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

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First Version: March 2002
Final Version: July 2005

Abstract: Empirical research on complementarity between organizational design decisions has traditionally focused on the question of existence of complementarity. In this paper we take a broader approach to the issue, combining a “productivity” and an “adoption” approach, while including a search for contextual variables in the firm’s strategy that affect complementarity. Analysis of contextual variables is not only interesting per se, but also improves the productivity test for the existence of complementarity. We use our empirical methodology to analyze complementarity between innovation activities: internal R&D and external knowledge acquisition. Our results suggest that internal R&D and external knowledge acquisition are complementary innovation activities, but that the degree of complementarity is sensitive to other elements of the firm’s strategic environment. We identify reliance on basic R&D – the importance of universities and research centers as an information source for the innovation process – as an important contextual variable affecting complementarity between internal and external innovation activities.

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

JEL classification: D21, O31, O32

* The authors are grateful for the comments received from Marco Ceccagnoli, Bronwyn Hall, Jordi Jaumandreu, Ulrich Kaiser, Scott Stern, Giovanni Valentini and two very helpful anonymous referees, as well as seminar participants at Harvard Business School, NYU Stern School of Business, Wisconsin School of Business, INSEAD, Rutgers University, Bocconi University (IGIER), HEC Paris, the Catholic University of Lisbon, the Universities of Navarra and Palma de Mallorca, the workshop on “Innovation and Supermodularity” in Montreal, the Strategic Management Society Conference 2000 in Vancouver, the Applied Econometrics Association Meeting 2001 in Brussels, the Applied IO CEPR conference in Bergen, the European Economic Association Meetings 2002 in Venice, the European Association for Research in Industrial Economics 2002 in Madrid, the 2003 CEPR-IFS conference on Innovation in London, and the 2003 ZEW conference on Innovation in Mannheim. Both authors acknowledge support from the European Commission Key Action “Improving the socio-economic knowledge base” through contract No. HPSE-CT-2002-00146, and the Flemish Government (SOOS), the first author from the MCYT (SEC 2003-08282), the second author from DWTC (IUAP P5/11/33) and KULeuven (OT/04/07A).

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**Introduction**

Today even the largest innovation active organizations cannot rely solely on internal sourcing; they also require knowledge from beyond their boundaries when developing their innovations (Rigby and Zook, 2002). In addition to doing own research and development, firms typically tap knowledge sources external to the firm: through licensing, R&D outsourcing, company acquisition, or the hiring of qualified researchers with relevant knowledge (Arora and Gambardella, 1990; Cockburn and Henderson, 1998; Granstrand et al., 1992). The fact that firms conduct such internal and external knowledge acquisition activities simultaneously suggests that these activities are complementary, i.e. the marginal return to one activity increases as the intensity of the others increases. 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), which stresses the importance of a stock of prior knowledge to effectively scan, screen and absorb external know-how. At the same time, access to external know-how may leverage the efficiency of internal R&D activities, at least if a firm is willing to accept external ideas and knowledge, overcoming the “not invented here” syndrome (Allen, 1986).

This paper contributes in two important ways to the analysis of complementarity between innovation activities. First, in search of evidence consistent with the existence of complementarity, we analyze both the organization of the firm’s innovation strategy and its effect on the performance of the innovation process. While the theoretical literature has only just started to unravel the complex links between internal and external sourcing, the existing empirical literature is, not surprisingly, unable to provide hard evidence on complementarity in the innovation strategy. And that despite the wider casual empirical evidence available on the combination of internal and external sourcing strategies. This paper presents a careful and rigorous empirical method for analyzing complementarity among innovation activities, focusing on own R&D and external knowledge acquisition.
Rather than merely searching for complementarity as such, we aim to identify contextual variables in the firm’s strategy that affect complementarity. Although our findings on the complementarity of internal and external innovation activities are not fully conclusive, we obtain interesting insights about contextual variables that affect whether or not such activities have complementary effects. We identify reliance on more basic R&D (i.e. the use of universities and research centers as information sources for the innovation process) as an important contextual variable that influences the extent to which combining internal and external innovation activities increases a company’s knowledge development potential. If we want the innovation process to be a manageable source of sustainable competitive advantage, understanding under what conditions innovation activities may in fact be complementary is more important than determining what activities are complementary per se (Porter and Siggelkow, 2000). Accordingly, we believe that the concept of complementarity will be more relevant to management if, rather than merely testing for complementarity, we try to identify contextual variables that affect complementarity.

The paper is structured as follows. In the next section we describe the literature on complementarity in innovation strategies. In Section 2 we discuss theoretical and empirical issues about how to assess complementarity, and outline our empirical strategy for assessing complementarity and identifying contextual variables that affect it. In Section 3 we present the data, and in Section 4 we analyze the results of our search for complementarity and related contextual variables. Section 5 concludes.

1. In Search of Complementarity

Although transaction cost theory suggests that acquisition of external knowledge may substitute for own R&D investment (Williamson, 1985; Pisano, 1990), both anecdotal evidence and rigorous empirical research suggest that in-house R&D and external know-how are complementary. A number of studies report casual empirical evidence consistent with complementarity among innovation activities. The Sappho study (Rothwell et al., 1974) showed that successful innovative firms developed better internal
and external communication networks, allowing 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 to facilitate the external linkages, were crucial in explaining successful innovation. More recently, Rigby and Zook (2002) have argued the benefits of opening up the innovation process to external knowledge flows – what is known as “open-market” innovation. Their case studies show that the ability to combine 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). On the one hand, companies may need internal know-how in order to screen possible projects. On the other hand, they may need internal know-how in order to use external know-how effectively. Using scientific know-how as a proxy for internal know-how, and technological know-how as a proxy for external know-how, Arora and Gambardella find support for both hypotheses. This evidence confirms Rosenberg’s (1990) view that “a basic research capability is often indispensable in order to monitor and evaluate research being conducted elsewhere”. Cohen and Levinthal (1989) find a very strong association between the industry’s reliance on more basic fields of science and external sources associated with more basic science on the one hand and firm’s own R&D efforts on the other. Together these findings suggest that the scientific and technological orientation of a firm’s R&D may be an important driver of the observed complementarity between internal and external technology acquisition. Arora and Gambardella (1990) examine the complementarity among four different external sourcing strategies of large chemical and pharmaceutical firms in biotechnology. They find evidence for the joint occurrence of all types of external sourcing strategies, even after correcting for a set of firm characteristics. More importantly, 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. Veugelers and Cassiman (1999) provide evidence on additional firm
characteristics that may drive the choice of internal know-how development and external sourcing at firm level. They show that firms with effective strategic protection mechanisms, such as secrecy, lead-time or complexity, are more likely to be involved in internal knowledge sourcing. Finally, Veugelers (1997) finds evidence of the reverse relationship, namely that external sourcing stimulates internal R&D expenditure, at least for firms with internal R&D departments.

Although all these papers deal with the co-occurrence of internal and external knowledge sourcing activities, they fall short of a direct test of complementarity. To the best of our knowledge, this paper is the first to systematically examine complementarity among different activities within a firm’s innovation strategy. Going beyond merely identifying complementarities, we also analyze the contextual variables that affect perceived complementarity.1 Our results suggest that the complementarity of any two organizational design choices may be sensitive to other elements of the firm’s strategic and economic environment.

2. Measuring Complementarity

2.1 Theory

The concept of fit or complementarity between activities thrives in the management literature, but often remains ill-defined. The study of 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.

Definition

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

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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 multi-tasking 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 those activities and trade secret protection.
\[ \Pi(1, 1) - \Pi(0, 1) \geq \Pi(1, 0) - \Pi(0, 0), \]

i.e., adding an activity while the other activity is already being performed has a higher incremental effect on performance (\( \Pi \)) than adding the activity in isolation.

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

Result 1 (correlation)
Assume \( \Pi(A_1, A_2, X) \) 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)
Suppose an increase in \( X_k \) increases only activity \( A_1 \) directly. But because of the complementarity between activities \( A_1 \) and \( A_2 \), \( X_k \) will indirectly increase activity \( A_2 \). \( A_2^* \) will, therefore, be non-decreasing in \( X_k \) in the presence of complementarity.

The first result states that two activities that are complementary will be positively correlated. Positive correlation, however, is neither necessary nor sufficient for complementarity if the conditions specified above do not hold (Arora, 1996). The main problem is that unobserved heterogeneity between different observations could bias the estimation results and lead either to accepting the hypothesis of complementarity while no complementarity exists, or to rejecting the hypothesis of complementarity when activities in fact are complementary (see Athey and Stern, 1998).

The second result allows for a less noisy empirical assessment of complementarity. 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, affecting only the likelihood of doing own R&D. Then, as result 2 states, in addition to the positive direct effect on own R&D activities of the ability to protect own R&D activities through secrecy, we should find a positive indirect effect, increasing external technology acquisition activities because of the complementarity between buying and investing in internal R&D.

The theory of supermodularity helps to clarify the notion of complementarity and so is useful for empirical research aimed at establishing the existence of complementarity. However, the theory takes
supermodularity as a characteristic of the performance measure $\Pi(A_1, A_2)$ and so avoids an important empirical issue that arises when dealing with a heterogeneous population of firms. Complementarity may be a characteristic of the performance function of all firms, or, more likely, it may be conditional on other characteristics of the firm. In the latter case, we argue that contextual variables affecting the supermodularity of the performance function allow us to better understand the conditions under which innovation activities may be complementary.²

### 2.2 Testing the Existence of Complementarity

#### 2.2.1 Productivity (direct) approach

In the productivity approach we test the existence of complementarity directly by regressing a measure of innovation process performance 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) – the firm’s innovation activities. From these dummy variables we construct different exclusive categories – the firm’s innovation strategy: firms that have no innovation activities (NoMake&Buy); firms that only have own R&D activities (MakeOnly); firms that only have external technology acquisition (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 generated by new or substantially improved products introduced in the past two years ($\Pi(A_1, A_2)$). By restricting the performance measure to innovation 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 (see, e.g., Crépon et al. (1998)). We estimate the following equation:

² Formally, given the performance function $\Pi(A_1, A_2, X, z)$, activities $A_1$ and $A_2$ are complementary when $z = 1$ and
\[ \Pi(A_i', A_j', X^i; \theta, \beta) = \left( 1 - A_i' \right) \left( 1 - A_j' \right) \theta_{00} + A_i' \left( 1 - A_j' \right) \theta_{10} + \left( 1 - A_i' \right) A_j' \theta_{01} + A_i' A_j' \theta_{11} + X^i \beta + \varepsilon^i \]

where superscript \( i \) refers to firm \( i \) and \( A_j' \in \{0, 1\} \quad \forall j = 1,2 \) indicates the innovation activity choices of firm \( i \).\(^3\) The \( \theta_{kl} \) are the coefficients on the firm’s innovation strategy choice and \( X^i \) is a vector of (exogenous) control variables affecting innovation performance. The test for complementarity between two innovation activities, \( A_1 \) and \( A_2 \), is:

\[ \theta_{11} - \theta_{10} \geq \theta_{01} - \theta_{00} \quad (1) \]

Adding an activity while already performing another activity will result in higher incremental innovation performance than when adding the activity in isolation. The proposed test follows directly from the theoretical development of complementarity and establishes the existence of complementarity, conditional on having unbiased estimates for the \( \theta \)-coefficients. A maintained assumption for this analysis, to provide unbiased estimates, is that the drivers of adoption decisions \( A_1 \) and \( A_2 \) are uncorrelated with the error term \( \varepsilon^i \). In section 2.2.3 we discuss and relax this restriction.\(^4\)

### 2.2.2 Adoption (indirect) approach

In the adoption approach we test the existence of complementarity through an exclusion restriction on a bivariate probit model, as discussed in result (2) of the theory. The bivariate probit regresses the non-exclusive innovation activities (MAKE and BUY) on assumed exogenous control variables (\( Z^i \)), but takes the correlation between them into account explicitly, as in the following model:

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\(^3\) If MAKE is \( A_1 = 1 \) and BUY is \( A_2 = 1 \), then NoMake & Buy = \( \left( 1 - A_1 \right) \left( 1 - A_2 \right) \), MakeOnly = \( A_1 \left( 1 - A_2 \right) \), BuyOnly = \( \left( 1 - A_1 \right) A_2 \), Make & Buy = \( A_1 A_2 \).\(^4\) 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. However, they have plant level data available on firms with similar technologies, which saves having to control for technology characteristics. Our data, a cross section of manufacturing firms, are likely to be noisier in innovation production practices.
\[ A_1^* = Z' \gamma_1 + v_1^*, \quad A_1^* = 1 \text{ if } A_1^* > 0, 0 \text{ otherwise} \]
\[ A_2^* = Z' \gamma_2 + v_2^*, \quad A_2^* = 1 \text{ if } A_2^* > 0, 0 \text{ otherwise} \]
\[ E[v_1] = E[v_2] = 0, Var[v_1] = Var[v_2] = 1, Cov[v_1, v_2] = \rho, \]

A variable that affects only one of the innovation activities directly, for example \textit{MAKE}, should – in the presence of complementarity – show up significant in both the \textit{MAKE} and the \textit{BUY} regression in the bivariate probit, since complementarity induces an indirect effect from this variable on the adoption of \textit{BUY}.

2.2.3 \textit{Combining productivity and adoption}

There are difficulties associated with using the performance approach to test for the existence of complementarity. The organization of the innovation strategy, i.e. which innovation activities are selected, is an endogenous decision. It is precisely the firm heterogeneity in the drivers of the innovation strategy choice that may cause a bias when estimating the \( \theta \)'s. That will occur if the heterogeneity, which we do not control for in the productivity estimation, is correlated with the error term (\( e_i \)) of the productivity equation. As Athey and Stern (1998) suggest, it would be more efficient to jointly estimate the system of innovation activities (adoption) and the productivity equation. We develop a two-step procedure – not a full joint estimation – in an attempt to improve our estimation while correcting for the potential biases due to unobserved heterogeneity.\(^5\)

The two-step procedure constructs predicted values for the innovation strategy from the adoption approach. It uses the predicted values of these non-linear regressions as \textit{instruments} for the firm’s

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\(^5\) Panel data would allow including firm fixed (or random) effects (see Miravete and Pernias, 2005). Our data set does not permit a panel data structure. In addition, we are interested in uncovering possible contextual variables affecting complementarity and, therefore, are more concerned about explaining any firm fixed effect rather than merely correcting for it.
innovation strategy in the productivity regression.\textsuperscript{6} For this procedure to successfully remove the problem of unobserved firm heterogeneity, however, we require adoption decision drivers that do not affect innovation performance directly\textsuperscript{7}, and a model with good explanatory power for the adoption decisions. Satisfying both these conditions is a daunting task. First, to find good instruments for organizational design decisions we would need variables that affect only the cost of such decisions, without directly affecting innovation performance. As “prices” for organizational design choices are unlikely to be available, one is bound to find poor instruments. Second, 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, as indicated by Maddala (1983). However, if after this correction the innovation strategy coefficients pass the complementarity test, the effect can be attributed to intrinsic complementarity between innovation activities in the innovation performance function.

\textbf{2.3 Finding Contextual Variables Affecting Complementarity}

While the previous section developed the methodology for testing the existence of complementarity, we now examine factors affecting complementarity. This issue has generated much less concern in the previous literature, but, from a management perspective, it is important to understand under what conditions decisions need to be treated as complementary to generate the desired effect. Furthermore, we argue that the two types of analysis provide complementary results for understanding the complementarity of organizational design decisions.

We estimate a multinomial logit model, examining the drivers for the combinations of innovation activities (in this case: \textit{NoMake&Buy}; \textit{MakeOnly}; \textit{BuyOnly}; \textit{Make&Buy}). This can be done if the number

\textsuperscript{6} Using the predicted values directly in the productivity regression would lead to inconsistent results in the case of endogenous limited dependent regressors (see Angrist (2001) for a formal derivation of this procedure).

\textsuperscript{7} The exogenous variables affecting adoption (Z) cannot all correspond to the exogenous variables affecting innovation performance (X').
of categories is not too large and there is sufficient variation in each category. We estimate the following model of innovation strategy choice:

\[
\text{Prob}(Y = j) = \frac{e^{z_i^k}}{\sum_{j=1}^{4} e^{z_i^k}}, \quad j \in \{\text{NoMake & Buy(1), MakeOnly(2), BuyOnly(3), Make & Buy(4)}\}
\]

where \(z_i^k\) is a vector of characteristics of firm \(i\).

Compared to the bivariate probit model, the multinomial logit model is less restrictive on the effects that exogenous control variables can have on the different choices, allowing coefficients to vary across exclusive combinations of innovation activities. The bivariate probit restricts the coefficients to be the same for all MAKE (BUY) decisions. The multinomial logit model, therefore, reveals drivers of exclusive combinations of the different innovation activities. More particularly, we are interested in the drivers that affect the joint adoption of innovation activities, i.e. variables that show up significantly in the multinomial logit results for Make&Buy, but that are not significant for other innovation strategy choices. These drivers explain the observed correlation between MAKE and BUY activities and, hence, are an indication of contextual variables affecting complementarity within a heterogeneous population of firms.

### 2.4 Empirical Strategy

Our empirical strategy for evaluating complementarity in the innovation strategy follows three steps. First, we directly test for the existence of complementarity as described in the productivity approach. An important problem is that, in this first analysis, we are unable to control for the endogeneity of the innovation strategies. Second, in an effort to understand the variables that affect the choice of different innovation strategies, we perform the multinomial logit. This analysis reveals different drivers of innovation activities and hints at contextual variables that may affect both the joint adoption of innovation activities and thus also complementarity. In a third step, we use this latter information to refine our search.
for complementarity. First, we improve the estimation of the bivariate probit model, using the innovation strategy drivers uncovered, and test a possible exclusion restriction. Second, using contextual variables that affect complementarity, we can cut the data into subsamples in which complementarity in the innovation strategy is more or less relevant. Finally, both the multinomial logit and bivariate probit provide a way to correct for endogeneity in the innovation strategy – biased estimates of the $\theta$’s – in the productivity approach by instrumenting for the actual innovation strategy choice.

3. The Data: Descriptives
The data used for this research are data on innovation in Belgian manufacturing industry that were collected as part of the Community Innovation Survey conducted by Eurostat in EU member states in 1993. A representative sample of 1,335 Belgian manufacturing firms was selected and a total of 714 usable questionnaires were collected. 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 innovation active firms in the sample. Innovation active firms are identified by their answer to the question whether they had been actively engaged in introducing new or improved products or processes in the previous two years. Our effective sample, without missing values, consists of 269 observations.

To characterize a firm’s innovation activities, 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. An alternative is to acquire technology externally. There are different ways in which a firm can be active on the external technology market: it 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

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8 Note that a direct comparison of coefficient has to be handled with care, given that we are comparing a logit with a probit with different distributional assumptions on the error terms.
we 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. *MAKE* and *BUY* activities are non-exclusive. Table 1 summarizes the information about firms’ innovation activities. The large majority of the innovating firms in our sample have own R&D activities (88%), and almost three quarters of them acquire technology on the external market, using at least one of the four possible external sourcing activities. As expected, own R&D activities and external technology acquisition are positively correlated (0.18). These results are consistent with complementarity between innovation activities. The significant positive correlation between the different 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, as this would give us too many cases to consider.\(^{10}\)

*Insert Table 1 here*

Further evidence consistent with complementarity can be found in the frequency with which firms combine these innovation activities – firms’ *innovation strategy*. The first column of Table 2 reports a high number of firms that *Make&Buy* (66%). Only 6% choose *BuyOnly* as a strategy, while 22% choose a *MakeOnly* strategy. We also find that 6% of the firms declare themselves to be innovation active, and yet are not engaged in any innovation activity (*NoMake&Buy*). Most of these firms (10) bought equipment or received “informal” knowledge transfers, activities that we did not formally consider as part of the innovation strategy. In addition, some firms may be actively engaged in innovation due to innovation efforts prior to the period of study and since discontinued.\(^{11}\)

\(^{9}\) 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).

\(^{10}\) 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 having sufficient observations and variation in each exclusive category for the multinomial logit estimations.

\(^{11}\) Furthermore, we have done the analysis where we drop these *NoMake&Buy* observations or include them in the *MakeOnly* or *BuyOnly* categories. The results are very similar. However, in order to test for complementarity we need 4 innovation performance estimation points to calculate the incremental effect of different innovation strategies on innovation performance.
If innovation activities are truly complementary, the effect of their complementarity should also show up in measures of innovation performance. The second column of Table 2 cross-tabulates our innovation performance measure – percentage of 1992 sales generated by new or substantially improved products introduced between 1990 and 1992 – with different exclusive combinations of MAKE and BUY activities. Results suggest that MakeOnly or BuyOnly firms tend to have lower innovation performance than NoMake&Buy firms. The most productive innovation strategy seems to be Make&Buy. Firms that combined 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, while a one-sided test of no complementarity, i.e. testing the incremental effect of adding an innovation activity, is rejected at a 5% level of significance.

4. Econometric Analysis

4.1 The Existence of Complementarity

In this section we analyze how combining innovation activities affects the performance of the innovation process. We regress our measure of innovation performance (% Sales from New Products) on the exclusive combinations of innovation activities, together with firm characteristics and industry dummies that may affect the performance of the innovation process. Table 3 presents the definitions of these variables and some summary statistics.

Since Schumpeter’s work, the size of the firm has traditionally been an important control variable (see, among others, Cohen and Levin, 1989). On the one hand, larger firms may have higher market

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12 Within the sample of innovation active firms innovation performance is not expected to be low (zero) for the NoMake&Buy case. Activities other than own R&D (MAKE) or external knowledge acquisition (BUY) such as buying new equipment or receiving “informal” knowledge transfers can result in positive innovation performance. Starting from this base level of innovation performance we are interested in the complementarity between MAKE and BUY.
power or may enjoy economies of scale and scope, raising the profitability of an innovation strategy. On the other hand, smaller firms are associated with less bureaucracy and so may be more innovation efficient (Acs and Audretsch, 1987). Or smaller firms may just have it easier than large firms when it comes to increasing sales of new or substantially improved products as a percentage of total sales. We measure size by the firm’s sales in 1992 (Sales). In addition, we control for the inputs into innovation activities, i.e. innovation expenditures relative to sales. The questionnaire asked for the amount (in Belgian francs) spent on all innovation activities, including own R&D, licensing and R&D contracting, and other development activities. Innovation intensive firms are likely to produce more innovations, thus making sales of new products a larger percentage of total sales (Innovation Intensity). Given that the profitability of an innovation strategy is likely to be affected by the competitiveness of the environment and that exporting firms tend to encounter a more competitive environment, a firm’s export intensity (Export Intensity), i.e. the percentage of 1992 sales generated from exports, should positively affect innovation performance. Last of the generic firm-specific control variables are lack of technological opportunity (Technology Obstacles) and lack of market opportunities (Market Obstacles), as perceived by the firm. These exogenous factors capture, respectively, supply factors and demand factors affecting the scope for innovative performance. Both types of obstacles are expected to reduce innovation performance. In addition, we include industry dummies at the two-digit industry classification level.

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The results are presented in Table 4. Consistent with complementarity, 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 ($\theta_{11} - \theta_{10} \geq \theta_{01} - \theta_{00}$) is accepted at a 5% level of significance (p-value = 0.018).\(^{13}\) Next to industry dummies, firm size,

\(^{13}\) To ease the interpretation of coefficients, we include all the exclusive innovation strategy 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 4.
innovation intensity and export intensity are important variables controlling for firm characteristics in innovation performance. The data suggest that small firms (Sales) and more intensive innovation spenders are more successful in terms of innovation performance. More export-oriented firms (Export Intensity) are also more innovation productive, presumably because of the more competitive environment they face. Unsurprisingly, perceived lack of technological and market opportunities reduces innovation performance. However, these effects are not significant.

As we only have information for innovation active firms, the coefficients in the productivity regression may be biased. The regression is corrected for sample selection, following a two-stage Heckman correction procedure in regression (2). 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 significance. Furthermore, as we have left-censored observations on innovation performance, we also performed a Tobit regression. The results are reported in regression (3). This regression, again, confirms 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 innovation intensity on innovation performance. We should note, however, that up to this stage we did not instrument for endogenous innovation strategies. This is an important issue to which we return in section 4.3.3.

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14 The sample selection is for whether firms are innovation active or not. In the first stage the innovation equation is estimated. In a probit model, we regress 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 (\( \lambda \)) to be included in the productivity regression.

15 Innovation 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 Finding Contextual Variables Affecting Complementarity

In the previous section we found evidence of the existence of complementarity between innovation activities by analyzing the direct effect of the innovation strategy on innovation performance. In this section we examine the innovation strategy adoption decisions. We search for variables that can explain the joint occurrence of innovation activities, or—stronger—variables that affect complementarity between innovation activities. The literature surveyed suggests that basic R&D capabilities often constitute the firm’s absorptive capacity. Firms with basic R&D capabilities are, therefore, more likely engaged in combining *MAKE* and *BUY* activities, as 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 (see Table 3). We use this variable to proxy for the firm’s reliance on more “basic” types of know-how.

Next, we include a number of variables that we expect will affect the adoption choices of the exclusive innovation strategies. Unfortunately, little theory exists to guide us in our selection of explanatory variables, especially for identifying differences across exclusive innovative strategies. 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*). Higher innovation expenditure, while controlling for size, also increases the likelihood of engaging in different innovation activities in general (*Innovation Intensity*).

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 and Cassiman, 1999). If legal protection of innovations (*Effectiveness of IP Protection Industry*) is tight, firms will probably be able to buy technology on the external market. At the same time, however, firms will have a greater incentive to develop such tradable technology through *MAKE*. Therefore, the effect of *Effectiveness of IP Protection* on the innovation strategy is not straightforward, but is expected to
have a positive effect on the *BUY* decisions. If innovations are easier to protect through strategic measures, such as secrecy, lead time or product or process complexity (*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 *Effectiveness of Strategic Protection* exclusively affects the firm’s *MAKE* decision. In a multinomial regression we expect a significant positive coefficient on the *Effectiveness of Strategic Protection* in the *MakeOnly* and *Make&Buy* decisions.

Finally, 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, resulting in a positive effect on the *BUY* decision. 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 importance of freely available information from patents, publications and conferences *relative* to information from customers and suppliers. Both *MAKE* and *BUY* activities might be affected when these involuntary “spillovers” are more important. Own R&D is stimulated by and capitalizes on these spillovers, while external knowledge acquisition results from a better understanding of the technology market. Finally, when information from competitors (*Competitor Information*) is important, the firm is more likely to be either a follower or an imitator with respect to innovation. Therefore, firms in the same industry are more likely to catch up by accessing relevant state-of-the-art technology on the external technology market, positively affecting the *BUY* decision, and in particular the *BuyOnly* strategy.
Table 5 presents 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.\textsuperscript{16} The Basic R&D Reliance of a firm significantly affects the probability of combining innovation activities (Make&Buy), while not significantly affecting stand-alone activities (MakeOnly and BuyOnly).\textsuperscript{17} A 10% increase in reliance on basic R&D increases the likelihood of combining internal and external sourcing by 2.7%. This confirms the importance of having an in-house basic R&D capability for creating the environment to exploit the complementarity between internal and external sourcing.

Insert Table 5 here

Furthermore, the multinomial logit model reveals that firm size positively affects all combinations of innovation activities, relative to not doing any innovation activity. Effectiveness of IP Protection is only marginally significant for the Make&Buy case. But, as hypothesized, 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. Interestingly, Competitor Information does increase the firm’s predisposition to rely solely on the external technology market, as an imitator would. More surprisingly, Resource Limitations seem to positively affect own R&D activities, possibly indicating that it is precisely firms that do internal R&D that experience this resource constraint.

4.3 Refining the Search for Complementarity

In the search to understand the contextual variables that affect individual innovation strategy choices – in particular, Make&Buy – we refine and improve our search for complementarity. First, we uncover

\textsuperscript{16} The benchmark case is NoMake&Buy. 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 change significantly. 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.

\textsuperscript{17} For a variable to significantly and exclusively affect the joint adoption decision, it should not affect MakeOnly and BuyOnly but should significantly affect Make&Buy. More generally, it should be true that $\delta_{\text{Make&Buy}} - \delta_{\text{MakeOnly}} - \delta_{\text{BuyOnly}} > 0$. This hypothesis cannot be rejected at standard levels of significance. As a consequence, this variable
variables that are relevant in specifying the structural MAKE and BUY decisions and that are needed for testing the existence of complementarity using an exclusion restriction. Second, the analysis directs us towards subsamples of firms in which complementarity between innovation activities may play out stronger. Finally, the outcome of this analysis provides the necessary first-stage estimation for correcting the endogeneity of the innovation strategy.

4.3.1 Adoption and Exclusion Restriction

Correlations between innovation activities – MAKE and BUY – constitute a weak test of the existence of complementarity through the adoption approach. In the bivariate probit analyses in Table 6, we first demonstrate that controlling for industry effects, firm size and innovation intensity does not significantly reduce the observed correlation between make and buy activities (regression (6.1)). Using the same specification of exogenous variables as in the multinomial logit, the final two columns include our other variables that may explain the perceived correlation (regression (6.2)). Including these variables in the adoption choices for MAKE and BUY in the bivariate probit model should reduce the observed positive correlation between the error terms if we believe we have found good contextual variables at the firm level explaining the joint occurrence of MAKE and BUY. After controlling for these additional firm-specific effects – in particular, Basic R&D Reliance and the Effectiveness of Strategic Protection – 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. reinforcing our previous findings from the multinomial logit.

Insert Table 6 here

Through an exclusion restriction, a stronger test of the existence of complementarity can be performed using the bivariate probit model. However, this requires finding a reasonable excluded variable
in one of the adoption equations of MAKE or BUY. We hypothesized that if a firm is better at protecting its rents from innovation through secrecy, lead time or complexity, it is significantly more likely to be engaged in own R&D activities. Our results from the multinomial logit regression are consistent with such an exclusion restriction, where 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, but does not affect the BuyOnly innovation strategy.\(^\text{18}\) Our maintained assumption is that Effectiveness of Strategic Protection does not affect innovation performance directly, but only through its effect on the decision to do more own R&D, i.e. performing R&D in-house is less costly than acquiring knowledge externally. In the bivariate probit results, strategic protection significantly affects the MAKE decision of innovating firms and, consistent with complementarity, also indirectly affects firms’ external technology acquisition, or BUY, decision, albeit to a lesser extent.

4.3.2 Split Sample: High versus Low Basic R&D Reliance

Our results from the multinomial logit indicate that Basic R&D Reliance is an important contextual variable affecting complementarity. This implies that complementarity is relatively more important for firms with a high reliance on Basic R&D than it is for the rest of the population of firms. We test this implication of our results by splitting the sample between firms with a Basic R&D Reliance score above the mean, and firms with a score below the mean. Results presented in Table 4, regressions (4) and (5), clearly show that, for firms with a high Basic R&D Reliance, the coefficient on the Make&Buy strategy jumps up relative to the other strategies and complementarity is confirmed. The coefficients on the other variables remain comparable, except for the effect of Export Intensity, which loses significance. For firms with low Basic R&D Reliance, the impact is not as impressive, although we cannot reject complementarity even for this subset of firms.

\(^{18}\) As the coefficient of the multinomial logit regression is estimated relative to the NoMake&Buy case, for this to hold we need to assume that Effectiveness of Strategic Protection has no effect on the NoMake&Buy category. We believe this is a reasonable assumption.
4.3.3 Endogeneity of the Innovation Strategy: A Two-Step Procedure

Finally, we correct for potential sample selection in the decision variables, i.e. the innovation strategy in the innovation performance regression. Using the results from the adoption approach, we construct predicted innovation strategy decisions (from multinomial logit) or predicted innovation activities (from bivariate probit) and use these as instruments in the innovation performance regression (Angrist, 2001). As discussed in section 2.2.3, two conditions need to be satisfied for the TwoStep procedure to generate reliable results. First, for identification we need independent variables that affect adoption without affecting innovation performance directly. Short of “input prices” for the adoption decision, we can only propose imperfect instruments, a problem closely related to our discussion of a reasonable exclusion restriction. Nevertheless, we believe that our search for contextual variables affecting complementarity has revealed some interesting drivers of the adoption decision, which could serve as potential instruments. The multinomial logit regression indicates that Basic R&D Reliance and appropriation conditions are important joint (Basic R&D Reliance) and exclusive (appropriation conditions) drivers of innovation activities.\(^{19}\) Second, the value added of a two-step procedure depends on the predictive power of the adoption regressions. We therefore 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 power 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: only 51% and 43%, respectively, of these cases are correctly classified.\(^{20}\) Both models clearly have a tendency

\(^{19}\) One might worry that, in addition to the direct effect on adoption, these variables would affect performance of the innovation process directly. In results not reported, but available on request, these variables turn out to be insignificant when included in the productivity equation.

\(^{20}\) This low level of predictive power persists over various alternative specifications and variables we tried. Inherent to activities which are complementary is the low level of occurrence of exclusive categories, i.e. *MakeOnly* and in
to put relatively too many cases in the *BuyOnly* and *NoMake&Buy* category, and to underpredict the *Make&Buy* cases. As the last row shows, despite the many cases of misclassifications, the predicted *Make&Buy* category still comes out on top in terms of percentage of sales from new and improved products. The predicted *BuyOnly* category, in particular, has a higher innovation performance compared to 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 (7) and (8) in Table 8 present the two-step results for the innovation performance regression, where the exclusive dummy categories are instrumented by the predicted probabilities on the basis of the multinomial (regression (7)) or bivariate (regression (8)) adoption results.\(^{21}\) The results for exogenous 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. Nevertheless, the results of the correction using the multinomial logit specification are still consistent with complementarity. The *Make&Buy* coefficient is higher than the other coefficients, but the coefficients are too imprecisely estimated to reject the null of no complementarity. With the more restrictive bivariate specification of adoption decisions, as discussed before, the coefficient for *BuyOnly* increases substantially. The poor predictive power of the adoption rates is an obvious explanation for the poor outcome of the two-step procedure. An additional reason for the weak statistical significance lies in the two-stage method itself, which is often found to have multicollinearity problems, as suggested by Maddala (1983). Furthermore, these results suggest that the full-fledged joint estimation of the productivity equation and the adoption decisions, as suggested by Athey and Stern (1998), is unlikely to

\(^{21}\) 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. This should again lead to unbiased estimates of the $\theta$ parameters (see Gouriéroux et al. (1987)). However, in this case, all estimated $\theta$ coefficients are non-significant, due to the multicollinearity with the score variables, which is not surprising given the poor predictive performance
improve the overall performance of the estimation. 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, including good potential instruments. Our understanding of factors driving joint occurrence and eventual complementarity could only be enhanced by such improvements.

Insert Table 8 here

5. Conclusions

Improving a firm’s innovation performance has become an important top management concern. For that reason, firms are experimenting in their innovation process, combining internal R&D and external knowledge acquisition activities. Our results are consistent with the existence of complementarity between internal and external innovation activities. Therefore, innovation management requires a tight integration of internal and external knowledge within the firm’s innovation process to capture the positive effects each innovative activity has on the marginal return of the other. More importantly, our analysis reveals that the extent to which the innovation process relies on basic R&D affects the strength of the complementarity between innovation activities. Hence, complementarity is context-specific. As this reliance on basic R&D is an organizational decision within the firm’s innovation process, we claim to have uncovered a possible source of complementarity. Thus, success in innovation will depend not only on combining various innovation activities, but also on creating the right context. Careful management of the innovation process, based on an understanding of these principles, may thus provide sustainable competitive advantage.

Given the scarcity of previous empirical work on this topic, these results provide some interesting cues for further theoretical work on the complementarity of innovation activities and the context as a of the multinomial logit regression. A further problem with the generalized residual is that it is not very informative
critical factor in assessing innovation success. At the same time, additional empirical work is needed to improve the predictive power and confirm the robustness of these results, through a search for better instruments for innovation activities. We therefore feel that the most important avenue for future research is the search for firm characteristics that affect complementarity. This is a call for both theoretical and empirical work in the area of innovation management and strategy.

**References**


if few continuous variables are included.


Table 1: Innovation Activities and Correlations

<table>
<thead>
<tr>
<th>Innovation Activity</th>
<th>Variable Construction</th>
<th>Number of Firms without missing values N = 269</th>
<th>1.</th>
<th>2.</th>
<th>2.1</th>
<th>2.2</th>
<th>2.3</th>
<th>2.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. MAKE</td>
<td>Innovative firms that have own R&amp;D activities and have a positive R&amp;D budget (0/1).</td>
<td>237 (88%)</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. BUY</td>
<td>Innovative firms acquiring technology through at least one of the following external technology acquisition modes: licensing; R&amp;D Contracting/R&amp;D advice; Take-over; Hire-away (0/1).</td>
<td>194 (72%)</td>
<td></td>
<td>0.18*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.1 Buy License</td>
<td>Innovative firms acquiring technology through licensing (0/1).</td>
<td>88 (33%)</td>
<td>0.09</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.2 R&amp;D Contracting</td>
<td>Innovative firms acquiring technology through R&amp;D Contracting (0/1).</td>
<td>100 (37%)</td>
<td>0.21*</td>
<td>0.32*</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.3 Take-over</td>
<td>Innovative firms acquiring technology through Take-over (0/1).</td>
<td>44 (16%)</td>
<td>-0.02</td>
<td>0.21*</td>
<td>0.18*</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.4 Hire-away</td>
<td>Innovative firms acquiring technology through hiring away personnel.</td>
<td>113 (42%)</td>
<td>0.08</td>
<td>0.05</td>
<td>0.12</td>
<td>0.30*</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>

* are significantly different from zero at 1% level of significance

Table 2: Frequency of Innovation Strategies and Innovation Performance by Innovation Strategy

<table>
<thead>
<tr>
<th>Innovation Strategy</th>
<th>Frequency of Innovation Strategy</th>
<th>% Sales from New Products</th>
</tr>
</thead>
<tbody>
<tr>
<td>NoMake&amp;Buy</td>
<td>16 (6%)</td>
<td>14.9%</td>
</tr>
<tr>
<td>MakeOnly</td>
<td>59 (22%)</td>
<td>13.5%</td>
</tr>
<tr>
<td>BuyOnly</td>
<td>16 (6%)</td>
<td>9.7%</td>
</tr>
<tr>
<td>Make&amp;Buy</td>
<td>178 (66%)</td>
<td>20.5%</td>
</tr>
<tr>
<td>TOTAL</td>
<td>269 (100%)</td>
<td>18.0%</td>
</tr>
</tbody>
</table>

Complementarity Test

\[ F(1, 265) = 2.67^{**} \]

\[ p-value = 0.052 \text{ one-sided} \]

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 3: Variable Definitions

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Variable Construction</th>
<th>SAMPLE MEAN (STD)</th>
<th>MEAN MAKE=1 (237)</th>
<th>MEAN BUY=1 (194)</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Sales from New Products (dependent variable)</td>
<td>Percentage of total sales derived from new or substantially improved products introduced between 1990 and 1992.</td>
<td>0.18 (0.197)</td>
<td>0.188 (0.20)</td>
<td>0.196 (0.208)</td>
</tr>
<tr>
<td>Sales</td>
<td>Firm Sales in 10^8 Belgian Francs in 1992.</td>
<td>0.462 (2.063)</td>
<td>0.48 (1.29)</td>
<td>0.507 (1.28)</td>
</tr>
<tr>
<td>Innovation Intensity</td>
<td>Expenditures on innovation activities relative to Sales</td>
<td>0.036 (0.05)</td>
<td>0.037 (0.05)</td>
<td>0.039 (0.05)</td>
</tr>
<tr>
<td>Export Intensity</td>
<td>Export Intensity in 1992 (Exports/Sales x 0.1)</td>
<td>0.059 (0.033)</td>
<td>0.062 (0.032)</td>
<td>0.060 (0.033)</td>
</tr>
<tr>
<td>Market Obstacles</td>
<td>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)).</td>
<td>2.23 (0.67)</td>
<td>2.26 (0.63)</td>
<td>2.25 (0.66)</td>
</tr>
<tr>
<td>Technological Obstacles</td>
<td>Importance of lack of technological opportunities as barrier to innovation (on scale 1 (unimportant) to 5 (crucial)).</td>
<td>2.23 (0.97)</td>
<td>2.28 (0.96)</td>
<td>2.31 (0.98)</td>
</tr>
<tr>
<td>Effectiveness IP Protection Industry</td>
<td>Industry Average (Nace2) of measure of effectiveness of patents as means to protect innovation (firm-level measure on scale 1 (unimportant) to 5 (crucial)).</td>
<td>2.10 (0.46)</td>
<td>2.14 (0.46)</td>
<td>2.16 (0.49)</td>
</tr>
<tr>
<td>Effectiveness Strategic Protection</td>
<td>Average measure of effectiveness of secrecy, complexity and/or lead time as means to protect innovation (on scale 1 (unimportant) to 5 (crucial)).</td>
<td>3.33 (0.91)</td>
<td>3.46 (0.82)</td>
<td>3.46 (0.82)</td>
</tr>
<tr>
<td>Basic R&amp;D Reliance</td>
<td>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.</td>
<td>0.710 (0.269)</td>
<td>0.733 (0.268)</td>
<td>0.735 (0.272)</td>
</tr>
<tr>
<td>Resource Limitations</td>
<td>Importance of lack of innovation and technical personnel as barrier to innovation (on scale 1 (unimportant) to 5 (crucial)).</td>
<td>2.58 (0.93)</td>
<td>2.63 (0.94)</td>
<td>2.61 (0.90)</td>
</tr>
<tr>
<td>Public Information</td>
<td>Importance of patents, conferences and publications, relative to suppliers and customers, as information sources for the innovation process.</td>
<td>0.53 (0.16)</td>
<td>0.53 (0.176)</td>
<td>0.53 (0.16)</td>
</tr>
<tr>
<td>Competitor Information</td>
<td>Importance of competitors as information sources for the innovation process (on scale 1 (unimportant) to 5 (crucial)).</td>
<td>3.09 (1.09)</td>
<td>3.08 (1.06)</td>
<td>3.19 (1.07)</td>
</tr>
<tr>
<td>INDUSTRY DUMMIES</td>
<td>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 &amp; 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&amp;Instruments (Nace 32, 37, 29 obs), Food&amp;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).</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOW TECH INDUSTRIES</td>
<td>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</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A total of 714 firms responded, 445 firms innovated in the full sample, 269 firms without missing values.

*NACE2: Statistical Classification of Economic Activities in the European Community at two-digit level (Nomenclature Statistique des Activités économiques dans la Communauté Européenne)
| Table 4: Productivity Regressions: dependent variable % Sales from New Products |
|---|---|---|---|---|
|   | (1) | (2) | (3) | (4) | (5) |
| Sales  | -0.0195***  
(0.00652) | -0.0180*  
(0.010) | -0.0203*  
(0.011) | -0.0182**  
(0.0079) | -0.0171  
(0.0135) |
| Innovation Intensity  | 0.522**  
(0.263) | 0.524**  
(0.269) | 0.748**  
(0.313) | 0.597*  
(0.365) | 0.264  
(0.511) |
| Export Intensity  | 0.0827**  
(0.033) | 0.098*  
(0.053) | 0.093**  
(0.043) | 0.04  
(0.05) | 0.166***  
(0.057) |
| Market Obstacles  | -0.0032  
(0.0178) | -0.00495  
(0.0196) | -0.0030  
(0.0223) | 0.00418  
(0.0255) | -0.00434  
(0.0266) |
| Technological Obstacles  | -0.0132  
(0.0132) | -0.0130  
(0.0132) | -0.0158  
(0.0152) | -0.0232  
(0.0195) | 0.0058  
(0.0192) |
| Make&Buy  | 0.183***  
(0.058) | 0.166**  
(0.069) | 0.162***  
(0.0653) | 0.242***  
(0.089) | 0.0457  
(0.079) |
| MakeOnly  | 0.11*  
(0.061) | 0.092  
(0.071) | 0.0726  
(0.0687) | 0.163**  
(0.082) | 0.0238  
(0.087) |
| BuyOnly  | 0.086  
(0.057) | 0.066  
(0.082) | -0.0368  
(0.082) | 0.087  
(0.078) | -0.0251  
(0.08) |
| NoMake&Buy  | 0.141***  
(0.053) | 0.119  
(0.08) | 0.0918  
(0.0846) | 0.206*  
(0.119) | 0.087  
(0.067) |
| Industry Dummies  | Included | Included | Included | Included | Included |
| Complementarity Test:  |  |  |  |  |  |
| Make&Buy > MakeOnly > BuyOnly > NoMake&Buy  | F(1, 247) = 4.47**  
Chi2(1) = 3.02** | F(1,248) = 5.70***  
F(1, 112) = 3.33**  
F(1, 114) = 3.15** |  |  |  |
| N=269 OLS (Huber White Sandwich estimator)  |  |  |  |  |  |
| Heckman Correction Observations 269 uncensored, 169 censored  |  |  |  |  |  |
| N=269 Tobit: 43 left-censored observations  |  |  |  |  |  |
| N=134 OLS (Huber White Sandwich estimator)  |  |  |  |  |  |
| N=135 OLS (Huber White Sandwich estimator)  |  |  |  |  |  |
| Model  | F(22,247) = 13.34***  
λ=-0.0232  
(0.057)  
χ2(21) = 55.79***  
χ2(33) = 246.31***  
F(22,112) = 8.81***  
F(21,114) = 7.77*** |  |  |  |  |
| Coefficients Significant at: 1%***, 5%** and 10%*, standard deviations between brackets. |
Table 5: Multinomial Logit

<table>
<thead>
<tr>
<th></th>
<th>MakeOnly</th>
<th>BuyOnly</th>
<th>Make&amp;Buy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales</td>
<td>5.309*</td>
<td>5.465*</td>
<td>5.311*</td>
</tr>
<tr>
<td>(3.012)</td>
<td>(3.012)</td>
<td>(3.011)</td>
<td></td>
</tr>
<tr>
<td>Innovation Intensity</td>
<td>-2.459</td>
<td>8.685</td>
<td>1.150</td>
</tr>
<tr>
<td>(9.496)</td>
<td>(9.747)</td>
<td>(9.226)</td>
<td></td>
</tr>
<tr>
<td>Effectiveness IP Protection Industry</td>
<td>0.925</td>
<td>1.108</td>
<td>2.220*</td>
</tr>
<tr>
<td>(1.342)</td>
<td>(1.537)</td>
<td>(1.364)</td>
<td></td>
</tr>
<tr>
<td>Effectiveness Strategic Protection</td>
<td>1.549***</td>
<td>0.687</td>
<td>1.731***</td>
</tr>
<tr>
<td>(0.448)</td>
<td>(0.451)</td>
<td>(0.445)</td>
<td></td>
</tr>
<tr>
<td>Basic R&amp;D Reliance</td>
<td>2.279</td>
<td>0.943</td>
<td>3.519***</td>
</tr>
<tr>
<td>(1.429)</td>
<td>(1.777)</td>
<td>(1.315)</td>
<td></td>
</tr>
<tr>
<td>Resource Limitations</td>
<td>0.714**</td>
<td>0.158</td>
<td>0.748**</td>
</tr>
<tr>
<td>(0.364)</td>
<td>(0.385)</td>
<td>(0.359)</td>
<td></td>
</tr>
<tr>
<td>Public Information</td>
<td>-0.260</td>
<td>0.191</td>
<td>0.462</td>
</tr>
<tr>
<td>(2.298)</td>
<td>(2.749)</td>
<td>(2.194)</td>
<td></td>
</tr>
<tr>
<td>Competitor Information</td>
<td>-0.249</td>
<td>0.619*</td>
<td>0.00697</td>
</tr>
<tr>
<td>(0.262)</td>
<td>(0.352)</td>
<td>(0.255)</td>
<td></td>
</tr>
<tr>
<td>Low Tech Industry</td>
<td>-1.425</td>
<td>-0.0644</td>
<td>-0.900</td>
</tr>
<tr>
<td>(1.276)</td>
<td>(1.536)</td>
<td>(1.250)</td>
<td></td>
</tr>
</tbody>
</table>

Pseudo $R^2 = 0.201$
$\chi^2(27) = 78.30***$
N = 269

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

Table 6: Bivariate Probit

<table>
<thead>
<tr>
<th></th>
<th>Make</th>
<th>Buy</th>
<th>Make</th>
<th>Buy</th>
</tr>
</thead>
<tbody>
<tr>
<td>(6.1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales</td>
<td>-0.0067</td>
<td>0.0565</td>
<td>-0.0270</td>
<td>0.0234</td>
</tr>
<tr>
<td>(0.094)</td>
<td>(0.0821)</td>
<td>(0.076)</td>
<td>(0.082)</td>
<td></td>
</tr>
<tr>
<td>Innovation Intensity</td>
<td>0.3119</td>
<td>3.643*</td>
<td>-3.397</td>
<td>2.119</td>
</tr>
<tr>
<td>(2.668)</td>
<td>(2.034)</td>
<td>(2.533)</td>
<td>(1.861)</td>
<td></td>
</tr>
<tr>
<td>Effectiveness IP Protection Industry</td>
<td>0.639</td>
<td>0.788***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.425)</td>
<td>(0.270)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effectiveness Strategic Protection</td>
<td>0.703***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.131)</td>
<td>(0.103)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Basic R&amp;D Reliance</td>
<td>1.345***</td>
<td>0.781**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.513)</td>
<td>(0.363)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resource Limitations</td>
<td>0.324**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.155)</td>
<td>(0.0445)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public Information</td>
<td>0.237</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.857)</td>
<td>(0.435)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competitor Information</td>
<td>-0.0218*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.114)</td>
<td>(0.176**)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Tech Industry</td>
<td>-0.779***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.235)</td>
<td>(0.230)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Correlation 0.31**
(0.122)
$\chi^2(6) = 18.19***$
N = 269

Coefficients Significant at: 1%***, 5%** and 10%*. Standard deviations between brackets.
### Table 7A: Actual vs Predicted Cases: Multinomial Logit

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th>MakeOnly (75)</th>
<th>BuyOnly (31)</th>
<th>Make&amp;Buy (137)</th>
<th>NoMakeBuy (26)</th>
<th>Innovative Performance Mean (std)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MakeOnly (59)</td>
<td></td>
<td>30</td>
<td>7</td>
<td>19</td>
<td>3</td>
<td>0.135 (0.158)</td>
</tr>
<tr>
<td>BuyOnly (16)</td>
<td></td>
<td>4</td>
<td>7</td>
<td>2</td>
<td>3</td>
<td>0.0969 (0.166)</td>
</tr>
<tr>
<td>Make&amp;Buy (178)</td>
<td></td>
<td>40</td>
<td>16</td>
<td>115</td>
<td>7</td>
<td>0.205 (0.210)</td>
</tr>
<tr>
<td>NoMakeBuy (16)</td>
<td></td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>13</td>
<td>0.149 (0.158)</td>
</tr>
<tr>
<td>Innovative Mean (std)</td>
<td></td>
<td>0.163 (0.189)</td>
<td>0.169 (0.213)</td>
<td>0.194 (0.196)</td>
<td>0.168 (0.211)</td>
<td></td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th>MakeOnly (79)</th>
<th>BuyOnly (34)</th>
<th>Make&amp;Buy (133)</th>
<th>NoMakeBuy (23)</th>
<th>Innovative Performance Mean (std)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MakeOnly (59)</td>
<td></td>
<td>26</td>
<td>8</td>
<td>22</td>
<td>3</td>
<td>0.135 (0.158)</td>
</tr>
<tr>
<td>BuyOnly (16)</td>
<td></td>
<td>2</td>
<td>7</td>
<td>2</td>
<td>5</td>
<td>0.0969 (0.166)</td>
</tr>
<tr>
<td>Make&amp;Buy (178)</td>
<td></td>
<td>48</td>
<td>16</td>
<td>108</td>
<td>6</td>
<td>0.205 (0.210)</td>
</tr>
<tr>
<td>NoMakeBuy (16)</td>
<td></td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>9</td>
<td>0.149 (0.158)</td>
</tr>
<tr>
<td>Innovative Mean (std)</td>
<td></td>
<td>0.175 (0.190)</td>
<td>0.190 (0.226)</td>
<td>0.191 (0.194)</td>
<td>0.117 (0.188)</td>
<td></td>
</tr>
</tbody>
</table>

### Table 8: Productivity Regressions: dependent variable % Sales from New Products, TwoStep

<table>
<thead>
<tr>
<th></th>
<th>(7) Multinomial</th>
<th>(8) Bivariate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales</td>
<td>-0.0194*** (0.0067)</td>
<td>-0.0204** (0.0085)</td>
</tr>
<tr>
<td>Innovation Intensity</td>
<td>0.521 (0.328)</td>
<td>0.434 (0.423)</td>
</tr>
<tr>
<td>Export Intensity</td>
<td>0.0848** (0.0423)</td>
<td>0.0788* (0.045)</td>
</tr>
<tr>
<td>Market Obstacles</td>
<td>-0.00176 (0.0191)</td>
<td>0.00253 (0.0241)</td>
</tr>
<tr>
<td>Technological Obstacles</td>
<td>-0.0116 (0.0165)</td>
<td>-0.0157 (0.0173)</td>
</tr>
<tr>
<td>Make&amp;Buy</td>
<td>0.164 (0.106)</td>
<td>0.189 (0.246)</td>
</tr>
<tr>
<td>MakeOnly</td>
<td>0.120 (0.217)</td>
<td>0.112 (0.271)</td>
</tr>
<tr>
<td>BuyOnly</td>
<td>0.128 (0.20)</td>
<td>0.2804 (0.62)</td>
</tr>
<tr>
<td>NoMake&amp;Buy</td>
<td>0.1257 (0.097)</td>
<td>0.0255 (0.234)</td>
</tr>
<tr>
<td>Industry Dummies</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>Complementarity Test: Make&amp;Buy – MakeOnly &gt; BuyOnly – NoMake&amp;Buy</td>
<td>F(1, 247) = 0.03</td>
<td>F(1, 247) = 0.09</td>
</tr>
</tbody>
</table>

N=269  N=269

Model F(21,247) = 2.34*** F(21, 247) = 2.02***

Coefficients Significant at: 1%***, 5%** and 10%*

Standard deviations between brackets.