Complementarity in the Innovation Strategy: Internal R&D, External Technology Acquisition, and Cooperation in R&D[*]

by

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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 and cooperate actively in R&D with other firms and research organizations. In this paper we provide evidence on complementarity between different innovation activities. Using data from the Community Innovation Survey on Belgian manufacturing firms, we show that firms that are only engaged in a single innovation strategy, 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. This result is consistent with complementarity between own R&D and external technology sourcing activities. Furthermore, we show that the different innovation activities are strongly positively correlated and identify common drivers, resulting in the perceived complementarity between these innovation activities. An important finding is that a capacity to strategically protect intellectual property and a more basic R&D base which may serve as an absorptive capacity, are important *common* drivers for the different innovation activities.

Keywords: Complementarity, Innovation, R&D, Technology Acquisition, Cooperation in R&D

JEL classification: D21, O31, O32

Introduction

Successful innovation depends on the development and integration of new knowledge in the innovation process. Today even the largest and most technologically self-sufficient organizations require knowledge from beyond their boundaries. In order to access alternative knowledge sources, the *innovation strategy* of the firm will combine different *innovation activities*. In addition to doing own research and development, firms typically are engaged in the trading of knowledge on the technology market and cooperate actively in R&D with other firms and research organizations.

Most of the literature based on transaction costs concentrates on the choice between internal and external sourcing for individual transactions, as substitute modes for generating innovation (a.o. Williamson, 1985, Pisano, 1990). Although the availability of external technology may substitute for own research investment by the receiver firms, there are also arguments to stress the complementarity between in-house R&D and external know-how, as the recent literature suggests (a.o. Arora & Gambardella, 1994; Cockburn & Henderson, 1998; Granstrand et al., 1992). Own R&D activities allow the firm to better scan the environment for existing technology. Once a suitable technology is located, the firm with in-house R&D capabilities is better able to evaluate the technology. Often the external technology is only available on an exchange basis, leading to many cooperative types of sourcing. When the firm decides to buy the technology, its own R&D operations allow it to better integrate the technology because external knowledge sources do not automatically find their way into the firm's innovation process. The notion of 'absorptive capacity' introduced by Cohen & Levinthal (1989) and further developed by a.o. Kamien & Zang (2000), stresses the importance of a stock of prior knowledge to effectively absorb external know-how. At the same time the access to external know-how may leverage the productivity of the internal R&D activities, at least when the organization exhibits a willingness to take on external ideas (Veugelers, 1997). Finally, internal R&D resources can serve as appropriation capacity, e.g. by increasing the complexity of the new product/process or by establishing a lead time. The existing appropriation opportunities indicate whether technology will dissipate easily, or, whether the firm needs complementary assets to appropriate the returns to its innovation strategy (Teece, 1986).

An important task in innovation management, therefore, is 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. If the innovation activities of a firm are complementary, 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.

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. This paper presents an empirical analysis of the complementarity between the activities of the innovation strategy where we restrict attention to own R&D, external technology acquisition and cooperation in R&D. Two main questions are addressed. First, are innovation activities indeed complementary? And second, why are innovation activities complementary?

Both establishing complementarity and identifying the sources for complementarity are important for managing the innovation strategy. When innovation activities are found to be complementary, this would imply that it is less efficient to concentrate on one activity at a time. Successfully experimenting with these innovation activities, requires re-adjusting the whole strategy. In addition, it makes copying the innovation strategy of a successful player more difficult because of its increased complexity (Rivkin, 2000). Therefore, the innovation process, i.e. managing the complementarity between the different innovation activities, can be an important source of sustainable competitive advantage. Our results not only tie in with the activity systems literature in management strategy, but might also shed some light on the resource based view of the firm. The resource based view of the firm relates the profitability of the firm to resources of the firm that are exploited through the activities of the firm (Ghemawat and Pisano, 1999; Teece et. al, 1997). These resources are scarce and hard to replicate. The capability to manage a complex innovation strategy might be such a resource. The existence of such an innovation management capability actually provides an explanation for the observed complementarity between innovation activities because the combination of different innovation activities allows to better capitalize on this capability. We develop two dimensions which might proxy for the firm's innovation capability: the nature of the research performed and the capability to appropriate the results of the innovation process. Our results indicate that our measures of basicness of R&D and strategic protection of innovations are important drivers of complementarity between own R&D activities and the external acquisition of technology.

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 asses complementarity: the productivity approach and the adoption approach. Section 5 concludes.

1. Literature on Complementarity

In the face of complementarity among activities, it is hard to understand the decision of a firm on how to organize an individual transaction, without taking into account the other activities the firm performs in its innovation strategy. For example, a firm, when deciding to buy a technology license, needs to analyze whether it *fits* with its existing activities. Viewed from the firm's perspective rather than the individual transaction, buying technology and doing own R&D could possibly be complementary activities.

The issue of *fit* between activities is more general than the question of activities in the innovation strategy (Porter, 1996). The most researched question has been the fit between human resource practices and the strategy of the firm. Ghemawat (1995) studies the case of Nucor, a US steel minimill, which combines innovative human and capital resource management practices with a low cost strategy. Similarly, Ichniowski, Shaw and Prennushi (1997) study the effects of human resource management practices on productivity in a sample of steel finishing lines. Both these studies find that there are important complementarities between different human resource management practices and the strategy of the firms. Firms that are able to combine these activities properly, significantly outperform their counterparts in the industry. Hence, understanding complementarity between these activities is crucial for firm performance and ultimately for firm survival rates.

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. This suggests a strong complementary relation between in-house basic knowledge development and external knowledge acquisition. Similarly, firms performing in-house research drew most heavily upon the public research associations set up after World War I in the UK. These research associations were intended to assist firms in technical matters. Firms without any internal research facilities were expected to use these research associations most heavily. But, contrarily, the research associations served as an important complementary source of scientific and technical information for firms performing in-house R&D. Further evidence on complementarity comes from examining the payment streams for licenses where the flows are primarily between firms performing in-house R&D and not from firms that lack any in-house R&D capabilities to firms that have strong in-house R&D programs.

The complementarity between internal and external sourcing is more rigorously explored in Arora & Gambardella (1994), where they identify two effects from internal know-how. 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 R&D orientation of the firm might be an important driver of the observed complementarity between internal and external technology acquisition. Rosenberg (1990) as well identifies the absorptive capacity of a firm by its basic research orientation. 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, basic research will act as an important driver for complementarity. Blonigen & Taylor (1997) also identify two possible hypotheses for the effect of R&D activities of the firm on its acquisition strategy. While internal R&D and technological acquisitions are substitutes, leading to a negative relationship between the two, internal R&D stimulates synergy gains from potential targets, and thus supposes a positive relationship. Both hypotheses are supported for a panel of US electronics firms, using R&D intensity to test for the former hypothesis, and R&D expenditures for the latter. Veugelers & Cassiman (1999) also provide evidence for internal know-how development and external sourcing to be combined at the firm level. In addition, they show that the choice of innovation activities strongly depends on the appropriation opportunities. Veugelers (1997) uncovers the reverse relation, namely that external sourcing stimulates internal R&D expenditures, at least for firms with internal R&D departments. This finding further reinforces the hypothesis of complementarity between internal and external knowledge sourcing. Finally, Arora and Gambardella (1990) examine the complementarity among external sourcing strategies of large firms in the biotechnology industry. They study four types of external sourcing strategies for large chemical and pharmaceutical companies in biotechnology (agreements with other firms, with universities, investments in and acquisitions of new biotechnology firms). They find evidence for complementarity between 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 strategy of external linkages.

The multiple links between internal R&D capabilities and external technology acquisition suggest that external technology sourcing is typically embedded in the wider innovation strategy of the firm. Within this wider innovation strategy, there are also other activities that the firm might use to build up and exploit its technology-base besides the traditionally considered buying of technology through licensing or R&D contracting. Compared to market transactions and internal development, R&D cooperation allows a faster, less costly and lower risk mode of accessing new technology, while exploiting partner complementarity and actively managing the transfers of know-how between partners (a.o. Pisano (1990)). The inherent reciprocity allows to manage the risks of partner opportunism, reducing transaction costs (Oxley (1997)). We will consider an innovation strategy that includes R&D cooperation as evidence of simultaneous buy and sell activities of the firm (see Granstrand et al. (1992)).

Most studies provide strong evidence for R&D active firms to be more active in R&D cooperation (Kleinknecht & van Reijnen (1992), Colombo & Gerrone (1996)). Dutta & Weiss (1997), however, find a negative correlation which they attribute to the need to protect "tacit know how". None of these papers, when assessing causes and effects, properly account for the simultaneity between own R&D and R&D cooperation arising from complementarity. Kaiser (2002) using a simultaneous equations framework, finds a positive but only weakly significant effect of cooperation on own R&D expenditures. Cassiman and Veugelers (2001) provide evidence of a strong positive effect of own R&D activities on cooperation in R&D, but after controlling for endogeneity this effect is less significant. However, the appropriation regime does affect the decision to cooperate significantly.

This paper is the first to systematically examine complementarity between different activities of the firm's innovation strategy: internal sourcing, acquiring external know-how and cooperating in R&D with external partners.[1] Going beyond the identification of complementarities, the analysis will also focus on the sources of complementarity. 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.

[1] In a related paper Mohnen and Röller (2001) analyse the impact of various barriers to innovation, on whether and how much firms innovate, to assess complementarity between innovation *policy* measures aimed at alleviating these barriers to innovation.

Providing optimal incentives for multidimensional effort choices by researchers implies providing equal marginal incentives, i.e. high powered or low powered, for all possible activities by the researcher, leading to complementarity in the type of incentives schemes observed within the same team (Holmstrom and Milgrom, 1991). In the case of innovation activities, the literature suggests that the R&D orientation of the firm and the appropriation regime might be important candidates for drivers of this observed complementarity. We use firm level data from the Eurostat Community Innovation Survey (CIS) of Belgian manufacturing firms (1992-1993). This survey contained questions on the different innovation activities used by the firms and on the innovative performance of the firms in terms of new or improved products. In addition, it includes information on the innovation context and strategy, which allows identifying possible candidate drivers of complementarity. Before we present the data and the empirical results, we first elaborate on the methodology used to establish complementarity between innovation activities.

2. *Theory and Empirical Model*

2.1 Theory

The formal foundations for the study of fit or complementarities between activities can be traced back to the theory of supermodularity (see Milgrom and Roberts, 1990 and 1995). This elegant mathematical theory states the necessary conditions for activities to be complementary.

<u>Definition</u>

Suppose there are 2 activities A_1 and A_2, each activity can be done by the firm ($A_i = 1$) or not ($A_i = 0$). 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.

<u>Result 1 (correlation)</u>

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.

<u>Result 2 (excluded variables)</u>

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. Furthermore, suppose that in-house R&D and external technology sourcing are complementary activities and the information that is available on external technologies in the environment is an exogenous variable only affecting the number of transactions in the technology market. Then, as result 2 states, in addition to the *direct effect* of external technological information on external sourcing strategies, we should find an *indirect effect*, increasing own R&D investments because of the complementarity between the activities of technology buying on the one hand, and, own R&D investments on the other. Own R&D allows firms to better appropriate the benefits from externally acquired information. Hence, one should expect these activities to be positively correlated and the availability of external technological information to have a positive effect not only on technology acquisition, but also on own R&D activities.

Although empirically finding positive correlation between different innovation activities is necessary to establish complementarity, it is not sufficient to conclude that they are complementary. 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.

2.2 Empirical Model

The empirical model explains how we attempt to derive evidence for complementarity between innovation activities.

2.2.1 Productivity (direct) approach

In the productivity approach we regress a measure of performance on exclusive combinations of innovation activities. In particular, we create a dummy variable that indicates whether the firm performed internal R&D, acquired technology externally or cooperated in R&D. From these dummy variables we construct different exclusive categories such as firms that only have own R&D activities, firms that combine own R&D activities and external technology acquisition, but do not cooperate in R&D, etc.

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 (Π). By restricting the performance measure to innovative performance only rather than overall performance, we attempt to minimize the problem of unobserved sources of firm heterogeneity.

$$\Pi = F(\mathbf{D}, X_1, \ldots, X_m; \theta, \beta),$$

where D is a matrix of exclusive dummy variables indicating how the firm is organized with respect to its innovation activities. With two innovation activities, D={(0,0), (0,1), (1,0), (1,1)}. X is a matrix of (exogenous) control variables affecting innovative performance, θ is a vector of parameters on the organizational dummies D, β is the vector of parameters of the exogenous variables.

The test for complementarity between two innovation activities, A_1 and A_2, is the following:

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

where θ_{ij} is the coefficient of the organizational dummy variable where A_1 = i and A_2 = j, and i, j $\in$ {0, 1}. This test implies that complementarity is established when the following holds: introducing an innovation activity will lead to a larger increase in innovative performance when the firm is already using another innovation activity, as compared to when the activity would be introduced in isolation. The proposed test establishes complementarity conditional on having unbiased estimates for the θ-coefficients. This requires an error term in the productivity equation, which is free of firm heterogeneity, that is correlated with the adoption of activities, but unobserved.

2.2.2 Adoption (indirect) approach

The adoption approach works in two steps. First, we examine simple correlations between the different innovation activities. Positive correlation is a necessary condition for complementarity (corr(A_i, A_j) > 0), but it is not sufficient. This positive correlation can be due not only to complementarity, but also to common exogeneous variables, some of which may be observable. Others may not be observable or there may be common measurement errors.

Second, we regress the innovative activities on exogenous control variables (X) fitting both a multinomial logit model and a multivariate probit model. The **multinomial logit** model examines the drivers for the exclusive categories for innovation activities, using the matrix of exclusive dummies D as the dependent variable. This can be done if the number of categories is not too large and there are sufficient observations in each category. The **multivariate probit** uses the matrix of innovation activities A, with A_i a dummy variable that takes the value 1 if the firm is engaged in innovation activity i. This model estimates the activities non-exclusively but taking the correlation between them into account explicitly as in the following model with *n* different innovation activities:

$$\begin{cases} A_1 = G_1(X_1, \dots, X_m; \alpha) + \nu_1 \\ \dots \\ A_n = G_n(X_1, \dots, X_m; \alpha) + \nu_n \end{cases}$$

Contrasting the results of both models reveals drivers of the exclusive categories in the multinomial logit that are nevertheless significant explanatory variables in non-exclusive categories in the multivariate probit regressions, testing our exclusion restrictions.

Finally, we test the correlation between the generalized residuals of the regressions ($corr(\nu_i, \nu_j) > 0$). If these remain positively correlated after including our set of control variables, this is evidence consistent with activities being complementary, but we cannot "explain" the remaining correlation (see Arora and Gambardella, 1990). If the residuals are no longer correlated, we have successfully explained the correlation and with our set of control variables have potentially identified the drivers of complementarity.

An important caveat remains. We are unable to unequivocally conclude that complementarity exists if generalized residuals 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. Furthermore, these same unobserved firm-specific effects can cause the coefficients of the productivity regression to be biased, as indicated above. Panel data would allow to include fixed firm effects (Miravete &

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, more concerned about uncovering the sources for any fixed firm effect rather than to merely correct for them. As Athey & Stern (1998) suggest, it would be more efficient to estimate the system of innovation activities and the productivity equation jointly. We develop a two step procedure in an attempt to improve our estimation.

2.2.3 TwoStep procedure

How the innovation strategy is organized, i.e. which innovation activities are selected, is clearly a decision made by the firm. Therefore, our results might be subject to a selection bias. It is precisely the firm heterogeneity in the drivers for the innovation strategy choice which we cannot control for, that may cause this bias when estimating the θ parameter in the productivity equation. Controlling for industry and firm characteristics, the decision of how firms organize should not affect innovative performance if we are able to control for all elements affecting the decision of the firm on how to organize (Shaver, 1998). We use the predicted values of the adoption approach to construct the predicted innovation strategy of the firm and use these predicted values in the productivity regression, controlling for the selection bias. According to Shaver, if the innovation strategy, after this correction, does not affect the innovation performance of the firm, we have effectively explained what drives the innovation strategy decision, i.e. explaining complementarity.[2] In order to remove the problem of unobserved firm heterogeneity, the two-step approach requires a good explanatory power for the adoption decision. If the prediction for (one of) the adoption decisions is poor, the noise will contaminate the estimation of the productivity equations.

3. The Data

[2] 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 & Irish (1987), Kaiser (2002)).

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.[3] 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 innovative firms in the sample, distinguished by their answer on the question whether they introduced new or improved products or processes in the last two years and returned a positive amount spent on innovation. The non-innovating firms did not provide information about several variables, used in the analysis.[4]

In characterizing the innovative activities of the firm, we will distinguish between three 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 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.[5] Finally, a more hybrid form of obtaining knowledge and developing new technology is through cooperative R&D agreements between firms or with research institutions. Here again we consider different types of cooperative agreements: cooperation with competitors, cooperation with suppliers or customers, or, cooperation with universities and research institutes. These activities are aggregated in the variable *COOP*. Table 1 summarizes the information about the

[3] 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 & Fleurent, 1995).

[4] In our regression analysis we correct for sample selection using the two-step Heckman correction. Sample selection with respect to innovating firms is rejected and does not significantly affect our results (see below).

[5] 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 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 and as an alternative to developing the technology internally.

firm's innovation strategy. For each of the firms in the innovating subsample, we identify the following innovation activities: own R&D activities (*MAKE*), external technology acquisition (*BUY*), and, cooperation in R&D (*COOP*). The table indicates how many times the different innovation activities are observed in our sample. The large majority of the innovating firms have own R&D activities (81%). More than two thirds of the innovating firms acquire technology on the external market using at least one of the four possible activities. Only thirty percent of the innovating firms also have cooperative agreements in R&D. Most of these agreements are with suppliers, customers or research institutes.

Insert Table 1 here

Table 2 shows simple correlations between the different disaggregated innovation activities. All activities are positively correlated and the shaded boxes indicate the correlations that are significantly different from zero at the 1% level. At the aggregate level cooperation is highly correlated with own R&D activities (0.38) and external technology acquisition (0.28). As expected, own R&D activities and external technology acquisition are positively correlated (0.14) as well. These results are consistent with complementarity between these innovation activities. In the remainder of the analysis we will not use the disaggregated *BUY* and *COOP* categories since this would lead to too many cases to consider.[6]

Further evidence consistent with complementarity can be found in the frequency with which combined choices are observed in our sample.[7] Table 3A reports for the subsample of firms with non-missing observations on innovative performance, a high number of cases of firms that *Make&Buy* (35%) or *Make&Buy&Coop* (27%). Cooperation seems to be an option typically taken in combination with *MAKE* and/or *BUY* since there are almost no cases of *CoopOnly* or *Buy&Coop*. This is why the second column in table 3A reports the cases

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[6] The productivity approach needs to create a dummy for each possible combination of activities, i.e. with n activities we need 2^n variables.
[7] See Table A.1 in Appendix for a definition of the Dummy variables for combinations of innovation activities.

distinguishing only among *MAKE* and *BUY* activities: 62% of the sample firms choose *Make&Buy*, while only 10% choose *BuyOnly* as strategy.

Insert Table 3A here

If innovation activities are truly complementary, their effect should also show up in measures of innovation performance. Table 3B cross-tabulates our innovation output measure[8] with different exclusive combinations of innovation activities at the aggregate level of *MAKE*, *BUY* and *COOP*. The firms report the percentage of 1992 sales that was generated by new or substantially improved products introduced between 1990 and 1992 *(%SalesNewP).* Table 3B seems to suggest that firms, which are restricted to using *MakeOnly* or to external acquisition (*BuyOnly*), do not significantly increase their innovative performance relative to firms that choose to ignore *MAKE* or *BUY*, i.e. *NoMake&Buy&Coop*.[9] The most productive choice of innovative activities seems to be the *Make&Buy* option, which provides strong evidence in favor of complementarity. Firms combining technology *MAKE* and *BUY* activities generated 23.3% 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.

Insert Table 3B here

Adding to the *Make&Buy* option the *COOP* option does not increase innovative performance in terms of new or improved products. This suggest that the contribution of the *COOP* option with respect to innovation performance is rather limited, as witnessed by the low frequency of occurrence—and low performance in

[8] 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. Most of the companies in the sample however 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 conductive to improvements in products. The complementarity between product and process innovations is analysed in Miravete & Pernias (1999).

[9] One could wonder which innovative inputs are generating the innovative output for this category of firms. One possible explanation could be the use of innovative inputs prior to 90-92 and not continued in 90-92. Or firms that acquired technology through the purchase of equipment or some alternative unspecified external source.

terms of percentage of sales from new products—of *Buy&Coop* and *Make&Coop*, and the restricted increase in performance in terms of percentage of sales when combining *COOP* with *BUY* and *MAKE*. After testing this observation more rigorously, we will restrict attention to the *MAKE* and *BUY* activities.

4. Econometric Analysis

4.1 The Control Variables

Besides characterizing the different innovation activities of the companies, the questionnaire also allows to assess other important dimensions of the innovation process, such as the importance of different information sources for innovation, the effectiveness of protection mechanisms, the obstacles, costs and motives for innovation. These dimensions may drive either the innovation productivity of the firm or the choice of innovative activities. Table 4 summarizes the variables that will be used as control variables in the productivity and the adoption regressions in order to assess complementarity between the different innovation activities. In addition to industry dummies at the NACE 2 digit industry level, we characterize three groups of firm specific variables. [10]

First, we define a number of generic firm specific variables. The size of the firm is an important control variable. Larger firms may have higher market power or they may enjoy economies of scale, which raises the payoffs to all or some innovation activities and affect the innovation potential of the firm. We measure size by the number of employees (*EMPL*) or the total sales (*SIZE*). The number of employees is expected to affect the innovation productivity of a firm directly because of the lower bureaucracy associated with fewer employees. Acs and Audretsch (1987) find evidence that smaller firms might be more innovative. Furthermore, we expect that economies of scale and scope are likely to affect the choice of innovation activities. Here, the total sales of the organization are a more appropriate measure.[11] A more competitive environment is likely to stimulate innovation. The export intensity

[10] Table A.2 in Appendix contains summary statistics (mean, standard deviation) for all exogenous variables included in the analysis

[11] The results however are not sensitive to the use of either measure.

(*EXPINT*) of the firm, i.e. the percentage of 1992 sales generated from exports should positively affect innovation productivity. Last of the generic firm specific control variables are the lack of technological opportunity (*OBSTTECHNOLOGY*) and the lack of market opportunities (*OBSTMARKET*) as perceived by the firm. These exogenous factors capture respectively supply and demand factors affecting innovative performance.

Insert Table 4 here

Second, we include a number of variables that characterize the R&D orientation of the firm. The research orientation of the firm is approximated by using variables on the (lack of) resources and the information sources for the innovation process. The data allow to test first whether obstacles to innovations such as a lack of innovation and technical personnel (*OBSTRESO*) influences 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. *BASICRD* 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. We use this variable to proxy for the "basicness" of R&D performed by the firm (see also Kaiser (2002)). The literature suggests that basic R&D capabilities often constitute the firm's absorptive capacity. Through this absorptive capacity, basic R&D capabilities can act as a driver for complementarity. In addition, a more basic nature of innovation suggests less codifiable know-how in the initial phases of the technology life cycle and would favour innovation activities that are typically related to more basic R&D, such as cooperation in R&D, which combines internal and external technology acquisition.

FREEINFO 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 (*COMPINFO*) 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.

Third, we characterize the appropriation regime faced by the firm. In the theoretical literature the appropriation regime has been identified as an important factor affecting the (relative) importance of (different) innovation activities for a firm. The survey assessed how effective the sample firms could appropriate the rents from their innovations (*PROTECTION*). Different appropriation mechanisms could be identified: legal protection (patents and trade marks: *PROTLEG*), and, strategic protection (complexity, secrecy or lead time: *PROTSTRAT*). Firms that are more effective at appropriating the benefits from innovation will have larger payoffs from innovation activities. It remains to be seen whether this holds for any innovation activity, or whether some choices are affected more. More particularly, a complex strategy choice combining various innovative activities might allow to benefit more from appropriation mechanisms. Moreover, different appropriation mechanisms might affect innovation activities differently. One could hypothesize that if legal protection of innovations is tight, firms are more likely to be able to trade technology on the external market. If innovations are easier to protect through strategic measures such as secrecy, lead time, or complexity of the product or process, firms may find it harder to acquire technology externally and may only be able to acquire technology tied to complementary assets such as in firm acquisitions and hiring personnel. Furthermore, if strategic protection is more effective, the firms can generate lead time, secrecy and complexity by combining externally acquired technology with its own developed R&D, leading to complementarity and higher returns to innovation.

In our search for variables that can explain the sources of complementarity, we will be looking for control variables that will show up significantly in the multinomial logit results for *Make&Buy.* This can be further confirmed in the bivariate probit results where these control variables should show up significantly both in *MAKE* and *BUY.* Furthermore, including these variables in the adoption rates should reduce the positive correlation among error terms. Finally, we can have control variables that affect only one of the exclusive categories *MakeOnly* or *BuyOnly* in the multinomial logit. When these variables show up significant in both the *MAKE* and the *BUY* regression in the multivariate probit, we will use this as evidence to establish complementarity, as stated in Result 2 (excluded variables).

4.2 Results

4.2.1 Productivity Approach

In this section we analyze the effect of combining innovation activities on innovation output. If innovation activities are truly complementary, one should observe that the incremental performance of adding an innovation activity is worse for firms that engage in a single activity, compared to firms already engaged in several other innovation activities. We measure innovative performance as the percentage of sales that are generated by new or substantially improved products, introduced in the past two years *(%SalesNewP).* To correct for other firm characteristics that may drive the productivity of innovative strategies, we regress the innovative performance measure on the exclusive dummies of innovative activities choices (using the **D** matrix) together with firm characteristics and industry dummies (see Table 5).[12] The set of firm characteristics included are (*EMPL*, *EXPINT*, *PROTECTION*, *OBSTMARKET*, *OBSTTECHNOLOGY*). The sample includes all firms with non-missing observations (N=316).

Insert table 5 here

In the first column we include exclusive dummy categories (D) for all possible combinations of *MAKE*, *BUY* and *COOP* (Regression (1)). However, as suggested by the results in Table 3B and confirmed in regression (1), we can restrict attention to testing complementarity between the *MAKE* and *BUY* activities (Regression (2)), as adding the *COOP* activity does not seem affect innovative performance.[13] The

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[12] To ease interpretation of coefficients, we include all the exclusive dummy variables in the regression, but do not include a constant term.

[13] Complementarity of R&D cooperation, i.e. $\theta_{MakeBuyCoop} - \theta_{MakeBuy} \geq \theta_{MakeCoop} - \theta_{MakeOnly}$, is clearly rejected.

coefficient on *Make&Buy* in regression (2) is highly significant, while the other coefficients are not significant. The direct test for complementarity (1) is accepted at 10% level of significance. However, the test is weakened by the high standard errors on the coefficients. Inspired by the results of Table 3B, we resort to a sequential test where we first test if the coefficients of *MakeOnly, BuyOnly and NoMake&Buy* are significantly different. Although the *MakeOnly* category seems to be the worse performer compared to *BuyOnly* and even to *NoMake&Buy*, this difference is not statistically significant. Restricting these coefficients to be equal (regression (3)) the complementarity test (1) then simplifies to testing that the coefficients of *Make&Buy* and *Other* are equal. This hypothesis is clearly rejected at the 1% level of significance. Hence, we conclude that there is evidence of complementarity between *MAKE* and *BUY* activities. The size of the coefficient for *Make&Buy* indicates a superior performance of about 7% more new products introduced, confirming the results from Table 3B.

Next to industry dummies, firm size and export intensity are important variables controlling for firm characteristics in innovative performance. The data suggest that small firms (*EMPL*) are more successful in terms of innovative performance. More export oriented firms (*EXPINT*) are more innovation productive, presumably because of the more competitive environment they face. Furthermore, firms that are better able at appropriating the rents from innovation, both through legal mechanisms as well as strategic protection measures, are significantly more successful (*PROTECTION*). The perceived lack of technological opportunities, unsurprisingly, reduces the innovative performance.

As we only have information for those firms that are innovation active, the coefficients in the productivity regression might be biased because of sample selection. The regression is corrected for sample selection following a two-stage Heckman correction procedure in regressions (4) and (5).[14] The hypothesis of sample

[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

selection is rejected, and the correction does not affect our results. We still confirm complementarity between *MAKE* and *BUY* activities.[15] Furthermore, as we have left-censored observations on innovative performance, we also performed a Tobit regression.[16] The results are reported in regressions (6) and (7). These regressions again confirm complementarity between *MAKE* and *BUY* activities.[17]

4.2.2 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 directly. The first three columns of Table 6 represent the result of a multinomial logit where we use the exclusive combinations of make and buy decisions as the dependent variable (using the **D** matrix).[18] The next four columns represent the results of two bivariate probit analyses on the make and buy decisions (using the **A** matrix). Comparing the bivariate probit with the multinomial logits allows to discuss exclusion restrictions as tests for complementarity and to identify drivers for complementarity.

In the bivariate probit analyses, we first demonstrate that controlling for industry effects and firm size does not reduce the observed correlation between make and buy activities significantly. The final two columns include other firm-specific variables that might explain the perceived correlation. Variables included are (*PROTLEG, PROTSTRAT, BASICRD, OBSTRESO, FREEINFO, COMPINFO*). Once controlling for these additional firm specific effects, the residual correlation between technology *MAKE* and *BUY* activities becomes insignificant. Therefore, the added firm specific effects seem to be able to explain the perceived correlation and, hence, complementarity.

Insert Table 6 here

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development of this result). From the resulting estimation we construct the Heckman correction term (λ) to be included in the productivity regression.

[15] The direct test for complementarity is again significant at the 10% level. The sequential test is significant at 1%.

[16] Innovative performance is measured as a percentage of sales. 50 firms reporting 0% of sales from new or substantially improved products introduced between 1990 and 1992.

[17] The direct and sequential tests for complementarity are again significant at 10% and 1% respectively.

[18] The benchmark case is NoMake&Buy.

The multinomial logit model reveals that firm size positively affects all combinations of innovation activities relative to not doing any innovation activity.[19] Strategic protection positively affects the probability that the firm does own R&D, i.e. *PROTSTRAT* is highly significant in the *MakeOnly* and *Make&Buy* cases. Legal protection, on the contrary, is never significant. When the firm is better in protecting the rents from innovation through secrecy, lead time or complexity (*PROTSTRAT*), it is significantly more likely to be engaged in combining different innovation activities. In particular, the role of performing own R&D seems crucial. This is reflected in the high and significant coefficient which *PROTSTRAT* displays also in the *Makeonly* regression. This result is further confirmed in the bivariate probit model. Strategic protection significantly affects the *MAKE* decision of the innovating firms. However, because of complementarity, it also indirectly affects the firm's external technology acquisition *BUY*, albeit to a lesser extent. We, therefore, claim that the appropriation regime is a driver of the perceived complementarity between innovation activities.

As indicated by the multinomial logit regression, the basicness of the R&D performed 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 driver for exploiting the complementarity between internal and external sourcing. *FREEINFO* positively affects the *Make&Buy* category, but this effect is not significant. In the bivariate probit model this effect is confirmed, with *FREEINFO* positively affecting both *MAKE* and *BUY*, be it only at 10% significance level and indicating a relatively stronger effect on the technology *MAKE* decision. Information from competitors (*COMPINFO*) on the other hand does increase the predisposition of the firm to rely solely on the external technology market, as an imitator would.

[19] 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.

4.2.3 Two-Step Procedure

Finally, we correct for potential sample selection of the decision variables, i.e. the innovation strategy. Using the results from the adoption approach, we construct predicted *MAKE* and *BUY* decisions from which to derive our exclusive categories of combinations of innovation activities. We use both the results from the multinomial logit (regression (6.1)) and bivariate probit (regressions (6.3)). 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

Table 7 shows the poor predictive performance of the adoption regressions. Overall, the percentage of correctly predicted cases is 49% for the multinomial logit and 47% for the bivariate probit. Especially the exclusive categories *MakeOnly* and *BuyOnly* are poorly predicted : resp 32% and 33% of these cases are correctly classified.[20] Both models clearly have a tendency to put relatively too many cases in the *NoMake&Buy* category and to underpredict the *Make&Buy* cases. As the last row shows, the many cases of misclassifications do not seem to affect the average innovative performance of the predicted cases, with the *Make&Buy* category still coming out on top in terms of percentage of new and improved products. But they do increase the variation around the mean in each category.

Regressions (8) and (9) in Table 5 present the two-step results for the productivity regression, where the exclusive dummy categories are replaced by the predicted cases on the basis of the multinomial (regression (8)) or bivariate (regression (9)) adoption results.[21] The results for exogeneous factors seem relatively

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[20] 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* or *BuyOnly*. It is especially with these skewed cases that logit/probit models have problems predicting sufficiently accurately.

[21] We prefer to include the predicted binary cases rather than the fitted values, because of the interpretation of the coefficients in terms of assessing complementarity. However, results are very similar if the fitted values are included rather than the predicted binary ones. Also, similar results were

little affected by the correction procedure. However, the coefficient for *Make&Buy* no longer shows up significant, once corrected for selection.[22] Along with Shaver (1998) we could claim this is because we have been able to account for relevant factors explaining the decision underlying a firm's innovation strategy, i.e. complementarity. However, the poor predictive power of the adoption rates especially for the *MakeOnly* and the *BuyOnly* categories and a tendency to predict relatively too many *NoMake&Buy* cases and relatively too few *Make&Buy* cases is an obvious explanatory factor for the poor outcome of the two-step procedure. Furthermore, these results suggest that the 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. Hence, rather than claim that we have fully explained the sources of complementarity, 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 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 explain this complemenarity.

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obtained when estimating the productivity regression using a standard instrumental variables estimation (2SLS), not taking into account the binary nature of the innovation activities dummies.

[22] Rather than including the predicted cases, 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 also 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 adoption rates. A further problem with the generalized residual is that it is not very informative if few continuous variables are included. Beyond size, the independent variables are continuous only to a limited degree since they are based on Likert scale scores from 1 to 5.

Using several different approaches, we find evidence of complementarities between different innovation activities in the innovation strategy. The productivity approach confirms the higher innovation performance of firms 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 orientation of the firm and the appropriation conditions for innovation removes the residual correlation between innovation activities. We, therefore, hypothesise that these variables are important drivers of the observed complementarity between innovation activities. These results are further strengthened when performing a multinomial logit regression where these variables significantly explain the joint occurrence of MAKE and BUY activities.

Given the lack 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 to replicate 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 (percentage of innovating firms)
MAKE	Innovative firms that have own R&D activities and have a positive R&D budget.	**360 (81%)**
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.	**307 (69%)**
Buy License	Innovative firms acquiring technology through licensing.	132 (29%)
R&D Contracting	Innovative firms acquiring technology through R&D Contracting.	187 (42%)
Take-over	Innovative firms acquiring technology through Take-over.	74 (17%)
Hire-away	Innovative firms acquiring technology through hiring away personnel.	184 (42%)
R&D Cooperation (COOP)	Innovative firms that cooperate in R&D. Cooperative partners can be either research institutes, and/or vertical partners such as suppliers or customers and/or competitors.	**133 (30%)**
Research Institutes Cooperation	Innovative firms that cooperate in R&D with research institutes and universities.	132 (29%)
Vertical R&D Cooperation	Innovative firms that cooperate in R&D with suppliers and/or customers.	133 (30%)
Competitor Cooperation	Innovative firms that cooperate in R&D with competitors.	29 (7%)
A total of 714 firms responded, 445 firms innovated.		

Table 2: Unconditional Correlations between Innovation Activities										
	1	2	2.1	2.2	2.3	2.4	3	3.1	3.2	3.3
1. MAKE	1.00									
2. BUY	***0.14***	1.00								
2.1 *BUY LICENSE*	0.07		1.00							
2.2 *R&D CONTRACTING*	0.24		0.28	1.00						
2.3 *TAKE-OVER*	0.03		0.19	0.13	1.00					
2.4 *HIRE-AWAY*	0.07		0.11	0.16	0.27	1.00				
3. R&D COOPERATION	***0.38***	***0.28***	0.14	0.36	0.05	0.13	1.00			
3.1 *VERTICAL*	0.29	0.21	0.19	0.23	0.05	0.12		1.00		
3.2 *RESEARCH*	0.30	0.26	0.11	0.37	0.09	0.11		0.45	1.00	
3.3 *COMPETITORS*	0.11	0.14	0.13	0.22	0.00	0.04		0.33	0.30	1.00

Table 3A: Frequency of Occurrence per Innovation Activity

	MAKE/BUY/ COOP	***MAKE/BUY***
NoMake&Buy&Coop	21 (6%)	21 (6%)
MakeOnly	70 (19%)	85 (23%)
BuyOnly	32 (9%)	33 (9%)
Make&Buy	128 (35%)	227 (62%)
Make&Coop	15 (4%)	
Buy&Coop	1 (0%)	
Make&Buy&Coop	99 (27%)	
TOTAL	366 (100%)	

Note: Categories are exclusive (see Table A.1 in Appendix). There are no firms in the sample that choose "CoopOnly". This sample (N=366) only includes firms that reported non-missing observations on innovative performance

Table 3B: Innovative Productivity per Innovation Activity

	%SalesNewP	**%SalesNewP**
NoMake&Buy&Coop	14.2%	14.2%
MakeOnly	14.8%	14.8%
BuyOnly	15.3%	14.9%
Make&Buy	23.3%	21.8%
Make&Coop	15.2%	
Buy&Coop	0%	
Make&Buy&Coop	19.8%	
TOTAL	19.1%	

Table 4: The Variables	
%SalesNewP (dependent variable)	Percentage of total sales derived from new or substantially improved products introduced between 1990 and 1992.
SIZE	Firm Sales in 10^8 Belgian Francs in 1992.
EMPL	Number of Employees in 1992 in 10.000
EXPINT	Export Intensity in 1992 (Exports/Sales x 0.1)
OBSTMARKET	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)).
OBSTTECHNOLOGY	Importance of lack of technological opportunities as barrier to innovation (on scale 1 (unimportant) to 5 (crucial)).
PROTLEG	Average measure of effectiveness of patents or registration of brands as protection measure of innovation (on scale 1 (unimportant) to 5 (crucial)).
PROTSTRAT	Average measure of effectiveness of secrecy, complexity and/or lead time as a protection measure of innovation (on scale 1 (unimportant) to 5 (crucial)).
PROTECTION	Average measure of effectiveness of patents, copyright, registration of brands, secrecy, complexity and/or lead time as protection measure of innovation (on scale 1 (unimportant) to 5 (crucial)).
BASICRD	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.
OBSTRESO	Importance of lack of innovation and technical personnel as barrier to innovation (on scale 1 (unimportant) to 5 (crucial)).
FREEINFO	Importance of patents, conferences and publications relative to suppliers and customers as information sources for the innovation process.
COMPINFO	Importance of competitors as information sources for the innovation process (on scale 1 (unimportant) to 5 (crucial)).
INDUSTRY DUMMIES	Industry dummies are included where the industry is defined as groupings of NACE2 digit level industries.

Table 5: Productivity Regressions: dependent variable %SalesNewP									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8) Multinomial	(9) Bivariate
EMPL	-0.222*** (0.0676)	-0.225*** (0.0679)	-0.225** (0.0665)	-0.226** (0.0954)	-0.22** (0.0953)	-0.219** (0.102)	-0.219** (0.102)	-0.228*** (0.0622)	-0.231*** (0.0622)
EXPINT	0.739** (0.37)	0.737** (0.37	0.684* (0.36)	0.801 (0.52)	0.804 (0.52)	0.785* (0.44)	0.776* (0.36)	0.819** (0.37)	0.829** (0.37)
PROTECTION	0.0347** (0.016)	0.0349** (0.015)	0.0338** (0.015)	0.0374** (0.015)	0.0367* (0.015)	0.0433** (0.017)	0.0423** (0.017)	0.0494*** (0.0171)	0.0509*** (0.0173)
OBSTMARKET	0.0111 (0.0199)	0.0118 (0.019)	0.0109 (0.0195)	0.00804 (0.0205)	0.00668 (0.0204)	0.0165 (0.023)	0.0168 (0.023)	0.0214 (0.0169)	0.0211 (0.0171)
OBSTTECHNOLOGY	-0.0255* (0.0139)	-0.025* (0.014)	-0.0252* (0.014)	-0.0257* (0.014)	-0.0259* (0.014)	-0.028* (0.016)	-0.028* (0.015)	-0.0202 (0.0140)	-0.0209 (0.0140)
Make&Buy	0.139** (0.064)	0.128** (0.063)	0.141** (0.058)	0.121* (0.077)	0.126* (0.077)	0.0885*** (0.032)	0.096*** (0.030)	0.00427 (0.0398)	-0.00417 (0.0446
MakeOnly	0.0525 (0.066)	0.0487 (0.066)		0.0390 (0.078)		-.0087 (0.074)		-0.0048 (0.0362)	-0.0221 (0.041)
BuyOnly	0.0889 (0.0634)	0.0776 (0.060)	0.0725 (0.052)	0.0642 (0.086)	0.0540 (0.076)	-0.0191 (0.105)	-0.003 (0.067)	0.026 (0.032)	0.016 (0.033)
NoMake&Buy	0.0922 (0.058)	0.0883 (0.058)		0.0776 (0.086)		0.0182 (0.048)		0.0138 (0.0334)	0.0378 (0.044)
Make&Buy&Coop	0.126* (0.0724)								
Make&Coop	0.0593 (0.080)								
Buy&Coop	-0.091** (0.04)								
Industry Dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included
	N=316 OLS (Huber White Sandwich estimator)	N=316 OLS (Huber White Sandwich estimator)	N=316 OLS (Huber White Sandwich estimator)	Heckman Correction	Heckman Correction	N=316 Tobit: 50 left-censored	N=316 Tobit: 50 left-censored	N=316	N=316
	R^2=.523 F(24,291)= 13.02***	R^2=.522 F(22, 294)= 13.98***	R^2=.521 F(20, 296)= 14.85***	λ=0.017 (0.061) χ2(33) = 265.27***	λ=0.026 (0.060) χ2(31)= 263.81***	PseudoR^2=.44 χ2(21)= 49.88***	PseudoR^2=.44 χ2(19)= 49.65***	R^2=0.509 F(22,294)= 12.41***	R^2=0.510 F(22, 294)= 132.37***
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
SIZE	4.360** (2.050)	4.381** (2.050)	4.41** (2.050)	0.114 (0.147)	0.0577 (0.0547)	0.0624 (0.110)	0.0365 (0.058)
PROTLEG	-0.314 (0.455)	-0.438 (0.456)	-0.306 (0.431)			0.0395 (0.109)	-0.0164 (0.078)
PROTSTRAT	1.199*** (0.311)	0.605 (0.373)	1.392*** (0.307)			0.519*** (0.109)	0.163* (0.087)
BASICRD	1.376 (1.199)	1.131 (1.340)	2.646** (1.137)			0.768** (0.367)	0.687** (0.314)
OBSTRESO	0.376 (0.297)	0.248 (0.332)	0.468* (0.283)			0.121 (0.103)	0.0674 (0.085)
FREEINFO	-0.643 (1.590)	-2.006 (1.996)	1.365 (1.503)			1.13* (0.614)	0.887* (0.485)
COMPINFO	0.0525 (0.262)	0.541* (0.299)	0.374 (0.246)			-0.0557 (0.097)	0.213*** (0.072)
Industry Dummies	Included	Included	Included	Included	Included	Included	Included
	Pseudo R^2 = 0.185 $\chi^2(39)$ = 141.6*** N = 359			Correlation 0.19** (0.0902) $\chi^2(14)$ = 36.23*** N = 425		Correlation 0.016 (0.12) $\chi^2(39)$ = 124.61*** N = 359	

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

Table 7A: Actual vs Predicted Cases: Multinomial Logit

Predicted Actual	*MakeOnly* (77)	*BuyOnly* (43)	*Make&Buy* (162)	*NoMakeBuy* (84)	Innovative Performance Mean (std)
MakeOnly (85)	27	9	29	19	0.148 (0.176)
BuyOnly (33)	8	11	6	10	0.149 (0.215)
Make&Buy (227)	40	21	125	39	0.218 (0.168)
NoMakeBuy (21)	2	2	1	16	0.142 (0.168)
Innovative Productivity Mean (std)	0.170 (0.200)	0.157 (0.218)	0.219 (0.227)	0.174 (0.199)	

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* (77)	*BuyOnly* (43)	*Make&Buy* (162)	*NoMakeBuy* (84)	Innovative Performance Mean (std)
MakeOnly (85)	27	11	29	18	0.148 (0.176)
BuyOnly (33)	7	9	6	11	0.149 (0.215)
Make&Buy (227)	45	28	125	29	0.218 (0.168)
NoMakeBuy (21)	4	4	1	12	0.142 (0.168)
Innovative Productivity: Mean (std)	0.170 (0.201)	0.154 (0.200)	0.217 (0.228)	0.180 (0.203)	

APPENDIX

Table A.1: Definition of Exclusive Dummy Variables for Combinations of Innovation Activities (D matrix)

	MAKE	*BUY*	*COOP*	# observations
Dummies Considering MAKE and BUY innovation activities				
NoMake&Buy	0	0	—	21
MakeOnly	1	0	—	85
BuyOnly	0	1	—	33
Make&Buy	1	1	—	227
Dummies Considering MAKE, BUY and COOP innovation activities				
NoMake&Buy&Coop	0	0	0	21
MakeOnly	1	0	0	70
BuyOnly	0	1	0	32
CoopOnly	0	0	1	0
Make&Buy	1	1	0	128
Make&Coop	1	0	1	15
Buy&Coop	0	1	1	1
Make&Buy&Coop	1	1	1	99
Total				**366**

Table A2: Summary statistics

	SAMPLE MEAN (STD)	MEAN *MAKE*=1	MEAN *BUY*=1
EMPL	0.0699 (0.26)		
EXPINT	0.055 (0.035)		
PROTECTION	2.74 (.92)		
OBSTMARKET	2.29 (.75)		
OBSTTECHNOLOGY	2.24 (.97)		
SIZE	.562 (2.063)	.646 (2.24)	.669 (2.34)
BASICRD	.713 (.279)	.739 (.281)	.740 (.283)
PROTLEG	2.09 (1.21)	2.20 (1.23)	2.16 (1.17)
PROTSTRAT	3.30 (.96)	3.46 (.84)	3.40 (.88)
OBSTRESO	2.53 (.97)	2.57 (.94)	2.55 (.94)
COMPINFO	3.05 (1.11)	3.05 (1.10)	3.13 (1.10)
FREEINFO	.52 (.17)	.53 (.17)	.53 (.17)

Industry Dummies: Number of observations (innovating firms)

Steel (Nace 22)	15
Minerals (Nace 24)	22
Chemicals (Nace 25, 26, not 2571, 2572)	46
Pharmaceuticals (Nace 2571, 2572)	11
Metals & Metal products (Nace 31)	43
Electronics (Nace 33, 34, not 3441, 3451)	22
Telecom (Nace 3441)	9
Appliances (Nace 3451)	9
Transportequipment (Nace 35, 36)	21
Machinery&Instruments (Nace 32, 37)	40
Food&Beverages (Nace 41, 42)	57
Textiles (Nace 43, 44, 45)	55
Wood/Paper (Nace 46, 47)	53
Rubber (Nace 48)	20
Other	22
Total	445