In Search of Complementarity in the Innovation Strategy: Internal R&D and External Knowledge Acquisition[*]

by

Bruno Cassiman
IESE Business School[a]

and

Reinhilde Veugelers
Katholieke Universiteit Leuven and CEPR[b]

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[a] IESE Business School, Universidad de Navarra, Avenida Pearson 21, 08034 Barcelona, Spain; Email: bcassiman@iese.edu ; Tel: 34-932 534 200; Fax: 34-932 534 343.
[b] Naamsestraat 69, 3000 Leuven, Belgium, Email: Reinhilde.Veugelers@econ.kuleuven.ac.be; Tel: 32-16-32 69 08; Fax: 32-16-32 67 32.

Abstract

Successful innovation depends on the development and integration of new knowledge in the innovation process. In order to successfully innovate, the firm will combine different innovation activities. In addition to doing own research and development, firms typically are engaged in the acquisition of knowledge on the technology market. In this paper we provide evidence consistent with complementarity between these different innovation activities, i.e. the marginal returns to one activity are increasing in the other activity. Using data from the Community Innovation Survey on Belgian manufacturing firms, we first show that firms that are only engaged in a single innovation activity, either internal R&D activities or sourcing technology externally, introduced fewer new or substantially improved products compared to firms which combine internal and external sourcing. Next, we find that the different innovation activities are strongly positively correlated and identify the reliance on basic R&D as a source of complementarity between internal and external innovation activities. Furthermore, given that the effectiveness of strategic protection only directly affects the incentive to source internally, it provides evidence for the existence of complementarity because of a positive (indirect) effect on external knowledge acquisition. While we should interpret these results cautiously, taken together they do provide more convincing evidence for complementarity between different innovation activities.

Keywords: Complementarity, Innovation, R&D, Technology Acquisition.

JEL classification: D21, O31, O32

Introduction

Today even the largest and most technologically self-sufficient organizations not only rely on internal sourcing but require knowledge from beyond their boundaries when developing their innovation strategy (Rigby and Zook, 2002). In addition to doing own research and development, firms typically tap knowledge sources external to the firm through licensing, contracting out R&D, acquisitions and attracting qualified researchers embodying relevant knowledge (Arora and Gambardella, 1994; Cockburn and Henderson, 1998; Granstrand et al., 1992). The joint occurrence of these internal and external knowledge development activities at the firm level is suggestive of complementary between these activities, i.e. the marginal returns to one activity increase in the level of the other activity. Own internal know-how will increase the marginal return to external knowledge acquisition strategies. This is reminiscent of the notion of 'absorptive capacity' introduced by Cohen and Levinthal (1989) stressing the importance of a stock of prior knowledge to effectively scan, screen and absorb external know-how. At the same time the access to external know-how may leverage the efficiency of the internal R&D activities.

This paper contributes to the analysis of complementarity in innovation activities by analyzing both the organization of the firm's innovation strategy and its effect on the performance of the innovation process. If the innovation activities of a firm are found to be complementary, an important task for innovation management will be to optimally integrate internal and external knowledge within the firm's innovation process, to be able to benefit from the positive effects each innovative activity has on the other. In the presence of complementarities, a firm that has decided to be an innovator rather than an imitator will, by combining different activities in its innovation strategy, attain a higher probability of generating innovative output. Concentrating on one activity, be it some own R&D or buying technology on the external technology market, will have a lower probability of being successful in the absence of supporting—complementary— innovative activities. But not only establishing whether complementarity exists is vital, also identifying contextual variables affecting complementarity is important for managing the complementarity between the different innovation activities, if the innovation process is to constitute a source of sustainable competitive advantage (Porter and Siggelkow, 2000).

While the theoretical literature has only started to unravel the complex links between internal and external sourcing, it is not surprising that the existing empirical literature is far from being able to provide hard evidence on complementarity in the innovation strategy, despite the wider casual empirical evidence available on the combination of internal and external sourcing strategies. This paper presents a careful and rigorous empirical analysis of the complementarity between the activities of the innovation strategy where we restrict attention to own R&D and external knowledge acquisition. We combine evidence from the performance of innovation strategies and the strategy adoption choices. Two main questions are addressed. First, are innovation activities indeed complementary? And second, why are innovation activities complementary? Although our results are not conclusive on the issue of complementarity between internal and external innovation activities, we provide better insights on the joint occurrence of these activities and on the possible drivers of complementarity. Reliance on more basic R&D is identified as such a driver, increasing the knowledge development potential of combining internal and external innovation activities.

The paper is structured as follows. The next section describes the literature on complementarity. Section 2 discusses the theoretical and empirical issues related to assessing complementarity. Section 3 presents the data while in Section 4 we analyze the results of two econometric methods to assess complementarity: the productivity approach and the adoption approach. Section 5 concludes.

1. In Search of Complementarity

Although transaction cost theory suggests that the availability of external knowledge may substitute for own R&D investment (Williamson, 1985, Pisano, 1990), both casual evidence and more careful empirical research suggest the existence of complementarity between in-house R&D and external know-how. A number of studies report casual empirical evidence consistent with complementarity among innovation activities. The Sappho study (Rothwell, 1974) identified successful innovative firms, as those that developed better internal and external communication networks allowing a more efficient use of external know-how. While examining the critical success factors of 40 innovations, Freeman (1991) found that external sources of technical expertise combined with in-house basic research that facilitate these external linkages were crucial in explaining success of the innovation. More recently, Rigby and Zook (2002) have argued the benefits from opening up the innovation process to external knowledge flows, the so called "open-market" innovation. Their case studies show that combining internal and external information sourcing is a critical new source of competitive advantage in some of the fastest growing and most profitable industries.

The relation between internal and external sourcing is more rigorously explored in Arora and Gambardella (1994), where they discuss two effects from internal know-how on external sourcing. On the one hand, internal know-how is necessary to screen available projects. On the other hand, internal know-how serves to effectively utilize the assessed external know-how. Using scientific know-how as a proxy for the former, and technological know-how for the latter, they find support for both hypotheses about complementarity between internal and external know-how sourcing. This evidence suggests that the scientific-technological orientation of the R&D of the firm might be an important driver of the observed complementarity between internal and external technology acquisition. Also Rosenberg (1990) identifies the importance of basic research. He puts it as follows: "A basic research capability is often indispensable in order to monitor and evaluate research being conducted elsewhere." Viewed in its capacity to absorb external information efficiently into the in-house innovation activities, the basic R&D orientation of the firm will act as an important driver for the joint occurrence of these activities and their observed complementarity. Veugelers (1997) investigates the reverse relation, namely that external sourcing stimulates internal R&D expenditures, at least for firms with internal R&D departments. Arora and Gambardella (1990) examine the complementarity among four different external sourcing strategies of large chemical and pharmaceutical firms in biotechnology: agreements with other firms, partnerships with universities, investments in and acquisitions of new biotechnology firms. They find evidence for the joint occurrence of all types of external sourcing strategies, even after correcting for a set of firm characteristics. Furthermore, the correction for firm characteristics suggests that large firms with higher internal knowledge, measured by number of patents, are more actively involved in pursuing any combination of external linkages. Finally, Veugelers and Cassiman (1999) provide evidence on firm characteristics driving the choice of internal know-how development and external sourcing at the firm level. They show firms with effective strategic protection mechanisms, such as secrecy, lead-time and complexity, are more likely to be involved in internal knowledge sourcing. No explicit test on complementarity is provided though.

Although all these papers deal with the joint occurrence of internal and external knowledge sourcing activities, in the absence of evidence on the performance of the different innovation strategies, they fall short of a direct test of complementarity,. To the best of our knowledge this paper is the first to systematically examine complementarity between different activities of the firm's innovation strategy, combining two econometric methods to assess complementarity: to the more common adoption approach we add an analysis of the performance of different innovation strategies. Together these approaches do provide more convincing evidence for complementarity between different innovation activities. Going beyond the mere identification of complementarities, the analysis will also focus on the sources of this perceived complementarity.[1]

Before we present the data and the empirical results, we first elaborate the methodology used to establish complementarity between innovation activities.

2. *Measuring Complementarity*

2.1 Theory

The notion of fit or complementarities between activities thrives in the management literature, but often as an ill defined concept. The formal foundations for the study of complementarities between activities can be traced back to the theory of supermodularity (see Milgrom and Roberts, 1990 and 1995). This elegant

[1] In a related paper Cockburn et al. (2000) explain the source of the observed complementarity between providing high powered incentives in basic research and in applied research within research teams in pharmaceutical companies as the outcome of a multitasking problem. Novak and Stern (2003), in the context of vertical integration, explain the source of complementarity between integration decisions through the effect of the vertical integration decision in different activities on the non-contractible coordination effort across these activities and trade secret protection.

mathematical theory states the necessary conditions for activities to be complementary.

Definition

Suppose there are 2 activities A_1 and A_2, each activity can be done by the firm ($A_i = 1$) or not ($A_i = 0$) and $i \in \{1, 2\}$. *The function $P(A_1, A_2)$ is supermodular and A_1 and A_2 are complements only if:*

$$P(1, 1) - P(0, 1) \geq P(1, 0) - P(0, 0),$$

i.e. adding an activity while already performing the other activity has a higher incremental effect on performance (P) than when doing the activity in isolation.

Two interesting empirical predictions follow from this theory (See Arora, 1996; Athey and Stern, 1998).

Result 1 (correlation)

Assume $P(A_1, A_2, X)$ is supermodular in A_1, A_2 and X, and, X is a vector of exogenous variables. Then $A^*(X) = (A_1^*(X), A_2^*(X))$, the optimal choice of activities, is monotone non-decreasing in X. In a cross sectional study (heterogeneity in X across firms), $A_1(X)$ and $A_2(X)$ will be positively correlated.

Result 2 (excluded variable)

An increase in X_i might only influence activity A_1 directly. But because of the complementarity between the activities A_1 and A_2, X_i will affect activity A_2 indirectly. A_2^* will, therefore, be non-decreasing in X_i in the presence of complementarity.

The first result states that two activities that are complementary will be positively correlated whenever the performance function is supermodular in the activities and the exogenous variables. The amount of publicly available information might positively affect the likelihood of increasing own R&D and at the same time increase knowledge about external technologies and, hence, external technology acquisitions. Empirically we would, therefore, observe positive correlation between the make and buy activities which would be consistent with complementarity between these activities.[2] The second result is a much stronger manifestation of complementarity.

[2] Positive correlation, however, is neither necessary nor sufficient for complementarity if the conditions specified supra, do not hold (Arora, 1996). The main problem is that unobserved heterogeneity between different observations could bias the estimation results and can lead both to accepting the hypothesis of complementarity while none exists, or, to rejecting the hypothesis of complementarity when activities in fact are complementary. Athey and Stern (1998) review the problems related to different estimation methods.

Suppose that in-house R&D and external technology sourcing are complementary activities and that the ability to protect innovations through secrecy is an exogenous variable in the environment only affecting the likelihood of doing own R&D. Then, as result 2 states, in addition to the *direct effect* of the ability to protect through secrecy on own R&D activities, we should find an *indirect effect,* increasing external technology acquisition activities because of the complementarity between the activities of technology buying on the one hand, and, own R&D investments on the other.

The theory of supermodularity helps to clarify the notion of complementarity and as such is very helpful for empirical research aimed at establishing the existence of complementarity. However, since the theory takes supermodularity as a characteristic of the profit function $P(A_1, A_2)$, it leaves open the discussion on whether complementarity is exogeneously determined by technology or profit function characteristics or can endogeneously be influenced by firm strategy choices. In the latter case, we argue that these strategy choices are sources of perceived complementarity between innovation activities.

2.2 Empirical Model

The empirical model explains our search for evidence of complementarity between innovation activities. We focus not only on the existence of joint occurrence of activities but also, by looking at the characteristics of firms choosing combinations of innovation activities, contribute to the discussion on sources of complementarity. Although with the data available we are unable to unambiguously prove complementarity, the analysis offers a wide diversity of evidence consistent with complementarity.

2.2.1 Productivity (direct) approach

In the productivity approach we regress a measure of performance of the innovation process on exclusive combinations of innovation activities. In particular, we create a dummy variable that indicates whether the firm performed internal R&D (*MAKE*) or acquired technology externally (*BUY*). From these dummy variables we construct different exclusive categories: firms that have no innovation activities (*NoMake&Buy*); firms that only have own R&D activities (*MakeOnly*); firms that only have external technology acquisitions (*BuyOnly*); and, firms that combine own R&D activities and external technology acquisition (*Make&Buy*).

The innovation performance measure used is the percentage of sales that are generated from new or substantially improved products that have been introduced in the past two years ($\Pi(A_1, A_2)$)[3]. By restricting the performance measure to innovative performance only rather than overall firm performance, we attempt to reduce the problem of having to correct for other sources of firm heterogeneity that influence overall performance. Furthermore, innovation performance has been linked to overall firm performance (o.a. Crépon et al (1998)). We estimate the following equation:

$$\Pi^i\left(A_1^i, A_2^i, X^i; q, b\right) = \left(1-A_1^i\right)\left(1-A_2^i\right)q_{00} + A_1^i\left(1-A_2^i\right)q_{10} + \left(1-A_1^i\right)A_2^i q_{01} + A_1^i A_2^i q_{11} + X^i b + e^i$$

where superscript *i* refers to firm *i* and $A_j^i \in \{0,1\} \quad \forall j = 1,2$ indicating the innovation activity choices of firm *i*.[4] The q_{kl} are the coefficients on the innovation strategy choice of the firm. X^i is a vector of (exogenous) control variables affecting innovative performance. The test for complementarity between two innovation activities, A_1 and A_2, is:

$$q_{11} - q_{10} \geq q_{01} - q_{00} \tag{1}$$

Adding an activity while already performing another activity will result in a higher incremental performance than when choosing the activity in isolation. The proposed test follows directly from the theoretical development of complementarity and establishes complementarity conditional on having unbiased estimates for the *q*-coefficients. A maintained assumption for this analysis to provide unbiased estimates

[3] The innovative performance measure we use only relates to new or improved products while the innovative activities can relate both to new and improved products and processes. Fortunately, most of the companies in the sample combine product and process innovation trajectories and the few firms that report only process innovation activities also report having introduced new or improved products, indicating that process innovations are typically conducive to improvements in products. Miravete and Pernias (1999) analyse the complementarity between product and process innovations.

[4] *MAKE* is A_1=1 while *BUY* is A_2=1

$NoMakeBuy = (1-A_1)(1-A_2), MakeOnly = A_1(1-A_2), BuyOnly = (1-A_1)A_2, Make\&Buy = A_1A_2$

is that the drivers of adoption decisions are uncorrelated with the error term e^i. In section 2.2.3 we discuss this restriction. Ichniowski, Shaw and Prennushi (1997) need a similar restriction to study the effects of human resource management practices on productivity in a sample of steel finishing lines. They find that there are important complementarities between different human resource management practices as firms that are able to combine these activities properly, significantly outperform their counterparts in the industry.[5]

2.2.2 Adoption (indirect) approach

First, we examine simple correlations between the different innovation activities. As discussed before, positive correlation between innovative activities is consistent with complementarity ($\mathrm{corr}(A_i, A_j) > 0$), but it is neither necessary nor sufficient (Arora, 1996). Positive correlation can be due not only to complementarity, but also to common observable or unobservable variables or common measurement error.

Second, we regress the innovation activities on assumed exogenous control variables (Z^i) fitting both a multinomial logit model and a bivariate probit model. The **multinomial logit** model examines the drivers for the combinations of innovation activities (in casu: *NoMake&Buy*; *MakeOnly*; *BuyOnly*; *Make&Buy*). This can be done if the number of categories is not too large and there is sufficient variation in each category. We estimate the following model of innovation strategy choice:

$$\Pr ob(Y = j) = \frac{e^{Z^i d_j}}{\sum_{k=1}^{4} e^{Z^i d_k}},\ j \in \{NoMake\&Buy(0), MakeOnly(1), BuyOnly(2), Make\&Buy(3)\}$$

where Z^i is a vector of characteristics of firm i.

The **bivariate probit** estimates the activities non-exclusively (*MAKE* and *BUY*) but takes the correlation between them into account explicitly as in the following model:

[5] The advantage of Ichniowski et al. (1997) is that they have plant level data available of firms with similar technologies, which avoids having to control for technology characteristics. Our data, being a cross section of all manufacturing firms, is likely to be noisier in innovation production practices.

$$A_1^{i^*} = Z^i g_1 + n_1^i, \quad A_1^i = 1\, if\ A_1^{i^*} > 0,\ 0\, otherwis$$

$$A_2^{i^*} = Z^i g_2 + n_2^i, \quad A_2^i = 1\, if\ A_2^{i^*} > 0,\ 0\ otherwise$$

$$E[n_1] = E[n_2] = 0, Var[n_1] = Var[n_2] = 1, Cov[n_1, n_2] = r,$$

We assess the joint occurrence of innovation activities and complementarity between these activities by contrasting the results of both models.[6] The multinomial logit model reveals drivers of the different innovation strategies. Two types of adoption drivers are distinguished: drivers that affect the joint adoption and drivers that affect one of the activities exclusively. Both of these drivers explain the observed correlation between *MAKE* and *BUY* activities. Variables that show up significantly in the multinomial logit results for *Make&Buy*, while not being significant for other innovation strategy choices, are drivers of the joint occurrence. This can be further confirmed in the bivariate probit results where these variables should show up significantly both in *MAKE* and *BUY*. Furthermore, including these variables in the adoption choices should reduce the positive correlation between the error terms in the bivariate probit. Control variables that affect only one of the innovation activities directly, for example *MAKE*, should show up significant in the exclusive categories *MakeOnly* and *Make&Buy* in the multinomial logit. But, for evidence of complementarity, these variables should show up significant in both the *MAKE* and the *BUY* regression in the bivariate probit as complementarity has an indirect effect on the adoption of *BUY*. These exclusive drivers allow us to test complementarity between innovation activities through the exclusion restrictions.

2.2.3 Combining performance and adoption

There are difficulties associated with using either a performance or an adoption approach. For the adoption approach, we are unable to unequivocally conclude that complementarity exists if generalized residuals, i.e. residuals after controlling for different types of drivers, remain correlated. This correlation might be a mere result of some firm specific effect that we didn't control for or a common measurement error. Nevertheless, this is where the earlier literature has left of.

[6] Note that comparison of results has to be handled with care given that we are comparing a logit with a probit.

Furthermore, these same unobserved firm-specific effects can cause the coefficients of the productivity regression to be biased, if they also enter the productivity error term, as an unobserved explanatory factor for productivity as well, as indicated above. Panel data would allow including firm fixed effects (Miravete and Pernias (1999)). Our data set does not permit a panel data structure. In addition, we are interested in finding the drivers for complementarity and, therefore, are more concerned about uncovering the sources for any firm fixed effect rather than to merely correct for them.

As Athey and Stern (1998) suggest, it would be more efficient to jointly estimate the system of innovation activities and the productivity equation. We develop a two step procedure in an attempt to improve our estimation while correcting for the potential biases due to unobserved heterogeneity. The organization of the innovation strategy, i.e. which innovation activities are selected, is an endogenous decision by the firm. It is precisely the firm heterogeneity in the drivers for the innovation strategy choice that we do not control for in the productivity estimation, that may cause a bias when estimating the θ's, when correlated with the error term (ε^i) of the productivity equation.

The two-step procedure uses the predicted values of the adoption approach as instruments for the innovation strategy of the firm in the productivity regression, as such controlling for the potential selection bias due to unobserved heterogeneity.[7] If the innovation strategy remains significant in explaining differences in performance, the effect can be attributed to intrinsic complementarity between innovation activities in the innovation production function. For this procedure to successfully remove the problem of unobserved firm heterogeneity, however, we require a good explanatory power for the adoption decision. If the prediction for (one of) the adoption decisions is poor, the noise will severely contaminate the estimation of the innovation strategy coefficients in the productivity equation.

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[7] An alternative procedure used is to include in the productivity analysis, the generalized residuals (score variables) from the multinomial adoption regressions on the exclusive categories, (a procedure similar to the Heckman correction procedure). With this inclusion, the vector of parameters θ in the productivity equation can be estimated unbiased (see Gouriéroux et al (1987), Chesher and Irish (1987), Kaiser (2002)).

If we consider that the source of complementarity depends on the presence of critical firm characteristics, which the firms can endogenously choose to acquire, then controlling for all the elements affecting the decision of the firm on how to organize should not affect performance (Shaver, 1998). In that case we could claim when the innovation strategy coefficients in the second stage productivity equation are no longer significant, to have *explained* complementarity by controlling for its source. Observing the choice of the firm reveals no additional information, but complementarity remains intact for the subset of the firms that combine both innovation activities conditional on their previous strategic and organizational choices.

3. The Data

The data used for this research are innovation data on the Belgian manufacturing industry that were collected as part of the Community Innovation Survey conducted by Eurostat in the different member countries in 1993. A representative sample of 1335 Belgian manufacturing firms was selected resulting in a response of 714 usable questionnaires.[8] About 62% of the firms in the sample claim to innovate, while only 38% do not innovate. For the remainder of our analysis we restrict attention to the 445 innovation active firms in the sample, distinguished by their answer on the question whether they were actively engaged in introducing new or improved products or processes in the last two years. The non-innovation active firms did not provide information about several variables, used in the analysis. Due to missing values our effective sample is reduced to 269 firms.

In characterizing the innovation activities of the firm, we will distinguish between two different knowledge inputs into the innovation process. First, firms can do R&D in-house and develop their own technology, which we consider the firm's *MAKE* decision. A second alternative activity is to acquire technology externally. There are different ways in which the firm can be active on the external technology market: the firm can license technology, it can contract for technology and technology advice, it can acquire other companies for their technology content, or, it can hire

[8] The researchers in charge of collecting the data also performed a limited non-response analysis and concluded that no systematic bias could be detected with respect to size and sector of the respondents (Debackere and Fleurent, 1995).

away skilled personnel. For the empirical analysis we will aggregate these activities into the *BUY* decision. A firm is active on the external technology market whenever it performs at least one of these activities.[9] The *MAKE* and *BUY* activities are non-exclusive. Table 1 summarizes the information about the firm's innovation strategy. The large majority of the innovating firms have own R&D activities (88%). Almost three quarters of the innovating firms acquire technology on the external market using at least one of the four possible external sourcing activities.

Insert Table 1 here

Table 2 shows simple correlations between the different disaggregated innovation activities. The shaded boxes indicate the correlations that are positive and significantly different from zero at the 1% level. As expected, own R&D activities and external technology acquisition are positively correlated (0.18). These results are consistent with complementarity between these innovation activities. The significant positive correlation between the external knowledge acquisition activities, confirms the results from Arora and Gambardella (1990) in biotechnology. In the remainder of the analysis we will not use the disaggregated *BUY* category since this would lead to too many cases to consider.[10]

Insert Table 2 here

Further evidence consistent with complementarity can be found in the frequency with which firms combine these innovation activities. For this we construct four *exclusive* categorical variables, one for each combination of *MAKE* and *BUY* activities. The first column of Table 3 reports a high number of firms that *Make&Buy* (66%). Only 6% choose *BuyOnly* as a strategy and 22% choose a *MakeOnly* strategy. We also find that 6% of the firms declare to be innovation active, but are not engaged

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[9] We disregarded the "embodied technology" purchase of equipment, mainly because many firms responded positively on this item. The reported results are not affected by the inclusion or not of the purchase of equipment in the buy option. However, probably not all of the firms interpreted the question as buying equipment with the explicit purpose of obtaining new technologies.
[10] The productivity approach needs to create a dummy for each possible combination of activities, i.e. with n activities we need 2^n variables. Considering more combinations also introduces the problem of

in any of the innovation activities *NoMake&Buy*. The majority of these firms (10) did buy equipment or received "informal" knowledge transfers, activities that we did not consider formally as part of the innovation strategy. In addition, some firms might be actively engaged in innovation due to innovation efforts prior to the period of study and discontinued afterwards.

Insert Table 3 here

If innovation activities are truly complementary, their effect should also show up in measures of innovation performance. The second column of Table 3 cross-tabulates our innovation performance measure with different exclusive combinations of *MAKE* and *BUY* activities. The firms report the percentage of 1992 sales that was generated by new or substantially improved products introduced between 1990 and 1992 *(% Sales from New Products)*.[11] Results suggest that firms, which are restricted to using *MakeOnly* or to external acquisition (*BuyOnly*), tend to have lower innovative performance relative to firms in the *NoMake&Buy* category. The most productive choice of innovation activities seems to be the *Make&Buy* option. Firms combining technology *MAKE* and *BUY* activities generated 20.5% of their sales from new or substantially improved products, which is on average about 7% higher than firms relying on a single or no innovation activity. A joint test for equality of means is rejected with a p-value of 0.025 and a one-sided test of no complementarity is rejected at 5% level of significance.

4. *Econometric Analysis*

4.1 Productivity Approach

In this section we analyze the effect of combining innovation activities on the performance of the innovation process. If innovation activities are truly complementary, one should observe that the incremental performance of adding an

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having enough observations and variation in each exclusive category for the multinomial logit estimations.

[11] In the absence of a panel data structure, we are only able to relate innovative performance and innovation strategy choices in the same time period, while ideally we would like to consider a time lag. Nevertheless, for most companies the choice of a make and/or buy innovative strategy is highly time consistent.

innovation activity is worse for firms that engage in a single activity, compared to firms already engaged in other innovation activities. We regress our measure of innovative performance *(% Sales from New Products)* on the exclusive dummies of combinations of innovative activities together with firm characteristics and industry dummies that may affect the performance of the innovation process. Table 4 presents the definition of these variables and some summary statistics.

Dating back to Schumpeter's work, the size of the firm is an important traditional control variable (see o.a. Cohen and Levin, 1989). On the one hand, larger firms may have higher market power or may enjoy economies of scale and scope raising the incentive of firms to innovate. On the other hand, smaller firms are associated with lower bureaucracy and might be more innovative (Acs and Audretsch, 1987) or simply have it easier than a large firm to generate sales from new or substantially improved products as a percentage of total sales. We measure size by the sales of the firm in 1992 (*Sales*)[12]. In addition, we control for the inputs in innovation activities, i.e. innovation expenditures relative to sales. Innovation intensive firms are more likely to produce more innovations, positively affecting the percentage of sales from new products. A more competitive environment is likely to stimulate innovation and exporting firms encounter such an environment. The export intensity (*Export Intensity*) of the firm, i.e. the percentage of 1992 sales generated from exports should then positively affect innovation productivity. Last of the generic firm specific control variables are the lack of technological opportunity (*Technology Obstacles*) and the lack of market opportunities (*Market Obstacles*) as perceived by the firm. These exogenous factors capture respectively supply and demand factors affecting the scope for innovative performance. In addition, we include industry dummies at the two digit industry classification level.

Insert Table 4 here

The results are presented in Table 5. The coefficients on *Make&Buy* and *NoMake&Buy* in regression (1) are highly significant and large, while the other coefficients are lower and less significant. The direct test for complementarity (q_{11} -

[12] Results are insensitive when using alternative size measures such as employment.

$q_{10} \geq q_{01} - q_{00}$ see (1)) is accepted at 5% level of significance (p-value = 0.018).[13] Next to industry dummies, firm size, innovation intensity and export intensity are important variables controlling for firm characteristics in innovative performance. The data suggest that small firms (*Sales*) and more intensive innovation spenders are more successful in terms of innovative performance. More export-oriented firms (*Export Intensity*) are also more innovation productive, presumably because of the more competitive environment they face. The perceived lack of technological and market opportunities unsurprisingly reduce the innovative performance. But these effects are not significant.

Insert Table 5 about here

As we only have information for those firms that are innovation active, the coefficients in the productivity regression might be biased. The regression is corrected for sample selection following a two-stage Heckman correction procedure in regression (2).[14] The hypothesis of sample selection is rejected, and the correction does not affect our main conclusions. We still confirm complementarity between *MAKE* and *BUY* activities (p-value = 0.041) even though some of the innovation strategy coefficients did lose some of their significance. Furthermore, as we have left-censored observations on innovative performance, we also performed a Tobit regression.[15] The results are reported in regression (3). These regressions again confirm complementarity between *MAKE* and *BUY* activities (p-value = 0.009), reinforcing the large and highly significant coefficient on *Make&Buy* and the positive effect of the firm's innovation intensity on innovation performance.

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[13] To ease interpretation of coefficients, we include all the exclusive dummy variables in the regression, but do not include a constant term. The result of the actual test for complementarity (equation (1)) is indicated in a separate row in Table 5.

[14] The sample selection is for whether firms are innovation active or not. In the first stage the innovation equation is estimated. We regress in a probit model whether the firm innovates on the following independent variables: size, export intensity, a number of variables measuring obstacles to innovation (cost, lack of resources, lack of technological/market information, no technological opportunities, lack of demand) and industry dummies (see Veugelers and Cassiman (1999) for a development of this result). From the resulting estimation we construct the Heckman correction term (λ) to be included in the productivity regression.

[15] Innovative performance is measured as a percentage of sales. 43 firms reported 0% of sales from new or substantially improved products introduced between 1990 and 1992.

4.2 Adoption Approach

In the previous section we found evidence of the complementarity between innovation activities by analyzing the direct effect of complementarity on innovation performance. In this section we examine the adoption decisions. We search for variables that can explain the joint occurrence of innovation activities, or —stronger—complementarity between these activities. The literature suggests that basic R&D capabilities often constitute the firm's absorptive capacity (Rosenberg, 1990). Firms with basic R&D capabilities are, therefore, more likely engaged in combining both *MAKE* and *BUY* activities since their higher absorptive capacity will increase the marginal returns from *MAKE* in the presence of *BUY* and vice versa. Our variable, *Basic R&D Reliance*, measures the importance for the innovation process of information from research institutes and universities *relative* to the importance of suppliers and customers as an information source for the innovation process.[16] We use this variable to proxy for the reliance on more "basic" types of know-how by the firm (see also Kaiser (2002)).

Besides joint drivers, we look for exclusive drivers that help to establish complementarity through the exclusion restrictions. The appropriation regime has been identified in the theoretical literature as an important factor affecting the (relative) importance of (different) innovation activities for a firm (Teece, 1986; Veugelers & Cassiman 1999). One could hypothesize that if legal protection of innovations (*Effectiveness of IP Protection Industry*) is tight firms are more likely to be able to trade technology on the external market. But at the same time it has a higher incentive to develop such tradable technology. The *Effectiveness of IP Protection* is, then, expected to have a positive effect on the *BuyOnly* and *Make&Buy* decisions. If innovations are easier to protect through strategic measures such as secrecy, lead time, or complexity of the product or process (*Effectiveness of Strategic Protection*), firms may favor own R&D activities for which outcomes are easier to protect under these circumstances. We, therefore, assume that the *Effectiveness of Strategic Protection* exclusively affects the firm's *MAKE* decision. In a multinomial regression the *Effectiveness of Strategic Protection* should show up significant in the

[16] See Table 4 for the precise definitions of all variables.

MakeOnly and *Make&Buy* decisions. In the bivariate probit, however, this variable should affect both *MAKE **and** BUY* positively if activities are complementary.

Next we include a number of variables that we expect will affect the different adoption choices. Unfortunately, little theory exists to guide us in our selection of explanatory variables and in identifying exclusion restrictions for these variables. First, economies of scale and scope are likely to affect the choice of innovation activities. Furthermore, larger firms develop more projects and, therefore, are more likely to engage in innovation activities in general (*Sales*).[17] Higher innovation expenditures, while controlling for size, also increase the likelihood of engaging in different innovation activities (*Innovation Intensity*).

Second, we include a number of firm specific variables that characterize the resource and information environment in which the firm operates. We test whether obstacles to innovations such as a lack of innovation and technical personnel (*Resource Limitations*) influence the firm's decision about the organization of its innovation strategy. A lack of internal resources may drive the firm towards external sourcing. In addition, the respondents were asked to rate the importance to their innovation strategy of different information sources for the innovation process. *Public Information* measures the relative importance of freely available information from patents, publications and conferences *relative* to information from customers and suppliers. We expect that firms will combine *MAKE* and *BUY* when these involuntary "spillovers" are more important. This typically occurs in phases of the technology life cycle when the know-how is more standardized and codified. Finally, when information from competitors (*Competitor Information*) is important, the firm is more likely to be a follower or imitator with respect to innovation. Therefore, the relevant state-of-the-art technology is more likely to be accessed on the external technology market from firms in the same industry in order to catch up.

The results are presented in Table 6. The first three columns represent the result of a multinomial logit where we use the innovation strategies, i.e. the exclusive combinations of make and buy decisions as the dependent variable.[18] The next four columns represent the results of two bivariate probit analyses on the individual

[17] The results however are not sensitive to the use of either *Sales* or *Employment*.

innovation activities, i.e. the *MAKE* and *BUY* decisions. Comparing the bivariate probit with the multinomial logit allows us to discuss the exclusion restriction on the *Effectiveness of Protection* as a test for complementarity and to identify whether *Basic R&D Reliance* is a driver for the joint occurrence of these innovation activities.

In the bivariate probit analyses, we first demonstrate that controlling for industry effects, firm size and innovation intensity does not reduce the observed correlation between make and buy activities significantly. The final two columns include our other variables that might explain the perceived correlation. Once controlling for these additional firm-specific effects, the residual correlation between technology *MAKE* and *BUY* activities disappears. Therefore, the added firm specific effects seem to be able to explain the perceived correlation and, hence, the joint occurrence of innovation activities.

Insert Table 6 here

As indicated by the multinomial logit regression, the reliance on basic R&D significantly affects the probability of combining innovation activities *(Make&Buy)*. Therefore, we should expect this variable to show up positively and significantly in both the *MAKE* and the *BUY* regression of the bivariate probit model, which is the case. This confirms the importance of an in-house basic R&D capability as a driver for exploiting the complementarity between internal and external sourcing. The positioning of the firm to rely more on basic R&D for its innovation process increases the likelihood that a firm engages in own R&D and external knowledge sourcing: a 10% increase in the reliance on basic R&D increases the likelihood of combining internal and external sourcing by 2.7%.

The *Effectiveness of Strategic Protection* positively affects the probability that the firm does own R&D, i.e. is highly significant in the *MakeOnly* and *Make&Buy* cases. The *Effectiveness of IP Protection* is only marginally significant for the *Make&Buy* case. These results are consistent with our proposed hypothesis that when the firm is better in protecting the rents from innovation through secrecy, lead time or

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[18] The benchmark case is NoMake&Buy.

complexity it is significantly more likely to be engaged in own R&D activities.[19] If innovation activities are complementary, strategic protection should have a positive effect on both activities. This result is confirmed in the bivariate probit model. Strategic protection significantly affects the *MAKE* decision of the innovating firms and, consistent with complementarity, also indirectly affects the firm's external technology acquisition *BUY*, albeit to a lesser extent. Effective IP Protection has the reverse implications: it has a significantly positive effect on BUY and a marginally significant effect on MAKE.[20]

Furthermore, the multinomial logit model reveals that firm size positively affects all combinations of innovation activities relative to not doing any innovation activity.[21] *Competitor Information* does increase the predisposition of the firm to rely solely on the external technology market, as an imitator would, while more surprisingly, *Resource Limitations* seem to positively affect own R&D activities, possibly indicating that it is exactly the firms that do internal R&D that experience this resource constraint.

4.3 Robustness

4.3.1 Omitted Variables

Results from the adoption approach indicate that Basic R&D Reliance and appropriation conditions are important joint, respectively, exclusive drivers of innovation activities. Therefore, one might worry that in addition to the direct effect on adoption, these variables would affect performance of the innovation process directly, biasing the estimates of the θ's. Regression (4) in Table 5 includes these variables, which turn out to be insignificant in the productivity equation. Our results on complementarity are confirmed (p-value = 0.012).

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[19] The joint hypothesis that the *Effectiveness of Strategic Protection* does not affect *BuyOnly* while *Basic R&D Reliance* does not affect *MakeOnly* nor *BuyOnly* cannot be rejected at standard levels of significance.
[20] The coefficient of Effectiveness IP Protection Industry in *MAKE* is significant at 13%.
[21] We performed a Hausman test to check for the Independence of Irrelevant Alternatives (IIA) assumption in the multinomial logit. The test resorts to iteratively dropping one option and testing whether coefficients significantly change. In two cases the estimated model fails to meet the asymptotic assumptions of the Hausman test. In the other two cases, the coefficients are not significantly different.

4.3.2 TwoStep Procedure

Finally, we correct for potential sample selection of the decision variables, i.e. the innovation strategy in the performance regression. Using the results from the adoption approach, we construct predicted innovation strategy decisions (from multinomial logit) and predicted innovation activities (from bivariate probit) and use these as instruments in the performance regression. Since the value added of a two-step procedure depends on the predictive power of the adoption regressions, we first present a table linking actual and predicted cases for both the multinomial and the bivariate adoption regressions.

Insert Table 7 here

Although the models are significant, Table 7 shows the poor predictive performance of the adoption regressions. Overall, the percentage of correctly predicted cases is 61% for the multinomial logit and 56% for the bivariate probit. The exclusive categories *MakeOnly* and especially *BuyOnly* are poorly predicted: resp 51% and 43% of these cases are correctly classified.[22] Both models clearly have a tendency to put relatively too many cases in the *BuyOnly* and in the *NoMake&Buy* category and to underpredict the *Make&Buy* cases. As the last row shows, despite the many cases of misclassifications, the *Make&Buy* category still comes out on top in terms of percentage of sales from new and improved products, but especially the predicted *BuyOnly* category has a higher innovative productivity as compared to the actual levels. In addition, the predictions tend to increase the variation around the mean in each category, weakening the power of the complementarity test.

Regressions (5) and (6) in Table 5 present the two-step results for the productivity regression, where the exclusive dummy categories are instrumented by the predicted probabilities on the basis of the multinomial (regression (5)) or bivariate

[22] This low level of predictive power persists over various alternative specifications and variables that were tried. Inherent to activities which are complementary is the low level of occurrence of exclusive categories, i.e *MakeOnly* and in our case especially *BuyOnly*. It is especially with these skewed cases that logit/probit models have problems predicting sufficiently accurately.

(regression (6)) adoption results.[23] The results for exogeneous factors seem relatively little affected by the correction procedure, but complementarity can no longer be confirmed as the point estimates of the coefficients are more similar across activities. Although the coefficient of *Make&Buy* is still the largest in the multinomial two-step, the coefficient for *BuyOnly* has increased substantially, especially in the bivariate two-step. The poor predictive power of the adoption rates is an obvious explanatory factor for the poor outcome of the two-step procedure and these results suggest that the full-fledged joint estimation of the productivity equation and the adoption decisions is unlikely to improve the overall performance of the estimation (Athey and Stern (1998)). On the contrary, the poor predictive power of the adoption regressions will contaminate the productivity estimates. The overall conclusion should be that what is needed is a search for more informative firm characteristics that explain the adoption of individual innovation activities. Our understanding of factors driving joint occurrence and eventually complementarity could only be enhanced by such improvements.

5. Conclusions

While there is ample theoretical and empirical research on firm and industry determinants of internal R&D, the literature deals less with the combination of different innovation activities, which together form the innovation strategy of the firm. Using data from the Community Innovation Survey on Belgian manufacturing firms, we try to assess whether different innovation activities are complementary and which firm characteristics may affect this complemenarity.

Using several different approaches, we find evidence consistent with complementarities between different innovation activities in the innovation strategy. The productivity approach confirms the higher innovation performance of firms

[23] Rather than using the predictions as instruments, we also included the generalized residuals from the multinomial logit adoption rates in addition to the actual dummies, see previous footnotes. This should again lead to unbiased estimates of the θ parameters. However in this case all estimated θ coefficients are non-significant, due to the multicollinearity with the score variables, which is not surprising given the poor predictive performance of the multinomial logit regression. A further problem with the generalized residual is that it is not very informative if few continuous variables are included. Beyond size and innovation intensity, the independent variables are continuous only to a limited degree since they are based on Likert scale scores from 1 to 5.

combining technology *MAKE* and *BUY* activities. Acquiring external know-how is found to significantly increase innovative performance only when the firm at the same time is engaged in internal R&D activities. Consistent with complementarity, the adoption approach indicates that own R&D activities are highly correlated with external technology acquisition. Furthermore, controlling for the basic R&D reliance of the firm and the appropriation conditions for innovation effectively removes the residual correlation between innovation activities. We find that the basic R&D reliance of a firm has an important conditioning effect on the observed joint occurrence of internal and external knowledge sourcing activities. As this reliance on basic R&D is an endogenous organizational decision of the firms, we claim to have uncovered a source of complementarity rather than relying on the more classical explanation of complementarity as an exogenous technical characteristic of the innovation production function. Furthermore, we find that the effectiveness of strategic protection affects both the *MAKE* and *BUY* activities. Theoretically, we only expect the effectiveness of strategic protection to affect internal R&D sourcing. Therefore, we consider this evidence of complementarity as the effectiveness of strategic protection has an indirect effect on external knowledge sourcing activities through its complementary relation with own R&D.

Given the scarcity of previous empirical work on this topic, the first results generated by this paper provide some interesting suggestions for further theoretical work which treats the complementarity among innovative activities as critical in assessing innovation success. At the same time, more empirical work is needed to improve the predictive power and the significance levels, and, check the robustness of these results, especially for the systems approach combining the productivity and adoption equations. The EUROSTAT/CIS data proves to be a rich set of information, allowing replication of this exercise on other European countries. However, the qualitative nature of most of the information limits the analysis in terms of quantifying internal and external sourcing strategies. Furthermore, a panel data set would allow us to control for unobserved firm specific effects which might bias some of our current results. Nevertheless, we feel that the most important avenue for future research is the search for firm characteristics which *explain* complementarity. This is a call on both theory and empirical work.

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Table 1: Definition of Innovation Activities, Dummy variables 0/1

	Description Variable	Number of Firms without missing values N = 269
MAKE	Innovative firms that have own R&D activities and have a positive R&D budget.	**237 (88%)**
BUY	Innovative firms acquiring technology through at least one of the following external technology acquisition modes: licensing and/or R&D Contracting/R&D advice and/or Take-over and/or Hire-away.	**194 (72%)**
Buy License	Innovative firms acquiring technology through licensing.	88 (33%)
R&D Contracting	Innovative firms acquiring technology through R&D Contracting.	100 (37%)
Take-over	Innovative firms acquiring technology through Take-over.	44 (16%)
Hire-away	Innovative firms acquiring technology through hiring away personnel.	113 (42%)
A total of 714 firms responded, 445 firms innovated in the full sample, 269 firms without missing values.		

Table 2: Unconditional Correlations between Innovation Activities						
	1	2	2.1	2.2	2.3	2.4
1. MAKE	1.00					
2. BUY	***0.18***	1.00				
2.1 *BUY LICENSE*	0.09		1.00			
2.2 *R&D CONTRACTING*	0.21		0.32	1.00		
2.3 *TAKE-OVER*	-0.02		0.21	0.18	1.00	
2.4 *HIRE-AWAY*	0.08		0.05	0.12	0.30	1.00
In shaded cells correlations are significantly different from zero at 1% level of significance						

Table 3: Frequency of Innovation Strategies and Innovative Productivity by Innovation Strategy

	Frequency Innovation Strategy	***% Sales from New Products***
NoMake&Buy	16 (6%)	14.9%
MakeOnly	59 (22%)	13.5%
BuyOnly	16 (6%)	9.7%
Make&Buy	178 (66%)	20.5%
TOTAL	269 (100%)	18.0%
Complementarity Test Make&Buy – MakeOnly > BuyOnly – NoMake&Buy		F(1, 265) = 2.67** p-value = 0.052 one-sided

Note: Categories are exclusive. This sample (N=269) only includes firms that reported non-missing observations on all variables used in the analysis. The differences in means are significant (p-value 0.025).

Table 4: The Variable Definitions

Variable Name	Variable Construction	SAMPLE MEAN (STD)	MEAN *MAKE*=1 (237)	MEAN *BUY*=1 (194)
% Sales from New Products (dependent variable)	Percentage of total sales derived from new or substantially improved products introduced between 1990 and 1992.	0.18 (0.197)	0.188 (0.20)	0.196 (0.208)
Sales	Firm Sales in 10^8 Belgian Francs in 1992.	0.462 (2.063)	0.48 (1.29)	0.507 (1.28)
Innovation Intensity	Expenditures on innovation activities relative to Sales	0.036 (0.05)	0.037 (0.05)	0.039 (0.05)
Export Intensity	Export Intensity in 1992 (Exports/Sales x 0.1)	0.059 (0.033)	0.062 (0.032)	0.060 (0.033)
Market Obstacles	Average measure of importance of lack of market information, no need for innovation because of previous innovations, problems with regulations, little interest for new products by customers, uncertainty about market timing, as a barrier to innovation (on scale 1 (unimportant) to 5 (crucial)).	2.23 (0.67)	2.26 (0.63)	2.25 (0.66)
Technological Obstacles	Importance of lack of technological opportunities as barrier to innovation (on scale 1 (unimportant) to 5 (crucial)).	2.23 (0.97)	2.28 (0.96)	2.31 (0.98)
Effectiveness IP Protection Industry	Industry Average (Nace2) of measure of effectiveness of patents as a protection measure of innovation (firm level measure on scale 1 (unimportant) to 5 (crucial)).	2.10 (0.46)	2.14 (0.46)	2.16 (0.49)
Effectiveness Strategic Protection	Average measure of effectiveness of secrecy, complexity and/or lead time as a protection measure of innovation (on scale 1 (unimportant) to 5 (crucial)).	3.33 (0.91)	3.46 (0.82)	3.46 (0.82)
Basic R&D Reliance	Measure of importance for the innovation process of information from research institutes and universities relative to the importance of suppliers and customers as an information source.	0.710 (0.269)	0.733 (0.268)	0.735 (0.272)
Resource Limitations	Importance of lack of innovation and technical personnel as barrier to innovation (on scale 1 (unimportant) to 5 (crucial)).	2.58 (0.93)	2.63 (0.94)	2.61 (0.90)
Public Information	Importance of patents, conferences and publications relative to suppliers and customers as information sources for the innovation process.	0.53 (0.16)	0.53 (0.176)	0.53 (0.16)
Competitor Information	Importance of competitors as information sources for the innovation process (on scale 1 (unimportant) to 5 (crucial)).	3.09 (1.09)	3.08 (1.06)	3.19 (1.07)
INDUSTRY DUMMIES	Industry dummies are included where the industry is defined as groupings of NACE2 digit level industries: Steel (Nace 22, 9 obs), Minerals (Nace 24, 11 obs), Chemicals (Nace 25 and 26 excluding 2571/2572, 30 obs), Pharmaceuticals (Nace 2571/2572, 6 obs), Metals & Metal products (Nace 31, 29 obs), Electronics (Nace 33 and 34 except 3441/3451, 16 obs), Telecommunications (Nace 3441, 6 obs), Electronic Appliances (Nace 3451, 5 obs), Transport Equipment (Nace 35 and 36, 13 obs), Machinery&Instruments (Nace 32, 37, 29 obs), Food&Beverages (Nace 41 and 42, 28 obs), Textiles (Nace 43, 44 and 45, 32 obs), Wood/Paper (Nace 46 and 47, 31 obs), Rubber (Nace 48, 13 obs), Other (Nace 49, 11 obs).			
LOW TECH INDUSTRIES	Low Tech industry dummy includes NACE2 industries: processing of metals (22), non-metallic mineral products (24), metals (except mechanical, electrical and instrument engineering, 31), food and beverages (41/42), textiles (43), leather (44), clothing (45), wood (46), paper (47) and other manufacturing (49). Number of firms: 142			

Table 5: Productivity Regressions: dependent variable % Sales from New Products						
	(1)	(2)	(3)	(4)	(5) Multinomial	(6) Bivariate
Sales	-0.0195*** (0.00652)	-0.0180* (0.010)	-0.0203* (0.011)	-0.0184*** (0.0064)	-0.0194*** (0.0067)	-0.0204** (0.0085)
Innovation Intensity	0.522** (0.263)	0.524** (0.269)	0.748** (0.313)	0.476* (0.258)	0.521 (0.328)	0.434 (0.423)
Export Intensity	0.0827** (0.033)	0.098* (0.053)	0.093** (0.043)	0.0683** (0.033)	0.0848** (0.0423)	0.0788* (0.045)
Market Obstacles	-0.0032 (0.0178)	-0.00495 (0.0196)	-0.0030 (0.0223)	-0.0052 (0.0176)	-0.00176 (0.0191)	0.00253 (0.0241)
Technological Obstacles	-0.0132 (0.0131)	-0.0130 (0.0132)	-0.0158 (0.0152)	-0.0141 (0.0134)	-0.0116 (0.0165)	-0.0157 (0.0173)
Make&Buy	0.183*** (0.058)	0.166** (0.069)	0.162*** (0.0653)	0.205** (0.094)	0.164 (0.106)	0.189 (0.246)
MakeOnly	0.11* (0.061)	0.092 (0.071)	0.0726 (0.0687)	0.132 (0.095)	0.120 (0.217)	0.112 (0.271)
BuyOnly	0.086 (0.057)	0.066 (0.082)	-0.0368 (0.082)	0.109 (0.085)	0.128 (0.20)	0.2804 (0.62)
NoMake&Buy	0.141*** (0.053)	0.119 (0.08)	0.0918 (0.0846)	0.175** (0.081)	0.1257 (0.097)	0.0255 (0.234)
Effectiveness IP Protection Industry	—	—	—	-0.0265 (0.034)	—	—
Effectiveness Strategic Protection	—	—	—	0.0224 (0.015)	—	—
Basic R&D Reliance	—	—	—	-0.0418 (0.042)	—	—
Industry Dummies	Included	Included	Included	Included	Included	Included
Complemenarity Test: Make&Buy – MakeOnly > BuyOnly – NoMake&Buy	F(1, 247) = 4.47**	Chi2(1) = 3.02**	F(1,248) =5.70***	F(1, 244) = 5.18**	F(1, 247) = 0.03	F(1, 247) = 0.09
	N=269 OLS (Huber White Sandwich estimator)	Heckman Correction Observations 269 uncensored, 169 censored	N=269 Tobit: 43 left-censored observations	N=269 OLS (Huber White Sandwich estimator)	N=269	N=269
Model	F(22,247) = 13.34***	λ=-0.0232 (0.057) χ2(33) = 246.31***	χ2(21) = 55.79***	F(25,244) = 12.21***	F(21,247) = 2.34***	F(21, 247) = 2.02***
Coefficients Significant at: 1%***, 5%** and 10%*, standard deviations between brackets.						

Table 6: Multinomial Logit and Bivariate Probit

	Multinomial Logit			Bivariate Probit		Bivariate Probit	
	MakeOnly	BuyOnly	Make&Buy	Make	Buy	Make	Buy
Sales	5.309* (3.012)	5.465* (3.012)	5.311* (3.011)	-0.0067 (0.094)	0.0565 (0.0821)	-0.0270 (0.076)	0.0234 (0.082)
Innovation Intensity	-2.459 (9.496)	8.685 (9.747)	1.150 (9.226)	0.3119 (2.668)	3.643* (2.034)	-3.397 (2.533)	2.119 (1.861)
Effectiveness IP Protection Industry	0.925 (1.342)	1.108 (1.537)	2.220* (1.364)			0.639 (0.425)	0.788*** (0.270)
Effectiveness Strategic Protection	1.549*** (0.448)	0.687 (0.451)	1.731*** (0.445)			0.703*** (0.131)	0.176* (0.103)
Basic R&D Reliance	2.279 (1.429)	0.943 (1.777)	3.519*** (1.315)			1.345*** (0.513)	0.781** (0.363)
Resource Limitations	0.714** (0.364)	0.158 (0.385)	0.748** (0.359)			0.324** (0.155)	0.0445 (0.106)
Public Information	-0.260 (2.298)	0.191 (2.749)	0.462 (2.194)			0.237 (0.857)	0.435 (0.603)
Competitor Information	-0.249 (0.262)	0.619* (0.352)	0.00697 (0.255)			-0.0218* (0.114)	0.176** (0.085)
Low Tech Industry	-1.425 (1.276)	-0.0644 (1.536)	-0.900 (1.250)	-0.779*** (0.235)	-0.251 (0.175)	-0.453 (0.355)	0.230 (0.230)
	Pseudo R^2 = 0.201 $\chi^2(27)$ = 78.30*** N = 269			Correlation 0.31** (0.122) $\chi^2(6)$ = 18.19*** N = 269		Correlation 0.123 (0.16) $\chi^2(18)$ = 87.05*** N = 269	

Coefficients Significant at: 1%***, 5%** and 10%*. Standard deviations between brackets.

Table 7A: Actual vs Predicted Cases: Multinomial Logit

Predicted Actual	*MakeOnly* (75)	*BuyOnly* (31)	*Make&Buy* (137)	*NoMakeBuy* (26)	Innovative Performance Mean (std)
MakeOnly (59)	30	7	19	3	0.135 (0.158)
BuyOnly (16)	4	7	2	3	0.0969 (0.166)
Make&Buy (178)	40	16	115	7	0.205 (0.210)
NoMakeBuy (16)	1	1	1	13	0.149 (0.158)
Innovative Productivity Mean (std)	0.163 (0.189)	0.169 (0.213)	0.194 (0.196)	0.168 (0.211)	

Note: Cases are classified in the categories where they have the highest predicted value relative to sample average for each category.

Table 7B: Actual vs Predicted Cases: Bivariate Probit

Predicted Actual	*MakeOnly* (79)	*BuyOnly* (34)	*Make&Buy* (133)	*NoMakeBuy* (23)	Innovative Performance Mean (std)
MakeOnly (59)	26	8	22	3	0.135 (0.158)
BuyOnly (16)	2	7	2	5	0.0969 (0.166)
Make&Buy (178)	48	16	108	6	0.205 (0.210)
NoMakeBuy (16)	3	3	1	9	0.149 (0.158)
Innovative Productivity: Mean (std)	0.175 (0.190)	0.190 (0.226)	0.191 (0.194)	0.117 (0.188)	