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Abstract

The paper investigates the effects of industry-level competition on firm-level innovation and productivity. We propose a refined version of the CDM model that analyses the impacts of competition on four interrelated stages of the innovation process: the choice of a firm to engage in innovation, its R&D intensity, its innovation output and labour productivity. We test the model on a firm-level panel dataset based on the last three waves of the innovation survey for Norway (CIS3, CIS4 and CIS5). The econometric results provide empirical support for the refined version of the CDM model. They show that enterprises in oligopolistic sectors have on average a greater propensity to engage in innovative activities and tend to invest a greater amount of resources in R&D. On the other hand, firms in competitive industries are characterised by a stronger impact of innovation input on their technological and economic performance.

JEL codes: L1; O3

Keywords: Competition; Innovation; Productivity; CDM model; CIS data

1. Introduction

The relationship between competition and innovation has attracted scholarly attention for a long time already (Cohen and Levin 1989; Sutton, 1997). The traditional approach focused on the possible negative impacts that market competition may have on innovation and R&D activities. Competition may in fact decrease the monopoly rents of prospective innovative firms, thus reducing their incentives to engage in R&D activities (Scherer 1967; Geroski 1990; Nickell 1996). This is an argument traditionally known as the *Schumpeterian effect*, which postulates the existence of a negative relationship between the degree of competition in an industry and the R&D intensity of firms.

More recently, however, a set of models rooted in the distance-to-frontier theoretical tradition have pointed out that competition may also spur innovation, because it may increase the incremental profits that firms obtain by investing in R&D activities (Aghion, Harris and Vickers 1997; Aghion et al. 2009). This second argument, the *escape-competition effect*, points out that the relationship between the degree of market competition and innovation may hence be positive, and even more so in neck-to-neck industries where competiton between rival firms is fierce.

Our paper intends to re-examine this topic from a novel perspective. Instead of just focusing on the relationship between competition and innovation, we also look at the technological and economic performance of innovative activities, and ask: *how does competition affect the relationship between innovation and productivity?* We investigate this novel research question by making use of the CDM model, a recent empirical approach to the study of innovation and firm-level productivity that has become increasingly popular in the last few years (Crepon, Duguet and Mairesse 1998; Hall and Mairesse 2006).

The CDM model is rooted in the traditional knowledge production function approach (Griliches 1979), but it refines the standard approach in one important way: instead of studying directly the impacts of R&D investments on the productivity performance of enterprises, it analyses the various stages of the innovative process. More precisely, the CDM model studies four interrelated stages of the innovation chain: the choice of a firm whether or not to engage in innovative activities; the amount of resources it decides to invest in R&D; the effects of these R&D investments on innovation output; and the impacts of innovation output on the productivity of the enterprise.

What new insights can this innovation-stages model bring to the literature on competition and innovation? The general idea explored in this paper is that the effects of competition on innovation previously identified in the literature may have different impacts on the various stages of the innovation chain. In particular, the *Schumpeterian effect* (negative effect of competition on innovation) is a mechanism that relates to the *ex-ante* incentives to innovate, and it is therefore likely to be observed in the early stages of the innovation process – i.e. the decision of a firm whether to engage in R&D and how much resources to devote to it. By contrast, the *escape-competition effect* (positive effect of competition on innovation) may be reinterpreted as an argument about the *ex-post* effects of innovation, i.e. the incremental profits that a firm effectively achieves – given its prior decision to invest in R&D and to join the innovation race. The escape-competition effect is therefore more likely to be observed when we focus on the later stages of the innovation chain, i.e. the technological and economic performance of innovative investments.

The paper proposes a refined version of the CDM model that explicitly takes into account these possible distinct effects of competition on the innovative process. In a nutshell, the model explores the hypotheses that: (1) the probability that a firm engages in innovation and the amount of resources it decides to invest are higher in oligopolistic sectors than in competitive industries (Schumpeterian effect – early innovation stages); (2) the impact of innovative efforts on firm performance (technological output and productivity) is stronger in competitive sectors than in oligopolistic industries (escape-competition effect – late innovation stages).

We carry out an econometric analysis of this refined CDM model by making use of a rich firm-level panel dataset based on the three most recent waves of the *Innovation Survey* for Norway: CIS3 (period: 1998-2000; N=3899), CIS4 (period: 2002-2004; N=4655) and CIS5 (period: 2004-2006; N=6443). The results of the estimations of the four equations composing the CDM model provide empirical support for the main hypotheses investigated in the paper, and show that the effects of competition on innovation are substantially different in the various innovation stages considered by the model.

The paper is organized as follows. Section 2 explains the refined version of the model and the resulting hypotheses; section 3 presents the panel dataset, the main indicators and some descriptive evidence; section 4 discusses the econometric results; and section 5 summarizes the conclusions and implications of the results.

2. Theoretical framework

2.1 Competition and innovation

The study of the relationships between competition and innovation represents one traditional and important research topic in the economics of innovation.[1] Classical works in this field were originally motivated by the empirical investigation of the effects that the degree of competition and concentration of an industry may have on firms' R&D and innovative activities. One of the key hypotheses, corroborated in several empirical studies, was that industry-level competition may decrease the monopoly rents of prospective innovative firms, thus reducing their incentives to engage in R&D activities (Scherer 1967; Geroski 1990; Nickell 1996). This is an argument traditionally known as the *Schumpeterian effect*, which postulates the existence of a negative relationship between the degree of competition in an industry and the R&D intensity of firms (Nicoletti and Scarpetta 2004; Griffith, Harrison and Simpson 2006; Tang 2006).

However, more recent research has also pointed out the possibility that product market competition may also turn out to boost R&D investments, since it may increase the incremental profits that firms obtain by investing in R&D activities (Aghion, Harris and Vickers 1997; Aghion et al. 2009). This second argument, the *escape-competition effect*, points out that the relationship between the degree of market competition and innovation may hence be positive, and even more so in neck-to-neck industries where competiton between rival firms is fierce. Considering together these two contrasting forces, Aghion and others (2005) have recently pointed out the existence of an inverted U-shape relationship between market competition and innovation.

While the traditional literature has focused on the various channels through which competition affects innovation, another branch of innovation research has however pointed out the existence of a two-way dynamic relationship between market structure and R&D. According to this view, a set of technological characteristics that are specific to each industry (e.g. technological opportunities, cumulativeness and appropriability conditions) contribute to shape the sectoral technological regime, which is in turn an important factor to understand market structure and Schumpeterian

[1] Surveys of this rich empirical literature can be found in Cohen and Levin (1989), Sutton (1997) and Ahn (2002).

patterns of innovation in different industries (Nelson and Winter 1982; Malerba and Orsenigo 1996; Malerba 2005; Castellacci and Zheng 2010). Further, as pointed out by industry life cycle studies, market structure and Schumpeterian patterns evolve over time as a result of the evolution of industries' technological trajectories, e.g. shifting from an early phase characterized by high entry and strong competition (Schumpeter Mark I) to a later more concentrated (oligopolistic) stage where a few incumbents dominate the technology market (Schumpeter Mark II; see Klepper 1996; 1997).[2]

2.2 Model and hypotheses

Our model investigates the effects of industry-level competition conditions on firm-level innovation and productivity.[3] The model proposes an extension of the CDM approach. The standard version of the CDM model argues that, in order to investigate the impacts of innovation on the productivity performance of firms, it is important to analyse four different stages of the innovation-productivity link (Crepon, Duguet and Mairesse 1998; Hall and Mairesse 2006; Lööf and Heshmati 2006; Parisi, Schiantarelli and Sembenelli 2006). (1) First, the firm decides whether to engage in innovative activities; (2) if the enterprise decides to engage in innovation, it then sets the amount of resources it wants to invest in R&D activities; (3) subsequently, the innovative input leads to an innovative output (e.g. new products); (4) finally, the innovative output leads to an improvement of the labour productivity of the firm.

We propose a refinement of the standard CDM model that analyses the effects of market structure and competition conditions on these different stages of the innovative process. Our extension of the CDM model is presented in the diagram in figure 1. The main idea we put forward is that the Schumpeterian effect (negative impact of competition on innovation) is mainly relevant for the first two stages of the innovative process (the innovative choice and R&D intensity of a firm), whereas the escape-competition effect (positive impact of competition on innovation) is more

[2] Surveys of the economics of innovation literature discussing similarities and differences between different theoretical approaches have recently been presented by Castellacci (2007; 2008) and Antonelli (2009).

[3] For a comprehensive overview of previous works on the determinants of firm-level productivity, see Bartelsman and Doms (2000). Wieser (2005) presents a useful survey of firm-level studies on the relationships between innovation and productivity rooted in Griliches' (1979) knowledge production function approach.

likely to be observed when we focus on the subsequent two stages (innovative output and productivity performance). The reason is the following. The Schumpeterian effect is about the firm's *ex-ante* incentives to innovate. In particular, as previously pointed out in the literature, a high degree of competition in the industry may negatively affect the firm's choice whether or not to engage in innovative activitites, and the amount of resources to invest in R&D. By contrast, the escape-competition effect may be interpreted as an argument about the *ex-post* results of innovative activities. Specifically, we argue that if a firm has previously decided to invest in R&D activities, the resulting innovation output and productivity performance may give the enterprise a greater advantage over its rivals in a competitive industry than in an oligopolistic sector (because, as explained below, only a few rivals innovate in the former case, while most of the competitors are innovators in the latter case).

< Figure 1 here >

The model assumes there are two industries in the economy, a competitive (C) and an oligopolistic (O) sector. The former has a population of N_C firms, and the latter N_O enterprises. We assume that there are more firms in the competitive than in the oligopolistic industry ($N_C > N_O$), and that, on average, enterprises in the former (latter) sector have a low (high) market share MS_{ij} (i.e. $MS_{iC} < MS_{iO}$).

Stage 1: Innovative choice

$$\Pr\{R\&D_{ij}\} = \begin{cases} \alpha_C \bullet FS_i & \text{if } j = C \\ \alpha_O \bullet FS_i & \text{if } j = O \end{cases} \qquad (1)$$

The probability that firm *i* decides to engage in R&D activities, $\Pr\{R\&D_{ij}\}$, is a function of a set of firm-specific characteristics FS_i (e.g. size, international orientation, managerial and organizational capabilities, etc.). This function is however affected by the degree of competition that characterizes industry *j*. In line with the Schumpeterian effect previously pointed out in the literature, we assume that: $\alpha_O > \alpha_C$, which implies that: $\Pr\{R\&D_{iO}\} > \Pr\{R\&D_{iC}\}$. This assumption is the first hypothesis that we seek to investigate in the empirical analysis.

Hypothesis 1 – Schumpeter effect I:
The probability that a firm decides to engage in R&D is higher in an oligopolistic industry than in a competitive sector.

This hypothesis also implies that: $(N_O^{INN} / N_O) > (N_C^{INN} / N_C)$, i.e. the share of innovative firms in the industry is greater in an oligopolistic than in a competitive market.

Stage 2: R&D intensity

$$R\&D_{ij} = \begin{cases} \beta_C \bullet FS_i & \text{if } j = C \\ \beta_O \bullet FS_i & \text{if } j = O \end{cases} \tag{2}$$

Once an enterprise has decided to engage in innovative activities, it must set the amount of resources to devote to R&D investments. Analogously to the previous equation and in line with the standard formulation of the CDM model, the R&D intensity of firm *i* in industry *j* ($R\&D_{ij}$) is represented as a function of the set of firm-specific characteristics FS_i. Again, we extend this standard formulation and allow this function to differ in the two industries of the economy. We assume that: $\beta_O > \beta_C$, which implies that: $R\&D_O > R\&D_C$. This is the second hypothesis that we put forward:

Hypothesis 2 – Schumpeter effect II:
The amount of resources that an enterprise decides to invest in R&D is on average higher in an oligopolistic industry than in a competitive sector.

Stage 3: Innovation output

$$IO_{ij} = \begin{cases} \gamma_C \bullet FS_i + \delta_C \bullet R\&D_{iC} & \text{if } j = C \\ \gamma_O \bullet FS_i + \delta_O \bullet R\&D_{iO} & \text{if } j = O \end{cases} \tag{3}$$

The R&D investments done by firm *i* in industry *j* subsequently lead to the innovation output of the enterprise (IO_{ij}). We focus here on a specific form of innovation output, the commercialization of new products. In line with the standard version of the CDM model, we define the variable IO_{ij} as the share of innovative sales of the firm (i.e. the turnover from the commercialization of new products divided by the total turnover of the enterprise). We assume this variable to be a linear function of two factors: firm-specific characteristics (FS_i) and innovation input (i.e. the R&D intensity of the firm $R\&D_{ij}$ that was analysed in equation 2 above). In order to highlight the effect of market structure on the input-output relationship, we then depart from the standard CDM model and make the specific assumption that: $\delta_C > \delta_O$. This assumption represents the third hypothesis that we seek to empirically investigate.

Hypothesis 3 – Escape-competition effect I
The effect of R&D expenditures on innovative output (share of innovative sales) is on average stronger in a competitive market than in an oligopolistic sector.

The reason for this proposition is that, for any given amount of sales from new products realized by a firm, the innovative output *share* is likely to be greater in a competitive than in an oligopolistic market, because the total turnover of the firm is on average smaller in the former than in the latter. In other words, smaller firms in competitive markets typically have a more narrow product range and smaller turnover size, so that the commercialization of any given amount of a new product will have a relatively stronger impact for them than for large oligopolistic enterprises in concentrated sectors.[4]
Notice that this hypothesis about the elasticity of innovation output with respect to innovation input ($\delta_C > \delta_O$) does not necessarily imply that: $IO_{iC} > IO_{iO}$. In fact, if hypothesis 2 holds true, the amount of innovative input invested by an enterprise is on average higher in an oligopolistic industry than in a competitive sector ($R\&D_O > R\&D_C$), and this would tend to counterbalance the effects of a greater input-output elasticity in competitive markets. All in all, the average level of IO_{ij} in the two

[4] Simply to illustrate this hypothesis, suppose to compare two firms: the one in the competitive sector (C) has a total turnover of 1000, whereas the one in the oligopolistic market (O) is larger and has a turnover of 2000. Suppose also, for simplicity, that the two firms face the same probability to produce a new product. Each unit of the new product is sold, say, at a unit price 20. This unit of innovative sale will represent 2% of the total turnover for firm C, but only 1% of the turnover for firm O.

industries is the result of these two contrasting forces: IO_{iC} will be greater than IO_{iO} if the effect of a higher input-output elasticity in the competitive industry is strong enough to counterbalance the greater R&D intensity that characterizes the average firm in an oligopolistic market.

Stage 4: Labour productivity

$$LP_{ij} = \begin{cases} \theta_C \bullet FS_i + \eta_C \bullet IO_{iC} & \text{if } j = C \\ \theta_O \bullet FS_i + \eta_O \bullet IO_{iO} & \text{if } j = O \end{cases} \qquad (4)$$

The fourth stage of the CDM model focuses on the effects of innovation output on labour productivity. The commercialization of new products enables firms to strengthen their competitive position, and hence increase their market shares, total turnover and labour productivity. The latter is represented as a linear function of two factors: firm-specific characteristics (FS_i) and innovation output (i.e. the share of innovative sales that was studied in equation 3 above). We refine this standard CDM model formulation by assuming that the impacts of innovative output on labour productivity may differ in the two sectors of the economy. In particular, we assume that: $\eta_C > \eta_O$. This is the fourth hypothesis that we put forward.

Hypothesis 4 – Escape-competition effect II

The effect of innovation output on labour productivity is on average stronger in a competitive sector than in an oligopolistic industry.

The rationale underlying this assumption is the following. Assume for simplicity that market demand Q_j is given in both sectors. In the competitive industry, there is a relatively low share of innovative firms (see hypothesis 1 above). Therefore, if firm *i* is an innovator, it will be able to increase its market share, total turnover and labour productivity substantially, thus strengthening its competitive position *vis-a-vis* its many non-innovative rivals. By contrast, in the oligopolistic market, the share of innovative enterprises is large (most incumbents innovate in order to maintain their competitive position), so that any given amount of innovation output realized by an enterprise will lead to a relatively small change in market shares, turnover and productivity *vis-a-vis* its competitors.

Similarly to what pointed out above in relation to the third hypothesis, this fourth assumption on the elasticity of labour productivity with respect to innovation output ($\eta_C > \eta_O$) does not necessarily imply that on average: $LP_{iC} > LP_{iO}$. The relative labour productivity of firms in the two industries is in fact a combined effect of two different forces: the elasticity of productivity with respect to innovation output, and the overall amount of innovative output realized by the average firm *i*. Our fourth hypothesis refers specifically to the former effect, whereas we do not formulate any a priori statement on the latter.

3. Data, indicators and descriptive evidence

Our empirical test of the model outlined in the previous section makes use of firm-level data from the *Community Innovation Surveys* (CIS) for Norway. The Community Innovation Survey is based on a questionnaire that is collected every two years for several thousands of firms in all European countries. The general guidelines for the questionnaire structure and data collection are provided by the EU agency *Eurostat*, whereas the data collection in each country is carried out by national statistical agencies. In Norway, the CIS firm-level data provider is the national statistical office (Statistisk sentralbyrå, SSB).

CIS data provide a rich set of information on the innovative activities, strategies, expenditures and results for thousands of firms in all European countries. The increasing availability and popularity of this useful data source has been one of the main driving forces behind the development of the CDM model (e.g. Crepon, Duguet and Mairesse 1998; Hall and Mairesse 2006; Griffith et al. 2006), since CIS data make it possible to measure both the inputs and outputs of the innovative process, and to analyse their effects on the economic performance of enterprises (Castellacci and Zheng 2008).

We make use of CIS firm-level data for Norway, and focus on the three most recent waves of the survey, which are those that present a better data quality and comparability of the questionnaires: the CIS3 (period: 1998-2000; N=3899), CIS4 (period: 2002-2004; N=4655) and CIS5 (period: 2004-2006; N=6443). The firms included in the surveys represent a large and representative sample of the Norwegian private sector. The sectoral coverage is broad, and it comprises around 40 two-digit level industries in both the manufacturing and the service branches.

In the empirical analysis, we make use of the following indicators, all of which are available in the three periods and have identical definition in the three waves of the innovation survey.

- **Labour productivity (log)**: Turnover divided by employment (log).

- **Productivity gap**: Difference between the highest labour productivity in each industry (technological frontier) and the firm's productivity. Each industry is defined at the 2-digit level.

- **Employment (log):** Number of employees (log), a standard measure of firm size.

- **Part of a group**: a dummy variable indicating whether a firm belongs to a group.

- **Market location:** a categorical variable that indicates whether a firm sells its products and services in local, national, European or other international markets. A higher value of this variable indicates a greater international propensity of the enterprise.

- **Engaged in R&D:** a dummy variable that indicates whether a firm has carried out R&D activities in each period.

- **R&D intensity**: R&D employees, share of total number of employees (log).

- **R&D purchase**: a dummy variable indicating whether a firm has carried out expenditures for the purchase of R&D from external providers.

- **Turnover from new products (log)**: Turnover from the commercialisation of new products, share of total turnover of the firm (log).

- **Appropriability strategies (A):** Two dummy variables that indicate whether a firm has made use of 'design' and 'complex design' as strategies to protect the results of their product innovation activities.

- **Hampering factors (H):** A set of dummy variables indicating whether a firm considers the following factors as important obstacles to its innovative activities: 'high costs'; 'lack of qualified personnel'; 'lack of other information'.

- **Herfindahl index**: The index is defined as the sum of squares of firms' turnover shares in each 2-digit industry. In some of the regressions we have transformed this into a dummy variable, which takes value 1 if the Herfindahl index for a sector is above the median value of the period (more concentrated, oligopolistic sector), and value 0 otherwise (less concentrated, competitive industry).[5]

Table 1 presents some basic descriptive statistics of the main variables in each of the three survey periods. The table indicates that, in general terms, there are no large differences across the three periods, and that the survey results are therefore quite comparable with each other. However, some of the variables in the CIS5 sample seem to differ somewhat from those in the previous two periods: the CIS5 sample is larger, the share of enterprises engaged in R&D activities is slightly smaller, and the average firm size and international propensity are also lower than in the previous two periods.[6]

Table 2 presents a comparison of the main firm-specific characteristics of innovative and non-innovative enterprises (the former are defined as those that have been engaged in R&D activities in the survey period, whereas the latter have not been

[5] Besides using the Herfindahl index as our main variable of industry concentration and competition conditions, we have also used two other indicators: (1) the C1 concentration index, and (2) the share of firms belonging to a group. The results obtained by measuring industry competition conditions through these variables are largely in line with those for the Herfindahl index. These additional results are not reported in the next section, and are available upon request.

[6] Table 1 suggests two implications for the regression analysis (see next section). The first is that it is important to take into account and correct for the possible bias deriving from the somewhat different sample composition and time-specific shocks in the three periods, e.g. by mean of time dummies. The second implication is that, given the little time variation shown by the data, it is unlikely that a fixed-effects panel model may estimate the parameters of interest with accuracy. A random-effect model may in this case be a useful alternative because it also exploits the large cross-sectional variability component contained in the data.

engaged in R&D). The comparison shows a remarkable difference between the two groups, which is stable across the three survey periods and in line with previous CDM analyses based on firm-level data for other countries (Hall and Mairesse 2006). On average, innovative enterprises have higher levels of labour productivity (hence a smaller gap from the industry frontier), greater firm size and probability to belong to a group, and a much greater propensity to internationalize.[7]

Table 3 reports the coefficients of correlation for the main variables that will be used in the regression analysis. In general terms, the table does not indicate the presence of any major problem of multicollinearity among the variables. The only indicator that may possibly be affected by this problem is the employment variable, which is negatively correlated with the R&D intensity indicator (since the latter is also defined in terms of R&D employees). We will consider this aspect further in the next section, which will present the results of the econometric analysis.

< Tables 1, 2 and 3 here >

[7] The difference between innovative and non-innovative firms is a well-established fact in this branch of applied literature. The resulting bias that may arise in the econometric estimation of this data sample is typically taken into account by means of procedures that correct for this type of selection bias (e.g. the Heckman two-step procedure). We will consider this aspect further in the next section.

4. Econometric analysis of the CDM model

4.1 Model specification and estimation methods

The econometric model we estimate is the refined version of the standard CDM model that has been presented in section 2. The model specification is the following:

Stage 1: Innovative choice

$$\Pr \{R\&D_{ij}\} = \alpha_j \bullet FS_{ij} + \varepsilon^1_{ij} \qquad (1')$$

Stage 2: R&D intensity

$$R\&D_{ij} = \beta_j \bullet FS_{ij} + \varepsilon^2_{ij} \qquad (2')$$

Stage 3: Innovation output

$$IO_{ij} = \gamma_j \bullet FS_{ij} + \delta_j \bullet R\&D_{ij} + \varepsilon^3_{ij} \qquad (3')$$

Stage 4: Labour productivity

$$LP_{ij} = \theta_j \bullet FS_{ij} + \eta_j \bullet IO_{ij} + \varepsilon^4_{ij} \qquad (4')$$

Given the four successive stages of the innovation-productivity link, the model is a system of four recursive equations, each of which focuses on one of the stages of the innovative process. The first equation estimates the probability that an enterprise engages in R&D activities, Pr $\{R\&D_{ij}\}$, and it is estimated for the whole sample of firms, including both innovative and non-innovative enterprises. The remaining equations focus instead on innovative firms only and exclude non-innovative ones (since these, by definition, do not have any innovative input and output). The second equation studies how the R&D intensity of the firm ($R\&D_{ij}$) is affected by a set of firm-specific characteristics (FS_{ij}). The third analyses the link between innovation input ($R\&D_{ij}$) and output (IO_{ij}, i.e. the share of turnover from innovative sales). Finally, the fourth equation estimates the effects of innovation output on the labour productivity of the firm (LP_{ij}).

As explained in section 2, our proposed refinement of the standard version of the CDM model is that we investigate the effects of industry-level competition conditions on each of the four stages of the model. We do this by allowing the parameters of interest to differ between more concentrated (oligopolistic) sectors (O) and more competitive markets (C). Specifically, in each of the four equations we augment the standard CDM model with two new variables: the Herfindahl index (measured at the 2-digit industry level) and an interaction term given by the product of the industry Herfindahl index and the main variable of interest in each CDM equation. The four hypotheses put forward in section 2 about the impacts of competition on the innovation-productivity link imply the following expectations on the model parameters:

1. Hypothesis 1 (Schumpeter effect I): $\alpha_O > \alpha_C \Rightarrow \Pr\{R\&D_{iO}\} > \Pr\{R\&D_{iC}\}$; in equation 1, the coefficient of the *Herfindahl index* variable is expected to be positive.

2. Hypothesis 2 (Schumpeter effect II): $\beta_O > \beta_C \Rightarrow R\&D_O > R\&D_C$; in equation 2, the coefficient of the *Herfindahl index* variable is expected to be positive.

3. Hypothesis 3 (Escape-competition effect I): $\delta_C > \delta_O$; in equation 3, the coefficient of the interaction term *Herfindahl • R&D intensity* is expected to be negative.

4. Hypothesis 4 (Escape-competition effect II): $\eta_C > \eta_O$; in equation 4, the coefficient of the interaction term *Herfindahl • Turnover from new products* is expected to be negative.

Three important econometric issues arise in the estimation of this type of CDM model. The first is the possible selection bias due to the fact that only a fraction of the firm population innovates, whereas a large number of enterprises in the sample are not engaged in R&D activities at all. In line with previous CDM empirical studies, we correct for the selection bias by means of a 2-step Heckman correction procedure. The first step (equation 1) estimates the probability that a firm is engaged in innovation by considering the whole sample of enterprises, while the remaining equations only focus on innovative firms and use the inverse Mills ratio (generated in step 1) to correct for the selection bias.

The second econometric issue refers to the endogeneity of some of the main explanatory variables. Since we are working with a system of recursive equations, it is natural to assume that the main explanatory variable in equation 4 (innovation output) is endogenously determined in the previous innovation stage, i.e. in equation 3; in turn, the main explanatory variable in equation 3 (innovation input) is determined in the previous innovation stage (i.e. the R&D intensity equation). In equations 3 and 4, we also take into account the possible endogeneity of the Herfindahl index variable, since it is reasonable to expect that the technological and market performance of firms may in turn affect the level of concentration of the industry in which they operate. In order to endogeneize these variables, we follow the standard CDM econometric approach and make use of a two-stages least squares estimator (2sls) in the analysis of equations 3 and 4. The Appendix provides information about the instruments used in these two equations and an assessment of their adequacy.

Thirdly, since we are working with a panel dataset (pooled data from the three waves of the innovation survey: CIS3, CIS4 and CIS5), it is important to use an appropriate panel estimation strategy. For each of the four equations, we will present results based on two distinct strategies, pooled data estimation, and random-effects estimates on the panel dataset. Regarding the latter, we have decided to use a random-effects model instead of a fixed-effects estimator for the following reason.

The fixed-effects estimator focuses on the time variation of each unit and ignores information about the cross-sectional variability. By contrast, the random-effects estimator exploits both the *within* and *between* components of the variability, and it is therefore more efficient. Such an advantage of the random-effects *versus* the fixed effects estimator becomes crucial when the time variation of the dataset is limited. In fact, for variables that change only slowly over time, the *between* part of the variance is substantially larger than the *within* component, and this tends to make fixed-effects estimates inefficient and unreliable (Beck 2001; Plümper and Troeger 2007). As previously shown in table 1, most of the variables in our dataset have this characteristic, i.e. they are rather stable and change only slowly over time (the results of the three innovation surveys are in fact quite similar to each other). Given the limited time variation in the dataset, a fixed-effects model is not capable of estimating the parameters of interest with the due precision, whereas the random-effects estimator, by exploiting also the large cross-section variability of the dataset, leads to a more efficient estimation in this type of innovation survey context.[8]

[8] A disadvantage of the random-effects model is that the assumption it makes about the fixed-effects component of the error term may not be valid and therefore lead to biased estimates. In the tables below, we present the results of a Hausman specification test, which in fact points out the existence of

4.2 Estimation results

The results of the estimations of the four equations are presented in tables 4, 5, 6 and 7 respectively. Table 4 focuses on the equation for the propensity to innovate, which estimates the probability that a firm is engaged in R&D activities in the period. As explained above, the first two columns report results of the Heckman step 1 procedure applied to the pooled data set, whereas the other two columns are based on random effects probit estimations on the unbalanced panel.

The Herfindahl index turns out to be positive and significant in all the regressions reported in table 4. The interpretation of this result is that firms in more concentrated (oligopolistic) industries have on average a greater propensity to engage in R&D activities than enterprises in less concentrated (competitive) sectors. This result provides support for the first of our hypotheses (Pr $\{R\&D_{iO}\}$ > Pr $\{R\&D_{iC}\}$), which is interpreted as a standard Schumpeter effect according to which a higher (lower) degree of competition decreases (increases) the firm's incentives to invest in R&D.

The other explanatory variables in equation 1 do also provide additional interesting indications on the determinants of the propensity to innovate. The productivity gap variable is negative and significant, meaning that firms that are closer (more distant) to the industry technology frontier are more (less) likely to undertake innovative efforts. This result may be interpreted as a cumulativeness (success-breeds-success) mechanism, in the sense that enterprises that are closer to the industry frontier are more likely to invest further in innovative activities in order to maintain their competitive position in the market. Interestingly, this cumulativeness effect is stronger for enterprises in oligopolistic markets than in competitive sectors – as indicated by the estimated coefficient of the interaction variable *Herfindahl • Gap*, which turns out to be negative and significant (see columns 2 and 4). In other words, it is less likely that new innovators join the innovation race in an oligopolistic market, where barriers to entry for the newcomers are strong and the market is dominated by a few innovative incumbents. This cumulativeness result is therefore fully consistent with the Schumpeterian effect pointed out above.

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a systematic difference between the results obtained with a consistent (fixed-effects) and efficient (random-effects) estimators. A new estimator that provides a possible solution to this trade-off between efficiency and consistency of the random- and fixed-effects estimators has recently been proposed by Plümper and Troeger (2007) and employed by Kokko, Tingvall and Taavo (2010).

The results for the other explanatory variables are in line with previous results in the CDM model literature. The propensity to innovate is positively and significantly related to the size of the firm (employment). The enterprise's international propensity (market location variable) is also positively correlated with the probability that the firm is engaged in innovation activities, confirming the close relationship between technological capabilities and export propensity that has previously been established in the literature (e.g. Aw, Roberts and Winston 2007). Last, the regression results indicate a positive and significant relationship between the three hampering factors variables – costs, qualified personnel and access to information – and the innovation propensity. In line with previous CDM works, this is interpreted as an indication of the relevance of these variables as factors shaping the innovative process.

< Table 4 here >

Table 5 presents the results of the estimations for the second equation, which focuses on the determinants of R&D intensity. Following previous works in the CDM literature, the explanatory variables used in this second equation are the same used in the first one. The reason for this is that it is reasonable to assume that the factors explaining a firm's likelihood to engage in R&D are closely related to those explaining the amount of resources the enterprise decides to invest in R&D. The results of the estimations of equation 2 are in fact rather similar to those of equation 1. The coefficient of the Herfindahl index is positive and significant in this equation as well, and this provides empirical support for the second of our hypotheses – that the amount of resources invested in R&D by an enterprise is on average greater in an oligopolistic market than in a competitive industry ($R\&D_O > R\&D_C$). Further, similarly to equation 1, equation 2 does also indicate the existence of a cumulative mechanism according to which firms that have a larger (smaller) gap from the technology frontier of their industry tend to invest less (more) resources in R&D activities. Here again, this cumulativeness effect is found to be stronger for enterprises in oligopolistic than in competitive markets (as indicated by the interaction variable *Herfindahl • Gap*, see regressions 6 and 8).

The remaining explanatory variables do also behave as expected and in line with the results of equation 1.[9] The regressions indicate that the dependent variable is positively and significantly related to the firms' international propensity, on the one hand, and the three hampering factors variables, on the other.

< Table 5 here >

Table 6 reports the results of the estimations of equation 3, which focuses on the relationship between innovation output (the dependent variable, measured as the share of turnover from the sales of new products), R&D intensity and a set of firm-specific characteristics. The R&D intensity variable, as expected, turns out to be positively related to the innovation output dependent variable.

The input-output relationship seems however to be affected by the level of concentration in the market, as suggested by the interaction variable *Herfindahl • R&D intensity*. The estimated coefficient for this variable is negative (though not significant at conventional levels), indicating that the elasticity of innovation output with respect to R&D is higher (lower) in competitive (oligopolistic) industries. This is what our third hypothesis points out ($\delta_C > \delta_O$). The interpretation of this result is that smaller firms in competitive markets typically have a more narrow product range and smaller turnover size, so that the commercialization of any given amount of a new product will have a relatively stronger impact for them than for large oligopolistic enterprises in concentrated sectors.

Interestingly, the estimate of the Herfindahl index variable does also provide additional evidence on the validity of hypothesis 3. In fact, the negative and significant estimated coefficient for this variable indicates that firms in competitive industries have on average a greater share of turnover from new products than enterprises in oligopolistic sectors ($IO_{iC} > IO_{iO}$). Since we know from the results of equation 2 that the R&D intensity is on average higher (lower) in oligopolistic (competitive) markets ($R\&D_O > R\&D_C$), the fact that $IO_{iC} > IO_{iO}$ that we observe in

[9] The only major difference is the employment variable, whose estimated coefficient turns out to be negative in the estimations. This negative coefficient is likely to be explained by the fact that the dependent variable of equation 2 (R&D employment intensity) is measured as a share of the total employment of the firm, thus partly introducing a negative relationship between the two variables by construction (see their correlation coefficient in table 3).

equation 3 does imply that the input-output elasticity must increase with the degree of competition in the industry, which is precisely our third hypothesis.

Differently from the previous two equations, the productivity gap variable turns out to have a positive estimated coefficient in equation 3. Thus, instead of a cumulative mechanism according to which stronger and more innovative firms tend to increase their market position even further over time (as observed in equations 1 and 2 above), what we observe in equation 3 is a *catching up* type of mechanism: firms that are more distant from the technological frontier in their industry have a greater scope for imitation of advanced technologies, and hence are on average better able to transform innovation input into output.

The results for the remaining explanatory variables in equation 3 are also in line with our expectations and previous results in the literature. In particular, the appropriability strategy based on the design and complex design of new products turns out to be an important factor to enhance the commercialization of innovation output. Further, in line with the results of the previous two equations, the international propensity of the enterprise does also turn out to be positively related to its technological performance, confirming the close link between product innovation and export propensity previously pointed out in the literature (Aw, Roberts and Winston 2007).

< Table 6 here >

Table 7 reports the results for equation 4, which focuses on the determinants of labour productivity. In general terms, these results are closely in line with those of equation 3, and all of the estimated coefficients are significant at conventional levels. The innovation output variable is positively related to the labour productivity of firms, the obvious interpretation being that the commercialization of new products makes it possible to strengthen the firm's competitive position in the market and thus increase its market share, turnover and productivity.

The output-productivity relationship is however stronger in competitive than in oligopolistic industries – as shown by the negative and significant estimated coefficient of the interaction variable *Herfindahl • Turnover from new products*. This result provides empirical evidence in support of our hypothesis 4, that the elasticity of productivity with respect to innovation output is higher in a competitive than in an oligopolistic industry ($\eta_C > \eta_O$). As explained in section 2, the rationale underlying this hypothesis is the following: in a competitive (oligopolistic) market, the share of innovative enterprises is low (high), so that, once a firm has decided to invest in R&D, any given amount of innovation output that it will commercialize will lead to a relatively large (small) change in the innovative firm's market shares, turnover and productivity *vis-a-vis* its competitors. Besides, and as a consequence of this competition mechanism, the coefficient for the Herfindahl index variable is also negative and significant, suggesting that, on average, enterprises in less concentrated sectors have a higher productivity level than firms in more concentrated industries ($LP_{iC} > LP_{iO}$).

As for the other explanatory variables in equation 4, the purchase of R&D services from external providers is positively related to labour productivity, suggesting that the external acquisition of knowledge from specialized service providers represents an important complementary strategy through which firms are able to sustain their productivity performance. The dummy variable indicating whether an enterprise is part of a group is also positively and significantly related to labour productivity.

Finally, differently from the results of the previous equations, the market location variable turns out to be negatively related to the productivity of innovative firms in the sample. Interestingly, the interaction variable *Herfindahl • Market location*, which turns out to have a positive and significant coefficient, suggests that the effect of the international propensity variable on the productivity of firms decreases with the degree of market competition. In other words, the positive relationship between the international propensity variable and productivity is substantially stronger for firms in oligopolistic industries than in competitive markets. A reasonable interpretation of this result is that, in sectors characterized by a high degree of domestic competition, firms must first of all struggle to maintain their competitive position at home rather than competing internationally.

< Table 7 here >

5. Conclusions

The paper has studied the effects of competition on the innovation-productivity link. The main idea we have explored is that competition may have different impacts on the various stages of the innovation chain. On the one hand, a higher degree of competition may decrease the probability that a firm decides to engage in innovative activities and the amount of resources it invests in R&D. On the other hand, once an enterprise has decided to join the innovation race, a higher degree of competition may increase the impact of innovation on the technological and economic performance of the enterprise.

In order to explore this idea, we have made use of a refined version of the CDM model. The standard version of this model studies four different stages of the innovation chain: the innovative choice of the firm, its R&D intensity, its innovative output and labour productivity. Section 2 has presented a refinement of this model that explicitly takes into account the effects of competition on these different stages. Our empirical test of the model has made use of a rich set of firm-level panel data available in the three most recent waves of the Norwegian Innovation Survey: the CIS3 (1998-2000), CIS4 (2002-2004) and CIS5 (2004-2006). Section 3 has presented the indicators and descriptive analysis of this dataset. Section 4 has then presented the econometric results of the estimations of the refined CDM model. The results provide empirical support for the hypotheses investigated in the paper, and may be summarized as follows.

In more concentrated (oligopolistic) industries, firms have on average a high propensity to engage in innovation and tend to invest a great amount of resources in R&D activities. A cumulative mechanism is at stake in the early stage of the innovation chain, according to which incumbents continuously innovate whereas far-from-the-frontier followers do not. By contrast, in the later stages of the innovation chain, the impacts of innovation input on the technological and economic performance of the enterprises is on average low.

The opposite pattern is instead observed in less concentrated (competitive) industries. Here, the enterprises have on average a lower propensity to engage in innovation and tend to invest a more limited amount of resources in R&D. However, if they decide to join the innovation race, the impacts of innovation input on their technological and productivity performance is high. The reason for this is twofold. First, the elasticity of innovation output with respect to R&D is high, because any given amount of turnover from the commercialization of new products represents a greater incremental benefit for small enterprises in competitive markets than for large incumbents in oligopolistic industries. In fact, instead of a cumulative dynamics, a catching up mechanism seems to characterize less concentrated industries: follower firms are better able to exploit technological opportunities through imitation of advanced technologies available in their market and hence to transform technological input into innovation output. Secondly, the elasticity of productivity with respect to innovation output is also high: in competitive markets, there is in general a lower share of innovative firms, so that the few innovators may gain a relatively greater advantage over their (non-innovative) rivals through the commercialization of new products.

The overall implication of these empirical results is that an increase in market competition constitutes an important policy target, since it leads to a better technological and economic performance of enterprises and a greater aggregate level of innovative output and labour productivity in the industry. At the same time, however, an increase in market competition is likely to decrease firms' incentives to innovate, so that it must be accompanied by an appropriate R&D policy support strategy.

These results also provide implications for the academic literature in this field. On the one hand, they suggest a new avenue for research in the competition and innovation literature. Recent models in this tradition have emphasized the need to simultaneously consider the contrasting impacts of competition on innovation – namely the Schumpeterian *versus* the escape-competition effect. Our paper suggests that these effects of competition may have diverging impacts on the different stages of the innovation process. On the other hand, our results also contribute to the recent literature on innovation and firm-level productivity in the CDM model tradition. Whereas the typical endeavour of CDM model studies is to estimate the link (average elasticity) between input, output and performance of innovation, our results suggest that this relationship may be greatly affected by the industry-level context in which firms operate – and in particular the degree of market competition.

Appendix: Instruments used for the estimation of equations 3 and 4

As pointed out in section 4, equations 3 and 4 have made use of a 2sls estimation method in order to tackle the possible problem of endogeneity of some of the main explanatory variables: innovation input and the Herfindahl index in equation 3, and innovation output and the Herfindahl index in equation 4. We report here information about the instruments that have been used and a brief analysis of their adequacy.

In equation 3, the two endogenous variables innovation input (R&D intensity) and the Herfindahl index have been instrumented through the following indicators: (1) hampering factor: high costs; (2) hampering factor: lack of qualified personnel; (3) hampering factor: lack of other information; (4) average firm size of the industry; (5) coefficient of variation of labour productivity within each industry; (6) labour productivity gap in each industry; (7) industry concentration ratio (C1); (8) share of innovative firms in each industry; (9) average labour productivity in each industry. The first three of these variables have been chosen to instrument the innovation input variable (as suggested by the results of equation 2), whereas the other six variables measure industry-level characteristics that are used as instruments for the Herfindahl index.

In order to assess the adequacy of these instruments, we have first looked at the first stage regression of the two endogenous indicators on these instrumental variables (plus the other exogenous variables in the regression). For the regression reported in table 6, column 9, the R-squared of the first-stage are 0,594 and 0,760 for the two endogenous variables respectively; and for the regression reported in table 6, column 10, the corresponding R-squared are 0,733 and 0,836. In both regressions, the highly significant values of the F-tests indicate the joint relevance of these instruments to explain the two endogenous variables. Further, in order to test for the assumed absence of correlation between the instruments and the error term, we have run a set of Sargan tests (tests of over-identifying restrictions). For the regressions reported in columns 9 and 10, the Sargan tests report χ-squared values of 11,49 and 12,24, which are not significant at the 10% and 5% level respectively. These test results indicate that the null hypothesis of the absence of correlation between the instruments and the error term cannot be rejected.

The same analysis has been carried out in relation to equation 4. In this equation, the two endogenous variables are innovation output (turnover from new products) and the Herfindahl index. These have been instrumented through the following indicators: (1) R&D intensity; (2) average firm size of the industry; (3) coefficient of variation of labour productivity within each industry; (4) industry concentration ratio (C1); (5) share of innovative firms in each industry. The first variable is obviously used as an instrument for the innovation output variable (as suggested by the results of equation 3), while the other four variables are industry-level indicators that are used as instruments for the Herfindahl index.

Regarding the results of the first stage regression of the two endogenous indicators on these instrumental variables, for the regression reported in table 7, column 13, the R-squared of the first-stage are 0,217 and 0,981 respectively; and for the regression reported in table 7, column 14, they are 0,557 and 0,983. In both regressions, the highly significant values of the F-tests indicate again the joint relevance of these instruments to explain the two endogenous variables. As for the results of the tests of over-identifying restrictions, for both the regressions reported in columns 13 and 14, the Sargan tests report χ-squared values of 5,89 and 4,02, which are not significant at the 10% level. Again, these results indicate that the null hypothesis of the absence of correlation between the instruments and the error term cannot be rejected, and they therefore corroborate the validity of the instruments.

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Figure 1: Model and hypotheses

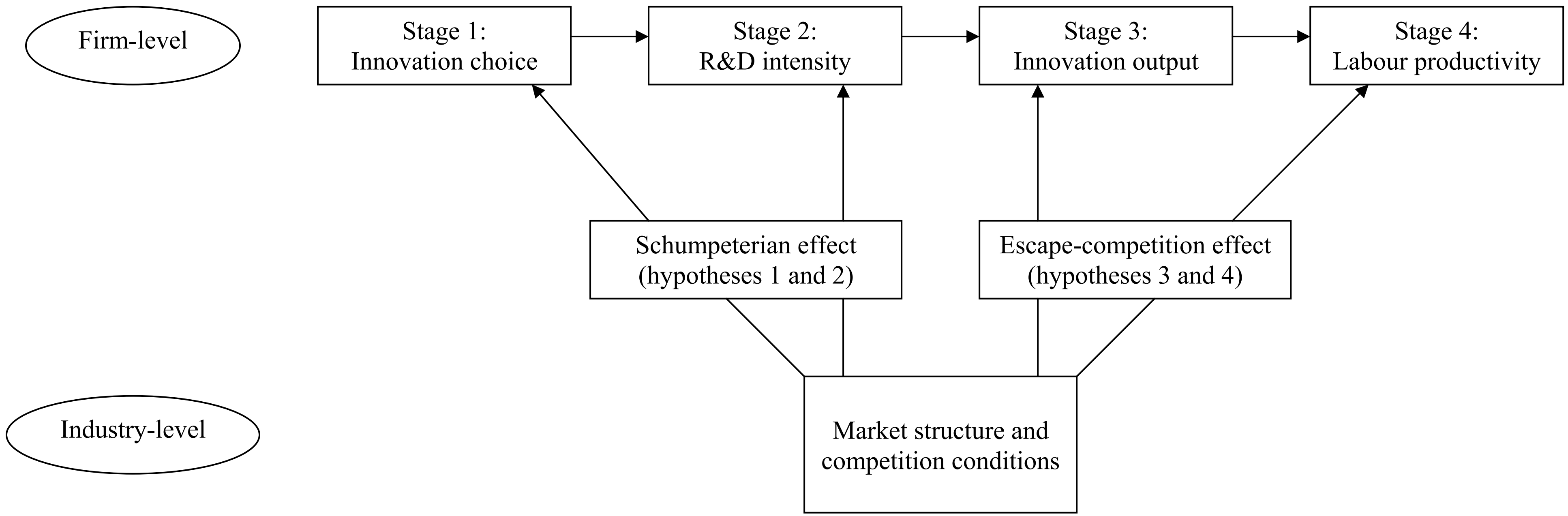

Table 1: Descriptive statistics: CIS3 (1998-2000), CIS4 (2002-2004) and CIS5 (2004-2006)

	CIS3 (N = 3899)				**CIS4 (N = 4655)**				**CIS5 (N = 6443)**			
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Labour productivity (log)	6.99	1.06	0.84	12.15	7.25	0.97	-0.78	12.21	7.04	1.01	0.58	12.09
Productivity gap	2.73	1.38	0	9.71	2.54	1.37	0	12.99	2.67	1.26	0	10.12
Employment (log)	3.90	1.21	2.30	9.19	3.67	1.16	2.30	9.31	3.17	1.32	1.61	9.44
Part of a group	0.63	0.48	0	1	0.52	0.49	0	1	0.44	0.49	0	1
Market location	2.36	1.18	1	4	1.76	0.87	1	4	1.58	0.86	1	4
Engaged in R&D	0.28	0.45	0	1	0.33	0.47	0	1	0.23	0.43	0	1
R&D intensity	0.04	0.13	0	2.22	0.06	0.15	0	1.33	0.06	0.19	0	3.09
R&D purchase	0.19	0.39	0	1	0.21	0.40	0	1	0.11	0.32	0	1
H – High costs	0.93	1.16	0	3	0.93	1.08	0	3	0.89	1.08	0	3
H – Lack of qualified personnel	0.60	0.88	0	3	0.66	0.85	0	3	0.82	1.02	0	3
H – Lack of information	0.54	0.80	0	3	0.63	0.79	0	3	0.61	0.80	0	3
Turnover from new products	0.09	0.19	0	1	0.07	0.18	0	1	0.07	0.18	0	1
Herfindahl index	0.069	0.078	0.013	0.991	0.073	0.082	0.015	1	0.055	0.067	0.014	1

Table 2: Innovative and non-innovative samples – Mean values for CIS3 (1998-2000), CIS4 (2002-2004) and CIS5 (2004-2006)

	CIS3		**CIS4**		**CIS5**	
	Innovative (N = 1121)	**Non innovative (N = 2778)**	**Innovative (N = 1532)**	**Non innovative (N = 3123)**	**Innovative (N = 1482)**	**Non innovative (N = 4961)**
Labour productivity (log)	7.05	6.97	7.31	7.22	7.12	7.02
Productivity gap	2.46	2.84	2.21	2.70	2.56	2.70
Employment (log)	4.25	3.76	4.00	3.52	3.80	2.98
Part of a group	0.73	0.60	0.60	0.49	0.59	0.39
Market location	2.84	2.16	2.17	1.56	2.12	1.42

Table 3: Correlation coefficients – Pooled sample (CIS3, CIS4 and CIS5)

	Labour productivity (log)	Productivity gap	Employment (log)	Part of a group	Market location	R&D employment (log)	R&D purchase	Turnover from new products (log)	Herfindahl index
Labour productivity (log)	1								
Productivity gap	-0.59	1							
Employment (log)	0.27	-0.16	1						
Part of a group	0.24	-0.15	0.43	1					
Market location	0.07	-0.15	0.15	0.20	1				
R&D intensity (log)	-0.18	0.13	-0.64	-0.26	-0.02	1			
R&D purchase	0.17	-0.14	0.28	0.18	0.17	-0.11	1		
Turnover from new products (log)	-0.18	0.10	-0.27	-0.08	0.10	0.35	-0.08	1	
Herfindahl index	0.05	-0.05	0.04	0.003	0.06	0.06	0.03	0.02	1

Table 4: Regression results – Equation 1: Propensity to innovate (selection equation)
Dependent variable: Engaged in R&D (dummy)

	(1)	**(2)**	**(3)**	**(4)**
Estimation method	Heckman (step 1)	Heckman (step 1)	Random effects probit	Random effects probit
Herfindahl index	0.134 (2.61)***	0.273 (3.13)***	0.140 (2.38)**	0.325 (3.19)***
Productivity gap	-0.057 (4.10)***	-0.023 (1.03)	-0.056 (3.37)***	-0.011 (0.43)
Herfindahl * Gap		-0.053 (1.98)**		-0.070 (2.22)**
Employment (log)	0.277 (22.44)***	0.278 (22.46)***	0.356 (22.97)***	0.357 (22.99)***
Market location	0.266 (16.90)***	0.265 (16.83)***	0.290 (15.18)***	0.289 (15.13)***
H – High costs	0.263 (16.70)***	0.263 (16.68)***	0.307 (16.28)***	0.307 (16.27)***
H – Lack of qualified personnel	0.154 (8.12)***	0.154 (8.11)***	0.168 (7.40)***	0.168 (7.38)***
H – Lack of information	0.184 (8.38)***	0.184 (8.38)***	0.204 (7.76)***	0.204 (7.76)***
χ^2	6386.15***	6293.63***	3863.01***	3867.93***
Observations	12819	12819	12954	12954
Censored observations	9249	9249	-	-
Uncensored observations	3570	3570	-	-

All regressions include a constant, industry dummies and time dummies.
Significance levels: *** 1%; ** 5%; * 10%.

Table 5: Regression results – Equation 2: Innovative intensity
Dependent variable: R&D intensity (log)

	(5)	(6)	(7)	(8)
Estimation method	Heckman (step 2)	Heckman (step 2)	Random effects	Random effects
Herfindahl index	0.763 (1.96)**	1.378 (2.68)***	0.295 (1.27)	0.742 (2.24)**
Productivity gap	-0.055 (3.10)***	-0.028 (1.30)	-0.018 (1.42)	0.000 (0.00)
Herfindahl * Gap		-0.306 (2.04)**		-0.231 (1.90)*
Employment (log)	-0.351 (10.62)***	-0.355 (10.91)***	-0.470 (18.11)***	-0.471 (18.12)***
Market location	0.268 (7.94)***	0.265 (7.94)***	0.132 (5.27)***	0.132 (5.31)***
H – High costs	0.177 (4.96)***	0.171 (4.88)***	0.081 (3.16)***	0.081 (3.15)***
H – Lack of qualified personnel	0.166 (6.04)***	0.162 (5.98)***	0.090 (4.71)***	0.090 (4.69)***
H – Lack of information	0.144 (4.60)***	0.143 (4.60)***	0.063 (2.93)***	0.064 (2.97)***
Mills ratio	1.121 (6.39)***	1.09 (6.34)***	0.498 (3.66)***	0.498 (3.67)***
χ^2	6386.15***	6293.63***	3684.50***	3690.83***
R^2	-	-	0.575	0.575
Hausman specification test (χ^2)	-	-	178.91***	158.29***
Observations	3570	3570	3570	3570

All regressions include a constant, industry dummies and time dummies.
Significance levels: *** 1%; ** 5%; * 10%.

Table 6: Regression results – Equation 3: Innovative output
Dependent variable: Turnover from new products (log)

	(9)	(10)	(11)	(12)
Estimation method	2sls, pooled data	2sls, pooled data	G2sls, random effects	G2sls, random effects
R&D intensity (log)	0.419 (2.22)**	0.428 (1.91)*	0.441 (1.92)*	0.429 (1.73)*
Herfindahl index	-0.296 (1.85)*	-0.609 (1.82)*	-0.325 (2.12)**	-0.665 (1.98)**
Herfindahl * R&D intensity		-0.194 (1.23)		-0.213 (1.33)
A – Design	0.156 (2.26)**	0.183 (2.83)***	0.157 (2.17)**	0.192 (2.97)***
A – Complex design	0.136 (2.38)**	0.160 (3.24)***	0.117 (1.99)**	0.143 (2.87)***
Productivity gap	0.090 (3.63)***	0.090 (3.60)***	0.083 (3.39)***	0.085 (3.40)***
Employment (log)	0.002 (0.03)	-0.059 (0.93)	0.017 (0.14)	-0.063 (0.81)
Part of a group	0.051 (1.05)	0.056 (1.17)	0.045 (0.91)	0.053 (1.06)
Market location	0.074 (2.30)**	0.087 (3.11)***	0.069 (2.11)**	0.084 (3.02)**
Mills ratio	-0.045 (0.55)	-0.039 (0.48)	-0.046 (0.56)	-0.038 (0,47)
χ^2	-	-	607.77***	632.89***
R^2	0.201	0.213	0.205	0.214
Hausman specification test (χ^2)	-	-	44.55*	306.56***
Observations	2661	2661	2661	2661

All regressions include a constant, industry dummies and time dummies.
Endogenous variables: R&D intensity (log) and Herfindahl index. For information about the instruments used and their adequacy, see the Appendix. Significance levels: *** 1%; ** 5%; * 10%.

Table 7: Regression results – Equation 4: Productivity
Dependent variable: Labour productivity (log)

	(13)	**(14)**	**(15)**	**(16)**
Estimation method	2sls, pooled data	2sls, pooled data	G2sls, random effects	G2sls, random effects
Turnover from new products (log)	0.331 (3.34)***	0.552 (3.48)***	0.242 (2.38)**	0.476 (2.74)***
Herfindahl index	-1.559 (3.48)***	-13.170 (4.49)***	-1.004 (2.99)***	-14.086 (4.11)***
Herfindahl * Turnover from new products		-3.854 (3.66)***		-3.643 (2.93)***
R&D purchase	0.097 (2.86)***	0.061 (1.62)	0.079 (2.57)***	0.072 (1.59)
Employment (log)	-0.313 (9.50)***	-0.342 (10.36)***	-0.290 (8.87)***	-0.447 (10.90)***
Part of a group	0.200 (5.37)***	0.212 (5.45)***	0.205 (5.70)***	0.233 (5.16)***
Market location	-0.423 (11.00)***	-0.510 (10.05)***	-0.371 (10.97)***	-0.614 (9.56)***
Herfindahl * Market location		1.343 (4.04)***		1.530 (3.77)***
H – High costs	-0.485 (14.22)***	-0.495 (13.65)***	-0.437 (14.54)***	-0.590 (12.22)***
H – Lack of qualified personnel	-0.240 (8.85)***	-0.248 (8.54)***	-0.212 (9.02)***	-0.304 (8.09)***
H – Lack of information	-0.348 (11.50)***	-0.346 (11.08)***	-0.305 (11.37)***	-0.426 (10.61)***
Mills ratio	-2.860 (15.51)***	-2.905 (14.86)***	-2.548 (15.57)***	-3.397 (13.60)***
χ^2	-	-	1073.14***	875.78***
R^2	0.173	0.090	0.266	0.227
Hausman specification test (χ^2)	-	-	120.52***	410.32***
Observations	2693	2693	2693	2693

All regressions include a constant, industry dummies and time dummies.
Endogenous variables: Turnover from new products (log) and Herfindahl index. For information about the instruments used and their adequacy, see the Appendix. Significance levels: *** 1%; ** 5%; * 10%.