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COMPLEMENTARITIES OF R&D STRATEGIES ON INNOVATION PERFORMANCE: EVIDENCE FROM TAIWANESE MANUFACTURING FIRMS

Eric S. LIN[a], Yi-Chi HSIAO[b], Hui-lin LIN[c]

[a]*Department of Economics, National Tsing Hua University, 30013 Hsin-Chu, Taiwan*
[b]*Department of Strategy and Management, National Taiwan University, 10055 Taipei, Taiwan*
[c]*Department of Economics, National Taiwan University, 10055 Taipei, Taiwan*

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Abstract. This paper aims to empirically test the R&D complementarities among three alternative R&D strategies, namely, internal R&D, external R&D and cooperative R&D, under different measures of innovation output. Using a firm-level data set based on the Taiwanese innovation survey (in accordance with CIS 3) conducted in 2003, we are able to compare the R&D activities in this newly-industrialized country with other developed countries. Additionally, we apply a two-step procedure to reduce the endogeneity problem caused by the firms' choices of strategies to obtain consistent estimators, which can be regarded as a combined method of adoption and productivity approaches. We show that the results of the estimation for R&D complementarities may be biased upwards or downwards if we do not include selection equations in the empirical models, thereby giving rise to endogeneity problems. Our empirical results generally support the existence of R&D complementarities, while the strength of complementary effects may vary across different measures of innovation output. Moreover, our finding suggests that the complementary relationship between external and cooperative R&D is fairly robust to various model specifications.

Keywords: R&D strategy, innovation, complementarities, multivariate probit model.

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Corresponding author Eric S. Lin
E-mail: *slin@mx.nthu.edu.tw*

Introduction

Needless to say, R&D activities play a crucial role in firms' product or process innovations. There are many types of R&D strategies, including internal R&D, external R&D, cooperative R&D, contracted R&D, technology purchasing R&D and so on[1]. It turns out that firms may conduct multiple R&D strategies simultaneously. The so-called R&D *complementarity* indicates that the firm that simultaneously engages in more than one type of R&D strategy has higher R&D or innovation output (Topkis 1998)[2]. Since the mid-90s, the concept of R&D complementarity has received extensive attention, and many theoretical and empirical studies have sought to provide explanations for complementarities among R&D strategies (Cassiman, Veugelers 2002). For instance, many studies point out that the sources of R&D complementarity arise from the absorptive capacity and learning ability of firms, the economic scale of R&D, and R&D cooperation and risk sharing[3]. A good understanding of the interrelation between different types of R&D strategies not only sheds light on firms' determinants of such activities but also provides governments with a sound basis for industry policies.

There are a large number of studies concentrating on the relationship between internal, external R&D and cooperative R&D as input factors to innovation, for example, the link between internal R&D and cooperative R&D (e.g. Serrano-Bedia *et al.* 2012; Abramovsky *et al.* 2009; Cassiman, Veugelers 2006; Schmidt 2010; López 2008), contracted R&D vs. internal R&D (Dhont-Peltrault, Pfister 2011), and contracted R&D vs. cooperative R&D (Arvanitis *et al.* 2013). However, as pointed out in Schmiedeberg (2008), the simple correlation between internal and external R&D is not able to capture complementarities of these activities. Several empirical studies utilize more elaborate methods to analyze the potential complementarity relationship[4]. Love and Roper (1999) make use of 1,300 UK manufacturing firms to empirically test the complementarity between internal and external R&D. They implement a three-step procedure, including internal and external R&D activities, an endogeneity test for the input factors, and the analysis of innovation output subject to R&D activities. Their empirical results suggest that internal and external R&D are substitutes rather than complements. In their subsequent research, Love and Roper (2001) find that the internal and external R&D are substitutes in the UK and Ireland, but in Germany a clear substitutive or complementary relationship can not be determined when innovation output is measured by the new products sales rate. Cassiman and Veugelers (2006) use data from 269 Belgian manufacturing firms, and find a clear complementary relationship between internal R&D and contracting R&D. Using a panel of Spanish manufacturing firms over the period of 1990–1996, Beneito (2006) focuses on R&D contracting and concludes that a positive effect of contracted R&D when

1 However, the definition of external R&D and/or contracted R&D is usually vague, e.g. Beneito (2006). In our empirical analysis, the external R&D includes the way of contracted R&D and technology purchasing R&D, since those R&D related activities are "external" by nature.

2 It is worth noting that "innovation output", "innovation activities" and "innovation performance" are often used interchangeably (e.g. see footnote 1 in Schmiedeberg 2008; Beneito 2006).

3 Please refer to Schmiedeberg (2008) for a detailed discussion on the main sources of complementarity in R&D.

4 There are a large number of existing studies that attempt to relate R&D cooperation or multiple R&D investment plans to the R&D output, see e.g. Kim *et al.* (2005); Miravete, Pernias (2006); Veugelers, Cassiman (1999) among many others.

combined with internal R&D. Jirjahn and Kraft (2011) employs the German establishment data to find a rather substitute relationship between R&D intensity and cooperative R&D. Recently, Schmiedeberg (2008) utilizes the cross-section data of German manufacturing industry to study the relationships among internal R&D, contract R&D and external R&D and finds that firms with internal R&D can increase their productivity if they further engage in cooperative R&D, and vice versa. Therefore, the complementary relationship between internal and cooperative R&D can be confirmed. Schmiedeberg (2008), however, also indicates that the complementary relationship between internal R&D and contracting R&D is very weak. Becker and Peters (2000) apply the number of patents to measure firms' innovation output, and their empirical results suggest the complementarity of internal and cooperative R&D. However, the complementarity is not clear if the innovation output is measured by the sales rate of new products. Similarly, Cassiman and Veugelers (2002) utilize the data from Community Innovation Survey on Belgian manufacturing firms and also reject that there is complementary relationship between internal and cooperative R&D when using the new products' sales rate as the measure of innovation output.

From the above discussion we know that there are a large number of studies on the complementarities between different modes of R&D activities, but the empirical results are inconsistent among the different countries, different samples, and different measures of innovation output (Schmiedeberg 2008)[5]. Besides, past research considers the endogeneity problem for only two types of R&D strategies, and then discusses their R&D complementarities. It seldom takes into account the choice problem of multiple R&D strategies, which is more interesting and closer to the real world. To simultaneously consider the complementarities among a variety of R&D strategies, we apply the multivariate dichotomous choice model (namely, the multivariate probit model) to analyze the firms' choice of multiple R&D strategies first, and then we proceed to the study of R&D complementarities[6]. Furthermore, most of the literature concentrates on the cases in developed countries (especially in Europe, such as German, Belgium, UK, Ireland, Spain, etc.), and exhibits little concern regarding the innovation activities in newly-emerging countries. Innovation activities in those countries, however, might be more active and need a thorough exploration. This paper fills the gap in the literature by studying innovative activities vs. R&D strategies nexus for the case of the newly-industrialized country – Taiwan.

Taiwan conducted its first innovation investigation in 2003, which not only provides information about the operation of the innovation system in Taiwan, but also makes it possible to empirically compare the Taiwanese innovation activities with similar activities in developed countries. In this paper, we first discuss three types of R&D strategies, which are internal R&D, external R&D and cooperative R&D, and then specify appropriate econometric models to explore the complementarities among these R&D strategies. In particular, we apply a two-stage regression procedure to alleviate the selection and endogeneity

[5] Schmiedeberg (2008) emphasizes that "What is more, the differences between the results of existing studies cast some doubt on the robustness of empirical findings on complementarity highlighting their sensitivity to model specification and measurement."

[6] Schmiedeberg (2008) utilizes a multivariate logit model to fit the decision problem among the three R&D strategies, i.e. internal, contracted and cooperative R&D activities.

problems[7]. Furthermore, as for the measurement of the innovation output, we consider three measurements, namely, the proportion of sales from new products, the proportion of sales from patents, and the marginal rate of return on R&D investment. By using different measures of the innovation output, we can compare our results with previous studies and evaluate whether the effect of R&D complementarities is invariant to those innovation output measures.

Our empirical results suggest that as the innovation output is measured either by the proportion of sales from new products or by the marginal rate of return on R&D investment, the complementarities among these R&D strategies are significant, and moreover, the complementary effect between internal R&D and external R&D is the strongest[8]. Hence, the transaction cost theory, which suggests that the availability of external knowledge may serve as a substitute for own R&D investment (Williamson 1985), is not supported. Firms that develop better internal and external communication networks can efficiently use resources and increase their innovation output. That is, the advantage (e.g. sharing of costs/risks, access to partner's know how/markets/products, and efficiency enhancement) associated with R&D cooperation will dominate the disadvantage (e.g. negotiation costs, investment in specific infrastructure, foregone opportunities, coordination and agency costs of running the co-operation, etc.) argued by the transaction cost theory (Veugelers 1998). When the innovation output is estimated by the patents revenue, however, the R&D complementary relationship only exists between external R&D and cooperative R&D. Hence, different measures of innovation output will generate different results for R&D complementarities, suggesting that it is useful to have several variables with which to compare innovation output. In addition, our results show that the results of the estimation are biased upwards or downwards as selection biases are not taken into consideration. Therefore, the application of the two-step procedure can alleviate the endogeneity problem caused by the firms' R&D strategic choices.

The remainder of this paper is organized as follows. In the next section, we describe the measurement of innovation output. Section 2 describes the data source. The econometric methodology and variables description are discussed in Section 3. Section 4 provides the empirical results, while the conclusion is discussed in final section.

1. The measurement of innovation output

In this study, we use the sales share of new products (INNOV1), patents behavior (INNOV2), and the marginal rate of return on R&D investment (INNOV3) to serve as the indicators of innovation output. The first two innovation indicators are frequently used as dependent variables in previous studies on complementarities among R&D strategies. For example, Becker and Peters (2000) and Beneito (2006) apply firms' patent applications to study the

[7] We first make use of the multivariate probit model to estimate the probability of R&D strategy adoption (step 1), and then apply the estimation results to the innovation output equations (step 2). The two-step procedure will be detailed in Section 4.1. Note that Schmiedeberg (2008) also considers three types of R&D strategies, which are, however, treated as exogenous right-hand-side variables in equations of the innovation output.

[8] The significant results for the complementary relationship between internal R&D and external R&D, however, contradict those of the studies of Love and Roper (1999, 2001).

complementarity between inner R&D and cooperative R&D, and between inner R&D and contract R&D, respectively. Belderbos *et al.* (2006), Cassiman and Veugelers (2002) and Love and Roper (2001) make use of the turnover generated by new products of firms to test the complementary relationship between inner R&D and cooperative R&D. The use of patent data or the sales share of new products, however, has some drawbacks. For instance, Schmiedeberg (2008) points out that patenting is not equivalent to innovating if firms use other strategies (instead of patenting) to protect their high-value inventions. Faems *et al.* (2005) indicate that patents should not be viewed as an innovation output but rather as an input factor in innovation; many companies do not have market novelties and therefore report no new products sales (Schmiedeberg 2008; Cassiman, Veugelers 2002; Love, Roper 2001). Nevertheless, the use of patent data or new products sales shares is a generally accepted proxy for innovative activities (Schmiedeberg 2008; Lin *et al.* 2013b).

The third indicator of innovation output – the marginal rate of return on R&D investment, on the other hand, is the direct measurement criterion for R&D investment output (Hall *et al.* 2010). The performance of R&D investment depends not only on the firms' number of patents, but also on the revenue from R&D input, which can further determine the firms' R&D strategies and scale during the next stage. Hence, it is useful for the analysis of R&D activities to observe the marginal rate of return on firms' R&D investment. There are two major methods used to calculate the marginal rate of return on R&D – case studies and regression analysis. Case studies usually focus on the revenue or output of certain specific cases. Two representative studies, for example, are Griliches (1958) who examines the yield rates of hybrid corn and hybrid sorghum, and Bresnahan (1986) who analyzes computer R&D projects. Regression analysis, on the other hand, is widely used by applying the Cobb-Douglas (C-D) production function to construct the marginal rate of return on R&D investment. In this study, we resort to a regression analysis based on the Cobb-Douglas production function to estimate the return on R&D.

The estimation method that bases on the Cobb-Douglas production function first involves obtaining the stock of technical knowledge, and then putting the stock of knowledge along with output, and the capital and labor inputs into the C-D type production function to estimate the output elasticity for R&D investment, before finally arriving at the marginal rate of return on R&D. If the technical knowledge is derived from the R&D investment as an input factor, then we can set up a C-D production function consisting of three input factors, namely, capital (K), labor (L) and R&D investment (RD), as follows:

$$Q = AK^{\eta_1} L^{\eta_2} RD^{\eta_3}, \tag{1}$$

where Q is the value added from production, A represents the technology level, η_1 and η_2 denote the output elasticity of capital and labor, respectively, and η_3 is the output elasticity of R&D investment. Taking the natural logarithms with respect to both sides in (1), we then have the following:

$$\ln(Q) = \ln A + \eta_1 \ln(K) + \eta_2 \ln(L) + \eta_3 \ln(RD).$$

Fitting the above equation the ordinary least squares method (OLS), we can obtain an estimate for the output elasticity of R&D, η_3. The marginal return on R&D investment (S) can be expressed as:

$$S = \frac{\partial Q}{\partial RD} = \frac{\partial Q}{\partial RD} \times \frac{RD}{Q} \times \frac{Q}{RD} = \eta_3 \times \frac{Q}{RD}.$$

By plugging η_3, Q and RD into the above equation, we then obtain the estimate for S.

2. The data set

The data used for the innovation-related variables are obtained from the 2003 First Taiwan Technological Innovation Survey (TTIS-I) in the Taiwan Area, which was conducted between August 1, 2001 and July 31, 2002 by the National Science Council and the Ministry of Economic Affairs (MOEA) of Taiwan[9]. The main purpose of the TTIS-I is to obtain information about how individual firms engage in the technological innovation process, and to serve as valuable reference for policy-makers within the government as well as firms. Besides, the TTIS-I was carried out in accordance with the Community Innovation Survey III (CIS 3), which was developed by the European Commission, to make the data internationally comparable. The survey covers Taiwanese enterprises, in both the manufacturing and service sectors, with 6 or more employees. TTIS-I respondent firms were asked a variety of questions based on their innovative or R&D-related activities, firm characteristics, and other detailed questions related to product innovation during 1998–2000. There were a total of 3,356 firms for which there were valid interviews, which consisted of 1,645 manufacturing and 1,711 service firms. In order to derive values for the marginal returns of firms' R&D investments, we needed information on firms' operating activities, such as the resource distribution, capital utilization, production structure and so on. We obtained these kinds of information by matching the TTIS-I data with those of the 2001 Industry, Commerce and Service Census (ICSC), conducted by the Directorate-General of Budget, Accounting and Statistics (DGBAS), Executive Yuan in Taiwan[10]. By combining these two data sets together, we had 1,379 firms in the manufacturing sector in our sample.

Table 1 shows the frequency distribution of the R&D strategies. According to this table, a total of 201 (14.58%) firms only engaged in internal R&D, 62 (4.50%) in external R&D, and 85 (6.16%) in cooperative R&D. Hence, it was most common for firms to have their own R&D activities. When considering multiple R&D strategies, we found that firms seldom engaged in internal R&D and external R&D together, with only 2.39% of the firms in our sample doing so. On the other hand, firms were more likely to simultaneously engage in internal R&D and cooperative R&D, or external R&D and cooperative R&D (9.21% and 7.18% of the

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9 The TTIS-I data set has also been utilized in Lin, H. and Lin, E. (2010) to empirically test the relationship between outward and inward foreign direct investment, imports and exports, and product innovation.

10 A mechanism has already been established for this census to be conducted every five years since it was first launched in 1954. The census results have played an important role in the government's formulation of important economic construction plans, the development of industrial areas, the stipulation of industrial counseling policy, and the clarification of a local industrial development strategy. Lin *et al.* (2013a) also compiled 2001 ICSC and the Survey on the Outward FDI of Taiwanese Manufacturers (SOFTM) conducted by the Ministry of Economic Affairs in Taiwan to evaluate the impact of different types of FDI activities on firm productivity and innovation performance.

Table 1. Frequency of R&D Strategies

R&D Strategies	Number of Firms	Proportion
no R&D strategies	654	47.43%
internal R&D only	201	14.58%
external R&D only	62	4.50%
cooperative RD only	85	6.16%
internal and external R&D	33	2.39%
internal and cooperative R&D	127	9.21%
external and cooperative R&D	99	7.18%
adopting all three R&D	118	8.56%
Total	1,379	100%

firms in the sample). This suggests that these two combinations are beneficial for firms, and the reason might lie in the complementarities between internal R&D and cooperative R&D, and between external R&D and cooperative R&D. Of course, the preliminary finding needs to be verified using more elaborate econometric models.

3. Econometric methods and description of variables

3.1. Econometric strategies

As clarified in Topkis (1998), the R&D complementarity means that firms can have higher R&D or innovation output if they simultaneously engage in multiple R&D strategies. According to this concept, we can first establish an empirical model to test the correlation between R&D strategies, and then build innovation output models for combinations of different R&D strategies (Leiponen 2005; Cassiman, Veugelers 2006), where the former is known as the adoption approach and the latter is the productivity approach in the literature. Our empirical strategy follows the line of Schmiedeberg (2008), which also uses the adoption approach and productivity approach separately to test the complementarities between three R&D strategies. In addition, we recognize that the potential endogeneity problem resulting from firms' R&D strategy choices (the first stage adoption approach) might cause an inconsistent estimation in the second stage productivity analysis. When performing the productivity analysis, this paper adopts a two-step procedure (i.e. a combination of the adoption and productivity approaches) to alleviate the possible selectivity bias and to obtain a more precise estimation.

Note that this paper is interested in firms which are able to conduct three R&D strategies – internal R&D (*rd1*), external R&D (*rd2*) and cooperative R&D (*rd3*). Then their strategies' selection functions are given by:

$$rd1_i^* = X_i^{'}\beta_1 + \varepsilon_{1i}\,;$$

$$rd2_i^* = X_i^{'}\beta_2 + \varepsilon_{2i}\,;$$

$$rd3_i^* = X_i^{'}\beta_3 + \varepsilon_{3i}\,,$$

where $rd1^*$, $rd2^*$ and $rd3^*$ are latent variables representing the choices of internal external and cooperative R&D strategies, respectively, and it is assumed that $rdj = 1$ if firms engage in

R&D strategy j (i.e. $rdj^* > 0$), and 0 otherwise. The X_i are factors that affect firm i's R&D strategy decisions, and the ε_{ji}, $j = 1,2,3$ are error terms that are distributed as multivariate normal, each with a mean zero and a variance-covariance matrix equal to[11]:

$$\Sigma = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{bmatrix},$$

where ρ_{12}, ρ_{13}, and ρ_{23} denote the conditional correlation between the three R&D strategies.

To estimate the above R&D strategy selection equations, we applied the simulated maximum likelihood method. In particular, the likelihood function is evaluated using the Geweke-Hajivassiliou-Keane smooth recursive simulator, which splits the joint normal probability density function into simulated conditional probabilities from a truncated normal distribution. The joint probability can then be written as the product of these conditional simulated probabilities. The estimators of the coefficients, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$, $\hat{\rho}_{12}$, $\hat{\rho}_{13}$ and $\hat{\rho}_{23}$ can be so derived[12].

Next, we have the following innovation output equations:

$$\text{INNOV}h_i = \gamma_j \cdot rdj_i + \gamma_k \cdot rdk_i + \gamma_{jk} \cdot rdj_i \cdot rdk_i + Z_i'\delta + \nu_i, h, j, k = 1,2,3; j \neq k, \tag{2}$$

where the INNOVh (h = 1,2,3) are the indicators for R&D or innovation output, which consist of the sales shares of new products (INNOV1), patents behavior (INNOV2), and the marginal rate of return on R&D investment (INNOV3); γ_{jk} represents the effects of complementarities between R&D strategies on innovation activities; and Z_i are control variables including firm-level, industry-level variables, and other factors that might impact firms' innovation output.

Since firms may endogenously choose their R&D strategies, this will result in inconsistent estimators if we directly use the Tobit procedure to estimate the above innovation output equations[13]. To solve this potential endogeneity problem, we apply a two-step method. First, the fitted values of the R&D strategy dummies are derived as follows[14]:

$$rdj\_hat = \begin{cases} 1 & \text{if} \quad \Phi(X\hat{\beta}_j) \geq \text{mean}(rdj) \\ 0 & \quad\quad \text{otherwise} \end{cases},$$

where $\Phi(.)$ denotes the normal cumulative distribution function.

11 Of course, the estimations can be run for each of the three R&D decisions individually, while the coefficients estimates would be inefficient in general if the adoption of R&D activities is not independent from each other. See the discussion in Schmiedeberg (2008).

12 We use a STATA procedure, mvprobit, written by Cappellari and Jenkins (2003) to obtain the simulated maximum likelihood estimators.

13 It is noted that we adopt sales shares of patents for the measure of INNOV2 to apply the Tobit model. Alternatively, we can also utilize a binary variable whether applied a patent for INNOV2 as in Schmiedeberg (2008), which leads to estimates very similar to our results in terms of the sales shares of patents. The empirical findings based on a binary patent variable are reported in Appendix Table A-3.

14 The reason for using the mean of *rdj* as a threshold is that the prediction rate is higher than that under a threshold value equal to 0.5. We have also experimented with different cutoffs (including 0.5) and the results are not significantly affected.

By plugging the fitted values, rdj_hat, into the innovation output equations in 2, we then apply the Tobit procedure in the second step[15]:

$$\text{INNOV}h_i = \gamma_j \cdot rdj\_hat_i + \gamma_k \cdot rdk\_hat_i + \gamma_{jk} \cdot rdj\_hat_i \cdot rdk\_hat_i + Z_i'\delta + \xi_i, h, j, k = 1,2,3; j \neq k.$$

It is apparent that the two-step procedure can be regarded as a combination of the adoption and productivity approaches. As noted in Schmiedeberg (2008), for approving the complementarity condition, the coefficient of the interaction term (i.e. γ_{jk}) has to be significantly larger than zero, while a significant and negative coefficient would be a sign for the two R&D strategies being substitutes.

3.2. Description of variables

In what follows, we describe the variables that are adopted in both R&D selection equation and innovation output regression, respectively.

Variables in the choice of R&D strategy equation

The dependent variables in the multivariate probit model are the three R&D strategies: internal R&D (*rd1*), external R&D (*rd2*) and cooperative R&D (*rd3*). The control variables are classified into three types, namely, the firm characteristics, impeding factors and industrial features.

Firm characteristics variables

a. Firm Age (*yr*): This is measured by the number of years a firm has remained in the market since its establishment;
b. Firm Size (*opert_rev*): We use the logarithm of a firm's operating revenue to measure the firm's size;
c. Profitability (*profit_ratio*): We use the ratio of profit before tax to total revenue to measure to a firm's profitability;
d. Capital Intensity (*cap_intens*): This is measured by the ratio of a firm's fixed assets to its total employees, and then by taking the natural logarithm;
e. Computer Application (*computer_using*): A dummy variable indicates whether a firm is using computer equipment to facilitate its production;
f. External Finance (*extern_finance*): A dummy variable indicates whether a firm's innovative activity received a subsidy from the local government, central government or other institutes;
g. Potentiality of Innovation: We use the number of employees with a college education (*emp_tech*), human capability (*hum_cap*) and innovation intensity (*innov_intensity*), respectively, to measure the firms' potentiality of innovation, where human capability is measured by the ratio of total salary expenditure to total employees and then taking the logarithm, and innovation intensity is measured by the proportion of expenditure expended on innovative activities[16].

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[15] Since the dependent variables, INNOV1, INNOV2 and INNOV3 are evidently censored at zero, it is more appropriate to adopt the Tobit procedure. It is also noted that to meet the exclusion restriction condition, we include some variables (such as several impeding factors and external finance) that are considered to affect the R&D strategies decision directly but not for the innovation output.

[16] Our calculation of "human capability" is essentially the average salary of a firm, which is to more or less reflect the capability of workers according to the human capital theory – labors are paid by their marginal revenue product.

Impeding factors variables[17]

a. Economic Factors (*imped_eco*): According to the TTIS-I survey, economic impeding factors include three factors, which are "high economic risk", "high cost of technological innovation", and "shortage of finance". Each of the factors is assigned three possible values – 0, 1 and 2, where "2" indicates that a factor is the cause of both serious delay and interruption for a firm, "1" means that a factor is the cause of either serious delay or interruption for a firm, and "0" indicates that there is no serious delay or interruption for a firm. We then implement principal components analysis to properly weight each impeding factor[18].

b. Internal Factors (*imped_inner*): These factors include "inelastic organization", "shortage of technical or R&D manpower", "shortage of technological information or no technological breakthrough", and "shortage of market information". Similarly, we also use principal components analysis to obtain the proper weight of each factor.

c. External Factors (*imped_exter*): These factors are "rigid regulations or standards|, "consumers' indifference toward new products or services", and "similar products or patent infringement from competitors".

Industrial features variable

The industry-level classification of technology for each firm is included as one of the controls. Specifically, we classify industries into four grades according to their technological level following the way of Schmiedeberg (2008). A dummy variable, *tech1*, represents industries with the lowest technological level, including the Food & Beverage, Textile, Leather, and Wood/Paper industries; *tech2* includes the Metal & Non-metal Product industries; *tech3* includes the Rubber, Machinery & Instruments, Electricity & Instruments, and Transport Equipment industries; and *tech4* includes the Chemicals, Information Equipment and Electronics industries.

Variables in the innovation output equations

To relate the choice of R&D strategies to innovative productions, we have mentioned in Section 2 that three different measures of innovation output are utilized. That is, the dependent variables in the innovation output equations consist of the sales share from new products (INNOV1), the sales share from patents (INNOV2), and the marginal return on R&D investment (INNOV3). Besides, for each measure of innovation output, we include three R&D strategy dummies – *rd1* (internal R&D), *rd2* (external R&D), *rd3* (cooperative R&D), and their cross-product items – *rd12*, *rd13*, *rd23*, as explanatory variables, e.g. *rd12 = rd1*rd2.* Besides, the definitions of internal R&D, external R&D and cooperative R&D are as shown below:

1. Internal R&D (*rd1*): R&D activities that are performed by the firm itself to improve the accumulation of knowledge, or to use existing knowledge to generate new applications.

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[17] In the TTIS-I survey, two questions concerning the hindrances to a firm's product innovation include whether its innovative activity was seriously delayed, and whether its innovative activity was interrupted. If a firm answered yes to either one or both questions, the firm was further asked to report the reasons out of ten impeding factors.

[18] The main advantage of principal components analysis is that we can reduce a complex data set to a lower dimension without much loss of information (see Johnson and Wichern (2002) for more details). It is often the case that there are too many categorical variables for the regression analysis to include them all together in the survey data. Principal components analysis is able to properly weight the original variables and come up with several key "components".

2. External R&D (*rd2*): R&D activities that are performed by other units, including outsourcing R&D plans, or buying outside R&D results, or entrusting R&D activities to other subsidiaries.
3. Cooperative R&D (*rd3*): R&D activities that are performed by a firm with other companies or institutions, including its subsidiaries, customers or consumers, suppliers of equipment or materials, competitors, consultants, commercial research institutions or laboratories, universities or other educational institutions, and government or private non-profit research institutions.

The other control variables include a firm's characteristics – firm age (*yr*), firm size (*opert_rev*), profitability (*profit_ratio*), capital intensity (*cap_intens*), the number of employees with a college education (*emp_tech*), human capability (*hum_cap*) – and four industrial dummy variables. In Appendix Table A-1, we provide the summary statistics for related variables discussed above.

4. Empirical results

First of all, Table 2 provides the conditional correlations between the three R&D strategies derived from the multivariate probit model[19], that is, $\hat{\rho}_{12}$, $\hat{\rho}_{13}$ and $\hat{\rho}_{23}$. We find that the correlations between internal R&D (*rd1*) and cooperative R&D (*rd3*), external R&D (*rd2*) and cooperative R&D (*rd3*) are significantly positive, while the correlation between internal R&D (*rd1*) and external R&D (*rd2*) is insignificant. The significantly positive correlations imply that firms are likely to further adopt internal or external R&D strategies given that they have already conducted cooperative R&D. Besides, the insignificant correlation between *rd1* and *rd2* might suggest that firms seldom adopt both strategies (*rd1* and *rd2*) together. The adoption approach, however, only provides a hint towards complementarity. In order to compare the relative magnitude of the complementary effects between the different types of R&D, we have to further conduct the productivity approach – the analysis of innovation output and multiple R&D strategies.

Table 2. Correlation between R&D Strategies

	internal R&D	**external R&D**	**cooperative RD**
internal R&D	1	–0.0047 (0.0554)	0.2403*** (0.0508)
external R&D		1	0.5691*** (0.0407)
cooperative RD			1

Notes: Standard errors are in parentheses. *** denotes statistical significance at the 1% level.

[19] The simulated maximum likelihood estimator is consistent as the number of draws and the number of observations tend to be infinity. In the mvprobit procedure, we set the number of draws equal to 500, which is more than the square root of the sample's size and thus is sufficiently large (Cappellari, Jenkins 2003). For details of the multivariate probit results, please refer to Appendix Table A-2.

Next, we focus on the estimation results of the innovative output equations, i.e. the productivity approach. Tables 3, 4, and 5 show the results of the pair-wise Tobit regressions for each measure of innovation output respectively[20]. In each table, the first three columns, for models (1), (2) and (3), provide the estimated results without selection equations, while the last three columns, for models (4), (5) and (6), present the results with selection equations. Table 3 presents the results for the case where the dependent variable is the sales share of new products (INNOV1). Models (1) and (4) aim to evaluate the complementary effect between internal and external R&D strategies (*rd1* and *rd2*). Similarly, complementarity between internal and cooperative R&D (*rd1* and *rd3*), and external and cooperative R&D (*rd2* and *rd3*) are examined using models (2) and (5), and models (3) and (6), respectively. It is worth noting that although the coefficients of R&D strategies and their cross-product terms are all positive regardless of whether the selection equations are included or not, most of those coefficients are smaller under the two-step procedure – implying that the coefficients for those variables are likely to be biased upwards if the endogeneity adjustment is not implemented. In addition, according to the coefficients of *rd12*, *rd13* and *rd23*, the significantly positive results support the existence of complementarities between the three R&D strategies pair-wisely – meaning that simultaneously engaging in multiple R&D strategies facilitates innovation output on the part of firms. Moreover, by comparing the coefficients of *rd12*, *rd13* and *rd23* with each other, we can infer that *rd12* contributes the highest innovation output (since the value is the highest under the two-step procedure), and *rd13* the least. This indicates that the complementary effect between internal R&D (*rd1*) and external R&D (*rd2*) is stronger than that between any other pair-wise combinations of R&D strategies. The highly complementary correlation between *rd1* and *rd2* explains why firms typically tap knowledge sources that are external to the firm through licensing, outsourcing R&D plans or purchasing outside R&D resutls in addition to engaging in their own research and development (Cockburn, Henderson 1998; Granstrand *et al.* 1992). It is also worth noting that the complementary effect of *rd12* and *rd23* is about the same magnitude, suggesting that conducting two external-type R&D activities generate similar marginal effects on sales share of new products to those of *rd12,* a combination of internal and external R&D strategies. Regarding the effect of each individual R&D strategy, both internal R&D (*rd1*) and external R&D (*rd2*) have significantly positive effects on innovation output, while the effect of cooperative R&D (*rd3*) is positive but not robust. For the impacts of other control variables across models (4)–(6), only firm size (*opert_rev*) and the number of highly-educated employees (*emp_tech*) have significant effects on the sales share of new products. Our results suggest that firms that are small in size can generate more innovation output than large firms, and the more high-end personnel that firms have, the more innovation output that the firms can produce.

Table 4, on the other hand, exhibits the results where the innovation output is measured by the sales share of patents (INNOV2). At first glance, we can see that R&D-related variables act quite differently in models with and without selection equations. Internal R&D (*rd1*), for

[20] Using the entire 1,379 observations to evaluate the complementarities between *rd1, rd2* and *rd3*, would lead to very mixed results. Therefore, in our empirical application, we adopt a pairwise estimation – excluding the sample of *rd1, rd2* and *rd3* in Models 3 (6), 2 (5) and 1 (4), respectively in Tables 3–5. Therefore, we see different sample sizes in each set of regressions.

Table 3. Estimation results of innovation output (measured by sales share of new products)

	Tobit w/o selection equations			Tobit with selection equations		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
rd1	35.816***	35.341***	–	16.212**	19.141***	–
	(4.368)	(4.065)		(6.465)	(6.312)	
rd2	32.210***	–	31.873***	22.044***	–	20.868**
	(6.189)		(6.314)	(5.579)		(9.690)
rd3	–	39.422***	39.067***	–	22.154***	10.763
		(5.078)	(5.516)		(6.209)	(7.757)
rd12	35.272***	–	–	27.951***	–	–
	(9.012)			(6.202)		
rd13	–	39.660***	–	–	19.978***	–
		(4.587)			(5.255)	
rd23	–	–	39.323***	–	–	26.059***
			(5.239)			(4.673)
yr	0.202	0.123	0.192	0.040	0.070	0.116
	(0.180)	(0.157)	(0.190)	(0.185)	(0.165)	(0.201)
opert_rev	−4.164***	−3.962***	−4.412***	−4.234***	−3.067**	−4.619***
	(1.424)	(1.296)	(1.461)	(1.600)	(1.483)	(1.543)
profit_ratio	0.099	0.123	0.246	−0.115	0.045	0.165
	(0.230)	(0.206)	(0.228)	(0.244)	(0.217)	(0.241)
cap_intens	−2.603*	−2.639**	−1.976	−0.308	−2.348*	−1.049
	(1.425)	(1.265)	(1.426)	(1.561)	(1.337)	(1.501)
emp_tech	5.501***	4.853***	6.807***	5.295***	5.345***	5.348***
	(1.638)	(1.454)	(1.756)	(1.709)	(1.585)	(1.919)
hum_cap	5.497	3.929	1.150	4.060	3.331	0.830
	(3.397)	(2.837)	(3.891)	(3.431)	(3.040)	(4.110)
Constant	−37.736	−17.486	10.400	−29.199	−18.086	15.591
	(40.050)	(33.730)	(45.709)	(40.599)	(36.405)	(48.396)
Obs.	903	1,014	862	903	1,014	862
lnL	−2281.34***	−2750.57***	−2152.27***	−2309.42***	−2803.35***	−2186.14***
	(154.22)	(226.72)	(161.74)	(98.08)	(121.20)	(94.00)

Notes: Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Industry dummies (tech2, tech3 and tech4 defined on page S143) are included in each regression.

example, positively affects the innovation output in models without selection equations, i.e. models (1) and (2), while this is not the case in models with selection equations, i.e. models (4) and (5). Therefore, without correcting the endogeneity problems, we might falsely draw wrong conclusions. We can see that the effects of *rd1*, *rd2* and *rd3* on innovation output (measured by patents) are also quite different. External R&D (*rd2*) has a significantly positive effect on innovation output, but the effects of internal R&D (*rd1*) and cooperative R&D (*rd3*) are indeterminate (i.e. alternate signs faced) and non-robust (not all significant effects),

Table 4. Estimation results of innovation output (measured by sales share of patents)

	Tobit w/o selection equations			**Tobit with selection equations**		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
rd1	9.900**	10.728***		−0.621	3.235	–
	(4.490)	(4.114)		(6.811)	(6.348)	
rd2	14.672**	–	15.078**	20.008***	–	25.794***
	(6.049)		(5.991)	(5.263)		(8.253)
rd3	–	7.252	7.089	–	22.722***	8.923
		(5.320)	(5.653)		(5.267)	(7.536)
rd12	2.180		–	7.344	–	–
	(9.491)			(6.386)		
rd13	–	16.494***	–	–	0.231	–
		(4.849)			(5.173)	
rd23	–	–	14.820***	–	–	22.695***
			(5.122)			(4.343)
yr	−0.403**	−0.165	−0.014	−0.520***	−0.170	−0.105
	(0.192)	(0.160)	(0.191)	(0.193)	(0.158)	(0.190)
opert_rev	−1.721	−1.872	−1.553	−0.933	0.056	−1.847
	(1.439)	(1.287)	(1.502)	(1.604)	(1.422)	(1.479)
profit_ratio	−0.068	−0.047	0.026	−0.306	−0.093	−0.046
	(0.246)	(0.215)	(0.231)	(0.254)	(0.217)	(0.230)
cap_intens	−2.010	−2.915**	−2.813*	0.100	−2.545*	−1.793
	(1.512)	(1.319)	(1.462)	(1.592)	(1.322)	(1.443)
emp_tech	7.050***	5.958***	6.008***	6.627***	6.088***	3.371*
	(1.712)	(1.476)	(1.763)	(1.750)	(1.542)	(1.776)
hum_cap	−0.949	−0.725	−5.222	−2.655	−1.637	−6.659
	(2.462)	(2.198)	(6.322)	(2.476)	(2.207)	(6.232)
Constant	7.611	17.411	62.230	13.054	6.471	79.569
	(6.404)	(26.428)	(73.849)	(29.066)	(26.457)	(72.832)
Obs.	908	1,021	864	908	1,021	864
lnL	−1038.07***	−1237.68***	−995.16***	−1304.87***	−1234.69***	−985.16***
	(154.22)	(226.72)	(161.74)	(98.08)	(121.20)	(94.00)

Notes: Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Industry dummies (tech2, tech3 and tech4 defined on page S143) are included in each regression.

respectively. As for the R&D complementarities, only *rd23* survives the endogeneity adjustment as its coefficient is significantly positive under the two-step procedure[21]. The significantly positive coefficient for *rd23* suggests that R&D complementarity only exists between external R&D (*rd2*) and cooperative R&D (*rd3*), which contradicts what we have obtained in Table 3, where complementarities between pair-wise R&D strategies are all significant given that the

[21] Even though the coefficients of *rd12* and *rd13* are both positive, they are not statistically significant to argue the existence of complementarity between internal vs. external and cooperative R&D strategies.

innovation output is estimated by the sales ratio from new products. Hence, the estimation results will largely depend on the measure chosen for innovation output. When innovation output is measured by the firms' patents sales, the complementarity between external R&D and cooperative R&D implies that firms requiring patent knowledge externally can further increase their marginal return by increasing the level of R&D cooperation, and vice versa. As for the performance of the other explanatory variables in Table 4, *emp_tech*, the number of highly-educated employees, has significant effects on innovation output. This suggests that the more professional personnel that firms hire, the higher the innovation output that firms are able to generate.

Lastly, when we measure the innovation output by the marginal return on R&D investment (INNOV3), the estimation results are report in Table 5. Regarding the separate performance of *rd1*, *rd2* and *rd3*, only internal R&D (*rd1*) both significantly and positively affects the innovation output, while the effects of external R&D (*rd2*) and cooperative R&D (*rd3*) are non-robust and indeterminate. We also see that the complementarities between R&D strategies are supported by estimating the results in both models with and without selection equations. However, the complementary effects may be biased downwards under models without selection equations, as the coefficients estimated for *rd12*, *rd13* and *rd23* are smaller in models (1), (2) and (3), than those in models (4), (5) and (6). In addition, Table 5 also shows that the complementary effect between *rd1* and *rd2* is the strongest among pair-wise combinations of R&D strategies, and the effect between *rd2* and *rd3* is the smallest. We note that Tables 3 and 5 reach consistent results in the sense that pair-wise complementary effects are confirmed regardless of using the marginal return on RD investment or the sales share of new products as the R&D output indicator. Tables 3 and 5 also indicate that internal R&D (*rd1*) and external R&D (*rd2*) can together help firms the most. As for the effects of the other control variables, models with or without selection equations have similar results. In particular, we observe that both firm size (*opert_rev*) and human capability (*hum_cap*) have significant positive impacts on the innovation output. It is worth noting that Tables 3 and 5 generate different estimation results for the firm size effect. A possible explanation may lie in the measurement of innovation output. This is because, for the introduction of new products, the determining reasons may not be the scale of the firms' operations, but the firms' creative ideas. The large firm can produce more new products but is not easier to get large proportion of sales from new products, while the small firm is the opposite[22]. On the contrary, the return on the R&D input usually depends on the accumulation of previous investment. Large firms are more capable of accumulating their R&D assets and generating higher R&D returns.

According to the above discussions, in summary, we can see that different measures of innovation output will generate different estimation results even though some complementarity effects are quite robust. It is useful to have several variables for innovation output with which to make comparisons from previous studies. Table 6 lists the comparison of complementarity effects among different R&D strategy combinations. As the innovation output is measured by the sales share of new products (INNOV1), we find that complementary effects are prevailing in all three R&D combinations under consideration in this paper (see the second

[22] We owe this interpretation to an anonymous referee.

Table 5. Estimation results of innovation output (measured by marginal return to R&D investment)

	Tobit w/o selection equations			**Tobit with selection equations**		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
rd1	0.621**	0.551**	–	1.075***	1.068***	–
	(0.258)	(0.251)		(0.391)	(0.384)	
rd2	0.410	–	0.396	1.168***	–	–0.144
	(0.417)		(0.391)	(0.410)		(0.624)
rd3	–	0.794**	0.777**	–	0.736	–0.280
		(0.342)	(0.330)		(0.466)	(0.528)
rd12	0.165	–	–	1.407***	–	–
	(0.498)			(0.401)		
rd13	–	0.674**	–	–	1.245***	–
		(0.289)			(0.332)	
rd23	–	–	0.876***	–	–	0.898***
			(0.299)			(0.285)
yr	0.023*	0.034***	0.024**	0.016	0.033***	0.021*
	(0.003)	(0.100)	(0.012)	(0.011)	(0.100)	(0.012)
opert_rev	0.383***	0.484***	0.386***	0.281**	0.365***	0.357***
	(0.113)	(0.105)	(0.111)	(0.121)	(0.113)	(0.111)
profit_ratio	0.004	0.018	0.006	0.001	0.025*	0.009
	(0.113)	(0.014)	(0.016)	(0.016)	(0.014)	(0.016)
cap_intens	0.035	–0.048	–0.090	0.152	–0.051	–0.058
	(0.101)	(0.093)	(0.098)	(0.108)	(0.094)	(0.099)
emp_tech	0.183*	0.136	0.217**	0.130	0.124	0.149
	(0.105)	(0.097)	(0.110)	(0.106)	(0.101)	(0.114)
hum_cap	1.000***	1.122***	0.743*	0.942***	1.151***	0.780*
	(0.361)	(0.333)	(0.393)	(0.361)	(0.340)	(0.401)
Constant	–20.974***	–23.185***	–17.095***	–20.016***	–22.405***	–17.325***
	(4.357)	(4.039)	(4.696)	(4.358)	(4.103)	(4.790)
Obs.	901	1,011	852	901	1,011	852
lnL	–523.954***	–679.057***	–395.250***	–519.011***	–675.645***	–394.048***
	(247.30)	(371.86)	(195.99)	(257.19)	(378.68)	(198.39)

Notes: Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Industry dummies (tech2, tech3 and tech4 defined on page S143) are included in each regression.

column in Table 6). In contrast to Love and Roper (1999, 2001), who find substitutive effects between the internal and external R&D, we conclude that these two types of R&D activities are complementary. In the case of internal vs. cooperative R&D, previous studies (e.g. Becker, Peters 2000; Schmiedeberg 2008; Jirjahn, Kraft 2011) tend to obtain a weak complementary or substitutive relationship (Table 6), while this study shows a significant complementary effect as found in Serrano-Bedia *et al.* (2012). Furthermore, a firm which conducts both the external and cooperative R&D is likely to increase the sales share of new products, indicating a complementary effect.

Table 6. Comparison of complementarity effects among different R&D strategies under different measures of innovation output

	Innovation output		
R&D types	New products (sales shares or #)	Patents (# or 0/1)	R&D return
int-ext R&D	Love & Roper (1999): **S**	This study: **WC**	This study: **C**
	Love & Roper (2001): **S**		
	Cassiman & Veugelers (2002): **C**		
	Serrano-Bedia *et al.* (2012): **C**		
	This study: **C**		
int-coop R&D	Jirjahn & Kraft (2011): **WS**	Jirjahn & Kraft (2011): **S**	This study: **C**
	Schmiedeberg (2008): **WS**	Schmiedeberg (2008): **C**	
	Becker & Peters (2000): **WC**	Becker & Peters (2000): **C**	
	Serrano-Bedia *et al.* (2012): **C**		
	This study: **C**	This study: **WC**	
ext-coop R&D	This study: **C**	This study: **C**	This study: **C**
	Serrano-Bedia *et al.* (2012): **WS**		

Notes: 1) **C** denotes a significant complementary effect; 2) **WC** denotes a weak (insignificant) complementary effect; 3) **S** denotes a significant substitutive effect; 4) **WS** denotes a weak (insignificant) substitutive effect.

As the innovation output is measured by the sales share of patents (INNOV2), we confirm the complementarity only in performing external and cooperative R&D. Other two R&D strategy pairs seem to be weakly (i.e. insignificantly) complementary. As for the internal vs. cooperative R&D, the relationship is mixed in the literature – substitutive in Jirjahn and Kraft (2011) and complementary in Schmiedeberg (2008) and Becker and Peters (2000). Our finding of weak complementarity is in-between. In regard to the third measure of innovation output (i.e. the marginal return to R&D investment), it is new in testing complementarity in the literature. In all three R&D strategy pairs, the complementarity is significantly supported.

Conclusions

To engage in innovation activities, firms cannot rely solely on internal sourcing, but also require knowledge from beyond their boundaries when developing their innovations (Rigby, Zook 2002). Hence, firms may simultaneously engage in many types of R&D strategies, and the joint occurrence of multiple R&D activities is suggestive of R&D complementarities, meaning that the marginal return on one activity increases as the level of the other activity increases (Cassiman, Veugelers 2002). A good understanding of complementarities is not only helpful for firms' R&D decisions but also crucial for government industry policies. If the complementarity is prevailing across various types of R&D combinations, one would expect that an ideal design of public policies that give incentives to adopt one R&D strategy should take into account the "externalities" of such policies for other areas of decision of firms. However, while there are a large number of empirical studies on R&D complementarities, the empirical results are fairly mixed among the different countries, different samples and different measurements of innovation output. Besides, most studies merely discuss the complementarity between *two* R&D strategies. In addition, most of them fail to take the firms' strategy selection problem into account, and directly jump into the innovation output analysis (or productivity approach). This may result in an endogeneity problem and thereby produce inconsistent estimates. In addition, to the best of our knowledge, the innovative activities vs. multiple R&D strategies nexus has not yet been extensively studies for the case of the newly-industrialized country.

To fill the gap in the literature, we attempt to uncover the complementarity between multiple R&D strategies in Taiwan – a newly-emerging country. The 2003 First Taiwan Technological Innovation Survey (TTIS-I) in the Taiwan Area was carried out in accordance with the Community Innovation Survey. The results on the basis of Taiwanese data can then make comparable to previous studies in developed countries such as German, Belgium, UK, Ireland, and Spain. Besides, we empirically test the pair-wise R&D complementarities among *three* R&D strategies, namely, internal R&D, external R&D and cooperative R&D. Moreover, to alleviate the potential endogeneity problem caused by firms' choices of R&D strategies, we apply a two-step procedure by combining the so-called adoption approach (first step) and productivity approach (second step). We show that the results of the estimation for R&D complementarities could be biased upwards or downwards if we do not take first stage R&D strategy selection into account in the second stage estimation of innovation output. Since the complementarity effect hinges on the measurements of innovation output, we make use of a firm's sales ratio for new products, sales ratio for patents and the marginal rate of return on R&D investment to test the validity of complementarities. The first two proxies are frequently used in the recent literature (Becker, Peters 2000; Beneito 2006; Belderbos *et al.* 2006; Cassiman, Veugelers 2002; Love, Roper 2001; Schmiedeberg 2008). To address the issue on the measurements of innovation output, our third measure adds to the literature on testing R&D complementarities by measuring the R&D investment output directly.

Our empirical results strongly support the existence of R&D complementarities among three types of R&D strategies – internal, external and cooperative R&D strategies, when innovation outputs are measured by sales share of new products and marginal return to R&D investment. This finding suggests that firms' are not making a traditional make-or-buy R&D decisions like traditional transaction cost theory, which suggests that the availability of external knowledge may serve as a substitute for own R&D investment (Williamson 1985). By contrast, the complementary relationship between internal and external R&D can be understood in terms of either absorptive capacity or economies of scope (knowledge spillover). Compared to previous studies, our finding is in line with Cassiman and Veugelers (2002) but in contrast to Love and Roper (1999, 2001), where the substitutive effect is obtained. We also find that the complementary effect between internal R&D and external R&D are the strongest in magnitude, indicating that firms benefit most from adopting this particular combination of R&D strategies. In addition, in some cases conducting two external-type R&D activities (i.e. external and cooperative R&D) generate similar marginal effects on sales share of new products to those of the combination of internal and external R&D strategies. We notice that using a direct measure of R&D output (marginal return to R&D investment) markedly leads to significant complementarities among all three R&D combinations.

When innovation output is measured by the sales ratio from patents, however, R&D complementarity only exists between external R&D and cooperative R&D. This implies that firms simultaneously adopting multiple sources of external knowledge can facilitate firms' patents production. Becker and Peters (2000) and Schmiedeberg (2008) find internal and cooperative R&D are complementary even though Jirjahn and Kraft (2011) concludes a substitutive effect. Our finding is in-between in that the coefficient estimate of internal and cooperative R&D is positive but is not statistically significant.

To sum up, using a manufacturing firm-level data set from the newly-industrialized country – Taiwan, generally we are able to establish the complementarities between three alternative R&D strategies. The complementary effects are supported not only between internal and external-oriented (including external and cooperative) R&D, but also between two external-oriented R&D strategies. Would our finding still hold for other emerging countries? Why does the interaction between two external R&D sources generate a consistent impact on three different innovation outputs? What is the mechanism behind this particular R&D adoption? It would be interesting and worthwhile for future work to examine those issues.

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APPENDIX TABLES

Table A-1. Summary statistics

Variables	Mean	S.D.	Min	Max	Obs.
INNOV1	23.250	30.244	0	100	1,379
INNOV2	7.875	18.914	0	100	1,379
INNOV3	3.559	33.013	–0.6551	904.867	1,379
internal R&D	0.347	0.476	0	1	1,379
external R&D	0.226	0.419	0	1	1,379
cooperative R&D	0.311	0.463	0	1	1,379
yr	19.650	10.702	0	88	1,379
opert_rev	11.978	2.256	0	19.552	1,379
profit_ratio	6.007	7.185	0	68.595	1,379
cap_intens	6.707	1.400	0	10.882	1,379
computer_using	0.949	0.220	0	1	1,379
emp_tech	2.387	1.712	0	8.676	1,379
hum_cap	12.829	0.627	0	14.354	1,379
innov_intensity	6.832	12.247	0	200	1,379
imped_eco	0.142	0.277	0	2	1,379
imped_inner	0.177	0.315	0	2	1,379
imped_exter	0.119	0.269	0	2	1,379
extern_finance	0.131	0.337	0	1	1,379
tech1	0.242	0.428	0	1	1,379
tech2	0.194	0.396	0	1	1,379
tech3	0.325	0.469	0	1	1,379
tech4	0.191	0.393	0	1	1,379

Table A-2. Multivariate probit results of choosing R&D strategies

Variables	Internal R&D		External R&D		Cooperative R&D	
yr	–0.006	(0.004)	0.005	(0.004)	0.002	(0.004)
opert_rev	0.363***	(0.038)	0.077**	(0.040)	0.105***	(0.038)
profit_ratio	–0.013**	(0.006)	0.005	(0.006)	–0.003	(0.006)
cap_intens	–0.036	(0.038)	–0.042	(0.378)	0.001	(0.036)
computer_using	–0.227	(0.269)	0.041	(0.243)	0.547*	(0.293)
employee_tech	0.055	(0.040)	0.065	(0.041)	0.099**	(0.040)
hum_cap	–0.071	(0.070)	0.259*	(0.140)	0.188	(0.132)
innov_intensity	0.011***	(0.003)	0.006*	(0.003)	0.004	(0.004)
imped_eco	0.201	(0.173)	0.140	(0.171)	0.155	(0.167)
imped_inner	0.169	(0.166)	0.372**	(0.161)	0.521***	(0.158)
imped_exter	0.109	(0.192)	0.388**	(0.188)	0.189	(0.185)
extern_finance	0.377***	(0.120)	0.715***	(0.111)	0.900***	(0.115)
tech2	–0.126	(0.121)	0.184	(0.124)	–0.194	(0.118)
tech3	0.083	(0.102)	0.222**	(0.107)	0.086	(0.100)
tech4	0.139	(0.119)	0.292**	(0.121)	–0.079	(0.117)
constant	–3.656***	(0.810)	–5.570***	(1.634)	–5.296***	(1.556)
$\hat{\rho}_{12}$			–0.005	(0.055)		
$\hat{\rho}_{13}$			0.240***	(0.051)		
$\hat{\rho}_{23}$			0.569***	(0.041)		
lnL			–1915.893***	(658.70)		
Obs.	1,379					

Table A-3. Estimation results of innovation output (measured by whether applying for a patent)

	Probit w/o selection equations			Probit with selection equations		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
rd1	0.227*	0.288**		–0.121	0.078	–
	(0.134)	(0.131)		(0.213)	(0.207)	
rd2	0.443**	–	0.572***	0.472***	–	0.529***
	(0.189)		(0.180)	(0.163)		(0.180)
rd3	–	0.223	0.283	–	0.761***	0.261
		(0.173)	(0.165)		(0.174)	(0.219)
rd12	0.404		–	0.183	–	–
	(0.261)			(0.186)		
rd13	–	0.600***	–	–	0.055	–
		(0.154)			(0.173)	
rd23	–	–	0.588***	–	–	0.595***
			(0.152)			(0.135)

Continued Table A-3

	Probit w/o selection equations			Probit with selection equations		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
yr	–0.009	–0.004	0.001	–0.012**	–0.005	–0.001
	(0.006)	(0.005)	(0.005)	(0.06)	(0.005)	(0.042)
opert_rev	–0.021	–0.027	0.031	0.005	0.025	0.005
	(0.043)	(0.042)	(0.042)	(0.047)	(0.045)	(0.425)
profit_ratio	–0.002	–0.002	–0.002	–0.008	–0.003	–0.003
	(0.007)	(0.006)	(0.007)	(0.046)	(0.007)	(0.007)
cap_intens	–0.053	–0.098**	–0.076*	0.244***	–0.085**	–0.058
	(0.042)	(0.039)	(0.040)	(0.051)	(0.040)	(0.041)
emp_tech	0.249***	0.217***	0.124**	0.244***	0.222***	0.083
	(0.050)	(0.047)	(0.051)	(0.051)	(0.050)	(0.053)
hum_cap	–0.144**	–0.110*	–0.112	–0.176***	–0.128**	–0.123
	(0.067)	(0.064)	(0.093)	(1.750)	(0.064)	(0.095)
Constant	1.424*	1.333	0.530	1.317*	0.939	0.915
	(0.787)	(0.776)	(1.108)	(0.749)	(0.769)	(0.221)
Obs.	908	1,021	864	908	1,021	864
lnL	–421.360***	–489.968***	–415.747***	–420.352***	–488.496***	–415.794***
Pseudo Rsq	0.1104	0.1105	0.0762	0.1125	0.1131	0.0761

Notes: Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Industry dummies (tech2, tech3 and tech4 defined on page S143) are included in each regression.

Eric S. LIN, BA in Economics (National Taiwan University, 1993); MA in Economics (National Taiwan University, 1995); PhD in Economics (University of Texas at Austin, 2004); Professor, Department of Economics, National Tsing Hua University (2013). His research and publications are in the areas of economic forecasting, industrial economics, labor economics, and defence economics.

Yi-Chi HSIAO, BA in Economics (National Central University, 2002); MA in Economics (National Taiwan University, 2004; University of Texas at Austin, 2008). Now he is a PhD student in the Department of Strategy and Management at National Taiwan University. Research interests include applied econometrics and industrial organization.

Hui-lin LIN is a Professor at the Department of Economics and the Dean of Social Sciences, National Taiwan University. She earned PhD from Brown University at USA in May 1991. She has been a professor of economics for 20 years. She has published many articles in international journal and 5 books in Taiwan. Her research focuses on econometrics, industrial economics and economic innovation.