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INNOVATION PERFORMANCE OF FIRMS IN MANUFACTURING INDUSTRY: Evidence from Belgium, Finland and Germany in 1998–2000

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Abstract: The objective of this study is to study whether the R&D expenditures in Finnish firms generate better innovation output than in Belgian and German firms following the studies of Mohnen et al. (2006) and Mohnen and Dagenais (2001) and using CIS 3 data on manufacturing firms in 1998–2000. First, we use generalised tobit model to scrutinise what factors impact the firm's propensity to innovate and the amount of innovation output, the share of sales in innovative products. Second, we construct an innovation indicator based on the estimates of pooled regression and compare the expected innovation output to the observed innovation output in sample countries and industries. We find that innovativeness is overall largest in Germany whereas the results of Belgium and Finland are nearly equal. The most surprising country differences are found in the effects of public funding, which do not have any significant impact on innovation output in Finland, have a negative impact in Belgium and positive in Germany.

Key words: Innovation, R&D, CIS, innovativeness, productivity, innovation and technology policy

Tiivistelmä: Tutkielman tavoite on tutkia tuottavatko suomalaisten yritysten T&K-panostukset parempaa innovaatiotuotosta kuin belgialaiset ja saksalaiset yritykset. Tutkimus seuraa aiempia tutkimuksia aiheesta (esim. Mohnen et al. 2006 ja Mohnen and Dagenais 2001). Tutkimuksen empiirinen osa on kaksivaiheinen: Ensin tutkitaan selittävien muuttujien vaikutusta yritysten innovaatioalttiuteen ja innovaatiotuotokseen. Seuraavaksi estimoiduista tuloksista muodostetaan innovaatioindikaattori, jossa odotettuja innovaatiotuotoksen arvoja verrataan havaittuihin. Tutkimusmenetelmänä käytetään Heckmanin mallia (Heckman 1979), jolla estimoimaan innovaatioalttiutta ja -tuotosta. Innovaatioindikaattorin tuloksena on, että innovatiivisuus on suurinta saksalaisissa yrityksissä, kun taas Suomen ja Belgian tulokset ovat hyvin lähellä toisiaan. Yllättävimmät ja toisistaan eroavat vaikutukset löytyvät julkisesta T&K-rahoitusta kuvaavasta muuttujasta: julkisella tuella ei vaikuta olevan tilastollisesti merkitsevää vaikutusta innovaatiotuotokseen Suomessa. Belgiassa vaikutus on merkitsevästi negatiivinen ja Saksassa merkitsevästi positiivinen.

Asiasanat: Innovaatio, T&K, CIS, innovatiivisuus, tuottavuus, innovaatio- ja teknologiapolitiikka

Contents

1. Introduction

The success story of the Finnish economy has been regarded as an outcome of efficient innovation and technology policy. According the new growth theory[1], economic growth is generated by endogenous investments in R&D. There is lot of evidence to support the view that Finland ranks high in R&D inputs. For example, in R&D expenditures share of GDP, Finland ranks third among the OECD countries. Therefore, many politicians in particular emphasise how investments in innovations should be further increased to guarantee the future growth when more and more manufacturing operations are transferred into low-cost countries. However, there is little evidence to support the notion that Finland would rank at the world's top also in innovation outputs. Furthermore, the average annual economic growth in Finland ranks only in the middle category within the OECD countries[2] in contrast to the assumptions of the endogenous growth theory.

Regardless of the large innovation investments and the strong reliance on its importance, there have been hardly any studies scrutinising how well investments in R&D generate sales and hence increase productivity. In several other countries these studies have been conducted by using data from Community Innovation Surveys (CIS) following the guidelines of Oslo Manual (1992)[3]. The CIS data are also available for Finnish companies but thus far they have been exploited only little.

The significance of innovations has traditionally been estimated by the number of patents. However, using the number of patents as a proxy for innovation output includes several caveats. Mairesse and Mohnen (2002) introduce innovative sales as an alternative innovation output measure for the number of patents. Innovative sales measure the share of sales generated by new or significantly improved products. This measure is available in the CIS surveys.

In this study we compare the firm innovation performance by using CIS 3 data of three EU countries: Belgium, Finland and Germany. We rely on the models of Mohnen and Dagenais (2001) and Mairesse and Mohnen (2002) to construct a two-stage tobit estimation (Heckman 1979) for each country separately. Finally we pool the data to estimate a common regression and construct an innovation indicator based on the estimation results. The indicator is then used to compare innovation performance. We try to find whether there is a common story between

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[1] See e.g. Jones (1998, p 32–33 and 88–94).

[2] 1990–2002, the ranking varies depending on the time period.

[3] OECD's Oslo Manual (1992) includes the guidelines for making comparable innovation surveys in different countries.

the countries. Furthermore, we aim at finding whether Finnish firm innovation performance stand out as superior due to the overall large investments in R&D.

This paper is structured as follows. Section 2 analyses earlier empirical studies on innovation and productivity. Focus of the analysis is on the foreign studies conducted by using CIS data. Furthermore, empirical studies conducted with Finnish data are briefly presented. Section 3 presents the data and variables. Section 4 introduces the methodology of our study: empirical model on propensity to innovate and innovation output and construction of an innovation indicator. Section 5 presents and analyses estimation results. Section 6 presents the innovation indicator for Belgium, Finland and Germany. Section 7 concludes and discusses the ideas for further research.

2. Empirical studies on innovation

The research linking expenditures on R&D to productivity has been one of the most challenging tasks in empirical economics for several decades. It has been particularly challenging to find a relevant proxy for innovation output since benefits from innovation are not easily measurable and they may take several years to be realised.

For a long time, empirical innovation research focused on input-oriented innovation indicators when analysing the impact of innovation on productivity. Most of these studies have used the production function approach including R&D based measures as additional input factors. However, it is well known that R&D does not capture all aspects of relevant innovation. For instance, innovation activities close to the market are excluded in the concept of R&D. Moreover, in these studies the link between the innovation resources and the outcome are treated as a black box. (Peters 2005)

Patents used to be a proxy for innovation output. However, using patents as a measure for innovation output includes several caveats: First, the number of patents tells very little about the significance of the patented innovations. Second, innovations can be protected by using other methods instead of patenting. Hence, not even close to all innovations appear in the patenting records.

Nowadays, it is possible to try to capture the innovation output by using other proxies. Community Innovation Surveys (CIS) conducted in Europe, following the guidelines of Oslo Manual (1992), enable the use of proportion of sales due to innovation, or more shortly *innovative sales,* as a proxy for innovation output. Mairesse and Mohnen (2002) characterise the intensity of innovation by a sales-weighted measure of innovation: the share of sales in innovative products. The measure only captures product innovations, but surveys indicate that most firms that are process innovators are also product innovators.[4] Benefiting from the CIS surveys, the focus of empirical innovation studies has shifted from input-oriented into output-oriented innovation indicators when measuring aspects of innovative activities like productivity or employment effects.

The early studies on innovations and productivity date back to Mansfield (1980), one of the first researchers to tackle the relationship between R&D input and output. He was the first to attempt to disaggregate R&D expenditures and to investigate the effects of the composition of an industry's or a firm's R&D expenditures on its rate of productivity increase. He found a statistically

[4] Mohnen et al. (2006) have found that in CIS 1 the proportion of firms that declared to be only process innovators (and not product innovators) seemed particularly small. It is also relatively small in CIS 2 and CIS 3.

significant and direct relationship between the amount of basic research carried out by an industry or a firm and its rate of increase of total factor productivity by using the US firm data from 1948–1966. However, the model was quite simplified since it did not include any measure for innovation output and thus left the black box of innovation unexamined.

To structure the connection between R&D, innovation and productivity, Crépon, Duguet and Mairesse (1998) introduced an original empirical approach (later called CDM model). They tackled the problem of assessing both the innovation impacts of research and the productivity impacts of innovation and research (see Figure 1). They admitted the fact that it is not the innovation input (R&D) but innovation output that increases productivity and therefore innovation output needs to be measured.

Figure 1. CDM Model[5]

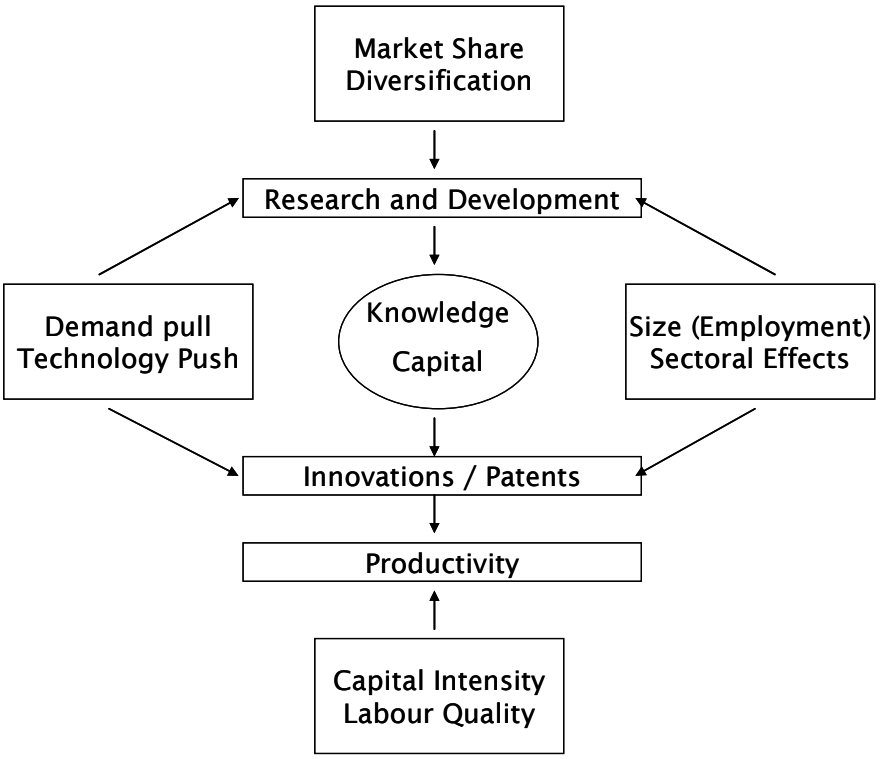

Figure 1 above illustrates the equation links in the CDM model. To estimate the model, Crépon et al. (1998) used data on innovation output in French manufacturing. The results of the research function were that the probability of engaging in R&D increases significantly with the firm size, market size and

[5] Crépon et al. (1998).

diversification. However, once the differences in the R&D effort were taken into account, significant impact of the firm size on its innovation output no longer existed, be it the average number of patents per employee or the percentage of innovative sales. As seems intuitive, the impact of R&D intensity was quite strong: for patents the elasticity of the firm R&D capital intensity was about 0.9, and for innovative sales it was about 0.4. Furthermore, both market demand and technological opportunities appeared to have positive effects on the firm R&D engagement and innovation output. Finally, considering the productivity equation, firm productivity correlated positively with a higher innovation output. As the authors admit, the main caveat of this study is the use of cross-sectional data. For further research, they suggest using panel data that would be richer than the data they used and implementing a dynamic model, which could give a better description of the complex relations between research, innovations and productivity.

CDM model has provided a useful basis for extending the scrutiny between innovation input and output and productivity. For instance, Parisi, Schiantarelli and Sembenelli (2002) used this model for searching the link between R&D output and productivity using Italian manufacturing firms. They use two innovation surveys (1992–1994 and 1995–1997) and take the results of firms that have answered to both of them resulting in a sample of 465 firms. To assess the effect of innovation on productivity they estimate a Cobb-Douglas production function in log-difference, augmented with the process and product innovation dummies that capture the effect of technological progress. They found that process innovation increased productivity by 15 % at a 10 % statistical significance level whereas the effect of product innovation was smaller. R&D intensity is positively and significantly associated with the introduction of product innovations but not with process innovations. The probability of innovating is also found to increase with firm size. They find that the coefficient of the interaction term between R&D and investment is significant. This provides support to the idea that internal formal R&D helps firms to absorb new technologies and thus improve productivity.

Duguet (2000) further elaborated on the model by examining whether the Solow residual (total factor productivity) is linked to technical progress and if so, how much. He uses data on French manufacturing firms from 1990 innovation survey (CIS 1) to formulate a model consisting of two parts: innovation function and the TFP growth equation. Moreover, he differentiates *incremental* innovations, which imply a small modification in the production function, from *radical* innovations, which imply a change of product or process. Thus, radical innovations are likely to affect TFP growth because they involve a larger shift in the production function. However, they conclude that incremental innovators do not seem to have significant effect on growth. They conclude that the Solow residual is linked to innovation at the firm level even though all types of innovations are not contributing to it.

Peters (2005) tackles the problem that CDM model does not include sufficient measures for process innovations. The model only contains an equation for product innovations as the output of innovation activities even though the input measure (R&D or innovation expenditure) is related to product and process innovations. Process innovations are also likely to increase productivity. She includes an output equation for process innovations and performs an unprecedented analysis of the determinants of the process innovation success by using German CIS 3 data. Although innovation input depends considerably on firm size, she does not detect a direct firm-size effect in the context of product innovation output. However, for process innovations she finds a significantly positive size effect indicating that larger firms realise higher cost savings per employee. Furthermore, newly established enterprises experience larger cost reductions due to process innovations.

Regarding Nordic countries, Lööf et al. (2002) elaborated on the CDM model to cross-country comparisons by using CIS 2 data for comparing innovation performance between Nordic countries. The first research question was to examine whether differences in aggregate productivity growth between countries can be partly explained by findings from the micro-based CIS data. The second was whether or not the CDM model is appropriate for handling CIS data collected in different countries. They restricted the comparison to Finland, Norway and Sweden using CIS 2 data collected in 1994–1996. The results revealed major discrepancies between the estimated firm level results. Furthermore, the aggregated figures did not produce similar results to those of Crépon et al. (1998). Finland and Sweden rank higher in labour productivity than Norway and have a higher patenting ratio per capita. However, for instance, regarding Finnish results, there was no significant correlation between innovation output and the intensity of innovation. Furthermore, the correlation from productivity to innovation was insignificant. Modest correlation was found between innovation output and productivity, nevertheless, with a low level of significance. The authors explained poor results with possible data error, model specifications and unobservable country-specific effects.

Janz, Lööf and Peters (2004) have also conducted a cross-country comparison following the guidelines of the CDM model. Their study compares innovation performance between Swedish and German firms elaborating on the knowledge function and productivity model. The asset of their study is the use of pooled original data in common regression of CIS 3 survey instead of micro-aggregated data. They estimate the model using generalised tobit model. The results follow mainly earlier empirical findings: First, the probability to innovative increases with firm size, human capital and international orientation. Second, innovation input has a strong effect on innovation output. Moreover, cooperation with competitors in Germany and public funding in Sweden has a negative and significant effect on innovation output. Third, the productivity increases largely and significantly with innovation output and firms with a high global market

orientation have a significantly higher productivity of introducing new products compared to the firms who operate mainly in the local markets. The innovation input, defined as innovation expenditure per employee, diminishes with firm size – with the firm size effect stronger in German firms. They conclude that the story behind innovation and productivity in firm-level seems to follow a similar path in different countries.

The number of studies tackling the relationship between innovation inputs and output in Finland is scarce. However there are some studies that have taken advantage of the innovation data collected in Finland. In addition, Sfinno survey data collected by VTT Technical Research Centre of Finland has been a source for innovation studies.

For instance, Berghäll (2006) applies a stochastic frontier model to firm level panel data from the Finnish ICT manufacturing sector to explore the role of R&D and technological progress in the outstanding Finnish productivity growth in the late 1990's. Her results show that increasing returns to scale and output growth have been, until recent years, more important than technical change in TFP growth. Physical and R&D capital appear to be substitutes to some extent, diminishing concern over low overall investment ratio. The technology policy mix seems to have encouraged R&D employment and R&D investment at the expense of other labour and physical capital. She also finds surprisingly persistent firm-specific differences in R&D productivity.

In addition to Community Innovation Surveys, a Sfinno survey on innovations in Finland has been conducted by VTT Technical Research Centre of Finland. Palmberg et al. (2000) present how Sfinno-database has been constructed of 642 Finnish innovations commercialised during the 1980's and 1990's. The whole data was compiled using a combination of three different methodologies for the identification of innovations: expert opinion, reviews of trade and technical journals, and reviews of the annual reports of large firms. In contrast to CIS, the Sfinno data comprises data on distinct innovations instead of firms' innovation activities, and the database lacks information on non-innovators. The Sfinno survey and the studies based on the data (eg. Niininen & Saarinen 2000) have provided new information on Finnish innovations. However, one can not say much about the link between innovation inputs and output relying solely on Sfinno data. There are two main reasons for this. First, the data comprises information only on innovators. Second, innovation output is only measured as patents and any financial proxies on innovation output are not included. Linking innovation characteristics directly to firm profitability neglects several phases in innovation process by jumping directly from inputs into firm performance. Furthermore, impacts of other firm- or industry-related issues on profitability remain unexplored.

Besides constructing econometric models following CDM model's guidelines, few authors have built indicators or accounting frameworks to better structure the comparisons between industries, regions or even countries. We present two of them: the accounting framework of Mohnen et al. (2006) and the composite innovation indicator of Mohnen and Dagenais (2001). These studies are the basis of our study.

In their paper Mohnen et al. (2006) build up an accounting framework to compare the extent of innovative ability, capacity or "innovativity". As the CDM model, the model of Mohnen et al. (2006) relies on the production function. Production output results from a process of transformation of inputs into outputs that can be represented and analysed in terms of a production function. Based on the production function, an accounting framework can be constructed. Changes in output between periods (years, decades) or differences between spatial units (firm, industries, countries) result from changes or differences in the inputs and in a residual that is known as total factor or multifactor productivity (TFP or MFP), or simply productivity. Similarly, they view innovation output resulting from innovation inputs, such as R&D efforts, and other contextual determinants, such as the pressure of the competition. The authors represent this linkage in terms of an innovation function and an innovation accounting framework. Based on this two-fold model, changes between spatial units can be ascribed to changes or differences in the factors of innovation and in a residual that the authors call *innovativity*, or the unexplained ability to turn innovation inputs into innovation outputs.

Innovativity thus corresponds to innovation function what TFP means for production function. Innovativity is conditional on a model of an innovation function and a set of factors of innovation, just as TFP is conditional on an assumed specification of the production function and measured factors of production. Both models include omitted factors of performance relating to for instance technology, organisation, culture or environment (and to other sources of misspecification errors). (Mairesse and Mohnen 2002)

Based on the accounting framework, Mohnen et al. (2006) build a comparison across seven European countries by using CIS 1 data. The data comprises information on manufacturing firms from Belgium, Denmark, France, Germany, the Netherlands, Norway and Italy for the year 1992. The firms are grouped into scientific and non-scientific firms. The scientific group includes high R&D sectors: vehicles, chemicals, machinery and electrical industries whereas low R&D sector are grouped into non-scientific sectors including food, textile, wood, plastic, non-metallic, basic metal and NEC[6] industries. In order to compare innovation performance across countries, they estimate the model on the pooled

[6] Industry definitions are found in Table 1 on page 13.

data of the seven countries using Heckman's (1979) tobit estimation. Based on the estimates, they compute the expected share of innovative sales for each country. As in the case of multilateral productivity comparison, it is appropriate to have some kind of average sample point as a fixed base of comparison. A hypothetical reference country the "average European country" is thus chosen giving equal weight to the seven countries. (Mairesse and Mohnen 2002)

In the accounting framework, the expected innovation intensity is the share of innovative sales that is expected in each country given its industry composition, the average size and the group membership of its firms, its R&D activities, and characteristics of its environment. These various *structural effects* and their total are measured in terms of deviation from the average European country of reference. Thus, together with innovativeness, by definition the unexplained residual in observed innovation intensity, they account for the bilateral differences in innovation intensity in each country and the European average country.

The estimation results for probability to innovate are as follows. An increase in size improves the propensity to innovate in both scientific and non-scientific groups. Group companies are also more likely to be innovators. The frequency of innovation is higher in the sectors producing machinery and equipment or electrical and electronic products than in those producing vehicles and chemicals. Among the non-scientific sectors the proportion of innovators is lower in the wood-based and textile-producing sectors. Regarding the results for intensity of innovation, an increase in size improves the innovation output in both groups but its effect is smaller than in the equation for propensity to innovate. Being a group company increases the share of innovative. A one %-point increase in R&D expenditures share of sales raises the share of innovative sales by 0.3 %-points for innovating firms despite the sector in which the firm operates. The effects of competition and proximity to basic research are quite high in the scientific sectors. Basically, the marginal effects of all structural variables are lower in non-scientific than in scientific sectors.

When computing the marginal effects for the whole sample i.e. regardless of whether the firm is innovative or not, the marginal effects of the explanatory variables are lower. The largest effects are those due to size, the combination of doing R&D continuously and in cooperation, perceived competition and proximity to basic research.

The main results of the accounting framework are that the most expected innovation-intensive firms are the German companies in the scientific sectors. The least expectedly innovation-intensive firms are the Dutch firms in the non-scientific sectors and the least unexpected innovative firms are the Italian firms in the non-scientific sectors.

Mohnen and Dagenais (2001) construct a composite innovation indicator, which allows the comparison across industries or classes of firms in a particular country and across countries. They apply the proposed indicator to the CIS 1 data for Denmark and Ireland. First, they estimate a two-stage generalised tobit model. From the estimates of the qualitative and quantitative information of innovation contained in the CIS 1 and resulting from the econometric model, they compute the mean expected innovation output conditional on the observed values of the explanatory variables for each observation in the sample. As explanatory variables in the first equation they introduce industry dummies, six different size classes, a dummy for being part of an enterprise group, sales growth rate 1990–1992. The second equation has basically the same explanatory variables but R&D variables, dummies for doing R&D on a continuous basis and doing cooperative R&D and continuous variable on R&D expenditures' share of sales have been included.

The results of the estimations are that large firms innovate more often than small firms but the relationship between size and innovation output is not significant. Danish firms which belong to a larger consortium have a significantly higher probability to innovate and also a higher share in sales of innovative products, whereas in Ireland this variable is hardly significant. On the other hand, the past growth in sales has no effect on innovation in Denmark, whereas in Ireland it significantly increases both dimensions of innovation. Regarding R&D, the innovation input, only being a continuous R&D performer has a significantly positive effect on the share in sales of innovative products in both countries. In Ireland, the coefficient of R&D expenditures' share of sales is marginally significant.

From these estimates, Mohnen and Dagenais (2001) compute the mean expected innovation output for each observation. They report the observed and expected averages in different sectors. In Denmark, the expected conditional average share in sales of innovative products for all firms is 35.2 %, which is not far from the observed 35.6 %. In Ireland, the two figures are even closer, 31.1 % expected versus 31.5 % observed. The top innovative sectors are machinery and equipment, vehicles, electronic products, chemicals and textiles in Denmark and machinery and equipment, electronic products and textiles in Ireland. However, this indicator did not suffice for comparing the two countries because it lacked a common structure. Mohnen and Dagenais (ibid.) tackle this problem by comparing the countries' performance taking the estimated structures of the other country. They compute the expected conditional means by using first the structure of Denmark and then the one of Ireland. They conclude that conditional predictions obtained with both estimates are nearly equal and that Denmark is slightly more innovative than Ireland and the potential to innovate for non-innovators is pretty much the same in both countries.

3. Data

In this section, we present the used data. First we discuss briefly the Third Community Innovation Survey. Second, we discuss the variables and how they were formulated. Third, we demonstrate how the sample was constructed from the original dataset. Finally, we present some descriptive statistics.

We use the panel data for Finland, Belgium and Germany from the Third Community Innovation Survey which contains firm data from 1998–2000. For Finland, we use original company data provided by Statistics Finland whereas for Belgium and Germany, we rely on the dataset provided by Eurostat, in which the data is in micro-aggregated[7] form. The original dataset received from Eurostat included CIS 3 data from altogether 15 countries: Belgium, Bulgaria, Czech Republic, Estonia, Germany, Greece, Hungary, Iceland, Latvia, Lithuania, Norway, Portugal, Romania, Slovakia and Spain. As the dataset had significant number of countries from Eastern Europe, we wanted to limit the comparison to countries, which have an adequately similar profile. This is why we chose EU countries Belgium and Germany. Furthermore, some of the countries we would have wanted include seemed to have data problems and we were forced to leave them out of the sample. Ideally, we would have repeated the accounting framework of Mohnen et al. (2006) with newer data but the data availability formed the main setback for applying their model. However, we are now confident that the data provided by Belgium and Germany are adequately robust for comparisons with Finland.

Regarding the robustness of the data, the micro-aggregation creates some noise in the data, as observations pertain to a moving average of three firms and not always the same three firms for each variable (Eurostat 2006). However, as shown by Hu and DeBresson (1998) and Mairesse and Mohnen (2001), the micro-aggregation does not seem to bias the results in any systematic way. Hence, we are confident that in spite of the micro-aggregation of the Belgian and German data we can reliably compare these countries using CIS data.

Before late eighties, innovation surveys were conducted in isolated ways. SPRU set up a database of innovations in mid 1970's. In the early 1990's, these studies became institutionalised in Europe in the form of Community Innovation Surveys (CIS). Up to now, three official rounds of CIS surveys have been conducted by Eurostat in co-operation with national statistics agencies (CIS 1 for

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[7] Micro-aggregation of variables is done as follows: The continuous variables have been micro-aggregated by applying individual ranking method. Only one variable at time was considered and the values were ranked in ascending order. The observations were then grouped by three and each one was replaced with the weighted mean of the cluster. (Eurostat 1996)

1990–1992, CIS 2 for 1994–1996 and CIS 3 for 1998–2000). (Mairesse and Mohnen 2004)

The CIS 3 survey, like the previous CIS surveys, is structured in such way that specific filter questions lead to the selection of firms that are innovators as opposed to non-innovators. Only the former is required to answer the full questionnaire. First, the firms are asked whether they have introduced a new product or a process in 1998–2000, or whether they have had any ongoing or abandoned activities to do so during this period. If they answer positively to one of these questions, they are asked additional questions regarding their innovation outcomes, their R&D expenditures, and other characteristics. If they answer no to all the filter questions they are considered as non-innovators and they have to report briefly on their size, group affiliation and industry.

Table 1 summarizes the definitions of different variables. Explanatory variables are grouped into five groups or vectors: variables regarding to the firm, R&D, policy issues, markets and industry. As dependent variables, we have first the dichotomous variable indicating whether a firm is innovator or not and second the measure for innovation output.

As a measure for the amount of innovation output *Y*, we take the share in sales of new or significantly improved products launched during the period 1998–2000. We do not define innovating firms as they are defined in the questionnaire "Did your enterprise introduce onto the market any new or significantly improved products?" The reason for this is that some firms declare to have introduced a new product or process but report no share in sales due to new products. The reason may be that there is a time-lag between the introduction of the product and materialisation of turnover due to this product. However, as we cannot take into account any time lags, we replace the dependent variable with zero if the innovative sales take the value of zero regardless if the firm itself declares to be an innovator. Since we do not have the measure for innovation output in process innovations, we limit the analysis on product innovations. However, most of the companies that are process innovators are usually also product innovators and introducing a new product often requires process innovations[8].

[8] Mohnen et al. (2006) have found that in the CIS 1 the proportion of firms that declared to be only process innovators (and not product innovators) seemed particularly small. It is also relatively small in CIS 2 and CIS 3.

Table 1. Variables

	Dependent Variable	Definition
	Innovation Output*	Firm's estimation on how the firm's turnover in 2000 was distributed to new or significantly improved products introduced during the period 1998-2000.
	Innovator	Answering a positive figure on the estimation on innovation output.
Vector	**Explanatory Variable**	**Definition**
FIRM	Small	Number of employees 10-49.
	Medium	Number of employees 50-249.
	Large	Number of employees more than 250.
	Group Company	Answering yes to the question "Is the enterprise part of an enterprise group?"
	Sales growth Rate in 1998-2000*	Turnover in 2000/ Turnover in 1998 -1.
R&D	Innovation Input*	Total R&D expenditure in 2000/Turnover 2000.
	Continuous R&D	Answering yes to the question "By the end of 2000, did your enterprise have any ongoing activities to develop or introduce new or significantly improved products or processes that were not yet completed, including any R&D activity?"
	Cooperative R&D	Answering yes to the question "Did your enterprise have any co-operation arrangements on innovation activities with other enterprises or institutions during 1998-2000?"
POLICY	Public Funding	Answering yes to the question "Did your enterprise receive any public financial support for innovation activities during the period 1998-2000 from either local or regional authorities, central government or the European Union?"
	Proximity to Basic Research	Anwering that the importance of universities or other higher education institutes and/or government or private non-profit research institutes as an innovation information source was high.
MARKETS	Pressure of Competition	Answering that the degree of impact of innovation on increasing market or market share was high.
	Operating Internationally	Answering that international market (with a distance more than 50 km) is the enterprise's most significant market.
INDUSTRY	Food	Manufactureof food, beverages and tobacco (NACE code 15-16).
	Textiles	Manufacture of textiles, wearing apparel, dressing and dyeing of fur, tannings and dressing of leather, luggage, handbags, saddlery, harness and footwear (NACE codes 17-19).
	Wood	Manufacture of wood and products of wood and cork, except furniture, manufacture of straw and plaiting materials, pulp, paper, and paper products, publishing, printing and reproduction of recorded media (NACE codes 20-22).
	Chemicals	Manufacture of coke, refined petroleum products and nuclear fuel, manufacture of chemicals and chemical products (NACE codes 23-24).
	Plastic	Manufacture of rubber and plastic products (NACE code 25).
	Non-metals	Manufacture of other non-metallic mineral products (NACE code 25).
	Metals	Manufacture of basic metals, fabricated metal products, except machinery and equipment (NACE code 27-28).
	M&E	Manufacture of machinery and equipment, manufacture of office machinery and computers (NACE codes 29-30).
	Electronic	Manufacture of electrical machinery and apparatus, radio, television and communication equipment and apparatus, medical, precision and optical instruments, watches and clocks (NACE codes 31-33).
	Vehicles	Manufacture of motor vehicles, trailers, semi-trailers, and other transport equipment (NACE codes 34-35).
	NEC	Manufacture of furniture, manufacturing NEC (NACE code 36).

*marked variables are continuous whereas other variables are dichotomous taking either value 0 or 1

To capture sector specific effects in innovation performance, we introduce industry dummies. Following Mohnen and Dagenais (2001) we expect the incentive to innovate to be a function of technological opportunities: the probability to innovate and the innovation output depending on the industry in which the firm operates. We divide total manufacturing into 11 sectors: food, textiles, wood, chemicals, plastic, non-metals, metals, machinery and equipment, electronic products, vehicles and NEC.

Regarding firm-specific variables, we anticipate that larger firms are more likely to innovate than smaller firms. Size effect could reflect i.e. access to finance or economies of scale. The firms are grouped in the CIS 3 dataset into three different size categories which differs from the six size intervals used by Mohnen and Dagenais (2001). Hence, we are only able to observe quite significant changes in size instead of minor differences. Fast past growth can determine propensity to innovate as a predictor of future growth, as a demand-pull effect (Brouwer and Kleinknecht 1999), or as a signal of easy access to finance. Group companies are assumed to benefit from knowledge spillovers, internal access to finance, or synergies in marketing, distribution, and so on, and thus to be more likely to innovate.

In addition to markets variables that Mohnen and Dagenais (2001) introduce, we include a variable for operating in international markets following e.g. Janz et al. (2004). The rationale behind inclusion is that, international firms are expected to face more competition and surviving requires new ideas and innovating. Furthermore, we introduce a dichotomous variable indicating the pressure of competition i.e. whether the effect of innovating has been an increase in market or market share.

To capture the effects of R&D we introduce three variables: First, a dichotomous variable doing R&D on a continuous rather than occasional basis, second, a dichotomous variable indicating whether R&D is done in cooperation with partners or alone and third a continuous variable for R&D expenditures as a percentage of total sales.

To have an indication how public innovation funding and institutions influence firm innovation performance we introduce two dummies: First, a dichotomous variable for public funding indicating whether the firm has received funding from local government, central government or from the EU and secondly a dichotomous variable for proximity to basic research indicating that importance of the universities or research institutes as sources of information for the firm is high.

In the pooled regression we also include country dummies which are expected to depict country-specific effects that are not defined in other variables. These can be for instance differences in innovation systems or access to capital markets.

We cleaned the data from outliers and missing observations in key variables such as turnover, R&D spending, or share of sales generated by new or significantly improved products. For less crucial variables we allowed missing values to be included. The firm data were restricted to manufacturing industries to improve the comparability to earlier studies. We excluded all enterprises with sales growth rates lower than -40 % and higher than 250 % from the sample. Furthermore, observations with R&D expenditures per sales higher than 100 % were excluded. We put to zero R&D/sales ratios positive but lower than 0.1 %. After the eliminating process, the sample consists of 960 observations from Finland, 684 observations from Belgium and 1431 observations from Germany.

Table 2 and Table 3 present the descriptive statistics of the sample firms. There are 48.7 % of innovating firms in the Finnish sample, 48.5 % of innovating firms in the Belgian sample and 53.9 % in the German sample. The innovation inputs, the share of R&D spending of sales in Finland, Belgium and Germany are 3.3 %, 3.3 % and 3.8 % respectively, whereas the respective average innovation output figures are 11.0 %, 9.9 % and 16.6 %. The OECD figures on R&D spending in 2000 as a percentage of GDP show slightly different figures: Finland spent 3.4 %, Belgium 2.0 % and Germany 2.5 % in R&D. Even though these figures include the R&D spending in all industries and the amount that governments spend on R&D, we have sufficient evidence to assume that both the German and Belgian samples are skewed towards innovators.

The Belgian sample has somewhat larger firms than the Finnish sample and in Germany the share of large firms is considerably bigger. In addition, a larger share of Belgian (55.4 %) and Finnish firms (47.3 %) belong to an enterprise group compared to firms in German sample (38.0 %). Whereas more of the Finnish firms cooperate in R&D compared to the Belgian and German sample, less of them do R&D on a continuous basis. On average, Finnish firms have experienced strongest revenue growth (27.2 %), though the variance in growth rate is also largest. Approximately half of the Belgian (52.0 %) and German (44.7 %) firms declare their main market to be international; whereas less than third of the Finnish companies (31.4 %) do so.

Observing only the sample of innovative companies, we see that the share of large firms increases in all countries by approximately 10 %-points in contrast to the total sample. Innovation input in the innovator sample is nearly equal in the different countries (5.4 % in Belgium and Finland and 5.5 % in Germany) whereas average innovation output varies from 20.4 % in Belgium to 30.7 % in Germany. Larger share of innovators are also group companies and operate internationally. Proximity to basic research and the pressure of competition increases in every country when we observe only innovators instead of the total sample. In Finland, the number of firms receiving public funding for innovation activities is approximately 25 %-points higher than in the German and Belgian samples. This finding gives further evidence on the strong presence of public

organisations in funding of Finnish innovations, which has been pointed out by for instance Finnish Venture Capital Association (2006).

Table 2. Statistics on Total Sample, %

Vector	Variable	Finland N=960 Mean	Finland N=960 SD	Belgium N=684 Mean	Belgium N=684 SD	Germany N=1431 Mean	Germany N=1431 SD
FIRM	Small	48.8	0.500	42.7	0.495	34.9	0.477
	Medium	33.5	0.472	36.0	0.480	34.7	0.476
	Large	15.7	0.364	21.3	0.410	30.4	0.460
	Group Company	47.3	0.500	55.4	0.497	38.0	0.486
	Sales Growth Rate	27.2	0.436	20.3	0.355	15.9	0.295
R&D	Innovation Input	3.3	0.076	3.3	0.080	3.8	0.069
	Innovation Output	11.0	0.196	9.9	0.169	16.6	0.232
	Innovative Firm	48.3	0.500	48.5	0.500	53.9	0.499
	Continuous R&D	40.5	0.491	49.3	0.500	57.7	0.494
	Cooperative R&D	38.0	0.486	22.7	0.419	20.6	0.405
POLICY	Public Funding	37.4	0.484	23.4	0.424	24.9	0.432
	Proximity to Basic Research	4.8	0.214	6.7	0.251	7.1	0.257
MARKETS	Operating Internationally	31.4	0.464	52.0	0.500	44.7	0.497
	Pressure of Competition	6.7	0.248	19.2	0.394	18.7	0.390

Table 3. Statistics on Innovator Sample, %

Vector	Variable	Finland N=464 Mean	Finland N=464 SD	Belgium N=332 Mean	Belgium N=332 SD	Germany N=771 Mean	Germany N=771 SD
FIRM	Small	39.7	0.490	30.1	0.459	23.9	0.427
	Medium	33.8	0.474	39.8	0.490	33.6	0.473
	Large	25.4	0.436	30.1	0.459	42.5	0.495
	Group Company	55.2	0.498	61.7	0.487	46.4	0.499
	Sales Growth Rate	33.7	0.476	22.8	0.350	18.2	0.299
R&D	Innovation Input	5.4	0.085	5.4	0.090	5.5	0.073
	Innovation Output	22.8	0.229	20.4	0.193	30.7	0.237
	Innovative Firm	-	-	-	-	-	-
	Continuous R&D	64.0	0.480	78.6	0.411	85.6	0.351
	Cooperative R&D	65.5	0.476	36.1	0.481	32.4	0.468
POLICY	Public Funding	62.7	0.484	38.0	0.486	37.6	0.485
	Proximity to Basic Research	8.0	0.271	11.7	0.322	10.9	0.355
MARKETS	Operating Internationally	40.7	0.492	63.3	0.483	56.7	0.496
	Pressure of Competition	13.1	0.338	33.7	0.474	31.0	0.478

Table 4 lists the average innovative input and output figures in different sectors. In terms of the innovation input, R&D spending, the electronic products industry

invests the most in R&D in each country. However in Finland this figure is significantly higher than in Belgium or Germany. The second largest R&D investors are the chemicals sector in Finland and Belgium and the vehicles sector in Germany, which is probably explained by the significance of the car industry in Germany. Least R&D spending is done in Finland by the food, wood and vehicle industries. The respective, low-investing industries in Belgium are the metals, plastics and non-metals and in Germany the textiles and non-metals sectors. In Finland, the R&D expenditures seem to vary significantly across the sectors whereas in Germany the differences are small.

The electronic sector seems to produce high innovative output, innovative sales, in all countries. In Belgium, vehicle sector reaches the highest rank whereas in Finland the machinery and equipment sector ranks after the electronic products. The comparisons of the innovation inputs and outputs in different countries reveal that several industries in Germany succeed in generating clearly higher innovation output with innovation inputs that are only slightly larger than in the other sample countries. As the figures are based on a survey, it is possible that there have been differences in interpreting the questions. Furthermore, the share of innovators in German sample is larger, which may result in larger innovation output. However, in that case, we would assume that the innovation input figures would also be significantly larger. Interesting particularity is also that Belgian non-metals sector's innovation input (2.4 %) is on average higher than output (0.1 %). Moreover, in Germany the food sector reports innovation output without any innovation output.

To sum up the industry statistics, the electronic sector seems to produce high results with high investments whereas the chemical sector fails to produce as good results in Finland and Belgium. In Belgium, the vehicle sector generates substantial innovative sales with only marginally larger than average innovation expenditures. In general, innovation inputs and outputs in particular are the largest in Germany.

Table 4. Industry Statistics, %

	Obs	Firm Size			Innovation Input		Innovation Output		Innovators	
Finland		Small	Medium	Large	Mean	SD	Mean	SD	Mean	SD
Food	88	51.1	21.6	23.9	1.6	0.041	6.1	0.130	42.0	0.496
Textiles	43	46.5	41.9	9.3	1.7	0.023	8.4	0.159	48.8	0.506
Wood	172	45.3	36.6	16.3	1.4	0.037	4.9	0.123	30.8	0.463
Chemicals	50	22.0	52.0	26.0	6.7	0.120	8.6	0.114	64.0	0.485
Plastic	67	59.7	25.4	14.9	1.8	0.031	9.9	0.166	50.7	0.504
Non-Metals	54	51.9	35.2	9.3	2.6	0.103	6.6	0.152	38.9	0.492
Metals	126	54.8	32.5	8.7	3.4	0.079	9.1	0.188	44.4	0.499
M&E	151	50.3	33.8	15.9	3.6	0.062	17.5	0.224	62.3	0.486
Electronic	113	46.9	30.1	20.4	8.4	0.131	21.9	0.288	64.6	0.480
Vehicles	46	45.7	37.0	15.2	1.6	0.026	12.3	0.225	32.6	0.474
NEC	50	45.7	34.0	10.0	2.0	0.031	11.5	0.179	56.0	0.501
Total	**960**	**48.8**	**33.5**	**15.7**	**3.3**	**0.076**	**11.0**	**0.196**	**48.3**	**0.500**
Belgium		Small	Medium	Large	Mean	SD	Mean	SD	Mean	SD
Food	55	52.7	18.2	29.1	2.7	0.083	2.7	0.040	41.8	0.498
Textiles	58	29.3	60.3	10.3	3.4	0.118	9.8	0.142	43.1	0.500
Wood	58	43.1	10.3	46.6	3.1	0.054	6.5	0.114	37.9	0.489
Chemicals	95	0.0	73.7	26.3	5.2	0.115	9.6	0.126	63.2	0.485
Plastic	51	62.7	0.0	37.3	2.0	0.040	9.7	0.156	51.0	0.505
Non-Metals	33	45.5	33.3	21.2	2.4	0.049	0.1	0.218	42.4	0.502
Metals	107	53.3	33.6	13.1	1.3	0.029	6.2	0.118	36.4	0.484
M&E	109	69.7	20.2	10.1	3.7	0.058	11.1	0.150	51.4	0.502
Electronic	62	14.5	82.3	3.2	5.4	0.077	15.9	0.228	58.1	0.497
Vehicles	40	57.5	0.0	42.5	3.8	0.136	24.5	0.329	62.5	0.490
NEC	13	46.2	38.5	15.4	2.5	0.032	8.8	0.179	46.2	0.519
Total	**684**	**42.7**	**36.0**	**21.3**	**3.3**	**0.080**	**9.9**	**0.169**	**48.5**	**0.500**
Germany		Small	Medium	Large	Mean	SD	Mean	SD	Mean	SD
Food	3	0.0	100.0	0.0	0.0	0.001	4.3	0.075	33.3	0.577
Textiles	99	41.4	26.3	32.3	1.6	0.032	11.1	0.208	35.4	0.481
Wood	140	48.6	27.9	23.6	3.8	0.096	11.2	0.229	33.6	0.474
Chemicals	117	21.4	32.5	46.2	4.6	0.076	15.4	0.179	65.8	0.476
Plastic	146	46.6	27.4	26.0	4.4	0.084	18.2	0.230	61.6	0.488
Non-Metals	81	37.0	29.6	33.3	2.1	0.042	13.2	0.214	45.7	0.501
Metals	254	41.7	39.0	19.3	3.0	0.057	9.9	0.189	36.2	0.482
M&E	251	27.1	40.2	32.7	3.9	0.059	21.2	0.246	66.1	0.474
Electronic	216	31.5	37.0	31.5	5.5	0.078	24.0	0.253	73.1	0.444
Vehicles	72	19.4	26.4	54.2	4.9	0.071	21.6	0.264	61.1	0.491
NEC	52	21.2	53.8	25.0	3.1	0.041	17.3	0.254	46.2	0.503
Total	**1431**	**34.9**	**34.7**	**30.4**	**3.8**	**0.069**	**16.6**	**0.232**	**53.9**	**0.499**

4. Methodology

Our final objective is to construct an innovation indicator from the variables and their estimated coefficients contained in the third round of Community Innovation Survey. However, we first need to construct an econometric estimation to be able to predict innovation performance in different countries. In this section, we analyse first the econometric estimation using generalised tobit model. Second, we present the formulas for computing marginal effects combining the two equations of the tobit estimation. Finally, we demonstrate how the indicator is constructed from the estimates. To illustrate the generalised tobit model and computing marginal effects, we rely on Dougherty's (2002, p. 280–301) book *Introduction to Econometrics,* Verbeek's (2003, p.197–212) book *A Guide to Modern Econometrics* and on the article of Dow and Norton (2003).

As our dataset contains data from innovators and non-innovators, estimating OLS regression including the observations with dependent variable on innovation output *Y* constrained to be 0, would yield inconsistent estimates. Estimator of the slope would be downwards biased and estimator of the intercept upwards biased.[9]. On the other hand, limiting estimation to innovating firms would neglect the information from non-innovating firms and even then OLS would be biased. To address these issues, we use generalised tobit model (Heckman 1979) assuming that the error term is normally distributed. The model, which is also known as the two-step selection model, the adjusted tobit, or the limited information maximum likelihood selection estimator, is effectively a hybrid between standard OLS model and a binary choice model.[10]

The Heckman model consists of two parts: the first equation is a probit estimation of the probability of having positive outcome (selection equation 2) and the second equation (1) estimates the dependent variable as continuous.

The linear OLS estimation is used to explain innovation output *Y** that is dependent on *k-1* variables, *X* [11] and a random term *u*:

$$Y_i^* = \beta_1 + \sum_{j=2}^{k} \beta_j X_{ji} + u_i \qquad (1)$$

The innovation output Y^* is not observed for firms that are not innovators (which explains the *). To describe whether a firm is an innovator or not, a second

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[9] See e.g. Dougherty (2002, p.293)

[10] The actual estimation is done with two-step Heckman estimation with Stata.

[11] Note that *Q* and *X* include several common variables. The variable vectors are given different notations to make a clear distinction between two equations and thus avoid confusion.

equation of a binary choice type with a dependent variable B^* and *m-1* explanatory variables Q is specified. That is,

$$B_i^* = \delta_1 + \sum_{j=2}^{m} \delta_j Q_{ji} + \varepsilon_i , \tag{2}$$

where we have the following observation rule:

$$Y_i = Y_i^*, B_i = 1 \text{ if } B_i^* > 0 \tag{3}$$

$$\text{not observed, } B_i = 0 \text{ if } B_i^* \leq 0 , \tag{4}$$

where Y denotes firm's actual innovation output and Y^* the firm's innovation conditional on the firm being innovative. The binary variable B simply indicates whether a firm is an innovator or not.

It is assumed that the standardised cumulative normal distribution, $\Phi(B^*)$ gives the probability p of the firm being an innovator for any value of B^*:

$$p_i\,(Y_i \ > 0 \,|\, Q_{ij}) = \Phi(B_i^*) . \tag{5}$$

The probit equation thus estimates a threshold $B^* > 0$ after which a firm is indicated as an innovator and the dichotomous variable B_i takes the value of one. Maximum likelihood estimation is used to generate estimations of the parameters.

The model is completed by a distributional assumption on the unobserved errors u and ε. The model (6) is, in fact, a standard probit model describing the choice of being an innovator or not. Therefore, a normalisation restriction is required and σ_ε^2 is set to 1. The ε and u are assumed to have a bivariate normal distribution N with the means zero, variances σ_u^2, σ_ε^2 respectively, and a covariance $\sigma_{u\varepsilon}$:

$$\begin{pmatrix} u_i \\ \varepsilon_i \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_u^2 & \sigma_{u\varepsilon} \\ \sigma_{u\varepsilon} & 1 \end{pmatrix} \right). \tag{6}$$

Innovation output is thus estimated conditional on $B^* > 0$ when a firm is defined as an innovator. It can be shown that for an observation in the sample,

$$E(u_i \mid B_i^* > 0) = E\left(u_i \mid \varepsilon_i > -\delta_1 - \sum_{j=2}^{m} \delta_j Q_{ji} \right), \tag{7}$$

where E denotes the expected value. If ε and u are distributed independently, $E\left(u_i \mid \varepsilon_i > -\delta_1 - \sum_{j=2}^{m} \delta_j Q_{ji} \right)$ reduces to the unconditional $E(u_i)$ and the selection

process does not interfere with the regression model. Nevertheless, if ε and u are correlated, $E(u_i)$ will be nonzero resulting in biased OLS estimates, as the intercept of the OLS estimation will be overestimated, and the slope of the coefficients underestimated. Hence a problem of selection bias arises.

It can be shown that,

$$E\left(u_i \mid \varepsilon_i > -\delta_1 - \sum_{j=2}^{m} \delta_j Q_{ji}\right) = \frac{\sigma_{u\varepsilon}}{\sigma_\varepsilon} \lambda_i \ , \tag{8}$$

where $\sigma_{u\varepsilon}$ is the population covariance of u and ε, and σ_ε is the standard deviation of ε and λ described by Heckman (1979) as the inverse Mill's ratio, is given by

$$\lambda_i = \frac{\varphi(v_i)}{\Phi(v_i)}, \tag{9}$$

where

$$v_i = \frac{\varepsilon_i}{\sigma_\varepsilon} = \frac{-\delta_1 - \sum_{j=2}^{m} \delta_j Q_{ji}}{\sigma_\varepsilon} \tag{10}$$

and function φ is a normal distribution and Φ a cumulative normal distribution for ε normalised by its standard deviation σ_ε and $\Phi(v)$ is the probability of the firm being an innovator. Inverse Mills ratio is a monotone decreasing function of the probability that an observation is selected into the innovator sample.

From error term assumptions, it follows that:

$$E(Y_i \mid B_i = 1) = \beta_1 + \sum_{j=2}^{k} \beta_j X_{ji} + E(u_i \mid B_i = 1) \tag{11}$$

$$= \beta_1 + \sum_{j=2}^{k} \beta_j X_{ji} + E\left(u_i \mid \varepsilon_i > -\delta_1 - \sum_{j=2}^{m} \delta_j Q_{ji}\right) \tag{12}$$

$$= \beta_1 + \sum_{j=2}^{k} \beta_j X_{ji} + \frac{\sigma_{u\varepsilon}}{\sigma_\varepsilon} \lambda_1, \tag{13}$$

which is the expected innovation output conditional on the firm being an innovator. The sample selection bias arising in regression of Y on the explanatory variables using only the observations on innovators can be regarded as a form of omitted variable bias, with λ as the omitted variable. However, since the components of λ depend only on the selection process, it can be estimated from

the results of probit analysis. When λ is included as an explanatory variable in the regression of Y, OLS yields consistent estimates.[12]

To estimate the marginal effects unconditional on the firm being innovative we need to elaborate on the generalised tobit model. Potential outcomes in equation (1) cannot be estimated directly because the censoring of the dependent variable Y causes selection bias ($Y = Y^*$ if $Y > 0$, Y = unobserved otherwise). However, assuming the error terms are normally distributed, the inclusion of the inverse Mills term in the equation corrects this selection bias, allowing coefficient vector β to be interpreted as a consistent estimate of β^*. In this case, β is the potential marginal effect of a change in X on potential innovative sales,

$$\beta_i = \partial E(Y_i^{'}) / \partial X_i \,. \tag{14}$$

Focusing attention only to β one implicitly analyses only potential effects when all firms are innovative neglecting the actual effects when some of the firms are non-innovators. Recovery of actual outcomes Y from the Heckman model requires a more complex calculation involving both equations (8) and (17):

$$E\left(Y_i \mid Q_i, X_i\right) = \Phi(\delta_1 + \sum_{j=2}^{m} \delta_j Q_{ji} + \varepsilon_i)\left(\beta_1 + \sum_{j=2}^{k} \beta_j X_{ji} + \frac{\sigma_{u\varepsilon}}{\sigma_\varepsilon}\lambda_i\right) \tag{15}$$

The equation (15) combines the probability of being an innovator (2) and the estimated innovation output (13). For the Heckman model with a linear Y^* in the main equation (13), the resulting actual marginal effect m is the derivative of equation (15):

$$m_i = \frac{\partial E\left(Y_i \mid Q_i, X_i\right)}{\partial X_i} \tag{16}$$

$$= \beta_i \Phi(\delta_1 + \sum_{j=2}^{m} \delta_j Q_{ji} + \varepsilon_i) + \delta_i \phi(\delta_1 + \sum_{j=2}^{m} \delta_j Q_{ji} + \varepsilon_i)\left(\beta_1 + \sum_{j=2}^{k} \beta_j X_{ji} + \frac{\sigma_{u\varepsilon}}{\sigma_\varepsilon}\lambda_i\right). \tag{17}$$

Equation (17) shows that variable vectors X and Q influence actual $E(Y)$ three ways: through its effect on the selection equation (captured by δ in (2)), through its direct effect in the conditional equation (captured by β in (13)), and finally through the inverse Mills ratio λ (captured by $\sigma_{u\varepsilon}/\sigma_\varepsilon$ in (13)). Correspondingly, the statistical significance of the marginal effect depends on the standard errors, variances, and covariances of all of these parameters. Because X, Q and λ are normally highly correlated, their coefficients will be correlated, and as a result β will often be less precisely estimated than the actual marginal effect m.

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[12] For more specific estimation equations, see Verbeek (2003, p. 200–201).

Initial estimates are obtained from Heckman's two-step estimation: first, estimating the probit equation and computing the inverse Mills ratio, and secondly, introducing this ratio as an additional regressor in the ordinary least squares regression of the second equation.

The index of innovation introduced by Mohnen and Dagenais (2001) is then defined as the expected percentage of innovative sales for each enterprise conditional upon the coefficients and values of the explanatory variables. The predicted values are based on the combined equation (14) and its marginal effects (17). The basis of the indicator is the average observed Y in the sample. The variations in explanatory variables X and Q are captured in the marginal effects. With the predicted values for each firm we can compute for the mean expected innovative sales for the three countries and for the different industries. The more detailed computation of the predicted values is found in Appendix 1.

5. Estimation results

This section presents the estimation results: First for each country separately and second, by pooling the data. To be able to construct an innovation indicator, we need to estimate a model with innovative sales as a dependent variable. Furthermore, it is interesting to see what factors impact innovation output in different countries. Does the generation of innovation output follow similar path in different countries? To examine the innovation process in different countries, the model is estimated separately in the three countries instead of just pooling the data to generate needed variables for innovation indicator.

The reference group in every regression is the smallest size class (between 10 and 49 employees) of firms in the non-metals minerals sector, with independent status, who do not engage in cooperative or continuous R&D or receive public funding and who operate in domestic markets. Furthermore, in the pooled regression we introduce country dummies for Belgium and Finland, German firms thus being the reference group.

In the regression tables, regression 1 describes the coefficients and asymptotic t-values of the explanatory variables of the selection estimation, the firm's propensity to innovate. Regression 2 describes the coefficients and asymptotic t-values of the estimation of the innovation output, innovative sales conditional on the firm being an innovator. Last two columns represent the marginal effects[13] and their t-values of the explanatory variables combining the two equations: the dependent variable is innovation output regardless of whether the firm is an innovator or not.

The propensity to innovate or selection equation includes firm-specific, industry and markets variables. However, markets vector only includes a variable on operating in the international markets. In the equation for innovation output, in addition to variables introduced to the selection equation, we include a vector for R&D and innovation policy including six additional variables. These variables are not introduced to the selection equation, as intuitively only innovators invest in R&D and apply public funding for that purpose. Within the markets vector, the variable operating in international markets is replaced with the pressure of competition to avoid high correlation between the two equations. All the variables are expected to have a positive impact on the innovation output.

The estimation results of the Finnish firms can be found in Table 5. Estimation has been completed with 960 observations of which 464 are included in the

[13] Marginal effect is the derivative of the combination of estimated equations (see Section 4).

second part of the tobit estimation. The variable on pressure of competition has been dropped due to collinearity in the Finnish Sample.

Table 5. Estimates of the Heckman Model, Finland[14]

Vector	Variables	1. Propensity to innovate Pr(y>0)	Asymptotic t-value	2. Innovation Output E (y | y > 0)	Asymptotic t-value	3. Innovation Output E(y)	Asymptotic t-value
FIRM	Medium (50-250 emp)	0.24 **	0.02	-0.04	-1.17	0.00	0.21
	Large (250+ emp)	0.97 ***	0.00	-0.05	-0.64	0.05 **	1.96
	Group company	0.04	0.73	-0.01	-0.25	0.00	0.02
	Sales growth rate 1998-2000	0.30 ***	0.00	0.10 ***	3.49	0.08 ***	5.55
R&D	R&D/sales	-	-	0.71 ***	5.67	0.34 ***	5.57
	Doing continuous R&D	-	-	0.02	1.04	0.01	1.04
	Doing cooperative R&D	-	-	-0.03	-1.15	-0.01	-1.15
POLICY	Public Funding	-	-	0.00	0.20	0.00	0.20
	Proximity to basic research	-	-	0.00	0.23	0.00	0.23
MARKETS	Operating internationally	0.27 ***	0.01	-	-	0.02	1.72
	Pressure of competition	-	-		-	-	-
INDUSTRY	Food	0.08	0.74	0.00	-0.04	0.01	0.17
	Textiles	0.34	0.20	0.03	0.38	0.05	1.00
	Wood	-0.34	0.10	0.00	-0.07	-0.03	-1.15
	Chemicals	0.45	0.09	-0.06	-0.88	0.00	0.10
	Plastic	0.33	0.16	0.03	0.46	0.05	1.15
	Metals	0.18	0.39	0.01	0.18	0.02	0.64
	M&E	0.51 **	0.02	0.08	1.29	0.10 **	2.53
	Electronic	0.51 **	0.02	0.08	1.23	0.10 **	2.35
	Vehicles	-0.25	0.35	0.23 ***	3.28	0.07	1.32
	NEC	0.50 **	0.05	0.02	0.31	0.06	1.31
OTHER	Constant	-0.64 ***	-3.44	0.17	1.13	0.10	
	Inverse Mills Ratio	-	-	-0.04	-0.32	-	-
	Correlation coefficient	-	-	-0.19	-	-	-

***	1% confidence level	Number of obs	960
**	5% confidence level	Censored obs	496
*	10% confidence level	Uncensored obs	464
		Wald chi2(34)	245.4
		Prob > chi2	0.0

Regarding the first estimation demonstrating the effects on propensity to innovate, machinery and equipment and electronic products industries are found to be significantly more likely to innovate than our reference group, non-metals. The effects of these two industries are also nearly equal. Furthermore, the propensity to innovate seems to increase with size. Large firms are more likely to innovate than medium size firms and medium size firms are more likely to be

[14] Maximum likelihood estimates, Original CIS 3 data, 2000.

innovative than small firms. The size effect is consistent with the earlier studies. Moreover, firms operating in the international markets are more likely to innovate than domestic firms and the propensity to innovate seems to increase with past sales growth.

The second part of the tobit estimation exhibits the effects on innovative output, share in sales of innovative products. In this estimation, the only industry effect significantly differing from the reference group is the effect of vehicle sector. Innovative output increases also with past sales growth rate and investments in R&D. The latter effect is large and significant demonstrating that in Finland R&D investments and innovation output have a clear link. However, the coefficients linking public innovation policy to innovative output (public funding and proximity to basic research) do not show any significant effects even though in Finland significantly more companies received public funding than in the two other countries. This may indicate decreasing returns to scale in public R&D funding. Even though the result is tentative, it is alerting, as public organisations play a major role in innovation funding.

In the third part of the estimation, the effects of propensity to innovate and innovation output are combined to estimate marginal effects of innovative output unconditional on being innovative. The constant term, predicted innovation output for reference group, which takes the value 9.7 % should be interpreted as a starting point for marginal effects.

Like in the first part of the estimation where machinery and equipment increased propensity to innovate, these sectors also improve the innovation output and the effects are nearly equal. Innovation output is on average 9.6 % larger in electronic sector and 9.7 % larger in machinery and equipment than in the non-metals reference sector. The size effect has diminished due to negative but insignificant coefficients in the second part, as a result only the large firm group being significantly different from the reference group. Innovation output of the large companies is 5.3 %-points larger than innovation output of the small companies. Furthermore, sales growth, R&D investments and operating in international markets increase innovation output also when non-innovative companies are included in the analysis. On average, 1 %-point increase in R&D spending increases innovation output by 0.34 %-points. Furthermore, a 1 %-point increase in sales growth rate increases innovation output by 0.05 %-points. Firms operating in international markets instead of domestic are likely to generate 2.4 %-points larger innovative output.

The estimation results of Belgian firms can be found in Table 6. Estimation has been done with 679 observations of which 327 are included in the second part of the tobit estimation.

Table 6. Estimates of the Heckman Model, Belgium[15]

Vector	Variables	1. Propensity to innovate Pr(y>0)	Asymptotic t-value	2. Innovation Output E (y | y > 0)	Asymptotic t-value	3. Innovation Output E(y)	Asymptotic t-value
FIRM	Medium (50-250 emp)	0.41 ***	2.89	0.03	0.65	0.04 **	2.39
	Large (250+ emp)	0.81 ***	5.12	0.02	0.40	0.07 ***	3.10
	Group company	0.00	-0.03	-0.04	-1.62	-0.02	-1.28
	Sales growth rate 1998-2000	0.23 *	1.64	0.10 *	3.08	0.06 ***	3.74
R&D	R&D/sales	-	-	0.11	0.97	0.05	0.96
	Doing continuous R&D	-	-	-0.01	-0.46	-0.01	-0.46
	Doing cooperative R&D	-	-	0.03	1.36	0.01	1.36
POLICY	Public Funding	-	-	-0.06 ***	-2.62	-0.03 ***	-2.61
	Proximity to basic research	-	-	0.00	0.05	0.00	0.05
MARKETS	Operating internationally	0.36 ***	3.28	-	-	0.03 *	1.94
	Pressure of competition	-	-	0.07 ***	3.13	0.03 ***	3.10
INDUSTRY	Food	0.13	0.47	-0.17 ***	-2.97	-0.08 ***	-2.59
	Textiles	-0.03	-0.12	-0.05	-0.85	-0.03	-0.80
	Wood	-0.19	-0.67	-0.13 **	-2.09	-0.07 **	-2.49
	Chemicals	0.31	1.16	-0.11 **	-2.11	-0.04	-1.33
	Plastic	0.31	1.05	-0.06	-1.01	-0.01	-0.33
	Metals	-0.05	-0.19	-0.07	-1.33	-0.04	-1.28
	M&E	0.44 *	1.69	-0.04	-0.69	0.01	0.22
	Electronic	0.41	1.43	0.02	0.36	0.04	1.06
	Vehicles	0.53 *	1.71	0.14 **	2.06	0.13 **	2.49
	NEC	0.18	0.44	-0.08	-0.90	-0.03	-0.56
OTHER	Constant	-0.79	-3.27	0.23	1.77	0.09	
	Inverse Mills Ratio	-	-	0.01	0.09	-	-
	Correlation coefficient	-	-	0.05	-	-	-

***	1% confidence level	Number of obs	679
**	5% confidence level	Censored obs	352
*	10% confidence level	Uncensored obs	327
		Wald chi2(34)	144.6
		Prob > chi2	0.0

In the selection equation of the tobit regression, we find that machinery and equipment and vehicle sectors are most likely to be innovative in Belgium. The effect of vehicles sector is slightly more significant. Furthermore, the effect of electronic sector is not too far for being significantly different from the reference sector. In the Belgian sample, there exists a similar size effect as in the Finnish sample and as in the earlier studies. As in the Finnish sample, sales growth rate and operating in international markets increase the propensity to innovate.

[15] Maximum likelihood estimates, Micro-aggregated CIS 3 data, 2000.

Considering the innovation output part of the model, vehicles sector has a positive and significant effect on the innovation output whereas the effect of food, wood and chemicals sectors are significantly and negatively different from the reference group. Innovative output seems to increase with past sales growth and the pressure of competition. However, the effect of innovation input is not significantly different from zero. Furthermore, the effect of public funding, one of the innovation policy variables is not only significant but also negative.

Considering the marginal effects, we observe that the positive and significant effect on innovation output by the vehicle sector remains whereas the effect of machinery and equipment has diluted. The constant innovation output for the reference group is 9.4 %. Operating in vehicles sector increases innovation output by 13 %-points compared to the reference sector[16]. Moreover, operating in food or wood sectors has a negative impact on innovation output unconditional on being innovative. The size effect from the first part of the model has remained, as innovative output increases with size. Medium-size firms are likely to generate 4.4 %-points larger innovation output and large firms 7.4 %-points larger innovation output than small firms. In addition, 1 %-points increase in past sales growth raises innovation output by 0.065 %-points. Pressure of competition increases innovation output by 3.1 %-points and public funding has a negative impact of -2.7 %-points. Furthermore, operating in international markets instead of domestic ones increases innovation output by 2.7 %-points.

The estimation results of German firms can be found in Table 7. Estimation has been done with 1,374 observations of which 715 are included in the second part of the tobit estimation and represent innovative firms. The food sector is dropped due to the small sample of firms in the industry.

From the estimation of the selection equation, we find that plastics, machinery and equipment and electronic sectors are most likely to innovate. Of those three sectors, the effect of the electronic sector is the most significant. The size effect is similar to those in the Finnish and Belgian samples i.e. the propensity to innovate increases with firm size. The past sales growth and international operations also enhance the propensity to innovate following the results in the earlier estimations. In the German sample, group companies seem to be more likely to innovate thus differing from the Belgian and Finnish samples.

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[16] Analysing the industry effects in the Belgian sample, it should be remembered that the reference sector, non-metals, performed worst in innovation output comparison (see Table 4).

Table 7. Estimates of the Heckman Model, Germany[17]

Vector	Variables	1. Propensity to innovate Pr(y>0)	Asymptotic t-value	2. Innovation Output E (y | y > 0)	Asymptotic t-value	3. Innovation Output E(y)	Asymptotic t-value
FIRM	Medium (50-250 emp)	0.22 **	2.44	-0.01	-0.45	0.01	0.58
	Large (250+ emp)	0.63 ***	5.73	-0.01	-0.26	0.03 *	1.82
	Group company	0.24 ***	2.76	0.02	0.85	0.03 **	2.18
	Sales growth rate 1998-2000	0.22 *	1.80	0.06 *	1.95	0.05 ***	2.68
R&D	R&D/sales	-	-	0.19	1.61	0.10	1.61
	Doing continuous R&D	-	-	0.01	0.41	0.01	0.41
	Doing cooperative R&D	-	-	0.01	0.62	0.01	0.62
POLICY	Public Funding	-	-	0.04 **	2.26	0.02 **	2.26
	Proximity to basic research	-	-	0.07 **	2.39	0.03 **	2.39
MARKETS	Operating internationally	0.41 ***	5.29	-	-	0.01 ***	2.63
	Pressure of competition	-	-	0.03 *	1.83	0.02 *	1.83
INDUSTRY	Food	-	-	-	-	-	-
	Textiles	-0.27	-1.33	0.01	0.23	-0.02	-0.51
	Wood	-0.18	-0.95	0.04	0.73	0.00	0.15
	Chemicals	0.30	1.54	-0.03	-0.56	0.00	0.06
	Plastic	0.50 ***	2.67	0.04	0.68	0.06	1.61
	Metals	-0.14	-0.84	-0.03	-0.71	-0.03	-1.06
	M&E	0.48 ***	2.75	0.07	1.40	0.08 **	2.44
	Electronic	0.74 ***	4.15	0.07	1.35	0.10 ***	2.80
	Vehicles	0.11	0.50	0.01	0.17	0.01	0.38
	NEC	0.01	0.05	0.09	1.41	0.05	1.15
OTHER	Constant	-0.71 ***	-4.51	0.12	1.15	0.15	-
	Inverse Mills Ratio	-	-	0.12	1.55	-	-
	Correlation coefficient	-	-	0.49	-	-	-

***	1% confidence level	Number of obs	1 374
**	5% confidence level	Censored obs	659
*	10% confidence level	Uncensored obs	715
		Wald chi2(34)	210.8
		Prob > chi2	0.0

In the second part of the model, the impact of industries is not significantly different from the reference group. The past sales growth rate still increases the innovation output. The effect of innovation input is not significantly different from zero but not too far on being significantly positive. Regarding the innovation policy variables, Germany seems to be the only one of the three countries studied where public funding and proximity to basic research have a positive and significant influence on innovation output. Moreover, pressure of competition seems to improve innovation output.

[17] Maximum likelihood estimates, Micro-aggregated CIS 3 data, 2000.

Regarding the marginal effects when we observe the total sample, the constant innovation output in Germany (14.7 %) is significantly larger than in the Belgian (9.4 %) and in the Finnish (9.7 %) sample and therefore the marginal effects can be smaller and still indicate larger innovation output. Almost all firm and market effects have remained significant: Large firms generate 3.4 %-points larger innovation output than small firms. In group companies, innovation output is likely to be 2.7 %-points larger than in independent firms. A 1 %-point increase in past sales growth would increase innovation output by 0.047 %-points. Furthermore, public innovation policy variables still impact innovation output: firms that receive public funding are likely to generate 2.2 %-points larger innovation output and firms close to basic research 3.5 %-points larger innovative sales. Electronic (9.6 %-points) and machinery and equipment (7.6 %-points) sectors still significantly and positively differ from other industries whereas the effect of the plastic sector has diluted. Regarding the market factors, internationally operating companies are likely to generate 1.1 %-points higher innovation output than domestic companies. Moreover, in firms who declare increasing market share as an effect of innovation, the innovation output is from the average level 1.8 %-points higher than in other firms.

After examining the country regression, we pool the data to form a common story to depict innovation performance (see Table 8). In this regression we introduce two additional dummies: Finland and Belgium variables to demonstrate country effects with Germany as a reference group. The impacts can be for instance differences in innovation policy or more positive market conditions that are not captured in other variables. It must also be remarked that countries have not been weighted resulting to Germany having a substantially larger weight in the sample than Belgium or Finland. Altogether we have 3,013 observations of which 1,506 illustrate the performance of innovative firms.

In the selection equation part of the pooled regression, we find several industry effects that are significantly different from the reference group. First, the firms in the electronic and in the machinery and equipment industry seem to be most likely to innovate. Second, the effect of the plastic and chemicals industries are also positively and significantly different from zero. Third, firms operating in the wood industry are less likely to innovate. The effect of size follows earlier findings, as larger firms are more likely to innovate. Moreover, the effects of past growth and international operations support earlier findings.

In the second part, the industry effects are slightly different than in the first part: being part of the electronic industry or the vehicles industry increases innovation output whereas operating in the food sector diminishes innovation output. Past sales growth rate, R&D spending and the pressure of competition also increase innovation output. The effects of country dummies are significantly different from the reference group and negative indicating that German firms are likely to

generate higher innovative output than Finnish and Belgian firms. The Finnish firms are slightly more innovative than Belgian firms in this respect.

Table 8. Pooled Heckman Model Estimates: Belgium, Finland and Germany[18]

Vector	Variables	1. Propensity to innovate Pr(y>0)	Asymptotic t-value	2. Innovation Output E (y | y > 0)	Asymptotic t-value	3. Innovation Output E(y)	Asymptotic t-value
FIRM	Medium (50-250 emp)	0.253 ***	4.34	-0.009	-0.5	0.013	1.52
	Large (250+ emp)	0.766 ***	10.19	-0.007	-0.23	0.046 ***	3.64
	Part of a group	0.101	1.82	-0.001	-0.09	0.007	0.89
	Sales growth rate 1998-2000	0.254 ***	3.70	0.095 ***	5.41	0.066 ***	7.27
R&D	R&D/sales	-	-	0.354 ***	4.97	0.178 ***	4.95
	Doing continuous R&D	-	-	0.007	0.5	0.004	0.50
	Doing cooperative R&D	-	-	0.006	0.49	0.003	0.49
POLICY	Public Funding	-	-	0.012	1.02	0.006	1.02
	Proximity to basic research	-	-	0.021	1.12	0.010	1.12
MARKETS	Operating internationally	0.350 ***	6.62	-	-	0.025 ***	3.45
	Pressure of competition	-	-	0.043 ***	3.42	0.022 ***	3.41
INDUSTRY	Food	0.067	0.44	-0.082 **	-2.17	-0.038 *	-1.82
	Textiles	-0.059	-0.42	0.020	0.57	0.005	0.26
	Wood	-0.283 **	-2.27	-0.026	-0.79	-0.032 **	-2.03
	Chemicals	0.346 ***	2.61	-0.052	-1.57	-0.008	-0.40
	Plastic	0.396 ***	3.03	0.007	0.21	0.032	1.47
	Metals	-0.054	-0.46	-0.027	-0.9	-0.017	-1.04
	M&E	0.453 ***	3.81	0.052	1.57	0.063 ***	3.18
	Electronic	0.614 ***	4.95	0.063 **	1.77	0.083 ***	3.77
	Vehicles	0.086	0.58	0.104 **	2.88	0.061 **	2.46
	NEC	0.222	1.40	0.031	0.78	0.034	1.31
COUNTRY	Finland	0.071	1.21	-0.071 ***	-4.68	-0.031 ***	-3.61
	Belgium	-0.088	-1.38	-0.086 ***	-5.79	-0.048 ***	-5.94
OTHER	Constant	-0.688 ***	-6.2	0.175 **	2.4	0.118	
	Inversed Mills Ratio	-	-	0.061	1.1		
	Correlation coefficient	-	-	0.283			

***	1% confidence level	Number of obs	3013
**	5% confidence level	Censored obs	1507
*	10% confidence level	Uncensored obs	1506
		Wald chi2(38)	524.3
		Prob > chi2	0

When combining the results of the tobit model, we observe that the constant innovation output (11.8 %) is larger than in Belgium and Finland but smaller than in Germany. Furthermore, it is found that machinery and equipment, electronic products and vehicles are the sectors which generate more innovation

[18] Maximum likelihood Estimates, CIS 3 micro-aggregated and raw data 2000.

output regardless of the firms being innovators or not. From these sectors the effect of the electronic sector is the most significant, as innovation output is likely to be 8.3 %-points larger than in the reference group. The similar figure for machinery and equipment is 6.3 %-points and for vehicles 6.1 %-points. Furthermore, firms in the food and wood sector are less likely to generate innovation output the effects being nearly equal: -3.8 %-points for food and -3.2 %-points for wood sector. The size effect has diluted and only large firms seem to generate 4.6 %-points higher innovation output than small firms. Regarding innovation input, 1 %-point increase in R&D spending raises innovation output by 0.18 %-points. Market variables (international operations 2.5 %-points and pressure of competition 2.2 %-points) remain as a significant variables enhancing innovation output. Furthermore, Finland and Belgium generate less innovation output than Germany regardless of observing the whole sample or only innovators: the effect of Finland is -3.1 %-points and the effect of Belgium -4.8 %-points.

When comparing the estimation results to our reference study of Mohnen and Dagenais (2001) on Ireland and Denmark, we find that innovative industries, electronic products and vehicles, are roughly the same in both studies and all the countries. Effects of firm size are also alike: size influences positively to propensity to innovate but effects on innovative sales are not significantly different from zero. This relation is also known from other earlier discussed studies. Perhaps the most important difference between the studies is that Mohnen and Dagenais (ibid.) do not find significant relationship between innovation input and innovation output. On the other hand, in their study, undertaking continuous R&D is a positive and significantly different from zero whereas we do not find this proxy significantly different from zero in any country regressions.

6. Innovation indicator

This section presents the innovation indicator constructed with the aid of pooled regression. We can compute the mean expected share in sales of innovative products conditional on the observed values of the explanatory variables for each observation in the sample from the qualitative and quantitative information on innovation contained in the CIS 3 data. For computing the predicted innovation output values, we use the pooled regression to form a common story behind the different countries. Following Mohnen and Dagenais (2001) this expectation is computed from the joint probability distribution of the error terms in equations, the estimated threshold above which an enterprise becomes innovative, and the estimated regression line of the share of innovative sales. In Table 9, we report the industry specific weighted averages[19] of the expected conditional shares of innovation output and of the observed shares of innovation output over all firms (innovative or not).

We combine the methodology used by Mohnen and Dagenais (2001) and Mohnen et al. (2006) by computing the predicted values as in the former study but estimating the predicted values from pooled regression as in the latter study. However, it must be noted that the figures are entirely based on pooled estimates. Hence countries have not been given equal weights, like in the model of Mohnen et al. (2006). It is evident that German firms thus have a larger weight in the sample. Nevertheless, it can be stated that a bigger country should have a larger weight and, as we do not know the response rate in different countries, it would be difficult to correctly weight the countries. Following the terminology of Mairesse and Mohnen (2002) we call the residual between observed and predicted innovation output innovativeness, the unexplained part of the firm innovation performance. Thus the predicted values take into account the size differences, industry composition, innovation output, operating in international markets, sales growth and other variables explaining innovation output. Therefore, the innovativeness in the innovation function corresponds to total factor productivity in the production function.

[19] Natural logarithm of the sales has been used to weight the averages.

Table 9. Innovation Indicator and Innovativity, %

	Finland				Belgium			
	Innovation Output: Share in Sales of New Products							
Industry	**Predicted conditional mean in %**	**Observed average in %**	**Correlation between observed and predicted**	**Innova-tivity**	**Predicted conditional mean in %**	**Observed average in %**	**Correlation between observed and predicted**	**Innova-tivity**
All firms	11.6	11.5	0.58	-0.1	10.1	10.2	0.51	0.1
Innovators	18.2	22.5	0.49	4.2	15.6	20.3	0.36	4.7
Non-innovators	4.7	0.0	-	-4.7	4.6	0.0	-	-4.6
NACE:								
Food	4.0	12.2	0.39	8.2	2.9	2.9	0.19	0.1
Textiles	9.9	8.3	0.33	-1.6	10.5	10.2	0.33	-0.3
Wood	7.5	5.2	0.37	-2.4	7.7	6.7	0.63	-1.0
Chemicals	10.5	8.8	0.20	-1.7	8.0	9.7	0.35	1.6
Plastic	10.2	10.4	0.43	0.2	9.8	10.1	0.68	0.3
Non-Metals	9.4	6.8	0.44	-2.6	8.3	10.1	0.44	1.8
Metals	8.5	8.9	0.52	0.4	6.5	6.4	0.47	-0.1
M&E	16.9	18.0	0.58	1.0	14.8	11.6	0.55	-3.2
Electronic	21.1	23.7	0.66	2.6	15.1	16.5	0.59	1.4
Vehicles	14.5	13.7	0.47	-0.9	19.4	24.9	0.33	5.5
NEC	12.9	11.1	0.51	-1.8	13.9	8.9	0.39	-5.0

	Germany				Total			
	Innovation Output: Share in Sales of New Products							
Industry	**Predicted conditional mean in %**	**Observed average in %**	**Correlation between observed and predicted**	**Innova-tivity**	**Predicted conditional mean in %**	**Observed average in %**	**Correlation between observed and predicted**	**Innova-tivity**
All firms	16.5	17.3	0.38	0.8	13.9	14.3	0.45	0.4
Innovators	23.4	30.9	-0.03	7.5	20.6	26.8	0.20	6.2
Non-innovators	7.6	0.0	-	-7.6	6.2	0.0	-	-6.2
NACE:								
Food	-	-	-	-	3.3	4.6	0.30	1.3
Textiles	11.6	11.3	0.50	-0.3	11.0	10.6	0.44	-0.5
Wood	11.3	11.4	0.34	0.1	9.3	8.4	0.39	-0.9
Chemicals	13.2	15.7	0.30	2.5	10.9	12.5	0.34	1.6
Plastic	16.2	18.8	0.34	2.5	13.9	15.6	0.42	1.7
Non-Metals	11.7	13.9	0.43	2.2	10.5	11.6	0.43	1.1
Metals	11.2	10.2	0.36	-1.0	9.6	9.1	0.40	-0.6
M&E	21.7	21.6	0.41	0.0	19.1	18.6	0.48	-0.6
Electronic	23.9	25.3	0.32	1.4	21.8	23.5	0.44	1.6
Vehicles	22.0	24.2	-0.09	2.2	20.0	22.5	0.11	2.6
NEC	15.9	17.9	0.32	2.0	14.8	14.7	0.37	0.0

According to predicted and observed values, the most innovative firms in our sample are found in Germany (innovation outputs 16.5 % predicted and 17.3 % observed) whereas Finland ranks second (11.6 % predicted and 11.5 % observed) and Belgium third (10.1 % predicted and 10.2 % observed). In Finland, our model suggests that the average innovative sales should be 0.1 %-points smaller than the observed average. In Belgium, the respective figure is only 0.1 % higher than observed. In Germany the actual average innovative sales is 0.8 %-points higher than predicted. Regarding the innovative sample, the mean observed average of innovation output is higher than predicted in all countries. Moreover, in every industry the predicted innovation outputs are larger than the actual

observed outputs. The predicted means are also positive for non-innovators, which is due to the fact that in the first figure we use the probability of innovating and the predicted amount of innovation conditional on being above the innovative threshold, and in the second figure we use the actual amount of innovative sales.

The third column in Table 9 demonstrates the correlation between observed and predicted innovation output values. In the total sample, the correlation is 0.45. Regarding the country results, the model seems to predict innovation output best for Finnish firms (correlation 0.58) and worst for German firms (correlation 0.38). Considering different industries highest correlations are found in the machinery and equipment (0.48), electronic products (0.44) and wood (0.44) sectors. The lowest correlations are found in vehicles sector (0.11), which is intuitive as its performance varies between different countries.

The most innovative sectors seem to be roughly the same in all countries. Electronic products, machinery and equipment and vehicles are predicted and observed the most innovative sectors in each country. However, the significance of the vehicles sector is lower in Finland and the significance of the machinery and equipment is lower in Belgium. The least innovative sectors in the sample are food, food and metals industries. However, the significance varies in different countries and between predicted observed values.

Regarding the innovativity in different sectors and different countries, the German firms seem to generate larger innovative outputs than predicted whereas on average the innovativity is quite similar in Belgium and Finland. The largest positive differences are found in the Finnish food sector in which the observed innovation output is 8.2 %-points higher than predicted and in the Finnish electronic products sectors in which the difference between predicted and observed is 2.6 %-points. The good performance of the Finnish food sector is probably explained by the poor performance of food sector in Germany and Belgium, which reduces the expectations. The worst performing sectors compared to the expectations seem to be the machinery and equipment sector in Belgium and (difference -3.6 %-points) and non-metals sector in Finland (difference -2.6 %-points).

In general, the innovativity in Finnish firms seems to be lower compared to Belgian and especially to German firms. However, the country differences are quite small (<1 %-points) indicating that the model predicts innovation performance quite well and it is difficult to say whether the differences are large enough to draw a conclusion on the differences in innovation performance. One possible reason for high innovation performance in Germany is the large share of innovative industries in the sample: 56 % of the sample firms belong to electronic products, vehicles or machinery and equipment industries whereas the respective figure is 41 % in Finland and 22 % in Belgium. These sectors are

found to generate largest innovation outputs. The pooled regression also includes country effects, which are not implicitly explained. Hence, the inclusion decreases the unexplained part of the innovation function reducing innovativity. Nevertheless, it can be predicted that if we excluded country dummies from the estimation, innovativity would be smaller for Belgium and Finland due to negative effects.

Regarding the innovativity in different industries, innovativity in the electronic sector seems to be high in Finland. However, the performances in other sectors are not considerably better than in other countries. This would indicate that the large public attention towards innovations does not reflect innovation performance of Finnish companies apart from the electronic sector.

If we compare our results to the comparison of Ireland and Denmark by Mohnen and Dagenais (2001) the main observation is that both the predicted and observed means of innovative sales are larger in their study than in ours. This may be a result of their smaller samples (559 for Denmark and 692 for Ireland) which may be skewed towards innovators. In their sample, more than 60 % of the companies were innovators compared to the innovator share of around 50 % in our sample. Moreover, their estimates seem to predict the actual shares of innovation output better, as the correlations between observed and predicted are higher. Regarding the industry results, both models generate quite similar results: machinery and electronic products ranked high and wood sector performed worst already in 1992. Their results did not produce any considerable differences between the two countries. However, they concluded that Denmark seems to be more innovative than Ireland. Our conclusion is that Germany seems to be more innovative than Belgium and Finland whereas the differences in innovativeness in Belgium and Finland are so small that it is difficult to state which one is overall more innovative. However, it must be remembered that the models differ somewhat, as Mohnen and Dagenais (2001) do not use pooled results but use predicted values obtained from the country samples.

In comparison to the results of the accounting framework of Mohnen et al. (2006) in our model the differences in innovativeness are smaller. Nevertheless, the innovation outputs are significantly larger indicating that CIS1 has been more skewed towards innovators than CIS3. Furthermore, they also find that the innovativeness is largest in Germany (4.6 %-points) and the innovativeness in Belgium is 0.2 %-points (not too far from our 0.1 %-points). However, their model compares innovation performance of seven European countries with CIS1 data by using slightly different methods. For instance, they give each country an equal weight whereas in our sample the pattern how innovation output is generated is dominated by the German sample.

Figure 2. Predicted Conditional Means of Innovation Output, %

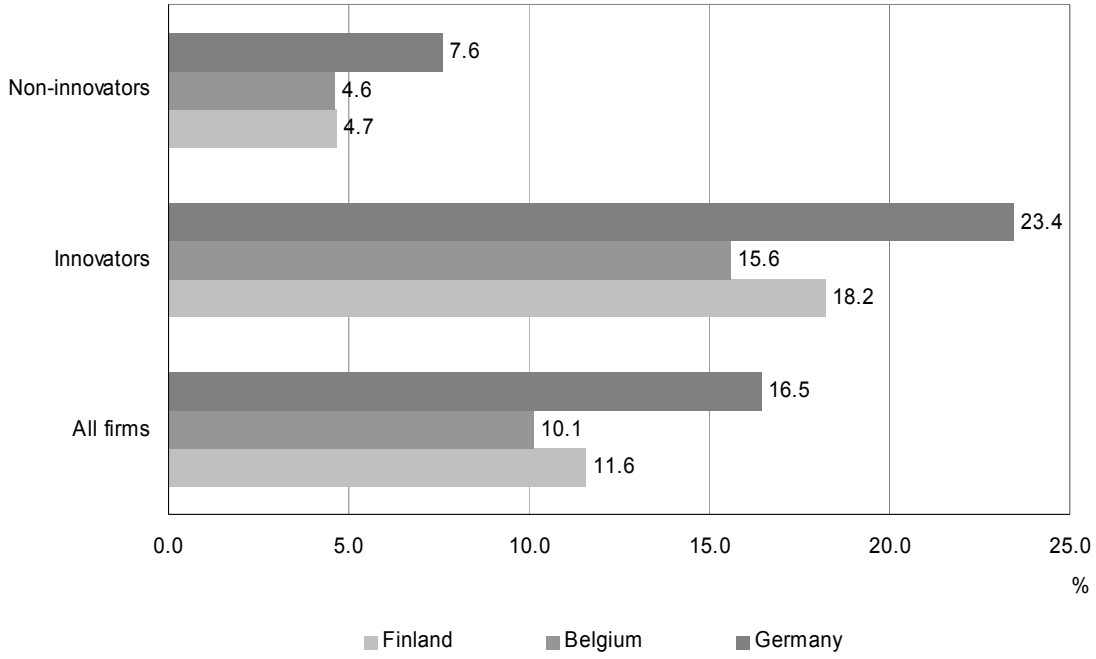
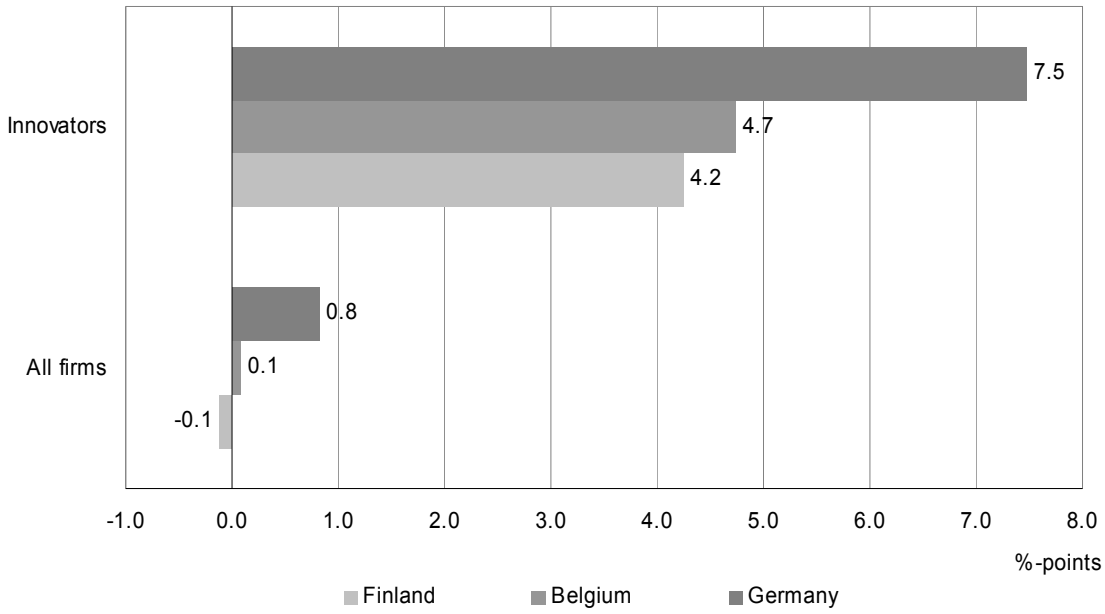


Figure 3. Innovativity[20], %-points



[20] Difference between observed and predicted innovation output.

7. Discussion and conclusions

In this paper, we elaborate on the studies of Mohnen and Dagenais (2001) and Mairesse and Mohnen (2002) by constructing an innovation indicator based on pooled regression estimates. Using a combination of explanatory variables including firm, industry, R&D, markets, and policy related effects for the propensity to innovate and the amount of innovation we estimate a generalised tobit model and use it to compute the expected share of innovative sales. Innovativeness is defined as the part of sales that is not explained by the model and corresponds to total factor productivity in the production function.

We construct the innovation indicator by using data from the third Community Innovation Survey (CIS3) for the manufacturing sectors of Belgium, Finland and Germany. As Lööf et al. (2002) point out the CIS measures for innovation input and output exhibit several shortcomings. For example, the figures are based on the subjective opinions of the respondent to the survey. Moreover, innovation is a heterogeneous phenomenon showing large variations between industries and firm sizes. For many firms these measures are not necessarily familiar enough to give accurate estimations. However, despite the shortcomings we consider the data to be accurate enough to make tentative conclusions on innovation performance in different countries.

Another limitation of our study is the use of data from period of only three years. As it is commonly known, innovation benefits are materialised in the long-term and thus three years' period is hardly long enough to capture how innovation inputs transform into outputs. In Finland, the average commercialisation time for innovation has been found to be 3.5 years (Palmberg et al. 2000, p. 29) indicating that some innovation benefits are not materialized within the sample period. However, a combination of investments and R&D expenditures is found to have a positive effect on productivity suggesting that also current R&D expenditures at least partially affect innovation output (Parisi et al. 2002).

Following the earlier studies, we find that the propensity to innovate increases with size but there is no direct link from size to innovation output in the sample of innovators. The result is intuitive since larger firms tend to have more innovation activities. However, the size does not indicate better innovation results. Operating in international markets is also found to be linked to high innovation output indicating that facing international competition puts more pressure to introducing new products. Past sales growth is also related to high innovation output, which may indicate better access to finance and new markets. Group companies are only found to be more likely to innovate in Germany.

Regarding R&D variables, innovation input, R&D expenditures per sales has the strongest correlation to innovation output in Finland whereas in Germany and

Belgium it is almost significant at 10 % confidence level indicating that the link between innovation input and output is most straightforward in Finland. Other R&D variables, doing continuous or cooperative R&D do not show up as significant variables.

The most contradictory results are found in the coefficients of variables relating to public funding. First of all, public funding is found to be significantly and positively correlated with innovation output only in Germany. In Belgium, on the other hand, public funding has a significant but negative effect in innovation output. In Finland, where 66 % more innovators declare receiving public funding compared to other sample countries, public funding has no significant effect on innovation output. Even though this topic requires more scrutiny, the tentative result is alerting since public innovation organisations and their financing plays a major role in Finnish innovation and technology policy. On the other hand, as suggested by Palmberg et al. (2000), radical and complex innovations in Finland are often generated in collaboration with universities and research organisations and are associated more frequently with public funding. These complex innovations also require longer commercialisation times. Hence, it may be also that our short observation period deteriorates the effect of public funding and proximity to basic research. One possible explanation can be decreasing returns to scale in public funding: as such a large number of firms receive public funding in Finland; all of them do not necessarily need it.

Our tentative findings of the insignificance of public funding to the innovation reveal that more research attention should be given to the efficiency of public innovation funding. To elaborate on our study and to further study the Finnish innovation system and the public support for innovations, it would be tempting to investigate how the subsidies from various innovation organisations affect firm innovation performance. Moreover, introducing innovation subsidies as continuous variables instead of dummies could also give more information on the relationship between the public funding and innovation outputs.

In the pooled regression German firms are found to generate more innovative output than Finnish and Belgian firms. The result is partly explained by the fact that in the German sample the firms are larger than in the Belgian and Finnish samples. Moreover the R&D intensity and the share of innovators are slightly larger in the German sample, which can be an indicator that the sample is skewed towards innovators. To eliminate sample selection effects, the innovativity is the best indicator to assess country differences instead of pure figures on innovation output.

Regarding the innovation indicator and the expected and observed innovations, we find the most expectedly innovative sectors in Germany and the least expectedly innovative sectors in Belgium. The innovativity, on the other hand, is largest in Finnish food and electronic products sectors and Belgian vehicle

sector. The smallest innovativity figures are found in Belgian manufacturing of furniture and machinery and equipment. When combining all the firms and sectors, the innovativeness is largest in Germany and smallest in Finland. This is explained by the fact that in Germany basically all the industries produce solid innovation results whereas in Finland the output varies largely between sectors. Moreover, the share of the most innovative sectors in the sample is the highest in Germany. The innovativity of Belgian and Finnish firms is nearly equal, as the difference is only 0.2 %-points.

The industry results support the findings[21] that Finland is largely dependent on the electronic products sector in innovation input and output. In this sector, the expected and observed innovation outputs are largest within the Finnish industries. Furthermore, during the sample period (1998–2000) Finland was in the middle of information technology boom and which was likely to further boost the results of the electronic sector. Other sectors, excluding food, do not seem to generate significantly larger innovation outputs than expected than in other countries. Up to now, the largest productivity gains have also been realised in information technology manufacturing (Jalava & Pohjola 2005).

Innovation performance of firms as an area of investigation is enormous. Even though our study has given more information on the link between innovation inputs and outputs in Finnish manufacturing firms, further research is needed to link innovation outputs to the productivity and profitability of firms. Hence, an interesting extension of this study would be to broaden the time line of the study and link innovation output to productivity following CDM-model to further examine the link between innovations and economic growth. Including accounting data to survey responses would also increase the reliability of the results. This extension could give an insight whether the Finnish economic growth could be regarded as the outcome of firm innovation outputs and indirectly as the outcome of the innovation policy. Moreover, the effect of the funding of public organisations on innovation output should be further scrutinised. Based on our study Finland does not seem to be significantly more efficient in innovating than Belgium or Germany even though the electronic sector generates better than expected innovation output.

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[21] See for instance Tiede ja Teknologia 2004 (2005, p. 83–84 and 140).

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Appendices

Appendix 1: Computing the Innovation Indicator

The mean of Y conditional on the observed values for the explanatory variables Q and X from both equations is equal to

$$E(Y_i^* \mid Q_{ji}, X_{ji}) = \int_{\delta Q}^{\infty} \int_{0}^{1} Y_i \varphi(\varepsilon_i, Y_i) d\varepsilon_i dY_i \ . \tag{14}$$

After some manipulations, this expression can be shown to be retrieved from the area under a bivariate standard normal distribution function by the following formula

$$E(Y_i^* \mid Q_{ji}, X_{ji}) = \int_{-\delta Q_1}^{\infty} \int_{-\infty}^{\infty} \exp(\beta_i X_i + \sigma_2 u_i^*) / (1 + \exp(\beta_i X_i + \sigma_1 \varepsilon_i^*)) \varphi(\varepsilon_i^*, u_i^*) d\varepsilon_i^* du_i^* \tag{15}$$

where $u_i^* = u_i / \sigma_u, \varepsilon_i^* = \varepsilon_i$ and $\varphi(\varepsilon_i^*, u_i^*)$ is the bivariate standard normal distribution with correlation coefficient ρ. This conditional mean is then evaluated at the estimated coefficient values of δ, β and σ.

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