

Firm Level Innovation and Productivity – Is there a Common Story across Countries?

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Abstract

Recent studies have documented extensive heterogeneity in firm performance within countries, and innovation has been found as an important determinant. This paper examines the issue of innovation firm performance across countries. A growing number of national firm level studies on the innovation-productivity link have been conducted by using new internationally harmonized survey data, known in Europe as Community Innovation Survey (CIS). Mainly due to confidentiality reasons cross-country comparisons of CIS data are still rare. The contribution of this paper is in its unique approach of pooling original firm observations from Germany and Sweden. Applying a knowledge production function that gives the relationship between innovation input, innovation output and productivity, we find a common cross-country story for knowledge intensive manufacturing firms. Some interesting country-specific effects are reported as well.

Key words: innovation, productivity, cross-country comparison, applied econometrics.

JEL-Classification: O33, D24, P52, C34, C51

Introduction

This paper reports new results on the relationship between innovation and productivity. With its unique approach by pooling an extensive set of original data from two different countries, it can be viewed as another link in a chain of a rather limited number of cross-country investigations on this topic using firm level data.

Four issues are explored in some detail. First, is there a common cross-country story in the innovation productivity link for firms mainly operating on the same global markets? This issue is addressed on a sample of so-called knowledge intensive manufacturing firms in Germany and Sweden. Second, the importance of the data quality. Third, the advantage of pooled regression. And finally, the robustness of the applied empirical model.

A large number of studies has been done on cross-country comparison on R&D, innovation and productivity at the national or industry level. Mainly due to confidentiality reasons the firm level comparisons are considerably fewer. To solve this problem several different methods have been explored. The literature shows at least three different alternatives: using micro-aggregated data (see Mairesse and Mohnen, 2001, Mohnen and Dagenais, 2002), moment-matrices (see Griliches, 1998, Griliches and Mairesse, 1998, Mohnen and Therrien, 2002) or an identical model separately estimated in the countries investigated using different individual data based on more or less identical innovation surveys (see Lööf et al., 2003).

The uniqueness of our study is that it is almost the first to use pooled original data in a common regression. Moreover, due to the direct access to the original data, and access to registered data for the observed firms as well, we have been able to control the quality of the data.

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This control includes treatment of missing values, identification of errors in the data sets, treatment of extreme outliers, and different sensitivity analyses. Finally, when specifying a common econometric model, we can take into account both industry specific and country specific aspects, and we can econometrically test identical parameters in both countries. Most of these important issues are normally ignored in cross-country analyses of the link between innovation and firm performance.

The data sets used are derived from the third Community Innovation Survey (CIS 3) and include data on more than 1000 German and Swedish knowledge intensive manufacturing firms observed in the period of 1998-2000. The motivation for this choice of category of firms is that we assume that knowledge intensive manufacturing firms are more homogeneous in a cross-country perspective than the total manufacturing sector or the service one. The typical knowledge intensive firm is characterised by a high R&D intensity, a high human capital intensity and a strong orientation on global markets. The condition for competitiveness is to a large extent internationally decided and innovation is a crucial issue for productivity and growth. However, as this paper will discuss, the data reveals also some interesting country-specific differences.

A central issue in the analysis is the choice of the methodological approach. We are estimating a model based on the knowledge production function approach in the spirit of Pakes and Griliches (1984) and Crépon et al. (1998) that gives the relationship between innovation input, innovation output and productivity.

The outline of the paper is as follows. In section 2 a brief overview of the literature dealing with the productivity effects of R&D and more general innovative activities is given. Section 3 describes the data sets used for the empirical analysis and comprises some information on the data treatment and on how to make the data sets comparable. Furthermore, it presents some descriptive statistics for both countries. The empirical model and its empirical implementation is outlined in section 4. The econometric results are presented in section 5. Section 6 summarized the obtained results.

2. Background

Analysing and quantifying the productivity effects of innovative activities has been one of the most challenging and controversial tasks in empirical economics for several decades (see Griliches, 1958 and Mansfield, 1965 for some pioneer work). Recently, this research topic has been enforced by new theoretical underpinnings from endogenous growth theory showing that economic output is supposed to be positively correlated with the flow of new products including both radical and incremental innovations (see Romer, 1990, Aghion and Howitt, 1998).

The majority of studies on the relationship between innovation and firms' economic performance uses the production function approach, where different measures of firm performance (mainly productivity) are explained by several independent variables such as physical capital, human capital, R&D and other innovation-related investments as well as firm size. Within the production function approach, the innovation process itself is treated as a black box, if it is treated at all. As reported by Nadiri and Prucha (1993) and Mairesse and Mohnen (2001) most studies on R&D expenditure find it to have a net positive effect on both value added and turnover, although the advantages of R&D decline when its effect is evaluated over time (see Klette and Kortum, 2002).

For a long time, empirical innovation research focused on the input to the innovation process (with the exception of patent studies). It is only recently, that the focus has changed towards the output-orientated view. In the most recent studies, relying on CIS data and using innovation output additional to R&D, Arundel et al. (2003) report that almost all studies find a positive and significant relationship between innovation and different measures of firm performance.

Our work contrasts to previous CIS-based studies in the sense that we are relying on original data sets from different countries, which allows us to specify an econometric model derived from theory as well as specific characteristics of the present data. Moreover, we are able to pool the data sets and study cross-country variation in firm performance which to some extent is

supposed to depend on institutional factors difficult to control for using data from within a single country.

The two countries compared, Germany and Sweden, have interesting similarities and differences. On the similarity side it can be noted that both are strongly export-oriented – nearly 8 of 10 firms in the samples used in the study report export figures – and the size of their subsidy programmes for R&D investments are in line with the OECD average. Nearly 10% of the commercial firms' R&D expenditure is publicly funded. As Germany is ten times larger than Sweden in population of firms, there is also a fundamental difference in, for example, public R&D policy. In contrast to Germany where the majority of funding programmes are oriented towards large firms, the Swedish R&D policy is focused on small firms. As reported by the US Department of labor's⁴ international comparison of manufacturing productivity in 13 countries, Sweden is placed in the OECD top, while Germany is somewhere in the middle.

Looking at the innovation performance in Germany and Sweden the European Trend Chart on Innovation reports that Sweden is ranked as the most innovative country among 17 countries compared (see Arundel et al., 2003). The US rank second, Finland third. Likewise to the productivity ranking Germany takes a middle position (9). Greece, Portugal and Spain have the lowest positions.

Our study relies on data from the CIS 3 launched in 2001. Great progress in measuring innovative output was achieved by a number of recent internationally harmonized innovation surveys which are based on the recommendations of the Oslo-manual published by OECD and Eurostat (1997). The well-known CIS has been launched three times (1993, 1997, 2001) in countries of the European Economic Area and associated OECD countries (Eurostat, 2000). Data collected within the CIS comprise input as well as output indicators to the innovation process, plus a number of variables characterising general and innovation related corporate strategies (see Janz et al., 2001). The information provided allows us to have a look at the "black box" of the innovation process at firm level, and not only analyze the relationship between innovation input and productivity, but also shed some light on the process in between.

3. Data and Descriptive Statistics

This section describes three aspects of the data: (1) general information on observations, distributions on industry groups, size and innovation as well as the data treatment, (2) the main variables used in the study, and (3) how these variables change when the sample is limited to only innovative firms.

The basic data used was collected by the Centre for European Economic Research (ZEW) for Germany and Statistics Sweden. Both samples are drawn as stratified random samples. To get as homogeneous comparison samples as possible we have (a) restricted the analysis to knowledge intensive manufacturing industries assuming that they compete on a global market under similar conditions, (b) limited the firm size to 10-999 employees, (c) eliminated the influence from extreme outliers⁵, (d) treated missing values in both samples in a similar manner (we use imputed values as specified by Eurostat⁶), and finally we have (e) used weighting factors for estimation. The latter means that the difference between the population number of firms in a given strata and the number of respondents in the survey is taken into account, so the observations represent the whole population of firms in the given size classes and industries.⁷

⁴ Annual growth rate (in percent) in labor productivity in manufacturing 1991-2001 among the 13 OECD-countries: Korea 9.5, Sweden 5.3, Taiwan 5.1, France 4.2, US 4.0, Netherlands 3.3, Belgium 3.1, Germany 2.8, Japan 2.6, UK 2.5, Canada 2.0, Italy 1.8 and Norway 0.7. The figures for the Netherlands refer to the period 1991-2000. Source: News, United States Department of Labor page 14, <http://stats.bls.gov>.

⁵ For identification of extreme values, see Table 9.

⁶ Quantitative variables are imputed by means of strata and qualitative variables by entropy estimates. For importance of missing values and imputations, see Table 10.

⁷ Due to a lower response rate a non-response analysis was carried out in Germany and the weighting factors are adjusted to potential non-response bias according to the Eurostat methodology.

The considered data sample is an aggregate of R&D intensive manufacturing industries including chemistry and pharmaceuticals, machinery and equipment, office machinery and computers, electrical and communication equipment, medical, precision and optical instruments as well as transport equipment (NACE 24, 29-35). The total number of observations is 575 for Germany and 474 for Sweden.

Table 1

Number of observations, innovation expenditure, innovation sales and innovative firms. Total samples

	Obs	Firm size ^a		Innovation expenditure ^b		Innovation sales ^b		Innovative firms ^c	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Germany									
NACE 24	89	130	183	0.054	0.237	0.127	0.171	0.561	0.498
NACE 29	227	99	136	0.040	0.059	0.208	0.247	0.626	0.484
NACE 30	12	143	232	0.064	0.057	0.377	0.281	0.761	0.444
NACE 31	91	108	145	0.028	0.039	0.163	0.204	0.564	0.498
NACE 32	28	69	107	0.062	0.074	0.191	0.258	0.608	0.496
NACE 33	74	72	117	0.092	0.191	0.211	0.245	0.560	0.499
NACE 34	32	168	216	0.037	0.054	0.118	0.191	0.397	0.497
NACE 35	22	116	191	0.041	0.098	0.093	0.152	0.359	0.491
Total	575	102	148	0.049	0.116	0.189	0.234	0.583	0.493
Sweden		Mean	SD	Mean	SD	Mean	SD	Mean	SD
NACE 24	63	70	86	0.027	0.049	0.110	0.182	0.433	0.499
NACE 29	123	64	111	0.027	0.053	0.121	0.198	0.463	0.500
NACE 30	17	88	135	0.174	0.621	0.144	0.293	0.265	0.455
NACE 31	70	72	130	0.036	0.088	0.088	0.190	0.309	0.465
NACE 32	39	92	140	0.093	0.144	0.188	0.302	0.509	0.506
NACE 33	60	69	112	0.202	0.623	0.190	0.257	0.652	0.480
NACE 34	69	105	167	0.018	0.072	0.068	0.166	0.234	0.426
NACE 35	33	71	118	0.008	0.021	0.092	0.183	0.278	0.455
Total	474	73	121	0.050	0.231	0.120	0.210	0.424	0.494

Notes: (a) Number of employees, (b) as a share of sales and (c) as a share of total number of firms.
 NACE 24: Chemicals and chemical products.
 NACE 29: Machinery and equipment.
 NACE 30: Office machinery and equipment.
 NACE 31: Electrical machinery and apparatus.
 NACE 32: Radio, television and communication equipment.
 NACE 33: Medical, precision and optical instruments.
 NACE 34: Transport equipment.

The descriptive statistics displayed in Table 1 show that the average expenditure on R&D and other innovation activities as a share of sales are nearly the same for both samples at the 2 digit NACE level, however the standard deviation is larger for the Swedish sample. The typical knowledge intensive firm in Germany is larger than in Sweden. When we define an *innovative firm* as one with both positive innovation expenditure and at least one product innovation launched on the market during the period of 1998-2000, somewhat surprisingly, this results in 58% of innovative firms in the German sample, but only 42% in the Swedish one. In consistence with this divergence the innovation output, or share of innovative sales of total turnover, is also considerably higher for the average German sample, 19% compared to 12%.

Table 2

Descriptive statistics for total and innovative sample. Weighted values

	Total sample				Innovative sample ^a			
	Germany N=575		Sweden N=474		Germany N=352		Sweden N=206	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Quantitative Variables								
Employment	102	148	73	121	124	166	93	142
R&D employment ^b	0.076	0.113	0.048	0.108	0.113	0.126	0.094	0.134
University educated ^b	0.166	0.167	0.151	0.157	0.192	0.168	0.219	0.177
Innovation input ^c	0.049	0.116	0.050	0.231	0.065	0.111	0.102	0.344
Innovation output ^c	0.189	0.234	0.120	0.210	0.301	0.232	0.280	0.241
Physical capital investment ^c	0.072	0.266	0.074	0.248	0.051	0.104	0.076	0.241
Export ^c	0.256	0.243	0.301	0.334	0.300	0.253	0.456	0.350
Qualitative Variables^d								
Innovative firm	0.583	0.493	0.424	0.494	-	-	-	-
Product innovation	0.614	0.487	0.432	0.495	1.000	0.000	1.000	0.000
Process innovation	0.376	0.481	0.242	0.429	0.499	0.500	0.449	0.498
Valid patents	0.364	0.481	0.356	0.479	0.496	0.500	0.597	0.491
Public funding	0.239	0.427	0.103	0.304	0.339	0.474	0.173	0.379
Continuous R&D	0.469	0.499	0.669	0.471	0.692	0.462	0.691	0.463
Group	0.270	0.444	0.563	0.496	0.307	0.462	0.583	0.494
Newly established	0.022	0.148	0.047	0.211	0.030	0.171	0.036	0.186
Most important market:								
- national <50km	0.136	0.343	0.206	0.404	0.095	0.294	0.106	0.309
- national market >50 km	0.345	0.476	0.380	0.486	0.344	0.475	0.221	0.416
- international market >50km	0.485	0.500	0.424	0.49	0.541	0.499	0.671	0.470

Notes: (a) Innovative firms are defined as firms with product innovations and positive innovation input.
(b) As share of employees, (c) as share of sales and (d) as share of firms.

Table 2 introduces the means and standard deviations for the major variables used in the study. Some additional interesting similarities and differences between the two total samples (i.e., samples including both innovative and non-innovative firms) are displayed. Starting with the dissimilarities, a majority of the Swedish firms belongs to a group, but only a quarter of the firms do in Germany. About 24% of the firms in the German sample received governmental subsidies for R&D investments. The corresponding figure in the Swedish sample is 10%. Keeping in mind the information that public funding corresponds to 1/10 of the total private R&D expenditure in both countries, we can conclude that the Swedish subsidy policy is more targeted. The recipients are fewer proportionally, but those who receive get more. Finally, the ratio of new firms to total firms is nearly 5% in Sweden, but only 2% in Germany. Turning to the similarities we see that the level of human capital (as proxied by university graduated to total employment) and the intensity of investments in tangible assets are about the same in both samples.

Let us now look at the innovative firms. First, we find that innovative firms in general are larger than non-innovative ones. However, there still is a significant country variation and the typical knowledge intensive German manufacturing firm has about 30% more employees^a than its Swedish equivalent. Quite interestingly, the innovation output to sales ratio is rather similar, 30% (Germany) versus 28%, but innovation investment intensity is higher in Sweden (10% versus 7%). Note, however, that the relative R&D employment is larger in Germany.

About 60% of the innovative Swedish firms had valid patents in the year 2000 compared to every second firm in Germany. Probably reflecting the differences in country size, the export to sales ratio is 46% for Sweden and 30% for Germany. Twice as many knowledge intensive manufacturing firms are R&D subsidised in Germany than in Sweden, (34% versus 17%). Nearly 60% of firms in the Swedish sample belong to a group compared to just over 30% in the German sample. Seven out of ten firms in both samples conduct R&D regularly. Finally, the share of human capital is larger in innovative firms compared to non-innovative firms in both countries and somewhat higher in Sweden (22%) than in Germany (19%).

4. Empirical Model and Implementation

A common empirical approach for studying the relationship between research, innovation and productivity is a model of a Cobb Douglas form. More recently, several studies have been done basing on the Pakes and Griliches (1984) knowledge production function. It is possible to identify two main denominators for many of these studies. The first concerns data and is connected to the release of a new kind of firm level information because of innovation surveys in many OECD-countries starting in the first half of the 1990s. The second can be derived from the introduction of an empirical knowledge production function model by Crépon, Duguet and Mairesse (1998) which is referred in the literature as the CDM-model.⁸

4.1. Formulation of the Model

The basic econometric problems that the empirical model aims to solve are selectivity and simultaneity biases. The CDM approach takes into account that not all firms are engaged in innovative activities. When only the innovation sample is used in some part of the model, the firms are not randomly drawn from the larger population, and selection bias may arise. Therefore, the CDM adds a selection equation to the system. When several links in the process of transforming innovation investment to productivity are considered in a simultaneous framework, one possible problem to emerge is that some explanatory variables often are not exogenously given and there will be simultaneity bias.

The general structure of the CDM approach can be interpreted as a three step model consisting of four equations. On the first step, firms decide whether to engage in innovation activities or not (selection equation) and what amount of money to invest in innovation. This is specified by a generalized Tobit model. Given the firm has decided to invest in innovative projects, the second step defines the knowledge production function in which innovation output results from innovation input and other factors. On the third step, the enhanced Cobb Douglas production function describes the effect of innovative output on productivity.

In this paper we will rely on a slightly modified version of the original CDM model, more specifically given by the following four equations:

$$y_{0i} = \begin{cases} 1 & \text{if } y_{0i}^* = X_{0i} \beta_0 + \varepsilon_{0i} > 0 \\ 0 & \text{if } y_{0i}^* = X_{0i} \beta_0 + \varepsilon_{0i} \leq 0 \end{cases}, \quad (1)$$

$$y_{1i} = y_{1i}^* = X_{1i} \beta_1 + \varepsilon_{1i} \quad \text{if } y_{0i} = 1, \quad (2)$$

$$y_{2i} = \alpha_{21} y_{1i} + \alpha_{23} y_{3i} + X_{2i} \beta_2 + \varepsilon_{2i} \quad \text{if } y_{0i} = 1, \quad (3)$$

$$y_{3i} = \alpha_{32} y_{2i} + X_{3i} \beta_3 + \varepsilon_{3i} \quad \text{if } y_{0i} = 1, \quad (4)$$

⁸ The empirical CDM approach using CIS data was adopted e.g. by Lööf and Heshmati (2004) and Lööf et al. (2003) and applied to Swedish and Scandinavian data, respectively. Klomp and Van Leeuwen (2001, 2002) have also used a CDM approach for Dutch data. Janz and Peters (2002) apply a similar approach to German data, but focus on the link between innovation input and output. The intuition behind the model is given by the following simple 3-equation model: (1) $dK=R+u$, (2) $P=a dK + v$, (3) $Z = b P + e$, where dK is additions to economically valuable knowledge, R is research expenditures, P is innovation output, Z is productivity and u , v and e are random components.

where y_{0i}^* is a latent innovation decision variable measuring the propensity to innovate, y_{0i} is the corresponding observed binary variable being 1 for innovative firms. y_{1i} , y_{2i} and y_{3i} describe innovation input, innovation output and productivity. X_{0i} , X_{1i} , X_{2i} and X_{3i} are vectors of various variables explaining innovation decision, innovation input, innovation output and productivity. The inverse Mills' ratio (Heckman, 1979) is included in X_{1i} , X_{2i} and X_{3i} to correct possible selection bias. The β 's and α 's are the unknown parameter vectors. ε_{0i} , ε_{1i} , ε_{2i} and ε_{3i} are i.i.d. drawings from a multivariate normal distribution with zero mean and $E(\varepsilon_{si} \varepsilon_{tj}) = \sigma_{st}$ for $i = j$ and $s, t = 0, \dots, 3$ and zero else.

One diverging point compared to CDM is that we estimate the elasticity of productivity with respect to innovation only for innovative firms in the last part of the model. A second difference is related to the possible problem that explanatory variables are often determined jointly with the dependent variable, i.e. they are not exogenously given, which highlights the simultaneity problem. We allow for potential feedback effects of productivity on innovation output. The main problem of using the original CDM in our case is that the model assumes data of time-serial nature, while the present study is a cross-sectional one. That is the motivation for the modification of the original model. Therefore, the last two equations are estimated in a simultaneous equation system relying on the instrumental variable approach (2SLS). In contrast, Crepon et al. (1998) relied on the Asymptotic Least Squares method estimating both structural parameters (interest parameters) and reduced form parameters (auxiliary parameters). However, both estimation methods lead to consistent estimates. The third main difference is that by splitting the model for estimation purposes into two parts we do not exploit the full correlation between the four residuals.

4.2. Specification of the Model

As these variables are introduced and described, several difficulties need to be discussed in some detail. A number of serious difficulties arises in using cross-sectional CIS data in the present econometric analysis. Perhaps the most important measurement problems are: (i) the measurement of innovation input, (ii) the separation of R&D capital from other non R&D machinery and equipment, (iii) double counting R&D and, (iv) spillover effects. Turning to the issue of spillover first, we actually have no explicit measure other than some indicator variables and they are hopefully captured by industry dummy variables.

The main drawback with the innovation input variable is that it is a flow variable and observed only in the year 2000, in other words the same year we observed innovation output. This means that the lag between investment in research and the actual product innovation is ignored, and the lag between product innovation and market acceptance as well. However, Griliches (1998) reported that there is some scattered evidence from questionnaire studies that such lags are rather short in the industry, since most of research expenditure is spent on development and applied topics. This can partly be confirmed by Swedish statistics for the whole manufacturing sector and firms with more than 50 employees showing that 45% of total R&D expenditures are used for improving existing products or for developing products new to the firm but not to the market (Statistics Sweden, 2003).

The problem of double counting R&D and other innovation expenditure both as innovation costs and by the variable human capital is not easily solved. In the early estimation process we tried to reduce the human capital variable (proxied by university graduated) by the observed number of R&D personnel in the data. But scrutinizing German and Swedish employment data showed that about 40% and 50% respectively of the wage cost for R&D activities go to non-graduated. Thus, this method is unsatisfactory blunt. Our second best solution is therefore to include the human capital variable in the equation determining the size of innovation input. Nor is the physical capital variable included in this equation because of problems splitting R&D-embedded from non-R&D-embedded machinery and equipment.

With this background we start the specification of the model with the selection equation (1). As reported in the surveys by Cohen and Klepper (1996) and Klette and Kortum (2002) size has been found as a highly significant firm determinant to engage in innovation. In addition, we include variables reflecting if the firm is a part of a group, if it is newly established, or variables indicating merging with other firms or downsizing. The selection equation also controls the importance of local, national or international markets. Finally, human capital is used as an explanatory variable in this equation, although we would have preferred a variable totally cleansed from R&D personnel.

The three dependent variables used in the study are all measured in intensity that is per employee terms. The size of innovation investment expenditure per employee (equation (2)) is explained by firm size and a number of indicator variables: continuous R&D activities (in contrast to occasional), process of innovation, public subsidies, most important markets, and indicators for cooperation on innovation characterized by demand pull or technology push, or if there is a cooperation with other firms.

In the innovation output equation (equation (3)) innovation input is the important explanatory variable. The two other continuous variables are capital intensity (expenditure on physical investments per employee) and labor productivity, proxied by turnover per employee. The discrete explanatory variables are innovation process, public subsidies, part of a group, establishment, and indicator variables for sources of information for innovation and cooperation on innovation. They are created both as nested variables to capture the network effects of various external knowledge sources and innovation partners, as well as demand and push variables for the role of science and technology, the market and other firms. See Table 7 in the appendix for a definition of the network and spillover indicators.

The final relationship is the productivity equation (4). Traditionally, the literature uses R&D as an independent variable. But thanks to an important novelty in the CIS data we can use innovation output instead. In addition, we follow the literature and control variations in firm size, physical capital and human capital. Moreover, the productivity equation controls innovations process if the turnover is heavily influenced by merger or downsizing. The export share is also included.

In all equations the intensity variables are expressed in logarithm terms. Finally, it should be noted that each of the four equations includes industry dummy variables. The whole structure of the model, including the exclusion restrictions made for identification of the model, can be seen in Table 8.

5. Empirical Analysis

5.1. Estimation Procedure

For estimation purposes we apply a two step estimation procedure. At the first step the generalized Tobit model, comprising the selection equation (1) and the innovation input equation (2), is consistently estimated by full maximum likelihood techniques, using observations on both innovative and non-innovative firms. The estimates of this first step are used to construct an estimate for the inverse Mills' ratio which is incorporated as an explanatory variable in the estimation of both structural equations (3) and (4) to correct for potential selection bias. At the second step these two equations are estimated in a simultaneous equation system only for innovative firms. We use a 2SLS approach allowing the endogeneity of both innovation output and productivity. On both steps we apply weighted estimation methods, the weights representing the inverse of the sampling rate in each stratum. Thus, inference about the population in both countries can be made.

The empirical results for the relationship between the level of productivity and innovation for knowledge intensive manufacturing firms in Germany and Sweden are reported in the Tables 3-6. We estimate the model both for the pooled data set and separately for the individual countries. In each table Panel A gives the result for the pooled sample, and panel B gives the parameter estimates for individual country regressions. In the pooled regression we estimate the model at a

first step using interaction terms for all variables and then we gradually test identical parameters in both countries using Wald tests. We include interaction terms for a variable if the test rejects the null hypothesis of identical parameters or if one coefficient is statistically significant at least at the 10 per cent level for one country but not significant for the other one. In the following we refer to the pooled regression and only to the individual regressions if necessary.

5.2. Empirical Results

As expected and in line with other empirical findings the probability of being innovative increases with firm size. Moreover, the firms' market orientation is an important explanatory factor for the occurrence of product innovations. Firms with a high global market orientation have a significantly higher probability of introducing new products compared to firms acting mainly on local markets, which is likely due to higher competition on international markets. This holds for both countries and we do not find any significant differences between German and Swedish knowledge intensive firms in this respect. However, in Germany the national market seems to play a more important role in explaining innovation activities than in Sweden. German firms acting primarily on domestic markets also have a significantly higher probability of being innovative than locally oriented firms.

Whereas the occurrence of product innovations is higher in larger firms, the innovation input, defined as innovation expenditure per employee, decreases with firm size – with the firm size effect being significantly stronger in German firms. Thus, the highest input to the innovation process (per employee) is realised by small firms. In contrast, a lot of empirical studies, beginning with Kamien and Schwartz (1975), have found out a non-linear U-shaped relationship between innovation intensity and firm size. We also test this hypothesis by adding a squared term, but we do not find support for this hypothesis. Perhaps, this is due to the restriction of our data set to firms with 10 up to 999 employees.

Mansfield (1968) stated in his well-known 'success breeds success' hypothesis that there is a positive impact of innovation success on further innovation activities and innovation success in following years. As we use cross-sectional data we cannot test this hypothesis directly, but we add two proxy (dummy) variables to the input equation to provide this potential effect. The first variable is continuity of R&D which captures the history of previous R&D activities and the second one is a dummy variable indicating whether the firm has at least one valid patent capturing the successfulness of previous innovation efforts. We find significant effects of the first variable in both countries. Regarding the pooled regression we find the patent variable significant for the Swedish firms but not for the German ones.

The modern literature on innovation stresses the importance of effective appropriability conditions for innovation activities (see e.g. Arrow, 1962; Spence, 1984; or Becker and Peters, 2000). Modeling the impact of appropriability conditions we use a protection measure in the input equation. However, we find only significant effects for Swedish firms.

Concerning the demand pull and science and technology push variables, as measured here by our two indicators, we do not find any significant effect on innovation intensity for the latter one. Thus, the hypothesis that there might be a cost-push effect of the technological opportunities on innovation intensity due to the absorptive capacity argument (see e.g. Cohen and Levinthal, 1989; Klomp and Van Leeuwen, 2001) is not supported in our estimation. However, as one may expect, market demands to enhance the innovation efforts, at least for Swedish firms.

Table 3

Selection equation. Dependent variable: Probability of doing innovation

Panel A: Pooled regression						
	Germany, N=575		Pooled, N=1,049		Sweden, N=474	
	Coeff	SE	Coeff	SE	Coeff	SE
Firm size			0.225 ***	0.054		
Human capital	1.465 ***	0.463			2.617 ***	0.506
Group	0.099	0.129			-0.306 **	0.133
Newly established			0.829 *	0.459		
Merged			0.086	0.237		
Downsized			-0.164	0.200		
Most important market ^a :						
- international <50km	1.208 ***	0.431			0.674 *	0.386
- national >50km	0.688 ***	0.261			-0.176	0.236
- international >50km			0.764 ***	0.255		
Germany			-0.301	0.199		
Constant			-1.448 ***	0.319		
Wald test ^b			18.80	0.0000		
Panel B: Individual country regressions						
	Germany, N=575		Sweden, N=474			
	Coefficient	SE	Coefficient	SE		
Firm size	0.230 ***	0.062	0.157 ***	0.056		
Human capital	1.530 ***	0.506	2.345 ***	0.437		
Group	0.085	0.142	-0.147	0.135		
Newly established	1.092 *	0.658	0.322	0.283		
Merged	0.185	0.335	-0.094	0.151		
Downsized	-0.082	0.313	-0.255	0.214		
Most important market ^a :						
- international <50km	1.215 ***	0.469	0.154	0.352		
- national >50km	0.667 **	0.294	-0.054	0.208		
- international >50km	0.739 **	0.306	0.937 ***	0.214		
Constant	-1.729 ***	0.404	-1.661 ***	0.333		
Wald test ^b	9.84	0.001	13.99	0.000		

Notes: (a) Reference is national market within a distance of around 50 km.

(b) Wald test of independence of the selection equation and innovation input equation. Both, teststatistic and marginal level of significance are reported. The teststatistic has a $X^2(1)$ distribution.

Four industry dummies are included in each regression. The Nace 2 digits 30-32 and 34-35 are put together respectively. Reference group is Nace 2 digit 29.

Significant at the 1% (***), 5% (**) and 10% (*) levels of significance.

Table 4

Innovation input equation. Dependent variable: Logarithm of innovation expenditure per employee

Panel A: Pooled regression						
	Germany, N=352		Pooled, N=558		Sweden, N=206	
	Coeff	SE	Coeff	Std err	Coeff	SE
Firm size	-0.386 ***	0.073			-0.178 *	0.091
Continuous R&D			0.650 ***	0.182		
Process innovation			0.183	0.123		
Public funding			0.065	0.149		
Valid patents	0.189	0.156			0.487 **	0.204
Protection	-0.135	0.152			0.442 ***	0.161
Cooperation						
- Science and Techn.			-0.224	0.162		
- Market demand	0.082	0.159			0.594 ***	0.176
- Competitors	0.313 *	0.183			0.046	0.332
Most important market ^a :						
- international <50km			-0.834	0.718		
- national >50km	-0.261	0.564			0.794 *	0.482
- international >50km			0.115	0.653		
Germany			1.458 ***	0.474		
Constant			2.096 ***	0.687		
Inverse Mills' ratio			-1.314 ***	0.182		
Panel B: Individual country regressions						
	Germany, N=352		Sweden, N=206			
	Coefficient	SE	Coefficient	SE		
Firm size	-0.385 ***	0.076	-0.067	0.091		
Continuous R&D	0.664 ***	0.213	0.528 **	0.226		
Process innovation	0.209	0.142	-0.080	0.193		
Public funding	0.063	0.168	0.071	0.255		
Valid patents	0.201	0.159	0.317	0.273		
Protection	-0.154	0.154	0.436 ***	0.163		
Cooperation						
- Science and Techn.	-0.278	0.199	0.120	0.271		
- Market demand	0.068	0.159	0.313	0.202		
- Competitors	0.328 *	0.188	0.011	0.344		
Most important market ^a :						
- international <50km	-0.738	0.816	0.294	0.665		
- national >50km	-0.131	0.642	0.468	0.474		
- international >50km	0.248	0.659	-0.257	0.501		
Constant	3.492 ***	0.947	2.341 ***	0.901		
Inverse Mills ratio	-1.277 ***	0.236	-1.498 ***	0.301		

Notes: See Table 3.

Table 5

Innovation output equation. Dependent variable: Logarithm of innovation sales per employee

Panel A: Pooled regression						
	Germany, N=352		Pooled, N=558		Sweden, N=206	
	Coeff	SE	Coeff	SE	Coeff	SE
Innovation input			0.489 ***	0.124		
Inverse Mills' ratio	-0.825 **	0.360			-0.304	0.236
Firm size	-0.147 **	0.067			-0.058	0.082
Productivity			0.731 **	0.339		
Physical capital			0.068	0.075		
Process innovation			0.273 **	0.107		
Public funding			-0.119	0.140		
Newly established			-0.360	0.319		
Group			-0.025	0.121		
Sources:						
- Science and Techn.	0.279	0.194			-0.680	0.653
- Market demand			0.123	0.158		
- Competitors	0.236	0.180			-0.359	0.309
Network eff. of sources:						
- >=1 source			-0.013	0.173		
- >=2 sources			-0.434 **	0.171		
- >=3 sources			0.290 *	0.167		
- >=4 sources			-0.168	0.180		
Cooperation:						
- Science and Techn.			-0.278	0.267		
- Market demand			0.090	0.200		
- Competitors	-0.496 **	0.210			-0.871	0.687
Network eff. of coop.:						
- >=1 cooperation			0.239	0.250		
- >=3 cooperations			0.181	0.231		
- >=5 cooperations			-0.079	0.349		
- >=7 cooperations	0.765 *	0.460			1.045	0.722
Germany			0.869	0.544		
Constant			-1.593	1.660		
R-squared			0.427			
Root MSE			0.885			

Notes: Four industry dummies are included in each regression.
Significant at the 1% (***), 5% (**) and 10% (*) levels of significance.

Table 5 (continuous)

Panel B: Individual country regressions				
	Germany, N=352		Sweden, N=206	
	Coefficient	SE	Coefficient	SE
Innovation input	0.495 ***	0.144	0.610 **	0.282
Inverse Mills' ratio	-0.655 *	0.344	-0.557 *	0.331
Firm size	-0.140 **	0.065	-0.105	0.099
Productivity	1.063 ***	0.353	0.595	1.309
Physical capital	-0.020	0.090	-0.024	0.109
Process innovation	0.232 **	0.111	0.521 **	0.202
Public funding	-0.016	0.177	-0.483 **	0.228
Group	0.049	0.130	-0.265	0.267
Sources:				
- Science and Techn.	0.232	0.200	-1.012	1.089
- Market demand	0.209	0.161	-0.093	0.239
- Competitors	0.220	0.178	-0.522	0.381
Network eff. of sources				
- >=1 source	0.023	0.195	0.840 ***	0.302
- >=2 sources	-0.567 ***	0.206	-0.493 **	0.210
- >=3 sources	0.315	0.200	0.623 ***	0.240
- >=4 sources	-0.130	0.171	-0.190	0.404
Cooperation				
- Science and Techn.	-0.191	0.318	0.174	0.250
- Market demand	0.232	0.201	-0.034	0.404
- Competitors	-0.496 **	0.193	-0.331	0.904
Network of coop.				
- >=1 cooperation	0.284	0.290	-0.017	0.541
- >=3 cooperations	0.074	0.245	0.012	0.261
- >=5 cooperations	-0.029	0.393	-0.626	0.599
- >=7 cooperations	-	-	1.211	0.750
Constant	-2.557	1.643	-0.825	6.269
R-squared	0.434		0.469	
Root MSE	0.870		1.008	

Notes: Four industry dummies are included in each regression.

Significant at the 1% (***), 5% (**) and 10% (*) levels of significance.

As can be gathered from Table 5 the innovation output is mainly determined by the innovation intensity.⁹ Again, this is valid for both countries and we do not find any significant differences between them in this respect. The coefficient indicates that a 10% increase in innovation expenditure per employee rises the innovation output per employee by 4.9% in knowledge-intensive manufacturing firms. This value is just a little higher compared to the results

⁹ It should be mentioned that the impact of innovation input was found to be sensitive to the choice of control variables in the generalized Tobit model for the Swedish single regression.

found by Lööf and Heshmati (2003) or Crépon et al. (1998), as both estimated an elasticity of about 3% for the whole manufacturing sector.¹⁰

Furthermore, we find significant feedback effects of productivity on innovation output. Whereas innovation input depends to a large extent on firm size, no direct firm size effect can be detected in the context of innovation output for the Swedish firms. For German firms we have found a significant negative size effect indicating smaller firms realised a higher innovation output per employee.

Nearly the same results as for the innovation input are found for the innovation output when we look at the demand pull or science and technology push variables. Surprisingly, we do not find any significant effects for any of them. Firms using clients or customers as a highly important information source for their innovations or even cooperating with them have no significantly higher innovation success. This is at variance with the findings of Crépon et al. (1998) for French or Klomp and Van Leeuwen (2001) for Dutch firms, although it should be mentioned that their demand pull and technology push variables are defined in a somewhat different manner. However, the results are in line with the findings of Janz and Peters (2002) using the innovation survey in the German manufacturing sector in 1999.

The literature has also highlighted the potentially important role of networks for innovative activities and success (see e.g. Love and Roper, 2001). Thus, it might be that not a specific cooperation partner or information source itself is decisive for the innovation success but rather the networks of cooperation or sources of information. Therefore, we add nested dummy variables to capture potential network effects. However, we do not find a clear pattern of network impacts. Similar results were also found by Brouwer and Kleinknecht (1996).

Table 6 displays results regarding the productivity effects of innovation and their differences and similarities between both countries. As expected, innovation is a crucial issue for productivity. The firms' overall performance, measured here as the level of labor productivity, increases largely and highly significantly with the innovation output. Our prior assumption that knowledge intensive manufacturing firms are rather homogeneous in a cross-country perspective is supported to a very large extent by the empirical findings. We cannot detect significant differences between the parameter estimates in the productivity equation. This is valid for almost all variables with the exceptions of the physical capital and innovation process variables, which are significant for the German firms but not for the Swedish knowledge-intensive manufacturers.

Furthermore and as expected, we've found out that firm performance is slightly higher in firms with a stronger orientation on the global market. The export share is significantly and positively correlated with labor productivity. The same is valid for (investments in) physical capital, at least for German firms. Surprisingly, we do not detect any significant effects of human capital in explaining productivity. The share of graduated employees is found not to be correlated with firms' overall performance in both countries.

The inverse Mills' ratio, included to correct potential sample selection, is significant in the productivity equation. In the innovation output equation we've found significant effects for Germany, but not for Sweden. All in all, the results highlight the selectivity issue.

Compared to other studies we get plausible estimates for productivity effects of innovation output. Griliches (1998) reported that the elasticity of productivity with respect to R&D expenditure usually clusters around 0.1. Using the broader definition of innovation expenditure instead of R&D, the empirical findings for the elasticity are somewhat higher, lying between 0.10 and 0.25 in the level dimension, but slightly lower – around 0.05 – in the growth rate dimension. (see e.g. Lööf and Heshmati, 2004, Lööf et al., 2003). Thus, our level estimates of 0.34 in the pooled and 0.27 and 0.29 in the single equations are established at the upper bound. One explanation for the relatively high estimates is that we are using only knowledge intensive firms. Another explanation could be that labor productivity as a proxy for value added per employee has been found to somewhat overestimate the elasticity of innovation output (see Lööf and Heshmati, 2004).

¹⁰ Although it should be noted, that Crépon et al. (1998) used the share of innovation sales in total sales as innovation output.

Table 6

Productivity equation. Dependent variable: Logarithm of sales per employee.

Panel A: Pooled regression						
	Germany, N=352		Pooled, N=558		Sweden, N=206	
	Coeff	SE	Coeff	SE	Coeff	SE
Innovation output			0.339 ***	0.092		
Inverse Mills' ratio			0.474 **	0.205		
Firm size			0.137 ***	0.034		
Human capital			0.088	0.257		
Physical capital	0.099 ***	0.034			0.061	0.039
Export share			0.265 *	0.152		
Process innovation	-0.158 **	0.066			-0.098	0.119
Merged			-0.017	0.151		
Downsized			0.438 **	0.194		
Germany			-0.097	0.108		
Constant			3.089 ***	0.380		
R-squared			0.393			
Root MSE			0.489			
Panel B: Individual regressions						
	Germany, N=352		Sweden, N=206			
	Coefficient	SE	Coefficient	SE		
Innovation output	0.268 ***	0.100	0.290 ***	0.084		
Inverse Mills' ratio	0.638 **	0.272	-0.066	0.186		
Firm size	0.146 ***	0.039	0.060 *	0.030		
Human capital	0.333	0.331	0.064	0.137		
Physical capital ^a	0.134 ***	0.038	0.040	0.032		
Export share	0.318 **	0.157	0.050	0.173		
Process innovation	-0.136 **	0.069	-0.030	0.119		
Merged	0.050	0.183	-0.102	0.089		
Downsized	0.481 **	0.199	0.064	0.137		
Constant	2.943 ***	0.410	4.181 ***	0.333		
R-squared	0.421		0.400			
Root MSE	0.475		0.517			

Notes: Four industry dummies are included in each regression.

Significant at the 1% (***) , 5% (**) and 10% (*) levels of significance.

To sum it up, the individual regressions have shown some differences at least in the magnitude of the coefficients of quantitative variables. Pooling the data set and taking interaction terms into account enable us to test econometrically whether these differences are statistically significant. To a very large extent there is a common story in the innovation-productivity link for knowledge intensive manufacturing firms in both countries. Most coefficients of quantitative variables measuring "hard" economic facts do not significantly differ. However, varying impacts were found for some qualitative variables measuring differences either in the institutional framework or innovation strategies which mainly reflect the differing country size.

5.3. Sensitivity Analysis

When comparing the magnitude and significance of the coefficients in the pooled with those in the single country regressions, they seem to be determined by the German firms to a larger extent. One explanation might be the weighting factor which gives the observed German firms a higher importance in the sample. To check the robustness of the results we also estimate the model without using weights. Table 11 displays the estimates for our main parameters of interest: the elasticity of innovation output with respect to innovation input and the elasticity of productivity with respect to innovation output. Comparing the first and the second rows of Table 11 we can conclude that the results seem to be rather robust to using weighted or unweighted estimation methods. Both elasticities are still significant in all regressions and have only slightly changed in these core variables.

Another important issue in our data handling is the treatment of missing values and usage of imputations as specified by Eurostat. Due to access to original data sets we check the validity by estimating the model without imputed values (and accordingly without weights). We find the productivity impacts of innovation output to be robust to this modification. The estimates are still highly significant and somewhat higher for the German individual regression. However, the innovation output equation is sensitive to this change in the sense that the innovation input is not significant anymore in explaining the output.

6. Conclusions

We have analyzed the relationship between productivity, innovation output and the R&D expenditure and other innovation activities for a pooled sample of 1,049 German and Swedish knowledge intensive firms with 10-999 employees. Out of these, 558 (53%) were classified as innovative firms.

Four issues were addressed in the paper: whether there is a common cross-country story in the innovation-productivity-link, the importance of the data quality for the analysis, the advantage of pooled regression, and the robustness of the applied empirical model. Turning to the cross country comparison first, interesting consistencies were found between the estimates for Germany and for Sweden in the pooled regression. The two main parameter estimates, the elasticity of labor productivity with respect to innovation output and the elasticity of innovation output with respect to innovation input, are not significantly different between the two countries. This is also valid for most of the other estimates.

However, some varying parameter estimates were also found reflecting country specific effects. The national market is more important for German firms, which can be explained by the difference in country size. Belonging to a group reduces the probability of doing R&D and other innovation activities in Sweden. The intensity of both innovation input and innovation output decreases with firm size in Germany. It is remarkable that the R&D subsidy system in Germany is more oriented towards larger firms than its Swedish equivalent and that the average sizes of innovative firms are higher in Germany.

We could not see any large differences between the parameter estimates in the pooled and the two individual regressions. We conclude that it is explained by a combination of a quite homogeneous sample of firms competing under similar conditions, the careful control of the data quality and an econometric specification taking into account firm, industry and country specific effects.

The applied econometric model was found to be rather robust. The only exception was the innovation output equation. Here the impact of innovation input was found to be sensitive to the choice of control variables in the generalized Tobit model as well as the treatment of missing values. As expected, the overall robustness of the model was found to be stronger in the pooled regression with more observations.

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Appendix

Table 7

Variable definitions

Quantitative variables	
Productivity^a	Sales per employee (in log.)
Innovation output	Sales income from product innovations, per employee (in log.)
Innovation input^a	Innovation expenditure, per employee (in log.)
Firm Size^a	Number of employees (in log.)
Physical capital^a	Gross investments in tangible goods per employee (in log.)
Export	Share of export per sales
Human capital^a	Share of employees with a university or college degree
Qualitative variables	
Innovative firm	Dummy variable being 1 for firms having introduced a new or significantly improved product into the market between 1998 and 2000 and having innovation expenditure in 2000.
Process innovation	Dummy variable being 1 for firms having introduced a new or significantly improved production process between 1998 and 2000.
Group	Dummy variable being 1 for firms belonging to a group
Newly established	Dummy variable being 1 if the firm was established during 1998-2000.
Merged	Dummy variable being 1 if turnover increased by 10 % or more due to merger with another enterprise or part of it during 1998-2000.
Downsized	Dummy variable being 1 if turnover decreased by 10 % or more due to sale or closure of part of the enterprise during 1998-2000.
Most important market	Dummy variable being 1 if the firm's most significant market is ...
- national <50km	... local (within a distance of 50 km) within its country.
- international <50km	... local (within a distance of 50 km) within neighbouring countries.
- national >50km	... national (with a distance of more than 50 km).
- international >50km	... international (with a distance of more than 50 km).
Continuous R&D	Dummy variable being 1 if the firm was engaged continuously in intramural R&D activities during 1998-2000.
Public funding	Dummy variable being 1 if the firm received any public financial support for innovation activities during 1998-2000.
Valid patent	Dummy variable being 1 if the firm had any valid patents at the end of 2000.
Protection	Dummy variable being 1 if the firm has made use of registration of design patterns to protect inventions or innovations developed within its firm.
Cooperation	Dummy variable being 1 if the firm had any co-operation arrangements on innovation activities during 1998-2000 with
- Science and Technology	... universities or other higher education institutes, government or private non-profit research institutes or commercial laboratories /R&D enterprises.
- Market demand	... clients or customers.
- Competitors	... competitors and other firms from the same industry.
Network effects of cooperation	Four nested dummy variables being 1 if the firm has used >=1, >=3, >=5 resp. >=7 cooperation partners.
Sources	Dummy variable being 1 if the firm has given a high importance as information source during 1998-2000.

^a Calculated using information from register data in Sweden if necessary.

Table 7 (continuous)

- Science and Technology	... universities, other higher education institutes, government or private non-profit research institutes or commerc. laboratories /R&D enterprises ...
- Market demand	... clients or customers ...
- Competitors	... competitors and other firms from the same industry ...
Network effects of sources	Four nested dummy variables being 1 if the firm has used ≥ 1 , ≥ 2 , ≥ 3 resp. ≥ 4 information sources with a high importance.

Table 8

Model Structure

	Selection	Input	Output	Productivity
Innovation input			X	
Innovation output				X
Productivity			X	
Firm size	X	X	X	X
Human capital	X			X
Physical capital			X	X
Export share				X
Inverse Mills' ratio		X	X	X
Most important market	X	X		
Process innovation		X	X	X
Public funding		X	X	
Continuous R&D		X		
Valid patents		X		
Protection		X		
Cooperation partners		X	X	
Network of cooperation			X	
Sources of information			X	
Network of sources			X	
Group	X		X	
Newly established	X		X	
Merger	X			X
Downsizing	X			X
Industry Dummies	X	X	X	X
Country Dummy	X	X	X	X

Table 9

Identification of extreme values

	Germany		Sweden	
	Censoring value	Number of Outliers	Censoring values	Number of Outliers
Investment in physical capital	3	T=2, I=0	3	T=2 I=1
Innovation expenditure	3	T=0	3	T=3, I=3

Notes: T= Total sample, I = Innovative sample.

Table 10

Imputed and missing values after logical control check and register usage

	Germany N=575			Sweden N=474		
	Observed	Imputed	Missing	Observed	Imputed	Missing
Turnover	575	0	0	474	0	0
Employees	575	0	0	474	0	0
Product innovation	562	13	0	473	1	0
Process innovation	559	16	0	474	0	0
Innovation expenditure	512	57	4	432	36	6
Innovation sales	551	24	0	455	16	3
R&D engagement	544	19	12	-	-	-
Cooperation	557	17	1	441	33	0
Export	511	64	0	472	2	0
Investments	519	56	0	358	16	0
Most important market	468	95	12	432	38	4
Share of high skilled personnel	535	40	0	-	-	-

Table 11

Sensitivity analysis: The importance of weights and missing values

Estimation method	Pooled regression		Individual country regression			
			Germany		Sweden	
	$\eta_{IO, II}$	$\eta_{P, IO}$	$\eta_{IO, II}$	$\eta_{P, IO}$	$\eta_{IO, II}$	$\eta_{P, IO}$
Weighted						
- with imputations	0.489***	0.339***	0.495***	0.268***	0.610**	0.290***
Unweighted						
- with imputations	0.399***	0.323***	0.551***	0.296***	0.413***	0.226***
- without imputations	0.296	0.355***	-0.019	0.510***	0.604*	0.321***

Notes: $\eta_{IO, II}$ is the elasticity of innovation output with respect to innovation input and $\eta_{P, IO}$ is the elasticity of productivity with respect to innovation output.