Technological Opportunities, Absorptive Capacities, and Innovation

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Abstract

The aim of this paper is to analyze the effects of technological opportunities on the innovation activities of firms, depending on their absorptive capacities. The importance and impacts of the ability of firms to use external knowledge sources were inquired especially for external knowledge stemming from scientific research. Using a simple theoretic model, different innovation effects were empirically outlined for the German manufacturing industry for the first time. On the innovation input side, the effects of science-related technological opportunities in combination with absorptive capacities variables are stronger on the intensities as in the estimations without such proxies. Further, the innovation output of firms is positively influenced by the ability to adapt external knowledge efficiently. Firms in the German manufacturing industry with inhouse absorptive capacities and a high importance of scientific knowledge are characterized by higher sales shares of new and improved products and higher probabilities of patent registrations than other firms.

Key words: Technological Opportunities, Absorptive Capacities, Innovation, Scientific Knowledge

JEL classification: O31, I20, L20, L60

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1. Introduction

R&D activities determine the economic success and competitiveness of firms. As a consequence of the dynamics of technological change, innovative firms continuously have to expand and optimize their inhouse R&D by applying *technological opportunities* (Dosi 1988; Griliches 1995; Mairesse/Saasenou 1991). This is closely related to the increasing importance of multi- and interdisciplinarity of R&D and the strengthened interrelation of basic research with industrial research (Becker 1996; Mansfield 1995; Nelson/Wolff 1997).

In general, the innovation capabilities of firms depend on the interaction of inhouse R&D and the extent to which technological opportunities from outside can be used for own purposes (Cohen 1995; Cohen/Levin 1989; Kline/Rosenberg 1986). By utilizing technological opportunities firms can expand their innovation capabilities with positive effects on the research efficiency, the probability of being successful in R&D and on the quality of new technologies (Cohen/Levinthal 1989; Harabi 1995; Klevorick et al. 1995). The improvement of innovation activities resulting from the use of external knowledge leads to larger competencies of the research personnel and to more efficient production processes.

The extent to which firms can implement exogenously generated knowledge, however, depends on their *absorptive capacities*. Empirical studies underline the particular role of absorptive capacities in the innovation process (Cantner/Pyka 1998; Peters/Becker 1998a; Tripsas 1997, Veugelers 1997). Level as well as quality of absorptive capacities are diverse, varying from one firm to another and, to a certain degree, from industry to industry. Capacities to absorb external knowledge are especially significant for high-tech firms in R&D intensive industries, such as the computer industry, aircraft industry, astronautics, and the pharmaceutical industry. Firms in innovative industries have to invest in complementary inhouse R&D in order to understand and use the results of externally performed R&D and to obtain full access to the research findings of other firms and institutions (Brockhoff 1995; Mowery/Rosenberg 1989). The degree to which firms (can) use technological opportunities is closely correlated with their capabilities prior to external knowledge used (Arvanitis/Hollenstein 1994; Levin/Reiss 1988). Further, empirical evidence could be found for differences in the kind or quality of absorptive capacities necessary to adapt technological opportunities (Arora/Gambardella 1994; Malerba/Torrisi 1992; Peters/Becker 1998b). Particular information generated in universities and other scientific institutions require higher absorptive capacities since the development of new and improved products increasingly depends on the (generic) findings and results of academic research (David 1994; Narin/Hamilton/Olivastro 1997; Rosenberg/Nelson 1994).

However, there hardly is any empirical evidence supporting that absorptive capacities enhance firms technological potentials and, along with it, their innovative activities. Therefore, we want to investigate the question, to which extent absorptive capacities affect the input and output level of innovative firms. Veugelers (1997) finds empirical support for the importance of absorptive capacities to the adaptation of external knowledge in the Flemish manufacturing industry. She identifies significant positive effects of R&D co-operations (as a proxy for high technological opportunities) on the level of R&D investments - if firms have established absorptive capacities as a full-time staffed R&D department – and negative effects otherwise. In addition, Peters/Becker (1998a) have shown for the German automobile supply industry that R&D arrangements with universities have no significant effects on the innovation outputs if absorptive capacities (existence of R&D labs) are neglected.

Therefore, we want to analyze the function of the absorptive capacities in the innovation process in more detail *connecting theoretical and empirical investigations*. Against the background of the state of the art, the importance and impacts of the ability of a firm to absorb external knowledge on the development of new and improved products (technologies) are inquired. Using input-, output- and market-related variables, differences in the innovation activities depending on the level of firms' absorptive capacities are empirically outlined for the German manufacturing industry for the first time.

The paper is organized as follows: In the second section, the interrelations of technological opportunities, absorptive capacities and innovation activities are theoretically discussed. In the third section, the data set and the definitions of the variables for the regressions are presented and the specification of the empirical models is given. Thereafter, the results of the econometric investigations regarding innovation effects of technological opportunities, especially from scientific research, and the absorptive capacities of firms in the German manufacturing industry will be presented in the fourth section. The main findings are summarized in the fifth section.

2. Theoretical Analysis

The development of new and improved products is a well-directed search and learning process, which involves technical as well as economic uncertainties and, in case of success, sets in with a lag (Cohen 1995; Dosi 1988; Flaig/Stadler 1998). Innovations are the results of a combination act of *firm-specific* determinants (R&D activities, firm size, etc.) and *external* influences (technological opportunities, R&D spillovers, etc.). Moreover, both factor groups are to be interpreted within the context of industry-specific conditions (sectoral technology levels, market dynamics, etc.).

R&D activities play a fundamental role referring to firm internal *'technological capabilities'*. They aim at a systematic broadening of the existing stock of knowledge and its efficient application in the innovation process. R&D activities are also meant to increase the probability of the arrival rate of product and process innovations, respectively. Furthermore R&D is performed on grounds of the associated positive impact of R&D-induced improvements and extensions in technical and organizational know-how on economic magnitudes such as an increase in productivity, turnover and profits (Cohen/Levin 1989; Griliches 1995; Mairesse/Saasenou 1991).

Addressing the external sphere of innovation-determining factors, it is the total amount of the currently existing and exploitable resources - *technological opportunities* - to be considered (Arvanitis/Hollenstein 1994; Dosi 1998; Klevorick et al. 1995). Such opportunities are diverse, varying in the kind and usefulness of technological knowledge not only from industry to industry but also from one firm to the other. "Due to variations in the degree of availability of these technological opportunities, innovations are 'cheaper' to realize ... This factor stands - in combination with others - behind the empirically observable inter-industrial differences in the rates of technical progress, of total factor productivity and of economic growth" (Harabi 1995, p. 67).

2.1. The Role of Technological Opportunities in the Innovation Process

Technological opportunities are related to the contribution of external sources to the innovation activities of firms. In our investigations, we concentrate on the *stock of knowledge (information)* firms are faced with. These stock can be splitted into industrial and non-industrial knowledge sources. Technological opportunities brought up by the innovation activities of suppliers, customers and competitors define the industrial stock of knowledge. Technological opportunities arising from innovation activities outside the private sectors, e.g. the academic sphere, constitute the non-industrial stock of knowledge.

Technological opportunities generated by scientific research activities are of major interest for firms in R&D-intensive technology branches such as microelectronics, chemical industry, ecological technologies, biotechnology, etc. Knowledge generated in scientific institutions is an important innovation resource for firms with high-leveled R&D activities due to the close interrelation of basic research and industrial research. Scherer (1992, p. 1424) points out that "... the mysterious concept of 'technological opportunities' was originally constructed to reflect the richness of the scientific knowledge base tapped by firms". In the early 60's, Nelson (1959) and Arrow (1962) emphasized the importance of 'new scientific knowledge' as a driving force behind innovation, technological and economic progress.[1] Ever since, its magnitude in developing new and improved products has continuously grown (Grupp 1994; Mansfield 1995; Rosenberg/Nelson 1994). The increasing dynamic of the technological progress as well as the increasing complexity of innovation process account for this. "What university research most often does today is to stimulate and enhance the power of R&D done in industry ..." (Rosenberg/Nelson 1994, p. 340). The bottom line is, "... as scientific knowledge grows, the cost of successfully undertaking any given, science-based invention declines ..." (Rosenberg 1974, p. 107). This leads - ceteris paribus - to a rise in productivity of the firms' own innovation activities. "The consequence is that the research process is more efficient. There is less trial-and-error; fewer approaches need to be evaluated and pursued to achieve a given technological end. From this perspective, the contribution of science is that it provides a powerful heuristic guiding the search process associated with technological change" (Cohen 1995, p. 217-218).

For further analysis we define the pool of technological opportunities Ω_i as

$$\Omega_i = \Omega(TO\_CUCO, TO\_SUPP, TO\_SINT) \qquad (1)$$

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[1] To the role of knowledge in the innovation process in general, see: Beckmann et al. 1998; Navaretti et al. 1998; Tamborini 1997.

where *TO_CUCO* represents the technological opportunities stemming from customers/competitors and *TO_SUPP* captures the knowledge pool generated by suppliers. *TO_SINT* reflects the contributions of scientific (university) knowledge to the technological capacities of firm *i*. We postulate that the marginal effects of increasing the external research resources *EX_R*, with *EX_R* = *TO_CUCO*, *TO_SUPP*, *TO_SINT* on the level of technological opportunities is strictly positive ($\partial \Omega_i / \partial EX\_R > 0$) with constant, diminishing or increasing returns ($\partial^2 \Omega_i / (\partial EX\_R)^2 \gtreqless 0$), depending on the initial level of firms' technological capabilities.

Strength and sources of technological opportunities are important factors explaining firm-specific and cross-industry variations in R&D intensity and R&D productivity (Klevorick et al. 1995; Nelson/Wolff 1997; Sterlacchini 1994). The adaptation of technological opportunities changes the characteristics and influences the performance of inputs required for innovations. For the recipients, specific utilization of exogenously generated knowledge leads to an improved quality of the factor inputs. Technological opportunities induce factor embodied technological progress which does not affect all production technologies to the same extent but unfold their effects selectively and cumulatively within a technological problem-solving process embedded in the scientific, methodological, analytical frame of a technological paradigm. "A technological paradigm defines contextually the needs that are meant to be fulfilled, the scientific principles utilized for the task, the material technology to be used. In other words, a technological paradigm can be defined as a 'pattern' for solution of selected techno-economic problems based on highly selected principles derived from natural sciences. ... Putting it another way, technological paradigms define the technological opportunities for further innovations and some basic procedures on how to exploit them. Thus they also channel the efforts in certain directions rather than others: a *technological trajectory* ... is the activity of technological progress along the economic and technological trade-offs defined by a paradigm ..." (Dosi et al. 1988, p. 224-225).

Empirical studies (Becker/Peters 2000; Geroski 1990; Harabi 1995) emphasize that technological opportunities - besides firm size, appropriability conditions, market structures, etc. - do have a crucial influence on the type, range and results of firms' innovative activities, e.g. the level of R&D expenditure and the share of new or improved goods in sales. Provided that the necessary, organizational requirements are available (such as qualified R&D personnel), the adaptation of external sources of knowledge enlarges and improves the firms' technological capabilities with positive effects on the probability of being successful in R&D and on the quality of technologies. The improvement of production performance resulting from the use of technological opportunities leads to more efficient production processes, larger technological know-how and competencies of the research personnel. Along this line, the higher the level of technological opportunities, the larger the incentive of firms to invest in innovation/R&D will be.

2.2. The Role of Absorptive Capacities in the Innovation Process

Absorptive capacities refer to firms' ability to adapt and apply external knowledge. Correspondingly, Cohen/Levinthal (1989, p. 569) define these abilities as the capability "... to identify, assimilate, and exploit knowledge from the environment".

Absorptive capacities represent the analytical link between the external stock of technological opportunities and the inhouse capabilities in developing new and improved products (Cantner/Pyka 1998; Cohen/Levinthal 1990; Malerba/Torrisi 1992). The competence "... to evaluate and utilize outside knowledge is largely a function of the level of prior related knowledge. At the most elemental level, this prior knowledge includes basic skills or even a shared language but may also include knowledge of the most recent scientific or technological developments in a given field" (Cohen/Levinthal 1990, p. 128). To solve technological tasks and problems it is drawn back on experiences and knowledge from the past in terms of a 'history dependency of technological progress'.

In order to implement externally generated knowledge, especially from scientific research, innovative (and R&D-intensive) firms have to invest a certain share of their financial endowment in the maintenance and improvement of their absorptive capacities unless they want to lose their competitiveness. The point is to anticipate potential and relevant technological tendencies in order to make use of them for one’s own, firm-specific objectives. This is about the investment in one’s own R&D activities in order to understand the results of externally performed R&D on the one hand (Cohen/Levinthal 1989; Veugelers 1997) and the investment in innovation management to achieve a well-directed and efficient exploitation of technological opportunities on the other (Brockhoff 1995; Gauglitz-Lüter 1998; Rothwell/Dodgson 1991). In general, science-based technological opportunities basically ask for a higher level of absorptive capacities than those generated by other knowledge sources such as customers (Nelson/Wolff 1997).

2.3. Firms' Inhouse Capabilities, Technological Opportunities, and Innovation Activities

To analyze the function of absorptive capacities in the innovation process as an intermediate factor between technological opportunities and the inhouse capabilities of firms in more detail, we have to differentiate the various effects of external knowledge sources on the innovation input and output side.

2.3.1. Innovation Input

Basic assumption is that firm *i* has to invest in idiosyncratic and generic R&D (innovation activities).[2] Whereas *idiosyncratic R&D* (R_i^{id}) primarily create specific knowledge for firms’ own R&D process,

[2] *R&D* is a part of the engagement of firms to develop new or improved products (technologies). *Innovation activities* include also expenditures for product design, trial production, purchase of patents and license, and training of employees etc. In the following, the theoretical discussion is concentrated on R&D as the *main* part of firms' innovation activities.

generic R&D (R_i^{ge}) produce information having more the character of a public good (Nelson 1992). In the extreme case, new generic information can spill over to other actors without purchasing the right to do so (R&D spillovers).[3] A further basic assumption relates to the fact that firms' idiosyncratic R&D can be divided in one part, which is necessary only to develop new technologies ($R_i^{id/dev}$) and in another part which is only necessary to adapt, transform and use technological opportunities for inhouse R&D ($R_i^{id/abs}$). By this, the whole *R&D (innovation) input* R_i can be written as

$$R_i = R(R_i^{id}, R_i^{ge}, \Omega_i), \qquad (2)$$

with $R_i^{id} = r(R_i^{id/dev}, R_i^{id/abs})$. In this context, we suppose that $\partial^2 R_i / \partial R_i^{id} \partial R_i^{ge} > 0$ and $\partial^2 R_i / \partial R_i^{id} \partial \Omega_i > 0$. Further, we postulate that the generic part of <u>inhouse</u> R&D *(R_i^{ge})* can be *substituted* by externally generated knowledge defined by Ω_i. Hereby, the rate of substitution *s* can vary within the range of $0 \le s \le 1$.

As argued above, the extent to which firm *i* can implement technological opportunities is determined by their absorptive capacities. Therefore, we take into consideration the parameter λ_i (with $0 \le \lambda_i \le 1$) reflecting firms' ability to make use externally generated knowledge.[4] Depending on the kind of Ω_i, absorptive capacities have to be maintained, focused or enlarged (Aora/Gam-bardella 1994; Klevorick et al. 1995; Peters/Becker 1998b).

The level of λ_i is a function of the extent of $R_i^{id/abs}$, with

$$\lambda_i = \lambda(R_i^{id/abs}), \qquad (3)$$

assuming positive marginal effects $\partial \lambda / \partial R_i^{id/abs} > 0$ with constant, increasing or decreasing rates. In this line, technological opportunities firm *i* can *factual use* Ω_i^{use} is a function of the stock of externally accumulated knowledge and λ_i:

$$\Omega_i^{use} = \lambda(R_i^{id/abs})\Omega_i . \qquad (4)$$

Using the relations (3) and (4), the R&D (innovation) input R_i (2) can be re-written as

$$R_i = R\left[R_i^{id/dev}, R_i^{ge}, \lambda(R_i^{id/abs})\Omega_i\right]. \qquad (5)$$

The process of internal transformation of technological opportunities can be described as follows (see also the graph): (1) Firms (decide to) substitute <u>inhouse</u> *generic* R&D (R_i^{ge}) by using externally generated knowledge Ω_i.[5] (2) Firms invest a part of *idiosyncratic* R&D to establish absorptive capacities $R_i^{id/abs}$.

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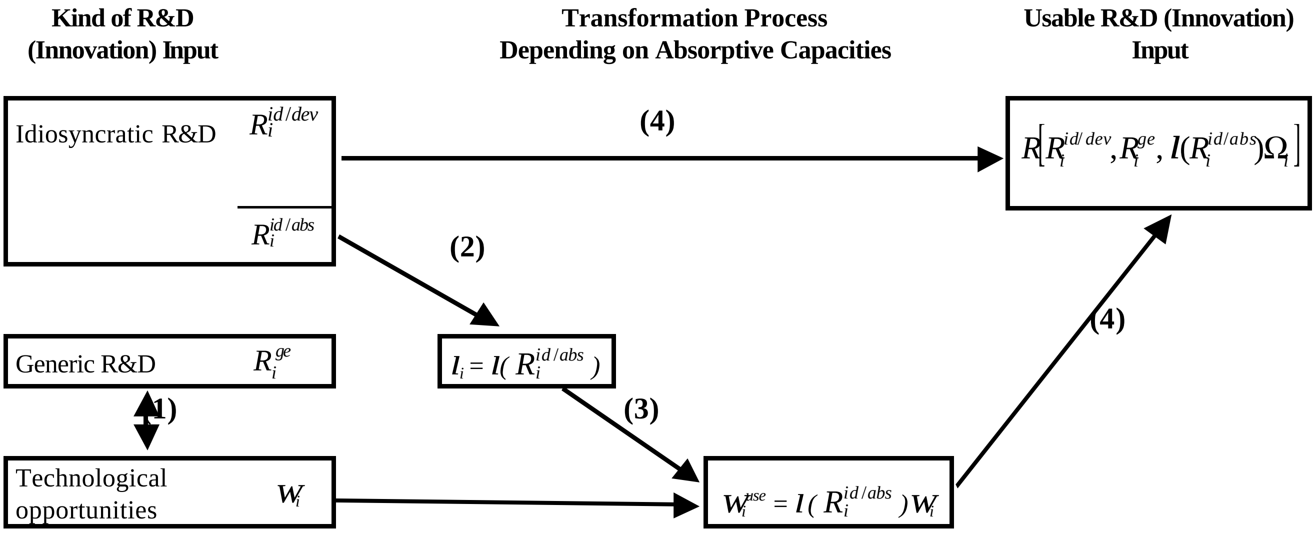
3 R&D spillovers are externalities of R&D activities beyond their primary definition, where not alone the innovator has the benefit, but also other actors can apply them for their innovative activities (Dosi 1988; Eliasson 1996; Griliches 1992).

4 For simplicity, we assume that firms have not to invest in activities to make use of their *inhouse generic* R&D.

5 In the graph we assume *full substitution* of R_i^{ge} by $\lambda_i \Omega_i$.

(3) Depending on the level of absorptive capacities l_i, technological opportunities (external *generic* R&D) can be transformed and used for own purposes Ω_i^{use}. (4) The *R&D (innovation) input* R_i defines firms' internal and external resources usable for the development of new technologies.

Graph: Internal transformation process of technological opportunities



After having highlighted the importance of l_i, in the internal transformation process of external knowledge, we have to discuss the impacts of $l_i\Omega_i$ on firms' R&D (innovation) input as a *whole*.

First, the influence of $l_i\Omega_i$ on R_i depends on *productivity effects* of using external resources. Productivity effects relate to the argument that the incentive for firms to invest in (idiosyncratic) R&D is positive correlated with the extent of usable technological opportunities. This comprehension "... corresponds to the function that maps the flow of R&D into increases in the stock of knowledge" (Klevorick et al. 1995, p. 188). At this, the stock of knowledge expands with diminishing returns of inhouse R&D at the margin because technological opportunities exhaust with further progress in a given technological area the more firms (markets) have to invest in R&D (Coombs 1988). In this line, higher levels of technological opportunities (e.g. large flow of scientific knowledge) enhance the productivity of inhouse R&D on product quality or cost reduction with stimulating impacts on R&D investments. Hereby, it is important to remember that the optimal level of R&D (investments) is determined by the interrelation of $R_i^{id/dev}$ and the degree technological opportunities can really used for own purposes.

Second, the impact of $l_i\Omega_i$ on R_i depends on *substitution effects* of using externally generated knowledge. If - as mentioned in (2) - *inhouse* generic R&D (R_i^{ge}) and $l_i\Omega_i$ are substitutes, firms are faced with the decision of either generating this kind of knowledge by oneself or adapting the necessary information from external sources. The decision to substitute generic R&D by $l_i\Omega_i$ is determined by the costs of inhouse R&D $c(R_i^{ge})$ and by the costs of adaptation external knowledge $c(l_i\Omega_i)$. If $c(l_i\Omega_i) \geq c(R_i^{ge})$, there will be no motivation for firm *i* to implement technological information generated outside. The adaptation of usable technological opportunities will be an efficient strategy, if the costs of searching and implementing are lower than the costs of generic R&D inhouse done: $c(l_i \Omega_i) < c(R_i^{ge})$. In this situation, firms can use external knowledge to reduce their costs of generic R&D.[6]

But the substitution effects on firms' *total R&D costs* necessary to develop new or improved products $c(R_i)$, with R_i described in (5), are ambiguous. To illustrate this, let us assume that $l_i\Omega_i$ and R_i^{ge} have the same productivity regarding to $R_i^{id/dev}$ as well as $c(l_i \Omega_i) < c(R_i^{ge})$. In order of these assumptions the main object of interest is $c(R^{id/dev})$. Let us define $\overline{R_i^{id/dev}}$ as the profit maximzation level of idiosyncratic R&D <u>without</u> using technological opportunities. In this case, we have to differ between two situations:

a.) As long as firms substitute the generic part of R&D only up to the cost level of generic R&D done formerly inhouse $c(l_i \Omega_i) \leq \overline{R_i^{ge}}$, the costs of R&D investments $c(R_i^{id/dev})$ can not be higher than formerly with inhouse activities in generic R&D. In the case of spillovers, the marginal costs of using technological opportunities are zero, because $l_i\Omega_i = 0$. This strategy of substitution will reduce R_i remarkably.[7]

b.) Because of positive productivity effects of $l_i\Omega_i$ as described above, firms which decide to utilize *more* generic knowledge than they had formerly generated inhouse ($l_i \Omega_i > \overline{R_i^{ge}}$) will also invest more in idiosyncratic R&D ($R_i^{id/dev} > \overline{R_i^{id/dev}}$). In this situation it is not possible to make a clear statement about the total R&D costs because $c(l_i \Omega_i) \gtreqless c(\overline{R^{ge}})$ and $c(R_i^{id/dev}) > c(\overline{R_i^{id/dev}})$. For firms with a high efficiency in $R_i^{id/abs}$ - that implicates a low level of $c(l_i \Omega_i)$ - it is more likely that $c(R_i^{id/dev}) < c(\overline{R_i^{id/dev}})$. But a high efficiency of $R_i^{id/abs}$ also rises firms incentives to absorb more external information than formerly generated inhouse. By this, the whole level of R_i can increase.

In general, the substitution effects depend on the elasticity of idiosyncratic R&D $R_i^{id/dev}$ with regard to $l_i\Omega_i$. For example, if the elasticity is small (high), the total R&D costs can be lower (larger) with the utilization of external knowledge than formerly with generic R&D activities done inhouse. Thus, the level of R&D expenditures will be lower in the case of high levels of technological opportunities than in the case of low levels.

The results of the theoretical dicussion of the productivity and substitution effects of $l_i\Omega_i$ on R_i can be summarized - in the sense of hypotheses for the empirical analysis - as follows: For an increasing efficiency in the utilization of generic R&D it is more likely that firms will substitute their inhouse production of generic knowledge by technological opportunities stemming, e.g. from scientific research. If technological opportunities are used as substitutes (complements) for inhouse R&D, it is more likely that the adaptation of Ω_i will discourage (encourage) the R&D (innovation) activities of firms. But to reach a high level of efficiency firms' have to invest more in their absorptive capacities. By this, firms with high (low) l_i have more (less) potentials to use external sources for own purposes and therefore can

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6 As Sterlacchini (1994) notes, basic research on their own can be more expensive and less effective for firms than funding academic research to realize an innovation (given firms' level of absorptive capacities).

7 For more theoretical discussions, see: Harhoff 1996.

implement external generic R&D more (less) efficiently.[8] If firms have high (low) absorptive capacities, the effects of $\lambda_i\Omega_i$ on the productivity of inhouse idiosyncratic R&D will also be high (low). Finally, firms with high (low) level of usable technological opportunities $\Omega_i^{use} = \lambda(R_i^{id/abs})\Omega_i$ will invest more (less) in R&D (innovation activities) R_i.

2.3.2. Innovation Output

To discuss the effects of $\lambda_i\Omega_i$ on the *innovation (R&D) output* y_i, indicated by the quality of new products or by the extent of cost reductions, we assume that y_i is given as a function of R&D investments, the usable pool of technological opportunities, and μ_i, the *'propensity to innovate'* (Scherer 1965) reflecting other factors above and beyond research inputs (including simple luck):

$$y_i = g(R_i^{id}, R_i^{ge}, \lambda_i, \Omega_i, \mu_i) \qquad (6)$$

As argued above, we assume that idiosyncratic and generic R&D are necessary to realize innovations. Further, the availability of technological opportunities Ω_i can substitute firms' own generic R&D investment (R_i^{ge}) depending on the level of absorptive capacities.

In general, firms' investment in λ_i does not directly stimulate the innovation output such as increasing firms' probability to be innovative. Rather, in up-sizing the level as well as the efficiency of using technological opportunities, λ_i has an *indirect* positive impact on y_i. By this, the relationship between y_i, firms' idiosyncratic and generic R&D, and $\lambda_i\Omega_i$ can be expressed by the following conditions:

$$\partial y_i / \partial R_i^{id} > 0;\ \partial y_i / \partial R_i^{ge} > 0;\ \partial y_i / \partial_i \lambda_i\Omega_i > 0, \qquad (7)$$

$$\partial^2 y_i / (\partial R_i^{id})^2 \gtreqless 0,\ \partial^2 y_i / (\partial R_i^{ge})^2 \gtreqless 0,\ \partial^2 y_i / (\partial \lambda_i\Omega_i)^2 \gtreqless 0,$$

$$\partial^2 y_i / \partial R_i^{id} \partial R_i^{ge} > 0,\ \partial^2 y_i / \partial R_i^{id} \partial \lambda_i\Omega_i > 0,$$

$$\partial^2 y_i / \partial R_i^{ge} \partial R_i^{id} > 0.$$

Higher investments in idiosyncratic or generic R&D enlarge the innovation output - e.g. improves the product quality of own products or reduce the cost of production - with diminishing, constant or increasing rates of return, depending on the initial level of inhouse R&D. The same conditions apply for the impacts of usable technological opportunities on y_i. Thus, given the level of inhouse R&D, an expansion of $\lambda_i\Omega_i$ increases y_i.

The adaptation of technological opportunities will be an *profit enhancing strategy*, if $c(\lambda_i\Omega_i) < c(R_i^{ge})$. The innovation output depends on firms' inhouse R&D activities primarily, if $c(\lambda_i\Omega_i) \geq c(R_i^{ge})$. Firms will

[8] Gambardella (1992) found empirical support for this assumption in the US drug industry.

have no motivation to invest in own generic R&D, if adequate information is available in the form of R&D spillovers.

Under the postulated conditions, the following hypotheses can be formulated: The innovation output y_i will increase with the extent of usable technological opportunities. The higher (lower) the level of absorptive capacities, the larger (smaller) the incentives for firms to be engaged in R&D (innovation activities). By this, an efficient adaptation of externally generated knowledge enlarges firms' inhouse capabilities with stimulating effects on y_i.

3. Data Set, Variables and Specification of the Empirical Models

3.1. Data Set and Variables for the Regressions

The data for the empirical investigations originate from the first wave of the Mannheim Innovation Panel (MIP) conducted in Germany in 1993.[9] About 2,900 firms participated in the survey and filled in a questionnaire about their innovation activities for the period of 1990-1992. They answered a broad range of questions related to input-, output- and market-related aspects of innovation activities. The original survey covers innovative as well as non-innovative firms. Innovative firm are defined as companies which have introduced new or improved products in the years 1990-1992 or have intended to do so in the period of 1993-1995. We restrict our analysis to *innovative* firms.[10] After having excluded the non-innovative firms from the original data set, 1988 innovative firms were included in the empirical analysis. Further, we concentrate the empirical analysis on the *manufacturing industry*. In Germany, more than 90 per cent of the entire R&D invested by private companies is performed by firms from the manufacturing sector (Federal Ministry of Education, Science, Research and Technology 1998).

To estimate empirically the importance and effects of the absorptive capacities as an intermediate factor between the external stock of technological opportunities and the inhouse capabilities for innovative firms in the German manufacturing industry, a set of input- and output-related variables of firms' innovation activities was used (see also Table 1).

The *input-related* innovation variables reflect the engagement of firms to generate product and process innovations. This engagement includes innovation expenditures for R&D, product design, trial production, market analysis, purchase of patents and license. We distinguish between three proxies of firms' innovation input: (1) the innovation intensity (INNO_INT), measured by the log of firms' innovation expenditures to sales ratio, (2) the R&D intensity (R&D_INT), measured by the log of firms' R&D

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9 We thank the ZEW for the permission to use the censored version of the survey data (Version 98-1). For a detailed description of the data and the data collection, see: Felder et al. 1995; Harhoff/Licht 1994.

10 We have tested the model specifications for *all* firms in the ZEW data set. In the regression, no basic differences related to the influences of the exogenous variables on the innovation input and output could be found. Further, we have split the data set in a sub-sample with *west* German firms only. No fundamental distinctions between the regressions results for the west firms and all firms were observable.

expenditures to sales ratio, and (3) the R&D employment intensity (R&D_E_INT), measured by the ratio of firms' R&D employment to their total employment. The log of these intensities are computed because of the problems with non-normal distributions of these variables. Unfortunately, given a lack of data, no distinction between idiosyncratic and generic R&D investments could be made. Therefore, we are not able to estimate the different effects of technological opportunities regarding to the engagement of firms in both kinds of inhouse R&D.

The *output-related* innovation activities are measured by the sales shares of new and improved products (INNO_NOV, INNO_IMP), based on ordered information (ten-point scale). The registration of patents (INNO_PA) is used to identify the relevance of invention for firms. We argue that patents are a specific output factor of R&D activities without direct market references.[11] Unfortunately, there were no information available on the number of patents.

Table 2 shows the exogenous variables used in the regressions to explain the innovation activities of firms in the German manufacturing industry: importance of external knowledge sources *(technological opportunities)*, ability to absorb externally generated information *(absorptive capacities)*, extent to which inhouse technological knowledge can protect from other firms *(appropriability conditions*), and other *market-related* control variables like firm size, international diversity, or sales expectations.

To measure the importance of different types of *technological opportunities*, especially from the academic sphere, the scores of factor analysis on external knowledge sources are employed (see Appendix 1). As in the theoretical part of the paper mentioned, we distinguish technological opportunities stemming from competitors/customers (TO_CUCO), suppliers (TO_SUPP), and scientific organizations (TO_SINT). Following Levin/Reiss (1988) we assume that the degree, firms rate scientific institutions (universities, technical institutions) as relevant sources of information for innovation activities, is closely correlated with the level of their technological opportunities (see also Arvanitis/Hollenstein 1994; Felder et al. 1996; Harabi 1995). In general, the higher the importance of universities and other scientific institutions as external knowledge sources, the higher firms' technological opportunity which affect their inhouse capabilities to develop new or improved products positively. Further, in the estimations a variable reflecting *separately* the role of universities as knowledge sources (TO_UNIV) is used. Moreover, the empirical evidence of R&D cooperations as the most *systematic* form of knowledge transfer between universities will be checked. COOP_UNI defines firms having developed new or improved products jointly with universities formally or informally in the year 1992.

The empirical measurement of the absorptive capacities of firms is difficult. Due to the lack of data, only two proxies for the absorptive capacities of firms could be used in the estimations.[12] Firstly, we used the

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[11] For the general discussion of the status of patents in the innovation process, see: Archibugi 1992; König/Licht 1995; OECD 1996.

[12] We have also tested the sales shares of expenditures for training and professional education of employees as an other proxy for absorptive capacities. As Rothwell/Dodgson (1991) show, the level of qualification is strongly connected with the ability to establish external linkages to other organizations. Especially in the case of utilizing

dummy variable R&D_REG indicating firms being regularly active in inhouse R&D. The idea behind these modeling is that firms which continuously are engaged in R&D have established inhouse capabilities for their idiosyncratic R&D as well as for the adaptation of external knowledge efficiently. As Malerba/Torrisi (1992) underline, firms which do not permanently invest in R&D have a smaller access especially to technological opportunities stemming from scientific research. Secondly, a dummy variable for the existence (but not on the level) of inhouse absorptive capacities is used. R&D_LAB defines firms having one or more own staffed R&D labs in 1992. Here, the same arguments of continuity can be made as for R&D_REG (Veugelers 1997).

The degree to which external (technological) information is internalized depends on the extent firms can protect their knowledge from other companies (Cohen/Levinthal 1989; König/Licht 1995; Levin et al. 1987). *Appropriability conditions* define the ability of innovators to retain the returns of R&D. The higher (lower) the appropriability conditions of firms, the less (more) R&D spillovers will occur.[13] The technological opportunities a single firm is faced with are not independent of these conditions. "For example, one firms' feasible advances in technology may be blocked by the property rights of another" (Klevorick et al. 1995, p. 186). Therefore, several variables related to the firms' appropriability conditions are used in the regressions (AP_). We employ the scores of factor analysis (see Appendix 2) on a specific mechanism of protecting technological knowledge from other firms regarding to (product and process) innovations.

Market-related variables, well-known from other empirical studies (for an overview, see Cohen 1995), are introduced in the estimations to reflect further factors determining the innovation process such as firm size (EMPL_MI, EMPL_G),[14] sales expectations in the medium term (SALE_EXP), degree of diversification (DIVERS) and intensity of international sales (INTERNAT). These variables allow us to control the influence of size and demand factors on innovation activities, which may explain differences in innovation activities on the firm level. The role of firm size is a priori unknown, because these variables "... can be used as a proxy for various economic effects" (Arvanitis/Hollenstein 1996, p. 18). It can be expected that sales expectations (Kleinknecht/Verspagen 1990; Schmookler 1966), high export shares of sales (Felder et al. 1996; Lunn/Martin 1986) and a high degree of diversification (Kamien/Schwartz 1982; Nelson 1959) will influence positively the innovation activities of firms.

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scientific knowledge, a high level of qualification of the employees seems to be necessary. In our data set, only a small fraction of firms have given information about their expenditures to qualify their employees. Due to the reduction of the sample size in a to large extent, we have to exclude this proxy from the empirical analysis.

13 In the case of intra-industry spillovers, the incentives of firms to invest in R&D will diminish (Harhoff 1996; Levin/Reiss 1988; Spence 1984). In the case of spillovers stemming from sources outside the market (e.g. from universities), positive effects of R&D-spillovers on the efficiency and output of innovation activities can be expected (Bernstein 1989; Nadiri 1993; Peters 1998).

14 Firm size is a categorial variable with three extensions. We define the category 'small firms' (up to 50 employees) as basic group. EMPL_MI (50 up to 249 employess) and EMPL_G (250 and more employees) are used as dummies in the estimations.

Restrictions of the data set make it impossible to include variables on the degree of competition in the firms' market (10-firm concentration ratio or Herfindahl index) in the model specifications. But other studies (Arvanitis/Hollenstein 1996; Crépon/Duget/Kabla 1996) have shown that the degree of competition has an impact of no significance or of a comparable small order of magnitude on the innovation or R&D activities of firms, if the estimations are controlled by variables of technological opportunities.

In the ZEW data set, the manufacturing industry encloses eleven sectors. According to the classification of the OECD (1992), these sectors are divided in *three technology groups* (LOW, MEDIUM, HIGH) depending on the sales shares of R&D. The variable MEDIUM is used as basic group in the regressions. The results, reported here are the same using dummies of different industries.

3.2. Specification of the Empirical Models

The basic model specification for explaining the innovation activities x_i of firms in the German manufacturing industry is as follows:

$$x_i = \alpha_1 + \alpha_2 TO\_CUCO_i + \alpha_3 TO\_SUPP_i + \alpha_4 TO\_SINT_i + \alpha_5 AP_i + \alpha_6 MR_i + \varepsilon_i \quad (8)$$

where TO_CUCO, TO_SUPP and TO_SINT represent proxies of technological opportunities stemming from *cu*stomers/*co*mpetitors, *supp*liers and *scie*ntific institutions, *AP* stands for the appropriability conditions of firms, and *MR* represents market-related determinants such as firms size, sales expectations, etc. ε_i is an unobserved, additive error term.

To assess the innovation effects of firms' absorptive capacities, we modify the basic equation (8) to

$$x_i = \alpha_1 + \alpha_2 TO\_CUCO_i + \alpha_3 TO\_SUPP_i + \alpha_4 TO\_SINT_i + \alpha_5 AC_i + \alpha_6 AP_i + \alpha_7 MR_i + \varepsilon_i \quad (9)$$

where AC_i measures the existence of absorptive capacities (λ_i) alone. At least, we try to estimate the *interaction* of absorptive capacities and technological opportunities ($\lambda_i \Omega_i$) in form of

$$\alpha_5 AC_i = \alpha_5 (\lambda_i, TO\_SINT_i) . \quad (10)$$

with concentration on *TO_SINT* as a proxy for *science-based* Ω_i.

The estimation of our model specifications raises several statistical problems. On the one side, the innovation and R&D intensities were censored in the upper tail of the distributions by 0.35 resp 0.15 to avoid the identification of firms. On the other side, some innovative firms did not performed any R&D as well as had no innovation expenditures. Accepting a misspecification of the model, the problem can be solved by using a Tobit model with censoring in both tails of the distributions. Possible misspecification may be attributed to the fact that independent parameters simultaneously determine the probability as well as the expenditures of innovation activities (Cohen/Levin/Mowery 1987). Therefore, we use the two-step version of the Heckman model (Heckman 1979). This model specification allows us to identify the parameters affecting a firm's decision to participate in R&D (innovation activities) and the degree of its intensity. In the case of discrete variables, we employ the probit methods for dichotomous response variables and ordered probit models for the various multinomial variables.

4. Empirical Analysis

In the following, the results of the empirical analysis testing the hypotheses formulated in the theortical part of the paper are presented. We investigate the effects of technological opportunities on the innovation activities of firms in the Germany manufacturing industry, depending on their absorptive capacities. The importance and impacts of the ability of firms to use external knowledge sources were inquired especially for external knowledge stemming from scientific research.

Our regression strategy is as follows: In a first step, we measure the impacts of technological opportunities among other factors on the innovation input and output activities of German firms without variables reflecting firms absorptive capacities. By this, we investigate whether the complementarity effects of using external knowledge dominate the substitution effects. In a second step, the influence of inhouse (absorptive) capacities on the investments of firms and on the results of their innovation/R&D activities are analyzed. Herewith, we want to show if the influence of technological opportunities remain for firms with high inhouse capacities. By this, empirical evidence of absorptive capacities as an intermediate factor between external knowledge sources and the engagement (performance) of firms to develop new or improved products can be specified will be given.

Due to the close connection between scientific knowledge and the development of new or improved products, the estimations are focussed on the effects of technological opportunities stemming from *scientific research*. We analyze these effects under three aspects: Firstly, we test the impacts of the importance of scientific institutions (universities, technical institutes, industry-financed research institutes, etc.) on the level of the factor scores on external sources of information (TO_SINT). Secondly, we check the contribution of universities separately as knowledge sources (TO_UNIV). Thirdly, we incure the dummy variable COOP_UNI to identify firms having developed new products or processes jointly with universities.

4.1. Innovation Effects of Technological Opportunities <u>without</u> Absorptive Capacities

4.1.1. Innovation Input Effects

The impacts of the exogenous variables are estimated with regard to the question, if and how they can explain the probability that firms are engaged in the development of new or improved products and the intensity of their innovation/R&D activities. The regression results for INNO_INT, R&D_INT, and R&D_E_INT are summarized in Table 3.

Using the two-step version of the Heckman model, no significant effects of the science-related variables TO_SINT, TO_UNIV and COOP_UNI on the probability being engaged in the *innovation* process could be found. But TO_SINT and COOP_UNI have very high significant effects on the intensities of innovation activities. Further, the regressions indicate highly significant effects (at the 0.01 level) of the science-related variables on the participation in *R&D*. High assessments to scientific/university knowledge and an establishment of R&D cooperations with universities increase the probability of being active in R&D. With exception of COOP_UNI, the estimations underline the importance of stimulating effects of TO_SINT and TO_UNIV on the intensity of R&D. The strongest effects could be found regarding the estimations of the *R&D employment intensity*. Technological opportunities stemming from scientific research increases the probability as well as the intensity of R&D investments in human capital (at the 0.01 level).

The regressions underline that scientific knowledge sources are used as *complements* in the German manufacturing industry. The adaptation of these kinds of technological opportunities encourage and stimulate the input activities of innovative firms because of an increasing productivity of inhouse research or of higher R&D investments in their absorptive capacities. Inhouse capabilities can be expanded with positive effects on the engagement and intensity of developing new or improved products. In this context, Nelson/Wolff (1997) gives empirical support on the level of certain lines of US business that the outcome of science can be regarded as pure opportunity enhancing. On the other hand, it has to be mentioned that "... by far the largest share of the work involved in creating and bringing to practice new industrial technology is carried out in industry, not in universities" (Rosenberg/Nelson 1994, p. 340).

However, as Harabi (1995) and Klevorick et al. (1995) remark, the impacts of scientific research on R&D and innovation activities can differ across industries. In some technology fields, the results of academic research are used as *substitutes* for industrial research. Peters/Becker (1998a), for example, find substitutive effects of scientific knowledge on inhouse activities in the German automobile supply industry. Some kinds of innovation activities, such as testing and prototype building are outsourced by German automobile suppliers to university and scientific laboratories, which yields remarkable savings in innovation costs (see also Peters/Becker 1998b). In this case, the cost savings are larger than the stimulating (complementing) impacts of scientific research on inhouse R&D.

In terms of technological opportunities, the regressions indicate no significant effects of TO_SUPP as the stock of external knowledge generated by suppliers on the innovation/R&D activities. The negative sign of the coefficients for the innovation intensities can partly be explained by the fact that information from suppliers tend to be *substitutes* for inhouse activities, as also found in studies for the US (Cohen/Levinthal 1989; Levin/Reiss 1988; Nelson/Wolff 1997). Against this, technological opportunities stemming from customers/competitors unfold stimulating and significant effects on the intensities of innovation/R&D. The coefficients of TO_CUCO related to the probability and the intensity of R&D investments in human capital are positive but, in general, without significance.

We identify stimulating effects of the appropriability conditions on the investments of German firms in the development of new or improved products. Firm-specific strategies to protect knowledge from other companies (AP_FIRM) increase the probability of an engagement in innovation/R&D and the level of expenditures significantly. Mechanisms of protecting innovations by law (AP_LAW) have strongly significant effects on the participation in R&D, but not on the intensity of R&D investments. Decision and intensity of firms to invest in R&D employment are positively influenced on the 0.01 significant level by AP_FIRM as well as by AP_LAW.

Highly significant explanatory power could also be found of firm size classifications (EMPL_MI, EMPL_G) on the probability for engaging in innovation/R&D and for investing in R&D employment. Large and middle-sized firms in the German manufacturing industry have a higher probability of investing in innovation input activities. The effects of the incurred firm size variables on the intensity of innovation/R&D expenditures are negative. These findings are in line with studies in other countries (Cohen/Klepper 1996; Evangelista et al. 1997; Kleinknecht 1996). In general, large firms have a higher probability to engage in the innovation process than small firms but - if they have invested - they spend less money in their innovation activities.

Other marked-related control variables have the expected signs. High shares of exports (SALE_EXP) stimulate the investment in innovation/R&D (significant at the 0.01 level) which strengthens the hypothesis of Schmookler (1966). The intensity in international sales (INTERNAT) and the degree of diversification (DIVERS) have positive and highly significant effects only on the decision of German firms to be active in R&D. Foreign trade encourages significantly (at the 0.01 level) the probability as well as the level of investments in R&D employment. Finally, the regressions indicate the expected (significant) effects of the technology level of industry groups (LOW, HIGH). The higher the technology level of industries, the more intensive the investments in innovation/R&D and R&D employment are.

4.1.2. Innovation Output Effects

To estimate the impacts of technological opportunities, especially of scientific research on the innovation *output* in the German manufacturing industry, the set of explanatory variables as on the input level is used with slight modifications. The effects are analyzed for the sales shares of new products (INNO_NOV), the sales shares of improved products (INNO_IMP), and the registration of patents (INNO_PA).

As shown in Table 4, technological opportunities stemming from scientific institutions (TO_SINT) have positive effects on the three innovation output variables, but without statistical significance. Only TO_UNIV reflecting information separately from universities has positive effects at the 0.05 significance level on the probability of patent registration in the German manufacturing industry. This reveals a pattern confirmed by the findings of Grupp (1996). In general, these outcomes verify the presumption that technological opportunities stemming from scientific research improve the quality of products more *indirectly* by increasing firms' R&D efficiency rather than by generating technical advance *directly*.

Similar to the innovation input estimations, the regressions point out positive, stimulating (significantly) effects of COOP_UNI. R&D cooperations with universities as the most systematic form of knowledge transfer increase the probability of higher sales shares of improved products (at the 0.05 level) and of the registration of patents (at the 0.01 level). The impacts on the probability of higher sales shares of new products are very weak and insignificant. This result is contrary to the findings of other studies (Faulkner/Senker 1994; Mansfield 1995). They found strong positive and significant effects of scientific knowledge sources on the sales shares of new products. More research have to been done to analyze the data set in more detail, especially to find out sectoral peculiarities, to reveal the reasons for the specific constellations in Germany.

Comparing the regression results with section 4.1.1, the explanation power of TO_SINT, TO_UNIV and COOP_UNI are much weaker than in the estimations for the innovation input variables. Especially the application of the Ordered Probit models for INNO_NOV yield insufficient results, which can be seen by the level of the McKelvey/Zavoina R^2.

Looking at the other kinds of technological opportunities, the regressions uncover the following remarkable connections: TO_SUPP has positive and highly significant impacts on INNO_NOV. The higher firms rank the importance of external knowledge from suppliers, the higher the sales shares of new products are. The estimations indicate stimulating and strong effects (significant at 0.01) of technological opportunities stemming from customers and competitors (TO_CUCO) only on INNO_IMP. Further, the effects of the appropriability conditions on the innovation output of firms in the German manufacturing industry are positive and mostly significant.

The econometric investigations point out the evidence of the market-related factors. By this, the effects of the firm size variables (EMPL_MI, EMPL_G) are ambiguous. On the one hand, larger firms have lower sales shares of new products (negative coefficient with lack of significance). On the other hand, positive effects on the sales shares of improved products could be identified for medium-sized firms (at the 0.05 significance level). At last, large firms have a higher probability of patenting their new findings. These findings strengthen the presumption that it is more likely that larger firms invest in process innovations than for smaller firms, which perform product R&D rather than process R&D (Peters 1998).

Further, high levels of exports (SALE_EXP) have significantly stimulating impacts on both sales shares. The intensity in international trade (INTERNAT) unfolds empirical evidence only on the probability of patent registration (at the 0.01 level), the degree of diversification (DIVERS) only on the sales shares of new products (with lack of significance). Finally, the regressions reflect stimulating and significant effects of the industry group HIGH on INNO_NOV. Firms in industries with high technology levels undertake R&D to develop novel products rather than firms in low technological.

4.2. Innovation Effects of Technological Opportunities with Absorptive Capacities

In section 2, we have argued that the degree to which firms (can) use technological opportunities Ω_i depends on their ability to adapt externally generated knowledge defined by l_i. In the theoretical considerations it was supposed that inhouse absorptive capacities encourage firms to invest more in the innovation process in order to enhance the stimulating effects of technological opportunities on the productivity of own (idiosyncratic) R&D. To investigate the empirical evidence of this hypothesis, we re-run the regressions.

We measure the influence of absorptive capacities on the innovation process as well as on the efficiency of using technological opportunities in two steps. In a first step, we include the two absorptive capacities proxies R&D_LAB and R&D_REG *additionally* in the estimations. By doing this, we can investigate if the existence and regularity of inhouse absorptive capacities by it self have stimulating innovation effects as expected theoretically. Further, as sign and significance of the coefficients of scientific opportunities (TO_SINT, TO_UNIV, COOP_UNI) will show, we can check whether the complementary or the substitution effects of using external knowledge dominate.

After this, we insert into the model specifications *interaction terms* as defined in (10). We build (multiple) interaction terms between the (three) science-related variables and the (two) proxies for absorptive capacities. By this, we are able to determine the connection between technological opportunities, absorptive capacities, and innovation activities *directly*. We expect that the sign of the coefficients of the interaction terms will be positive and their significance will be stronger than of the coefficients of the science-related variables alone, separately measured. Our hypothesis is that firms with absorptive capacities can use science-related knowledge sources more efficiently for their inhouse R&D/innovation activities than other firms and therefore have higher values of $l_i\Omega_i$.

4.2.1. Innovation Input Effects and Absorptive Capacities

The regression results of the innovation input effects of science-related technological opportunities with absorptive capacities proxies *separately* are listed in Table 5. In general, R&D_LAB has highly significant effects on the extent of the investments of German firms in innovation/R&D and R&D employment. With exception of INNO_INT, the existence of R&D labs increases the probability of an engagement in the innovation process (significant at the 0.01 level). This results correspond with other studies emphasizing the role of R&D labs as an explanatory factor of R&D intensities (for a review, see Cohen 1995; Kleinknecht 1996). The influence of R&D_REG is strongly significant only by R&D_E_INT traceable to the close linkage between the continuity of R&D and the necessity of expenditures for R&D employees. Further, R&D_REG raises the probability of inhouse R&D significantly. The effects on the intensity of R&D investments are positive but without statistical power.

Looking at the other exogenous variables, three main points can be remarked: Firstly, the direction of the parameter values are, on principle, similar to the estimations without the proxies for absorptive capacities. Secondly, the science-related variables, the factors reflecting the approriability conditions of firms, and the market-related variables lose on significance for R&D_INT and R&D_E_INT in the participation estimations. Thirdly, the significance levels reflecting the influence of scientific knowledge sources on the intensity of investments in R&D increase. The coincidence with higher significant levels of TO_UNIV and COOP_UNI confirms the importance of l_i in the innovation process. Firms have to invest in their own (idiosyncratic) R&D in order to profit from the productivity effects of scientific knowledge (Cohen/Levinthal 1989).

Stronger results for the hypothesis of stimulating effects of absorptive capacities on the *intensity* of inhouse R&D can be found in the regressions with inclusion of the *interaction terms* (LAB_, REG_) measuring the effects of $l_i\Omega_i$ immediately (Table 6a, 6b). Our findings underline the empirical evidence of absorptive capacities as an *intermediate* factor between external knowledge sources and the engagement of firms in the development of new and improved products. Compared to the estimations without absorptive capacities proxies, in general, the effects of the science-related variables in combination with the existence of R&D labs (LAB_SINT, LAB_UNIV, LAB_COOP) and the regularity of R&D (REG_SINT, REG_UNIV, REG_COOP) on the intensities are much *stronger*. It is more likely that firms are engaged in innovation/R&D and their invest more in R&D employment, if they dispose of absorptive capacities. The productivity of scientific knowledge sources for their inhouse activities is higher with positive effects on investments in the development of new or improved products. In the selectivity models for INNO_INT the coefficients reach a remarkable higher significance than in the estimations without interaction terms.

In general, the econometric investigations strengthen the theoretical assumptions of *enhancing effects of* $l_i\Omega_i$ *on the innovation input activities* of firms. Firms with inhouse absorptive capacities have more potentials to implement scientific knowledge (see also Veugelers 1997). Due to their increased efficiency, they can use more external generic R&D, thus enhancing the productivity effects of idiosyncratic R&D. Both effects increase the incentives to invest R&D (innovation) activities. In some estimations, controlling for absorptive capacities in the first specification form (without interaction terms), the significance of scientific knowledge as well as changes the signs of the related coefficients decreases. This can be interpreted that firms may also substitute their generic R&D by using technological opportunities.

4.2.2. Innovation Output Effects and Absorptive Capacities

As reported in Table 7, the existence of R&D labs and the continuity of R&D have stimulating effects also on the innovation output of German firms. However, very high significant coefficients for both proxies could only be found for INNO_PA. Inhouse absorptive capacities increase the probability of patent registrations. The enhancing influence on sales shares of new products (INNO_NOV) are significant at the 0.01 level for R&D_REG. Obviously, the long-run orientation of R&D is of more empirical evidence for the development of new technologies than the set up of one or more R&D lab.[15]

Generally, the directions and significance levels of the other exogenous variables are similar to the regression results without the absorptive capacities proxies reported in section 4.1.2. Two main points have to be notified: In the estimations for INNO_NOV the negative impetus of the large firms variable gains clearly on significance (up to the 0.01 level). In addition, the positive (insignificant) effect of these variable on the sales shares of improved products (INNO_IMP) changes into negative in model 3 with the science-related variable COOP_UNI.

The results of the estimations with *interaction terms* are given in Tables 8a and 8b. In consideration of the interaction terms, the highly empirical evidence of the absorptive capacities can be stressed impressively. In general, the effects of the three science-related variables in combination with the existence of R&D labs (LAB_) and the regularity of R&D (REG_) have higher significance as in the estimations without absorptive capacities. The innovation output in the German manufacturing industry is positively influenced by $l_i\Omega_i$. Firms with inhouse absorptive capacities and a high importance of scientific knowledge are characterized by higher sales shares of new/improved products and higher probabilities of patent registrations than other firms.

The empirical findings can be summarized as follows: The regressions verify the theoretical assumptions of *enforcing effects of* $l_i\Omega_i$ *on the innovation output* of firms. An efficient adaptation of knowledge generated in the scientific sphere enlarges technological capabilities with stimulating effects on the sales shares of new and improved products and the registration of patents.

5. Summary

Innovative firms continuously have to expand their technological capabilities and to optimize their inhouse R&D potentials by applying technological opportunities from outside. The extent to which firms can implement exogenously generated knowledge depends on their absorptive capacities. Therefore, firms invest in their technological capabilities in order to understand and use the results of externally performed R&D and to obtain full access to the research findings of other firms and institutions. Particular information generated in scientific research require adequate absorptive capacities.

Against this background, the aim of the paper was to analyze the effects of technological opportunities on the innovation activities of firms, depending on their absorptive capacities, in more detail connecting theoretical and empirical investigations. Due to the close connection between scientific knowledge and innovations, the importance and impacts of the ability of firms to use external knowledge sources were

[15] It has to be remarked that the two proxies used reflect different *qualitative* aspects of the ability of firms to adapt external knowledge. For more discussion about methodical aspects of the measurement of absorptive capacities see Peters/Becker (1998a).

inquired especially for technological opportunities stemming from scientific research. Using input-, output- and market-related variables, differences in the innovation input and output activities of firms were empirically outlined for the German manufacturing industry for the first time.

In a *first step*, we have measured the innovation effects of technological opportunities (among other factors) without variables reflecting the absorptive capacities. The regression results underline that scientific knowledge sources have significant effects on innovative activities of firms in the German manufacturing industry. On the innovation input side, technological opportunities from scientific research are used as complements. Inhouse technological capabilities can be expanded with positive effects on the engagement and intensity in R&D/innovation. On the output side, we found significant positive effects of scientific knowledge on the sales shares of improved products and on the registration of patents.

In a *second step*, the estimation models were re-run with (interaction) terms to investigate the influence of absorptive capacities on the investments of firms and on the results of their innovation/R&D activities. In consideration of interaction terms, the empirical evidence of absorptive capacities in the innovation process can be stressed impressively. On the input side, the effects of the science-related variables in combination with the existence of R&D labs and the regularity of R&D are stronger on the intensities as in the estimations without absorptive capacities proxies. The likelihood that firms are more engaged in innovation/R&D as well as the intensity of investments in R&D employment increase, if they have absorptive capacities and the importance of scientific knowledge sources for their inhouse activities is high. Further, the innovation output of firms is positively influenced by the ability to adapt external knowledge efficiently. Firms in the German manufacturing industry with inhouse absorptive capacities and a high importance of scientific knowledge are characterized by higher sales shares of new and improved products and higher probabilities of patent registrations than other firms.

On the basis of the regression results further theoretical and empirical work has to be done to analyze the interdependence between technological opportunities and innovation activities under more industry-specific aspects. Hereby, the function of time as an intermediate factor has to be taken into consideration. Investigations will also be conducted to specify the relevance of different quality levels of external (scientific) knowledge and their productivity and substitution effects on inhouse R&D/innovation. In addition, the conditions to adapt and implement technological opportunities efficiently have to be analyzed in more detail. In this context, the measurement of absorptive capacities has to been improved. More data has to been collected to identify and investigate the efforts and strategies of firms to build up absorptive capacities and to improve the quality of their capabilities to use external knowledge efficiently for the development of new technologies in the long run.

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Table 1: List of innovation variables

Variable	Description	Empirical measurement	Value (Range)	Mean	Std. Dev.
Innovation Input					
INNO_INT	Innovation intensity	Logs of innovation expenditures to sales ratio (1992)	Metric	-3.10	1.65
R&D_INT	R&D intensity	Logs of R&D expenditures to sales ratio (1992)	Metric	-5.74	2.72
R&D_E_INT	R&D employment intensity	R&D employment to total employment ratio (1992)	Metric	-5.35	3.00
Innovation Output					
INNO_NOV	Novelty of product innovations	Sales shares of new products in 1992 (0 = no sales share up to 9 = 100 percent)	Interval (0-9)	3.53	2.71
INNO_IMP	Novelty of product innovations	Sales shares of improved products in 1992 (0 = no sales share up to 9 = 100 percent)	Interval (0-9)	4.37	2.52
INNO_PA	Importance of patents	1 = Registration of patents in 1992, 0 = otherwise	Nominal	0.32	0.47

Table 2: List of exogenous variables

Variable	Description	Empirical measurement	Value (Range)	Mean	Std. Dev.
		Technological opportunities			
TO_CUCO	Importance of external knowledge to firms' innovation activities	Customers and competitors as knowledge source (factor scores)	Metric	0.00	1.00
TO_SUPP		Suppliers as knowledge source (factor scores)	Metric	1.00	1.00
TO_SINT		Scientific institutions as knowledge source (factor scores)	Metric	0.00	1.00
TO_UNIV		Universities as knowledge source (1 = very low up to 5 = very high)	Interval (1-5)	2.54	1.33
COOP_UNI	Joint R&D activities with universities	1 = R&D cooperation in 1992, 0 = otherwise	Nominal	0.22	0.42
		Absorptive Capacities			
R&D_LAB	Formal R&D lab	1= Formal R&D lab in 1992, 0 = otherwis	Nominal	0.38	0.49
R&D_REG	Regularity of R&D	1 = Regular R&D activities, 0 = otherwise	Nominal	0.62	0.49
LAB_SINT	Interaction terms	R&D_LAB * TO_SINT	Metric	0.92	1.28
LAB_UNIV		R&D_LAB * TO_UNIV	Metric	1.16	1.64
LAB_COOP		R&D_LAB * TO_COOP	Metric	0.15	0.36
REG_SINT		R&D_REG * TO_SINT	Metric	1.43	1.32
REG_UNIV		R&D_REG * TO_UNIV	Metric	1.81	1.70
REG_COOP		R&D_REG * TO_COOP	Metric	0.21	0.41
		Appropriability Conditions			
	Extent to which technological knowledge can be protected from others regarding to				
AP_FP_PR	- product innovations	Firm-specific mechanisms to protect product innovations (factor scores)	Metric	0.00	1.00
AP_LP_PR		Mechanisms to protect product innovations by law (factor scores)	Metric	1.00	1.00
AP_FP_PZ	- process innovations	Firm-specific mechanisms to protect process innovations (factor scores)	Metric	0.00	1.00
AP_LP_PZ		Mechanisms to protect process innovations by law (factor scores)	Metric	0.00	1.00
AP_FIRM	- product/process innovations	Firm-specific mechanism to protect innovations – all mechanism (factor scores)	Metric	0.00	1.00
AP_LAW		Mechanisms to protect innovations by law - all mechanism (factor scores)	Metric	0.00	1.00

Market Relations					
EMPL_MI EMPL_G	Firm size (small firms with up to 50 employees as basic group)	1 = 50 up to 249 employess, 0 = otherwise 1 = 250 employees and more, 0 = otherwise	Nominal Nominal	0.32 0.37	0.47 0.48
LOW HIGH	Industry groups (OECD classification) with different level of technology intensities (firms with medium technology level as basic group)	Sales shares of R&D: 1 = up to 3 percent, 0 = otherwise 1 = 5 percent and more, 0 = otherwise	Nominal Nominal	0.26 0.18	0.44 0.38
DIVERS	Degree of diversification	Inverse of the sum of squared sales share for the four major product groups	Metric	1.53	0.63
SALE_EXP	Sales expectations	Expected change of sales in 1993-1995 (1 = low up to 5 = very high)	Interval (1-5)	3.24	1.09
INTERNAT	Intensity in international sales	Foreign sales/whole sales	Metric	0.20	0.23

Table 3: Innovation *input* effects of technological opportunities without absorptive capacities

Variables	INNO_INT						R&D_INT						R&D_E_INT					
	1		2		3		1		2		3		1		2		3	
	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity
	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)
INTERCEPT	1.61***	-3.62***	1.67***	-3.78***	1.62***	-3.67***	-0.35*	-4.27***	-0.60***	-4.56***	-4.05**	-4.35***	-0.53***	-4.87***	0.80***	-5.16***	-0.59***	-3.92***
	(3.50)	(-11.98)	(3.39)	(11.62)	(3.53)	(12.09)	(-1.96)	(-4.00)	(-3.13)	(-3.81)	(-2.19)	(-4.14)	(-2.97)	(-7.61)	(-4.19)	(-7.44)	(-3.19)	(11.09)
EMPL_MI	0.71**	-0.06	0.71**	-0.04	0.71**	-0.07	0.52***	-0.48	0.52***	-0.49	0.46***	-0.49	0.59***	-0.12	0.59***	-0.14	0.53***	-050***
	(2.49)	(-0.34)	(2.49)	(0.18)	(2.47)	(-0.39)	(5.58)	(-1.37)	(5.54)	(-1.39)	(4.84)	(-1.53)	(6.44)	(-0.49)	(6.38)	(-0.58)	(5.65)	(-3.79)
EMPL_G	0.59**	-0.60***	0.59**	0.55***	0.57**	-0.62***	0.88***	-0.72	0.88***	-0.70	0.75***	-0.73*	0.97***	-0.25	0.96***	-0.26	0.82***	-0.91***
	(2.13)	(-3.32)	(2.13)	(2.89)	(1.98)	(-3.40)	(8.47)	(-1.44)	(8.47)	(-1.40)	(6.97)	(-1.73)	(9.44)	(-0.77)	(9.33)	(-0.85)	(7.79)	(-5.12)
SALE_EXP	0.01	0.21***	0.01	0.21***	0.01	0.21***	0.04	0.17***	0.04	0.17***	0.03	0.17***	0.04	0.16***	0.05	0.17***	0.03	0.15***
	(0.11)	(4.34)	(0.10)	(4.22)	(0.10)	(4.49)	(1.00)	(4.30)	(1.02)	(4.26)	(0.73)	(4.52)	(1.15)	(3.57)	(1.17)	(3.64)	(0.91)	(5.12)
INTERNAT	0.80	0.31	0.80	0.33	0.78	0.28	1.03***	0.71	1.03***	0.71	0.95***	0.66	0.93***	1.12***	0.93***	1.12***	0.84***	0.71***
	(1.17)	(1.32)	(1.17)	(1.32)	(1.14)	(1.17)	(5.13)	(1.56)	(5.15)	(1.56)	(4.59)	(1.63)	(4.78)	(3.78)	(4.81)	(3.84)	(4.18)	(4.19)
DIVERS	0.06	0.06	0.05	0.06	0.05	0.05	0.18**	0.03	0.19**	0.03	0.19**	0.02	0.22***	0.13*	0.22***	0.13*	0.22***	0.05
	(0.28)	(0.79)	(0.26)	(0.85)	(0.26)	(0.66)	(2.51)	(0.32)	(2.55)	(0.41)	(2.46)	(0.23)	(3.00)	(1.65)	(3.02)	(1.71)	(2.90)	(1.03)
LOW	0.09	-0.11	0.08	-0.12	0.09	-0.11	-0.42***	-0.54**	-0.43***	-0.55**	-0.37***	-0.54**	-0.41***	-0.82***	-0.41***	-0.82***	-0.36***	-0.59***
	(0.36)	(-0.86)	(0.37)	(-0.91)	(0.38)	(-0.87)	(-4.63)	(-2.07)	(-4.73)	(-2.11)	(-3.99)	(-2.39)	(-4.58)	(-4.63)	(-4.63)	(-4.74)	(-3.89)	(-6.03)
HIGH	0.36	0.40***	0.36	0.40***	0.36	0.39***	0.29***	0.65***	0.27**	0.63***	0.30***	0.64***	0.31***	0.66***	0.29***	0.63***	0.32***	0.53***
	(1.06)	(2.94)	(1.07)	(2.79)	(1.06)	(2.90)	(2.61)	(4.00)	(2.42)	(4.02)	(2.63)	(3.97)	(2.80)	(4.65)	(2.60)	(4.62)	(2.86)	(6.06)
AP_FIRM	0.25***	0.12*	0.25***	0.14**	0.24**	0.12*	0.14***	0.05	0.14***	0.06	0.13***	0.07	0.13***	0.19***	0.13***	0.19***	0.12***	0.12***
	(2.61)	(1.81)	(2.61)	(2.04)	(2.56)	(1.89)	(3.50)	(0.62)	(3.64)	(0.76)	(3.22)	(0.86)	(3.40)	(2.94)	(3.43)	(3.11)	(3.08)	(3.31)
AP_LAW	0.04	-0.03	0.04	-0.01	0.03	0.01	0.13***	0.07	0.14***	0.09	0.17***	0.12	0.13***	0.17***	0.13***	0.18***	0.16***	0.14***
	(0.38)	(-0.55)	(0.36)	(-0.03)	(0.28)	(0.05)	(3.01)	(0.81)	(3.34)	(1.14)	(3.98)	(1.28)	(2.94)	(2.68)	(3.09)	(3.01)	(3.80)	(3.65)
TO_CUCO	0.06	0.10*	0.06	0.09*	0.06	0.09*	0.06	0.10**	0.05	0.10**	0.07*	0.10**	0.06	0.06	0.05	0.06	0.08**	0.05
	(0.64)	(1.81)	(0.65)	(1.67)	(0.64)	(1.75)	(1.45)	(2.16)	(1.31)	(2.06)	(1.85)	(2.00)	(1.50)	(1.21)	(1.39)	(1.12)	(1.96)	(1.55)
TO_SUPP	-0.19*	-0.01	-0.18	-0.16	-0.18	-0.01	0.02	0.02	0.02	0.01	0.02	0.02	0.03	0.05	0.02	0.05	0.03	0.04
	(-1.64)	(-0.16)	(-1.62)	(-0.28)	(-1.61)	(-0.10)	(0.53)	(0.44)	(0.40)	(0.33)	(0.54)	(0.45)	(0.71)	(1.05)	(0.59)	(0.92)	(0.69)	(1.31)
TO__SINT	-0.03	0.14**					0.13***	0.20***					0.12***	0.17***				
	(-0.30)	(2.46)					(2.92)	(2.62)					(2.65)	(2.82)				
TO_UNIV			-0.21	0.05					0.10***	0.11*					0.11***	0.12***		
			(-0.25)	(1.08)					(3.17)	(1.93)					(3.54)	(2.64)		
COOP_UNI					0.02	0.31***					0.94***	0.39					0.99***	0.53***
					(0.06)	(2.64)					(6.84)	(1.21)					(7.35)	(4.45)
Number of observations	1197	1178	1197	1178	1176	1157	1468	1059	1468	1059	1445	1043	1489	1049	1489	1049	1466	1033
Log likelihood	-81.47		-81.48		-81.33		-704.34		-703.61		-669.76		-727.30		-724.54		-687.71	
McFaddens R^2	0.17		0.17		0.16		0.19		0.20		0.22		0.20		0.20		0.21	
Model F-statistic		16.3***		15.2***		15.8***		22.3***		21.2***		21.3***		35.8***		35.3***		34.6***

Notes: * significant at the 0.1 level. ** significant at the 0.05 level. *** significant at the 0.01 level.

Table 4: Innovation *output* effects of technological opportunities without absorptive capacities

Variables	INNO_NOV			INNO_IMP			INNO_PA		
	1	2	3	1	2	3	1	2	3
	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)
INTERCEPT	0.45***	0.36**	0.41***	0.88***	0.91***	0.86***	-1.32***	-1.49***	-1.36***
	(3.23)	(2.40)	(2.91)	(6.30)	(6.08)	(6.15)	(-7.17)	(-7.47)	(-7.22)
EMPL_MI	-0.03	-0.04	-0.03	0.16**	0.17**	0.17**	0.53***	0.52***	0.49***
	(-0.42)	(-0.48)	(-0.44)	(2.26)	(2.32)	(2.31)	(4.44)	(4.35)	(4.01)
EMPL_G	-0.11	-0.13	-0.12	0.05	0.07	0.02	1.26***	1.25***	1.16***
	(-1.35)	(-1.51)	(-1.39)	(0.66)	(0.87)	(0.26)	(10.68)	(10.56)	(9.53)
SALE_EXP	0.11***	0.11***	0.11***	0.05*	0.05*	0.05*	-0.02	-0.02	-0.02
	(3.72)	(3.74)	(3.71)	(1.89)	(1.89)	(1.85)	(-0.49)	(-0.48)	(-0.42)
INTERNAT	-0.12	-0.12	-0.13	0.06	0.06	0.03	1.06***	1.07***	1.05***
	(-0.86)	(0.85)	(-0.92)	(0.44)	(0.46)	(0.24)	(5.97)	(6.00)	(5.76)
DIVERS	0.03	0.03	0.03	-0.02	-0.02	-0.04	-0.01	-0.01	-0.30
	(0.55)	(0.57)	(0.70)	(-0.50)	(-0.48)	(-0.73)	(-0.08)	(-0.07)	(-0.50))
LOW	0.08	0.08	0.08	-0.12*	-0.13*	-0.12	-0.62***	-0.61***	-0.59***
	(1.07)	(1.14)	(1.15)	(-1.71)	(-1.82)	(-1.60)	(-5.62)	(-5.57)	(-5.29
HIGH	0.17**	0.16**	0.17**	0.10	0.10	0.12	0.20*	0.19*	0.20*
	(2.05)	(2.03)	(2.12)	(1.24)	(1.24)	(1.46)	(1.91)	(1.81)	(1.84)
AP_FP_PR	0.16***	0.16***	0.16***						
	(5.29)	(5.27)	(5.19)						
AP_LP_PR	0.04	0.03	0.04						
	(1.06)	(1.02)	(1.20)						
AP_FP_PZ				0.06**	0.06**	0.05			
				(2.05)	(2.49)	(1.62)			
AP_LP_PZ				0.07**	0.08**	0.06*			
				(2.11)	(2.35)	(1.91)			
AP_FIRM							0.10**	0.10**	0.09*
							(2.16)	(2.16)	(1.89)
AP_LAW							0.52***	0.52***	0.53***
							(11.04)	(11.35)	(11.60)
TO_CUCO	0.04	0.04	0.04	0.06**	0.06*	0.06**	0.04	0.04	0.04
	(1.38)	(1.33)	(1.44)	(2.03)	(2.00)	(2.06)	(0.84)	(0.85)	(0.84)
TO_SUPP	0.09***	0.09***	0.09***	0.01	0.01	0.01	-0.01	-0.02	-0.01
	(2.90)	(2.83)	(2.95)	(0.33)	(0.37)	(0.26)	(-0.28)	(-0.37)	(-0.15)
TO_SINT	0.02			0.01			0.06		
	(0.71)			(0.31)			(1.37)		
TO_UNIV		0.04			-0.14			0.07**	
		(1.52)			(-0.58)			(2.01)	
COOP_UNI			0.08			0.21**			0.47***
			(1.01)			(2.43)			(4.92)
Number of observations	1294	1294	1273	1250	1250	1228	1450	1450	1428
Log likelihood	-2692.45	-2691.62	-2648.70	-2550.20	-2550.08	-2502.09	-638.45	-637.37	-612.85
McKelvey/Zavoina R^2	0.03	0.03	0.07	0.07	0.07	0.08			
McFadden R^2							0.32	0.32	0.33

Notes: * significant at the 0.1 level. ** significant at the 0.05 level. *** significant at the 0.01 level.

Table 5: Innovation *input* effects of technological opportunities with absorptive capacities (R&D_LAB, R&D_REG)

Variables	**INNO_INT**						**R&D_INT**						**R&D_E_INT**					
	1		**2**		**3**		**1**		**2**		**3**		**1**		**2**		**3**	
	Particip.	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**
	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)
INTERCEPT	1.57*** (3.38)	-3.65*** (-12.61)	1.69*** (3.40)	-3.77*** (-12.38)	1.60*** (3.48)	-3.67*** (-12.75)	-0.86*** (-3.77)	-4.72** (-2.00)	-0.86*** (-3.53)	-4.96** (-2.09)	-0.86*** (-3.77)	-4.77** (-2.07)	-1.17*** (-5.08)	-6.18*** (-7.40)	-1.18*** (-4.82)	-6.39*** (-7.44)	-1.15*** (-4.97)	-5.82*** (-8.15)
EMPL_MI	0.65** (2.19)	-0.20 (1.21)	0.65** (2.19)	-0.18 (-1.02)	0.65** (2.19)	-0.20 (1.18)	0.23** (1.97)	-0.64*** (-3.40)	0.22** (1.97)	-0.65*** (-3.40)	0.21* (1.85)	-0.64*** (-3.41)	0.32*** (2.83)	-0.60*** (-4.20)	0.32*** (2.84)	-0.59*** (-4.03)	0.31*** (2.72)	-0.64*** (-4*.93)
EMPL_G	0.52* (1.70)	-0.82*** (-5.02)	0.52* (1.71)	-0.78*** (4.54)	0.52* (1.66)	-0.82*** (-4.96)	0.28** (2.12)	-1.12*** (-5.69)	0.28** (2.13)	-1.10*** (-5.60)	0.25* (1.86)	-1.12*** (-5.98)	0.39*** (2.99)	-1.13*** (-7.64)	0.38*** (2.90)	-1.12*** (-7.40)	0.34** (2.57)	-1.20*** (-9.03)
SALE_EXP	0.01 (0.01)	0.19*** (4.42)	-0.01 (0.03)	0.19*** (4.20)	0.01 (0.01)	0.19*** (4.47)	-0.03 (-0.59)	0.14*** (3.92)	-0.03 (-0.59)	0.14*** (3.91)	-0.04 (-0.67)	0.14*** (3.94)	-0.02 (-0.42)	0.11*** (2.69)	-0.02 (-0.41)	0.11*** (2.61)	-0.02 (-0.52)	0.11*** (2.95)
INTERNAT	0.72 (1.05)	0.15 (0.67)	0.72 (1.04)	0.16 (0.68)	0.69 (1.02)	0.12 (0.57)	0.36 (1.45)	0.50** (2.39)	0.36 (1.45)	0.50** (2.40)	0.35 (1.39)	0.45** (2.17)	0.15 (0.60)	0.42** (2.15)	0.15 (0.62)	0.43** (2.13)	0.12 (0.48)	0.38** (2.08)
DIVERS	0.04 (0.22)	0.04 (0.64)	0.04 (0.20)	0.05 (0.70)	0.04 (0.19)	0.04 (0.53)	0.16* (1.72)	0.01 (0.09)	0.16* (1.73)	0.01 (0.19)	0.17* (1.76)	-0.01 (0.03)	0.23** (2.41)	0.07 (1.21)	0.22** (2.38)	0.08 (1.25)	0.23** (2.34)	0.06 (0.98)
LOW	0.11 (0.46)	-0.05 (-0.47)	0.12 (0.47)	-0.06 (-0.52)	0.12 (0.46)	-0.06 (-0.52)	-0.27** (-2.47)	-0.46** (-2.54)	-0.27** (-2.48)	-0.47*** (-2.58)	-0.25** (-2.20)	-0.46*** (-2.78)	-0.26** (-2.34)	-0.55*** (-4.46)	-0.26** (-2.31)	-0.55*** (-4.42)	-0.23** (-2.02)	-0.50*** (-4.62)
HIGH	0.35 (1.04)	0.34*** (2.71)	0.36 (1.06)	0.34** (2.57)	0.35 (1.03)	0.34*** (2.67)	0.15 (1.34)	0.52*** (4.31)	0.19 (1.33)	0.50*** (4.13)	0.19 (1.35)	0.51*** (4.16)	0.21 (1.46)	0.45*** (4.04)	0.21 (1.43)	0.45*** (3.96)	0.21 (1.47)	0.43*** (4.24)
AP_FIRM	0.24** (2.47)	0.09 (1.45)	0.24** (2.45)	0.10* (1.68)	0.24** (2.43)	0.09 (1.57)	0.03 (0.51)	0.01 (0.35)	0.03 (0.52)	0.03 (0.62)	0.02 (0.34)	0.03 (0.66)	0.02 (0.48)	0.07 (1.43)	0.02 (0.36)	0.07 (1.48)	0.01 (0.20)	0.06 (1.39)
AP_LAW	0.04 (0.38)	-0.06 (-1.08)	0.04 (0.34)	-0.30 (-0.56)	0.02 (0.22)	-0.03 (-0.51)	0.03 (0.59)	0.01 (0.32)	0.03 (0.61)	0.04 (0.95)	0.03 (0.63)	0.06 (1.45)	0.02 (0.40)	0.04 (0.79)	0.01 (0.14)	0.04 (0.92)	0.01 (0.20)	0.05 (1.17)
TO_CUCO	0.07 (0.67)	0.09* (1.89)	0.07 (0.69)	0.09* (1.75)	0.07 (0.66)	0.09* (1.81)	0.09* (1.82)	0.11** (2.16)	0.09* (1.83)	0.11** (2.05)	0.09** (1.98)	0.11** (2.07)	0.09* (1.81)	0.07 (1.45)	0.09* (1.85)	0.07 (1.43)	0.10** (2.07)	0.07* (1.67)
TO_SUPP	-0.19* (-1.68)	-0.01 (-0.28)	-0.19* (-1.65)	-0.02 (-0.38)	-0.19* (-1.65)	-0.12 (-0.24)	0.05 (0.96)	-0.02 (-0.36)	0.05 (0.96)	-0.02 (-0.45)	0.04 (0.92)	-0.17 (-0.37)	0.04 (0.92)	0.04 (0.85)	0.05 (0.93)	0.04 (0.81)	0.04 (0.86)	0.04 (0.83)
TO_SINT	-0.06 (-0.51)	0.12** (2.22)					0.01 (0.02)	0.16*** (4.12)					-0.03 (-0.62)	0.05 (1.08)				
TO_UNIV			-0.04 (-0.48)	0.03 (0.72)					0.01 (0.01)	0.09*** (3.12)					0.01 (0.24)	0.04 (1.04)		
COOP_UNI					-0.05 (-0.15)	0.24** (2.09)					0.30* (1.82)	0.30*** (2.74)					0.40** (2.49)	0.33*** (3.44)
R&D_LAB	-0.14 (0.41)	0.30*** (2.63)	-0.14 (-0.43)	0.31** (2.53)	-0.14 (-0.41)	0.31*** (2.67)	0.68*** (4.19)	0.77*** (3.60)	0.68*** (4.19)	0.78*** (3.60)	0.67*** (4.09)	0.79*** (3.75)	0.75*** (4.87)	0.78*** (5.96)	0.75*** (4.85)	0.79*** (5.90)	0.74*** (4.76)	0.75*** (6.48)
R&D_REG	0.31 (1.08)	0.23* (1.71)	0.32 (1.09)	0.25* (1.81)	0.30 (1.03)	0.20 (1.50)	1.83*** (16.13)	0.52 (0.28)	1.83*** (16.07)	0.53 (0.28)	1.77*** (15.33)	0.50 (0.28)	1.87*** (16.70)	2.48*** (3.90)	1.86*** (16.60)	2.55*** (3.93)	1.79*** (15.75)	2.14*** (4.01)
Number of observations	1194	1175	1194	1175	1174	1155	1463	1059	1463	1059	1443	1043	1484	1049	1484	1049	1464	1033
Log likelihood	-80.81		-80.82		-80.76		-437.69		-437.69		-434.13		-438.46		-438.62		-433.52	
McFaddens R^2	0.17		0.17		0.17		0.49		0.49		0.48		0.51		0.51		0.51	
Model F-statistic		16.2***		15.4***		15.6***		32.2***		31.5***		31.3***		41.5***		41.4***		41.3***

Notes: * significant at the 0.1 level. ** significant at the 0.05 level. *** significant at the 0.01 level.

Table 6a: Innovation *input* effects of technological opportunities with interaction terms (LAB_)

Variables	INNO_INT						R&D_INT						R&D_E_INT					
	1		2		3		1		2		3		1		2		3	
	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity	Particip.	Intensity
	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)
INTERCEPT	1.63***	-3.59***	1.65***	-3.56***	1.62***	-3.64***	-0.40**	-4.36***	-0.38**	-4.35***	-0.40**	-4.31***	-0.57***	-3.22***	-0.55***	-3.12***	-0.58***	-3.74***
	(3.55)	(-12.81)	(3.59)	(-13.27)	(3.55)	(-12.15)	(-2.05)	(-4.12)	(-1.97)	(4.06)	(2.14)	(-4.18)	(-2.94)	(14.93)	(-2.85)	(-14.28)	(-3.13)	(-11.66)
EMPL_MI	0.71**	-0.13	0.68**	-0.16	0.71**	-0.66	0.43***	-0.57*	0.44***	-0.58**	0.47***	-0.49	0.52***	-0.77***	0.52***	-0.81***	0.55***	-0.54***
	(2.45)	(-0.76)	(2.37)	(-0.95)	(2.49)	(-0.36)	(4.45)	(-1.91)	(4.51)	(-1.95)	(4.97)	(-1.52)	(5.34)	(-8.36)	(5.34)	(-8.72)	(5.83)	(-4.30)
EMPL_G	0.57*	-0.75***	0.50*	-0.77***	0.60**	-0.63***	0.54***	-1.01***	0.55***	-1.00***	0.74***	-0.80*	0.63***	-1.30***	0.63***	-1.32***	0.82***	-0.92***
	(1.94)	(-4.38)	(1.73)	(-4.80)	(2.06)	(-3.46)	(4.73)	(-2.98)	(4.85)	(-2.92)	(6.92)	(-1.85)	(5.58)	(-13.23)	(5.64)	(-13.41)	(7.69)	(-6.09)
SALE_EXP	0.01	0.19***	0.01	0.19***	0.01	0.21***	0.01	0.14***	0.01	0.14***	0.02	0.17***	0.01	0.12***	0.01	0.12***	0.03	0.14***
	(0.10)	(4.45)	(0.06)	(4.58)	(0.11)	(4.49)	(0.14)	(4.15)	(0.05)	(4.16)	(0.65)	(4.50)	(0.21)	(4.72)	(0.10)	(4.76)	(0.84)	(5.14)
INTERNAT	0.78	0.18	0.73	0.18	0.79	0.27	0.83***	0.57*	0.82***	0.58*	0.99***	0.63	0.68***	0.44***	0.67***	0.43***	0.87***	0.65***
	(1.14)	(0.85)	(1.07)	(0.86)	(1.15)	(1.17)	(3.98)	(1.69)	(3.77)	(1.70)	(4.77)	(1.53)	(3.20)	(3.59)	(3.19)	(3.50)	(4.30)	(0.16)
DIVERS	0.05	0.05	0.03	0.05	0.05	0.05	0.16*	0.02	1.62**	0.02	0.21***	0.01	0.19**	0.02	0.20**	0.02	0.25***	0.04
	(0.25)	(0.74)	(0.17)	(0.80)	(0.26)	(0.67)	(2.04)	(0.24)	(2.06)	(0.36)	(2.74)	(0.12)	(2.47)	(0.42)	(2.50)	(0.45)	(3.19)	(0.83)
LOW	0.09	-0.08	0.10	-0.08	0.09	-0.10	-0.33***	-0.46**	-0.34***	-0.46**	-0.36***	-0.52**	-0.32***	-0.40***	-0.33***	-0.39***	-0.35***	-0.55***
	(0.38)	(-0.67)	(0.43)	(-0.70)	(0.38)	(-0.80)	(-3.43)	(-2.29)	(-3.53)	(-2.32)	(-3.87)	(-2.29)	(-3.37)	(-5.46)	(-3.43)	(-5.29)	(-3.78)	(-5.94)
HIGH	0.36	0.35***	0.34	0.34***	0.36	0.38***	0.17	0.57***	0.16	0.55***	0.30***	0.62***	0.20	0.40***	0.19	0.38***	0.32***	0.50***
	(1.05)	(2.77)	(1.00)	(2.78)	(1.06)	(2.84)	(1.36)	(4.11)	(1.30)	(4.21)	(2.62)	(3.92)	(1.61)	(5.96)	(1.56)	(5.67)	(2.82)	(6.10)
AP_FIRM	0.25***	0.11*	0.24**	0.11*	0.25***	0.12*	0.13***	0.04	0.14***	0.05	0.13***	0.06	0.13***	0.06**	0.13***	0.07**	0.13***	0.11***
	(2.58)	(1.84)	(2.54)	(1.89)	(2.58)	(1.92)	(3.21)	(0.54)	(3.33)	(0.67)	(3.36)	(0.75)	(3.20)	(2.06)	(3.26)	(2.17)	(3.29)	(3.14)
AP_LAW	0.03	-0.03	0.02	-0.02	0.03	0.01	0.09*	0.04	0.09**	0.06	0.16***	0.11	0.07	0.03	0.08*	0.05*	0.15***	0.13***
	(0.30)	(-0.57)	(0.19)	(-0.51)	(0.30)	(0.01)	(1.95)	(0.62)	(2.13)	(0.93)	(3.88)	(1.21)	(1.63)	(1.19)	(1.82)	(1.66)	(3.64)	(3.46)
TO_CUCO	0.06	0.09*	0.06	0.09*	0.06	0.09*	0.07*	0.11**	0.06	0.11**	0.07*	0.10**	0.07*	0.03	0..07*	0.03	0.07*	0.05
	(0.66)	(1.87)	(0.65)	(1.92)	(0.62)	(1.75)	(1.64)	(2.44)	(1.55)	(2.34)	(1.66)	(2.18)	(1.81)	(1.22)	(1.66)	(1.08)	(1.81)	(1.51)
TO_SUPP	-0.18	-0.19	-0.19*	-0.20	-0.18	-0.01	-0.01	-0.01	-0.01	-0.02	0.02	0.01	-0.01	0.02	-0.01	0.01	0.02	0.04
	(-1.64)	(-0.36)	(-1.68)	(-0.41)	(-1.63)	(0.15)	(-0.18)	(-0.30)	(-0.28)	(-0.62)	(0.52)	(0.31)	(-0.22)	(0.60)	(-0.27)	(0.28)	(0.56)	(1.17)
LAB_SINT	0.01	0.17***					0.75***	0.33*					0.71***	0.24***				
	(0.04)	(4.33)					(10.28)	(1.67)					(11.16)	(6.20)				
LAB_UNIV			0.07	0.14***					0.61***	0.25					0.57***	0.16***		
			(0.69)	(4.51)					(9.94)	(1.59)					(10.80)	(5.42)		
LAB_COOP					-0.10	0.39***					1.48***	0.65**					1.94***	0.69***
					(-0.25)	(2.81)					(5.13)	(2.02)					(4.68)	(5.82)
Number of observations	1197	1178	1197	1178	1176	1157	1468	1059	1468	1059	1445	1043	1489	1049	1489	1049	1466	1033
Log likelihood	-81.51		-81.25		-81.30		-614.75		-614.46		-672.13		-630.14		-631.21		-685.93	
McFaddens R^2	0.17		0.17		0.16		0.29		0.29		0.21		0.30		0.30		0.23	
Model F-statistic		17.9***		17.5***		16.1***		31.9***		30.7***		23.7***		42.5***		41.4***		37.2***

Notes: * significant at the 0.1 level. ** significant at the 0.05 level. *** significant at the 0.01 level.

Table 6b: Innovation *input* effects of technological opportunities with interaction terms (REG_)

Variables	INNO_INT						R&D_INT						R&D_E_INT					
	1		2		3		1		2		3		1		2		3	
	Particip.	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**	**Particip.**	**Intensity**
	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)
INTERCEPT	1.62***	-3.76***	1.62***	-3.71***	1.62***	-3.66***	-0.85***	-4.70	-0.78***	-4.64***	-0.42**	-4.35***	-1.05***	-3.24***	-0.98***	-3.09***	-0.60***	-3.76***
	(3.54)	(12.70)	(3.54)	(-13.17)	(3.54)	(12.01)	(-4.06)	(3.82)	(-3.77)	(-3.77)	(-2.25)	(-4.15)	(-5.10)	(-13.68)	(-4.79)	(-12.94)	(-3.23)	(-11.65)
EMPL_MI	0.68**	-0.15	0.66**	-0.16	0.71**	-0.07	0.33***	0.56**	0.36***	-0.55**	0.46***	-0.49	0.44***	-0.79***	0.45***	-0.81***	0.53***	-0.55***
	(2.34)	(-0.82)	(2.29)	(-0.96)	(2.48)	(-0.39)	(3.13)	(-2.10)	(3.37)	(-2.38)	(4.78)	(-1.57)	(4.23)	(-9.03)	(4.31)	(-9.24)	(5.59)	(-4.53)
EMPL_G	0.53*	-0.72***	0.50*	-0.73***	0.59**	-0.62***	0.45***	-0.86***	0.48***	-0.84***	0.73***	-0.76*	0.58***	-1.22***	0.58***	-1.23***	0.80***	-0.90***
	(1.84)	(-4.16)	(1.72)	(-4.48)	(2.01)	(-3.36)	(3.72)	(-3.15)	(3.96)	(-3.14)	(6.72)	(-1.84)	(4.91)	(-13.40)	(4.93)	(-13.54)	(7.51)	(-6.27)
SALE_EXP	0.01	-0.20***	0.01	0.20***	0.01	0.21***	0.01	0.16***	-0.01	0.16***	0.03	0.17***	0.02	0.13***	0.01	0.13***	0.04	0.15***
	(0.07)	(4.39)	(0.03)	(4.47)	(0.10)	(4.43)	(0.21)	(4.68)	(-0.05)	(4.57)	(0.76)	(4.52)	(0.42)	(5.20)	(0.06)	(5.15)	(0.93)	(5.27)
INTERNAT	0.75	0.21	0.71	0.22	0.78	0.27	0.71***	0.64**	0.74***	0.67**	0.95***	0.65*	0.62***	0.46***	0.62***	0.46***	0.83***	0.66***
	(1.09)	(0.91)	(1.04)	(1.00)	(1.15)	(1.14)	(3.08)	(2.22)	(3.23)	(2.15)	(4.57)	(1.64)	(2.82)	(3.72)	(2.82)	(3.67)	(4.13)	(4.16)
DIVERS	0.04	0.04	0.04	0.05	0.05	0.04	0.17**	0.02	0.18**	0.03	0.20**	0.01	0.21**	0.01	0.21**	0.01	0.23***	0.04
	(0.20)	(0.62)	(0.19)	(0.73)	(0.25)	(0.62)	(1.97)	(0.26)	(2.06)	(0.42)	(2.56)	(0.19)	(2.49)	(0.24)	(2.55)	(0.30)	(2.99)	(0.87)
LOW	0.11	-0.06	0.11	-0.07	0.09	-0.11	-0.28***	-0.49***	-0.32***	-0.51***	-0.37***	-0.54**	-0.27***	-0.61***	-0.31***	-0.41***	-0.36***	-0.56***
	(-0.43)	(-0.53)	(0.46)	(-0.64)	(0.36)	(-0.87)	(-2.68)	(-2.98)	(-3.07)	(-3.24)	(-3.99)	(-2.40)	(-2.72)	(-5.56)	(-3.04)	(-5.61)	(-3.90)	(-6.07)
HIGH	0.35	0.40***	0.35	0.38***	0.36	0.40***	0.30**	0.65***	0.27**	0.62***	0.31***	0.64***	0.32**	0.44***	0.29**	0.42***	0.33***	0.52***
	(1.04)	(3.02)	(1.03)	(3.00)	(1.06)	(2.92)	(2.29)	(4.20)	(2.09)	(4.41)	(2.67)	(3.97)	(2.56)	(6.30)	(2.30)	(6.00)	(2.89)	(6.19)
AP_FIRM	0.24**	0.10	0.24**	0.10	0.25**	0.12*	0.05	0.02	0.07	0.03	0.13***	0.06	0.04	0.05*	0.05	0.06**	0.12***	0.11***
	(2.51)	(1.50)	(2.52)	(1.61)	(2.56)	(1.83)	(1.04)	(0.38)	(1.50)	(0.67)	(3.18)	(0.81)	(0.97)	(1.84)	(1.20)	(2.14)	(3.03)	(3.17)
AP_LAW	0.03	-0.05	0.02	-0.03	0.03	0.01	-0.01	0.03	0.02	0.07	0.16***	0.11	-0.03	0.04	-0.01	0.06**	0.15***	0.13***
	(0.22)	(-0.84)	(0.19)	(-0.65)	(0.29)	(0.02)	(0.18)	(0.73)	(0.39)	(1.58)	(3.81)	(1.30)	(-0.53)	(1.40)	(-0.05)	(2.13)	(3.59)	(3.52)
TO_CUCO	0.07	0.10*	0.07	0.10*	0.06	0.09*	0.12***	0.12**	0.10**	0.11**	0.08*	0.10**	0.11**	0.03	0.10**	0.03	0.08**	0.05
	(0.67)	(1.90)	(0.70)	(1.90)	(0.62)	(1.73)	(2.66)	(2.23)	(2.32)	(2.04)	(1.95)	(2.00)	(2.56)	(1.15)	(2.21)	(0.88)	(2.07)	(1.52)
TO_SUPP	-0.19*	-0.01	-0.19*	-0.01	-0.18	-0.01	0.06	0.02	0.04	0.01	0.02	0.02	0.06	0.03	0.05	0.03	0.03	0.04
	(-1.65)	(-0.15)	(-1.69)	(-0.15)	(-1.61)	(-0.10)	(1.24)	(0.47)	(0.91)	(0.32)	(0.57)	(0.46)	(1.30)	(1.22)	(1.14)	(1.04)	(0.70)	(1.32)
REG_SINT	0.04	0.19***					0.80***	0.30					0.72***	0.16***				
	(0.44)	(4.35)					(16.56)	(1.06)					(16.87)	(3.25)				
REG_UNIV			0.06	0.13***					0.61***	0.21					0.58***	0.08**		
			(0.77)	(4.21)					(15.98)	(0.94)					(16.52)	(2.14)		
REG_COOP					-0.04	0.34***					1.13***	0.46					1.21***	0.55***
					(-0.12)	(2.75)					(7.12)	(1.30)					(7.68)	(4.62)
Number of observations	1194	1175	1194	1175	1174	1155	1463	1059	1463	1059	1443	1043	1484	1049	1484	1049	1464	1033
Log likelihood	-81.39		-81.18		-81.32		-517.12		-523.08		-661.40		-547.87		-544.12		-677.59	
McFaddens R^2	0.17		0.17		0.16		0.40		0.39		0.22		0.39		0.39		0.24	
Model F-statistic		17.9***		17.2***		15.9***		27.2***		25.9***		22.1***		36.4***		35.3***		34.5***

Notes: * significant at the 0.1 level. ** significant at the 0.05 level. *** significant at the 0.01 level.

Table 7: Innovation *output* effects of technological opportunities with absorptive capacities (R&D_LAB, R&D_REG)

Variables	**INNO_NOV**			**INNO_IMP**			**INNO_PA**		
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)
INTERCEPT	-0.31**	0.27*	0.28*	0.83***	0.86***	0.82***	-1.55***	-1.66***	-1.54***
	(2.16)	(1.75)	(1.94)	(5.73)	(5.66)	(5.69)	(-7.82)	(-7.89)	(-7.69)
EMPL_MI	-0.11	-0.11	-0.10	0.14*	0.15**	0.15**	0.39***	0.38***	0.38***
	(-1.42)	(-1.46)	(-1.36)	(1.95)	(1.99)	(2.06)	(3.11)	(3.06)	(3.03)
EMPL_G	-0.25***	-0.26***	-0.24***	0.01	0.02	-0.02	1.02***	1.00***	0.97***
	(-2.84)	(-2.96)	(-2.68)	(0.04)	(0.18)	(-0.28)	(8.06)	(7.95)	(7.56)
SALE_EXP	0.10***	0.10***	0.10***	0.05*	0.05*	0.05*	-0.04	-0.04	-0.04
	(3.39)	(3.40)	(3.37)	(1.87)	(1.87)	(1.86)	(-1.00)	(-1.01)	(-0.88)
INTERNAT	-0.23*	-0.23*	-0.23*	0.04	0.04	0.03	0.88***	0.89***	0.89***
	(-1.69)	(-1.68)	(-1.68)	(0.32)	(0.32)	(0.18)	(4.80)	(4.82)	(4.78)
DIVERS	0.01	0.01	0.02	-0.02	-0.02	-0.03	-0.02	-0.02	-0.04
	(0.25)	(0.25)	(0.44)	(-0.32)	(-0.32)	(-0.54)	(-0.32)	(0.33)	(-0.66)
LOW	0.12	0.12*	0.12	-0.10	-0.10	-0.09	-0.55***	-0.54***	-0.54***
	(1.63)	(1.70)	(1.60)	(-1.31)	(-1.39)	(-1.25)	(-4.84)	(-4.80)	(-4.70)
HIGH	0.14*	0.14*	0.15*	0.09	0.09	0.11	0.14	0.14	0.14
	(1.67)	(1.67)	(1.75)	(1.06)	(1.06)	(1.28)	(1.33)	(1.27)	(1.33)
AP_FP_PR	0.13***	0.13***	0.13***						
	(4.08)	(4.02)	(4.01)						
AP_LP_PR	0.02	0.02	0.02						
	(0.58)	(0.47)	(0.51)						
AP_FP_PZ				0.06*	0.06**	0.04			
				(1.92)	(2.03)	(1.51)			
AP_LP_PZ				0.07*	0.07**	0.06*			
				(1.96)	(2.15)	(1.76)			
AP_FIRM							0.07	0.07	0.06
							(1.55)	(1.51)	(1.38)
AP_LAW							0.51***	0.50***	0.51***
							(10.49)	(10.69)	(10.95)
TO_CUCO	0.03	0.03	0.04	0.05*	0.05	0.06**	0.04	0.04	0.03
	(1.15)	(1.16)	(1.20)	(1.95)	(1.94)	(2.01)	(0.77)	(0.81)	(0.75)
TO_SUPP	0.10***	0.09***	0.10***	0.01	0.01	0.01	-0.02	-0.02	-0.02
	(2.92)	(2.89)	(2.99)	(0.25)	(0.27)	(0.17)	(-0.41)	(0.48)	(-0.33)
TO_SINT	0.01			0.01			0.03		
	(0.17)			(0.08)			(0.69)		
TO_UNIV		0.02			-0.02			0.05	
		(0.77)			(-0.75)			(1.37)	
COOP_UNI			0.01			0.20**			0.36***
			(0.01)			(2.24)			(3.61)
R&D_LAB	0.07	0.07	0.07	0.06	0.06	0.07	0.30***	0.30***	0.28***
	(0.91)	(0.88)	(0.83)	(1.06)	(0.78)	(0.83)	(2.96)	(2.97)	(2.78)
R&G_REG	0.38***	0.38***	0.39***	0.07	0.07	0.03	0.49***	0.49***	0.40***
	(4.85)	(4.77)	(4.82)	(0.83)	(0.90)	(0.43)	(4.00)	(3.94)	(3.22)
Number of observations	1290	1290	1271	1245	1245	1225	1446	1446	1426
Log likelihood	-2667.27	-2966.99	-2627.87	-2539.91	-2539.63	-2495.12	-612.68	-611.98	-594.42
McKelvey/Zavoina R^2	0.03	0.03	0.07	0.09	0.09	0.09			
McFadden R^2							0.34	0.34	0.35

Notes: * significant at the 0.1 level. ** significant at the 0.05 level. *** significant at the 0.01 level.

Table 8a: Innovation output effects of technological opportunities with interaction terms (LAB_)

Variables	**INNO_NOV**			**INNO_IMP**			**INNO_PA**		
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)
INTERCEPT	0.44***	0.44***	0.41***	0.88***	0.88***	0.87***	-1.32***	-1.32***	-1.33***
	(3.20)	(3.20)	(2.94)	(6.30)	(6.30)	(6.21)	(-7.08)	(-7.11)	(-7.03)
EMPL_MI	-0.05	-0.05	-0.03	0.15**	0.15**	0.17**	0.45***	0.45***	0.49***
	(-0.69)	(-0.72)	(-0.37)	(2.07)	(2.09)	(2.36)	(3.74)	(3.71)	(4.02)
EMPL_G	-0.19**	-0.19**	-0.11	0.01	0.01	0.02	1.05***	1.06***	1.13***
	(-2.14)	(-2.13)	(-1.21)	(0.03)	(0.14)	(0.18)	(8.55)	(8.61)	(9.20)
SALE_EXP	0.11***	0.11***	0.11***	0.05*	0.05*	0.05*	-0.04	-0.04	-0.02
	(3.55)	(3.56)	(3.71)	(1.74)	(1.75)	(1.80)	(-0.98)	(-0.95)	(-0.47)
INTERNAT	-0.16	-0.15	-0.12	0.03	0.04	0.04	0.96***	0.97***	1.04***
	(-1.16)	(-1.12)	(0.87)	(0.22)	(0.27)	(0.29)	(5.32)	(5.35)	(5.70)
DIVERS	0.02	0.02	0.04	-0.03	-0.03	-0.03	-0.02	-0.10	-0.03
	(0.43)	(0.47)	(0.75)	(-0.57)	(-0.54)	(-0.69)	(-0.27)	(-0.17)	(-0.52)
LOW	0.10	0.10	0.08	-0.11	-0.11	-0.11	-0.56***	-0.56***	-0.57***
	(1.40)	(1.43)	(1.08)	(-1.48)	(-1.50)	(-1.57)	(-4.99)	(-4.98)	(-5.05)
HIGH	0.15*	0.15*	0.17**	0.09	0.09	0.12	0.16	0.14	0.18*
	(1.87)	(1.82)	(2.11)	(1.11)	(1.11)	(1.41)	(1.49)	(1.35)	(1.73)
AP_FP_PR	0.15***	0.16***	0.16***						
	(4.99)	(5.08)	(5.25)						
AP_LP_PR	0.03	0.03	0.04						
	(0.75)	(0.87)	(1.20)						
AP_FP_PZ				0.06*	0.06**	0.05*			
				(1.94)	(1.99)	(1.66)			
AP_LP_PZ				0.06*	0.07**	0.06*			
				(1.89)	(2.03)	(1.85)			
AP_FIRM							0.08*	0.09*	0.09*
							(1.78)	(1.95)	(1.86)
AP_LAW							0.50***	0.51***	0.53***
							(10.84)	(11.13)	(11.52)
TO_CUCO	0.04	0.04	0.04	0.06**	0.06**	0.06**	0.04	0.04	0.04
	(1.43)	(1.40)	(1.40)	(2.05)	(2.03)	(2.02)	(0.99)	(0.97)	(0.85)
TO_SUPP	0.09***	0.08***	0.09***	0.01	0.01	0.01	-0.02	-0.03	-0.01
	(2.70)	(2.62)	(2.95)	(0.17)	(0.16)	(0.21)	(-0.51)	(-0.71)	(-0.20)
LAB_SINT	0.08***			0.05*			0.20***		
	(2.72)			(1.74)			(5.98)		
LAB_UNIV		0.06***			0.03			0.15***	
		(2.73)			(1.49)			(5.81)	
LAB_COOP			0.04			0.25**			0.66***
			(0.43)			(2.48)			(5.86)
Number of observations	1294	1294	1273	1250	1250	1228	1450	1450	1428
Log likelihood	-2688.39	-2688.57	-2649.24	-2548.38	-2548.95	-2501.80	-621.43	-622.42	-607.38
McKelvey/Zavoina R^2	0.03	0.03	0.13	0.07	0.07	0.07			
McFadden R^2							0.35	0.33	0.34

Notes: * significant at the 0.1 level. ** significant at the 0.05 level. *** significant at the 0.01 level.

Table 8b: Innovation *output* effects of technological opportunities with interaction terms (REG_)

Variables	INNO_NOV			INNO_IMP			INNO_PA		
	1	2	3	1	2	3	1	2	3
	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)
INTERCEPT	0.35***	0.38***	0.41***	0.83***	0.83***	0.84***	-1.46***	-1.46***	-1.35***
	(2.65)	(2.66)	(2.93)	(5.80)	(5.89)	(5.93)	(-7.74)	(-7.72)	(-7.17)
EMPL_MI	-0.07	-0.07	-0.03	0.15**	0.15**	0.17**	0.44***	0.43***	0.48***
	(-0.94)	(-0.94)	(-0.35)	(1.97)	(2.07)	(2.26)	(3.59)	(3.54)	(3.90)
EMPL_G	-0.20**	-0.21**	-0.12	0.01	0.02	0.01	1.11***	1.11***	1.15***
	(-2.37)	(-2.40)	(-1.40)	(0.08)	(0.25)	(0.06)	(9.16)	(9.12)	(9.38)
SALE_EXP	0.11***	0.11***	0.11***	0.06*	0.06*	0.06**	-0.03	-0.03	-0.02
	(3.58)	(3.54)	(3.66)	(1.93)	(1.93)	(1.97)	(-0.82)	(-0.84)	(0.45)
INTERNAT	-0.18	-0.16	-0.12	0.05	0.06	0.05	0.98***	1.00***	1.05***
	(-1.27)	(-1.20)	(-0.89)	(0.39)	(0.47)	(0.38)	(5.44)	(5.53)	(5.76)
DIVERS	0.02	0.02	0.03	-0.16	-0.14	0.02	-0.02	-0.01	-0.03
	(0.34)	(0.41)	(0.66)	(-0.33)	(-0.29)	(-0.48)	(-0.34)	(-0.24)	(-0.55)
LOW	0.10	0.10	0.08	-0.10	-0.10	-0.10	-0.56***	-0.56***	-0.59***
	(1.44)	(1.46)	(1.04)	(-1.31)	(-140)	(-1.41)	(-5.04)	(-5.04)	(-5.25)
HIGH	0.17**	0.16**	0.17**	0.10	0.10	0.12	0.21**	0.19*	0.20*
	(2.06)	(1.96)	(2.13)	(1.22)	(1.20)	(1.46)	(1.97)	(1.80)	(1.89)
AP_FP_PR	0.14***	0.14***	0.16***						
	(4.48)	(4.60)	(5.09)						
AP_LP_PR	0.02	0.02	0.04						
	(0.45)	(0.63)	(1.22)						
AP_FP_PZ				0.05*	0.06*	0.05			
				(1.82)	(1.92)	(1.60)			
AP_LP_PZ				0.06*	0.07**	0.06*			
				(1.86)	(2.03)	(1.879)			
AP_FIRM							0.06	0.07	0.08*
							(1.40)	(1.56)	(1.82)
AP_LAW							0.49***	0.50***	0.53***
							(10.48)	(10.87)	(11.52)
TO_CUCO	0.04	0.04	0.04	0.06**	0.06**	0.06**	0.05	0.05	0.04
	(1.39)	(1.31)	(1.34)	(2.04)	(2.01)	(2.03)	(1.07)	(1.01)	(0.84)
TO_SUPP	0.09***	0.09***	0.10***	0.01	0.01	0.01	0.01	-0.02	-0.01
	(2.94)	(2.88)	(3.01)	(0.32)	(0.33)	(0.29)	(-0.23)	(-0.37)	(-0.14)
REG_SINT	0.11***			0.04			0.19***		
	(3.93)			(1.55)			(5.43)		
REG_UNIV		0.08***			0.02			0.15***	
		(4.16)			(1.12)			(5.49)	
REG_COOP			0.10			0.22**			0.51***
			(1.16)			(2.57)			(5.25)
Number of observations	1290	1290	1271	1245	1245	1225	1446	1446	1426
Log likelihood	-2676.38	-2675.71	-2643.62	-2539.85	-2540.48	-2495.60	-622.86	-622.57	-610.10
McKelvey/Zavoina R^2	0.03	0.03	0.12	0.08	0.08	0.09			
McFadden R^2							0.33	0.33	0.33

Notes: * significant at the 0.1 level. ** significant at the 0.05 level. *** significant at the 0.01 level.

Appendix 1: External sources of technological knowledge - Factor scores

	Factor TO_SINT	Factor TO_SUPP	Factor TO_CUCO
TEC_TI	0.85	0.04	0.04
TEC_UNIV	0.82	0.04	0.02
TEC_AGEN	0.76	0.12	0.06
TEC_RI	0.73	0.05	0.12
TEC_PADI	0.58	0.10	0.21
TEC_JOUR	0.16	0.82	-0.01
TEC_FAIR	-0.01	0.81	0.17
TEC_SUPP	0.06	0.49	0.10
TEC_CUST	0.11	0.13	0.82
TEC_COMP	0.14	0.13	0.80

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.80; Bartlett Test of Sphericity: 4373.64

Appendix 2: Firms' appropriability conditions - Factor scores

	Factor AP_LAW	Factor AP_FIRM
AP_PA_PR	0.82	0.03
AP_PA_PZ	0.82	0.15
AP_CO_PZ	0.79	0.17
AP_CO_PR	0.75	0.05
AP_DE_PZ	0.08	0.75
AP_LE_PZ	0.23	0.72
AP_LO_PZ	-0.04	0.71
AP_LO_PR	-0.04	0.61
AP_DE_PR	0.04	0.61
AP_SE_PZ	0.39	0.60
AP_LE_PR	0.29	0.55
AP_SE_PR	0.37	0.50

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.67; Bartlett Test of Sphericity: 9074.58

	Factor AP_FP_PR	Factor AP_LP_PR
AP_DE_PR	0.74	-0.02
AP_LE_PR	0.69	0.30
AP_LO_PR	0.68	-0.04
AP_SE_PR	0.58	0.36
AP_PA_PR	0.07	0.87
AP_CO_PR	0.10	0.86

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.70; Bartlett Test of Sphericity: 1670.99.

	Factor AP_FP_PZ	Factor AP_LP_PZ
AP_LE_PZ	0.80	0.22
AP_DE_PZ	0.78	0.10
AP_LO_PZ	0.77	0.01
AP_SE_PZ	0.63	0.39
AP_PA_PZ	0.14	0.90
AP_CO_PZ	0.14	0.90

Kaiser-Meyer-Olkin Measure of Sampling Adequacy: 0.74; Bartlett Test of Sphericity: 3064.64