal employment of R&D specialists, R&D competency and R&D outsourcing practice and underlying R&D strategy. The firm's strategic choice of acting as either integrator or specialist may lead to different internal R&D capacity. Compared with specializing R&D strategy, integrating R&D strategy usually means assembling knowledge from a broader range of external R&D partners, shallower outsourcing depth, more and higher proportion of internally employed specialists, which embodies a higher R&D capacity and leads to better innovation performance. The reason why integrating R&D strategy may better serve innovation purposes can be that, firm with more diversified R&D outsourcing partners are more likely to have a broader range of knowledge, which provides the firm a bigger window to see the situation, and "it is easier to innovate when the entire situation can be seen" (Lazear, 2005, p. 661). To some extent, the most important determinant of firm's innovation capacity is the breadth of knowledge, rather than the depth. Thus, a firm that would like to build a larger internal innovation capacity may consider broadening its knowledge pool and to prioritize developing the ability of integrating knowledge, rather than further advancing a specific expertise, even if specializing in one aspect of R&D may bring more profits in the short term. Similarly, because deepening outsourcing replaces internal knowledge production and R&D specialists, it may reduce internal innovation capacity and firms should therefore be cautious in adopting it. Thus, although deepening outsourcing may bring more profit in short term, it is better to investigate the reason that makes the deepening R&D outsourcing more profitable and to explore the possibilities of restoring the efficiency of internal knowledge production or integration. In this way, the firm that values internal R&D and innovation will not end up in the downward spiral from deteriorating comparative R&D efficiency to shrinking R&D capacity, triggered by the temptation of deepening R&D outsourcing.

For policy makers, the findings suggest at least one way to increase aggregate R&D/innovation capacity in the whole society: to facilitate R&D (outsourcing) partnership among different types of organizations and increase the market value for knowledge integration process, so that firm’s demand for R&D specialists and their equilibrium amount in labor market will increase.

6. Conclusion

This study looks into the black box that transforms R&D outsourcing strategy to innovation performance. Zooming into the link between R&D outsourcing and innovation performance found by previous studies, R&D specialist's employment is identified as a major intermediary in between. In a parallel way that innovation performance associates with R&D outsourcing, firm's internal employment of R&D specialists decreases with the deepening of R&D outsourcing but increases with the broadening of R&D outsourcing.

The theoretical analysis reveals the mechanism through which R&D specialists' employment may be associated with R&D outsourcing breadth and depth. In addition to demonstrating the existence of the above relations, the analysis also indicates that the relation with R&D outsourcing breadth may root in firm's strategic choice of acting either as a specialist or as a generalist in the process of opening R&D, while the relation with R&D outsourcing depth exists regardless of firm's R&D strategy.

The predictions from theoretical analysis are supported by systematic empirical evidence based on rich firm-level longitudinal data and econometric analysis with correlated random effect (CRE) Tobit, CRE selection and CRE fractional models. These methods increase the reliability of the results compared with those from the random effect (RE) Tobit or RE selection models used in previous related studies. In addition, this paper provides the comparison across CRE Tobit estimates and CRE selection estimates from different second-stage models, which may yield some new insights about the suitability of these alternatives and their assumptions in the context of empirical studies on R&D and innovation.

In addition to theoretical implications, the findings also have several practical implications for R&D specialists, firms and policy makers. With better understanding of how R&D specialists' employment within firms evolves with R&D outsourcing - a phenomenon of which has been becoming increasingly popular in recent years, R&D specialists can prepare in advance to smoothen the foreseeable job transition and reduce the labor market friction; firms get a clear roadmap connecting R&D strategy, internal R&D employment, R&D and innovation capacity as well as performance, which indicates the advantage of R&D integrating strategy in terms of nurturing internal R&D capacity and the reasons for being cautious with deepening R&D outsourcing.

Several issues are left for future research. First, another facet reflecting the quality R&D employees is their wages, which worth further exploration. By combining the changes in both wages and number of R&D specialist's employment, it is possible to further track the change in employment quality due to R&D outsourcing. Second, R&D collaboration is another related dimension worth for further attention. Although the variety of R&D outsourcing partners may to some extent reflects the range of R&D collaboration, other types of collaboration can also have important implications for R&D specialist's employment and R&D/innovation outcomes. Third, a more detailed picture linking employment and performance to the composition of R&D investment across different types of external R&D partners would also be interesting to look into.

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Table I. Descriptive statistics

Variables	*All firms* N = 3973		*Employing R&D specialists* N = 2987		*Without R&D specialists* N = 986	
	Mean	*S.D.*	*Mean*	*S.D.*	*Mean*	*S.D.*
R&D Outsourcing depth (share of purchased R&D)	0.17	0.30	0.09	0.18	0.38	0.46
R&D outsourcing breadth (types of R&D outsourcing partners)	0.74	1.11	0.75	1.17	0.72	0.89
Number of R&D specialists	15.16	90.16	20.16	103.50	0	0
Share of R&D specialists within R&D function	0.55	0.35	0.67	0.26	0/-	0/-
Total R&D expenditure (1000.000 DKK)	34.22	275.32	44.45	316.80	3.24	11.76
Average profit per employee (1000.000DKK)	0.0070	1.22	0.0126	0.78	-0.0098	2.05
Number of full-time-equivalent employees	229.97	865.28	265.71	975.21	121.67	347.12
Asset value (1000.000 DKK)	784.13	5873.20	941790.2	6572.43	306.50	2800.91

Table II. Breadth and depth of R&D outsourcing across quintiles (subsample with positive R&D outsourcing, N=1745)

Variable quintiles		*R&D outsourcing depth (share of purchased R&D)*				*R&D outsourcing breadth (R&D outsourcing partner types)*			
		Mean	*S.D.*	*Min*	*Max*	*Mean*	*S.D.*	*Min*	*Max*
R&D outsourcing depth	1st Quintile	0.03	0.02	0.00	0.07	1.52	0.82	1	5
	2nd Quintile	0.11	0.02	0.07	0.16	1.69	1.05	1	7
	3rd Quintile	0.23	0.05	0.16	0.33	2.00	1.41	1	7
	4th Quintile	0.51	0.13	0.33	0.80	1.88	1.20	1	7
	5th Quintile	0.99	0.03	0.81	1.00	1.32	0.71	1	6
R&D outsourcing breadth	1st Quintile	0.41	0.38	0.00	1	1	0	1	1
	2nd Quintile	0.33	0.31	0.00	1	2	0	2	2
	3rd Quintile	0.31	0.27	0.00	1	3.86	1.06	3	7

Table III. Estimates from CRE Tobit and CRE selection models for number of R&D specialists

Dependent Variable: Number of R&D Specialists	*CRE Tobit model*		*CRE selection model: second stage estimates*		
	Coeff.	*AMEs*	*CRE Probit - FE*	*CRE Probit - CRE*	*CRE Probit-POLS*
Variables of Interest					
Breadth of outsourcing	5.910***	2.812***	3.351**	3.339*	3.010
(Types of R&D outsourcing partner)	(0.858)	(0.410)	(1.416)	(2.019)	(2.680)
Depth of outsourcing	-0.465***	-0.221 ***	-0.178	-0.252**	-0.351**
(Share of purchased R&D, %)	(0.054)	(0.026)	(0.123)	(0.106)	(0.159)
Control Variables					
Total R&D expenditure (1000.000 DKK)	0.200***	0.095***	0.144	0.181	0.224
	(0.007)	(0.004)	(0.141)	(0.158)	(0.171)
Annual profit per employee (1000.000 DKK)	1.138	0.541	1.737	0.698	-0.136
	(0.939)	(0.447)	(1.944)	(1.581)	(2.539)
Log(Number of employee)	5.216**	2. 482*	5.641	5.716**	7.192**
	(2.889)	(1.375)	(3.537)	(2.274)	(3.500)
Log(asset, 1000.000 DKK)	-0.542	-0.258	1.228	0.284	-0.821
	(2.231)	(1.062)	(1.741)	(1.700)	(2.137)
R&D Department (Binary)	0.074	0.035	--	--	--
	(2.389)	(1.137)			
6 Industry dummies	$Chi^2(6)$=34.40***		--	$Chi^2(6)$=11.53***	$Chi^2(6)$=12.55*
	Prob >chi^2=0.000			Prob >chi^2=0.007	Prob >chi^2=0.051
7 Location dummies	$Chi^2(7)$=11.80		--	$Chi^2(7)$=6.56	$Chi^2(7)$=5.21
	Prob >chi^2=0.107			Prob >chi^2=0.477	Prob >chi^2=0.634
3 Year dummies	$Chi^2(3)$=3.80		$Chi^2(3)$=2.58	$Chi^2(3)$=5.78	$Chi^2(3)$=7.36*
	Prob >chi^2=0.283		Prob >chi^2=0.460	Prob >chi^2=0.123	Prob >chi^2=0.061
Lambda	--		17.921 (14.020)	12.490 (11.120)	11.69 (12.69)
Lambda*3 Year dummies	--		$Chi^2(4)$=2.89	$Chi^2(4)$=8.87*	Chi2(4)=8.97*
			Prob >chi^2=0.576	Prob >chi^2=0.065	Prob >chi2=0.062
Wald Chi2	3885 .89		--	--	--
Prob. > Chi2	0.000		--	--	--
Log likelihood	-16014.335		--	--	--
Rho	0.649*** (0.012)		--	--	--
Observations	3973				

***: Significant at 1%; **: Significant at 5%; *: Significant at 10%. Bootstrap standard errors for CRE selection models (500 repetitions).

Table IV. Estimates from CRE fractional response probit model for share of specialists

Dependent Variable: Share of R&D Specialists	*Coefficients*	*Marginal Effects*
Variables of Interest		
Breadth of outsourcing	0.154**(0.067)	0.025***(0.011)
(Types of R&D outsourcing partner)		
Depth of outsourcing (Share of purchased R&D)	-0.990**(0.422)	-0.160**(0.063)
Control Variables		
R&D Department	-0.157 (0.124)	-0.025 (0.020)
Total R&D Expenditure (1000.000 DKK)	0.018 (0.012)	0.003 (0.002)
Annual Profit per Employee (1000.000 DKK)	0.010 (0.090)	0.002 (0.015)
Log(Number of Employee)	-0. 012 (0.153)	-0.002 (0.025)
Log(asset, 1000.000 DKK)	-0.342** (0.148)	-0.055** (0.024)
6 Industry Dummies	Chi^2(6)=12.65**	Prob.> Chi2=0.049
7 Location Dummies	Chi^2 (7)=29.03***	Prob.> Chi2=0.0000
3 Year Dummies	Chi^2 (3)=30.09***	Prob.> Chi2=0.0001
Observations	3634	
Wald Chi^2	157.47	
Prob. > Chi^2	0.000	
Log likelihood	-1478.9955	
Rho	0.539*** (0.047)	

***: Significant at 1%; **: Significant at 5%; *: Significant at 10%. Based on bootstrap standard errors (400 replications).

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