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Abstract

According to a recent literature, the positive effect of competition is supposed to be growing with the proximity to the technological frontier. Using a variety of indicators, the paper tests the effect of competition and regulation on innovative activity measured by patenting. The sample consists of a panel of 15 industries for 17 OECD countries over the period 1979-2003. Results show no evidence of a positive effect of competition growing with the proximity to the frontier. Two main configurations emerge. First, regulation has a positive effect whatever the distance to the frontier and the magnitude of its impact is higher the closer the industry is to the frontier. Second, the effect of regulation is negative far from the frontier and becomes positive (or non significant) when the technology gap decreases. These results contradict the belief in the innovation-boosting effect of product market deregulation such as taken into account in the Lisbon Strategy.

Keywords: Innovation, competition, distance to frontier
JEL codes: O30, L16,

1 Introduction

Concerns about the lack of convergence of Europe's productivity level vis-à-vis the US over the past decade have been expressed not only in academic circles but also among policy makers and politicians. As numerous reports have shown (Kok, 2004; Sapir, 2004), Europe seems to be losing ground,

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not because of an insufficient rate of capital accumulation, but for lack of innovation capability. The so-called Lisbon Strategy, which aims at fostering innovation and productivity, proposes a series of structural reforms for labour, financial and product markets. Regarding the latter, a link between competition and innovation underlies the whole Lisbon Strategy: more product market competition should bolster innovation and thus productivity and growth.[1]

According to economic theory, the relation between competition and innovation is ambiguous. For Schumpeter (1934), monopoly profits are rewards to innovators; the appropriability of innovation output is thus a crucial incentive issue. A rise in competition is expected to decrease rents stemming from innovation and thus incentives to innovate. This traditional "Schumpeterian effect" of competition is featured in numerous innovation-based endogenous growth models, in particular Aghion and Howitt (1992) where innovation effort increases with the Lerner index.

On the other hand, competition may encourage innovation. Incumbents may innovate to keep their market power and fend off new entrants, or potential entrants may hope to capture the market position of incumbents by surpassing them with new and better products. In both cases, innovation would be the means for a firm to get the upper hand over its competitors. Extensions of the Schumpeterian innovation-based endogenous growth model allow to take into account differentiated influences of competition on innovation. The situation analysed in Aghion et al. (2005) is that of a competition between rivals with different productivity levels. Firms innovate to decrease their production costs "step by step": a technological laggard has to catch-up with the technological level of the leader before having the possibility of becoming itself a leader in the industry. The risks for the leader to lose its position are therefore increased when the competitor is only one step away from catching-up. When competitors have comparable productivity levels, i.e. the so-called "neck and neck" competition, a stronger competition will induce firms to increase their innovative investments in order to acquire a competitive lead over rival firms. This pro-innovation effect of competition is less prominent in industries where the leader has a marked advantage over its competitor. The incorporation of both innovation-inducing and innovation-deterring effects of competition into a single model leads to a non-linear, inverted U-shaped, relation between product market competition and innovation (Aghion et al., 2005).

The link between competition and innovation has been investigated primarily at the firm level. The possible existence of an effect of the firm's size

[1] e.g. the Integrated Guidelines 12 to 16 (European Commission, 2005).

or market power on its innovative activity is a well-known topic in the innovation literature (Baldwin and Scott, 1987; Cohen and Levin, 1989; Geroski, 1995). Although both pro- and anti-innovation effects of competition may be found in the empirical literature, the recent contributions tend to establish contrasted results differencing firm size effects from more general competition influences. Using a sample of French firms, Crépon, Duguet and Kabla (1995) found that market power stimulates innovation, although this effect seems to be small in magnitude. Crépon, Duguet and Mairesse (1998), in a four equation model for French manufacturing firms taking into account the firm's decision to engage in R&D activities, the R&D intensity, the effects of R&D on patenting and the effects of patenting on productivity, confirmed the existence of a size effect in the decision to engage in R&D activity but not the R&D intensity. On the other hand, market share and diversification affect positively both the decision to undertake R&D and R&D intensity. Competition may also exert negative effects such as those found in Crépon and Duguet (1997): competitors' R&D may have a negative impact on a firm's own innovation effort, indicating the existence of a rivalry externality that acts as a disincentive to innovate.

On the other hand, Nickell (1996) showed with a panel of 670 UK firms that competition, measured by a high number of competitors or low levels of rents, is associated to high rates of TFP growth. Whether this reveals a direct effect of competition on productivity, through a slack-reducing effect for instance, or an indirect effect through innovation is undecided. Blundell, Griffith and vanReenen (1999) used a panel of 340 British manufacturing firms between 1972 and 1982 and showed that the relation between competition and innovation possesses contrasted features. Industries where concentration is higher and import penetration lower have fewer innovations. This finding tends to support the existence of a positive relationship between competition and innovation. However, within industries, firms with a higher market share tend to commercialise more innovations. They also showed that larger firms produce innovations of a greater commercial value than smaller firms.

The duality of competition's effects on innovation is summarised in the findings of Aghion (2003) and Aghion et al. (2005). With the help of firm-level data and US Patent Office data quoted on the London Stock Exchange between 1968 and 1997, they presented evidence of an inverted U-shaped relationship between the Lerner index and the number of patents granted. The "Schumpeterian effect" of competition should dominate when the level of competition is high whereas the "escape competition" effect should be prominent at low levels of product market competition. Moreover, following the prediction of the theoretical model, the inverted U-shaped relationship was found to be steeper for firms that are closer to the leading edge in their industry.

Empirical evidence at the industry level is far less abundant than at the firm level. Industry-level studies have the advantage of allowing to escape from the limits of the proxies for competition usually taken into account by micro-level studies such as firm size, market power or profitability level, and consider actual industry-specific or macroeconomy-wide competition policy measures. Griffith, Harrison and Simpson (2006) measured innovation by Business Entreprise R&D expenditure for 12 industries and nine countries over the 1987-2000 period and investigated the effect of the Single Market Programme. Using a dummy variable for the post-SMP years, they found that the SMP had a positive impact on innovative activity in affected industries and countries. They interpreted their results as a support for the competition-enhancing reforms advocated within the Lisbon Agenda. Nicoletti and Scarpetta (2003) considered a sample of 23 industries for 18 OECD countries over the period 1984-1998. They tested a model of TFP growth using product market regulation indicators devised by the OECD both alone and in interaction with a technology gap variable. They found statistically significant positive coefficients on the interacted variables, a result they interpreted as a catch-up slowing-down effect of product market regulation. Conway et al. (2006) tested a similar model of labour productivity with interaction terms between product market regulation indicators and a technology gap measure on a slightly extended sample of OECD countries. They found a significantly positive coefficient on the interacted variables too, which they interpreted as a catch-up slowing-down effect.

The differentiated effect of product market competition according to the distance to the technological frontier is a central issue of the whole competition and innovation debate. The received argument is that the economic costs of product market regulation increase the closer an economy is to the technological frontier (Aghion, 2006). For Aghion et al. (2006), increased competition, represented by a higher entry threat, spurs innovation incentives in sectors close to the technological frontier, whereas it discourages innovation in laggard sectors through a traditional Schumpeterian rent-diminishing effect. Testing a model of TFP growth and a model of innovation (patenting) with foreign entry and distance to the technological frontier variables included both alone and interacted along with other competition variables on micro-level data for the UK, they concluded that, as an economy moves closer to the technological frontier, the competitiveness of all industries in a high-cost high-productivity economy depends on the ability to innovate. This applies to all sectors of the economy, "high-tech" or not, since the R&D intensity of all industries increases when economies move closer to the technological frontier (Acemoglu, Aghion and Zilibotti, 2006).

Concerning the inverted U-shape pattern, Tingvall and Poldahl (2006) find that, for Sweden firms, the support for this pattern depends on the indicator. While the Herfindal- index gives support to the inverted U-shape, the price cost margin does not allow to fit this pattern. Moreover, the use of time-series estimators reduces considerably the significance of results. Askenazy, Cahn and Irac (2007), using a panel of French firms, find that the concavity of the courbe linking competition and innovation is substantially reduced when the size of firms is small relatively to the cost of innovation. For the authors, this type of firms represents 85% of the sample.

The aim of this paper is to assess the validity of the argument according to which competition spurs innovation, and that this effect is all the more important that an economy is close to the technological frontier. A dynamic model including variables for the distance to the frontier, competition, as well an interaction term between them is estimated. The empirical strategy of this paper differs from the existing academic literature on three levels. First, the analysis is conducted at the industry level, while most empirical evidence focuses on micro studies. To the best of our knowledge, this is the first work testing the impact of competition on *innovation* at the industry level with a cross-country panel. Second, we use not only indicators for observed measures of competition but also indicators of regulation policy (institutional indicators, and output measure of competition). Finally, we run regressions using different estimators (OLS, fixed effects and system GMM) in order to take into account the dynamic nature of the innovative process and propose different extensions of the baseline model. The use of different variants of the model, different estimators and different indicators to measure the intensity of competition helps to assess the robustness of our findings. The evidence does not give support to an innovation-bolstering effect of product market competition at the technological frontier. Moreover, the marginal effect of regulation, conditional on the closeness to the technological frontier, tends to be upward sloping, meaning that regulation might indeed foster innovation at the leading edge. The measure of observed competition (relative number of firms) presents a positive effect only for laggard industries and it vanishes close to technological frontier. These results along with previous micro evidence, suggest that deregulation policiy does not seem to be a substitute for active science and technology policies, which do present a significant impact on technical change (Guellec and de la Potterie, 2003)

The paper is organised as follows. Section 2 presents the empirical strategy and the problems related with the estimations. Section 3 intrioduces the data used in the empirical analysis. The following Section presents the results of the baseline model. Section 5 proposes extensions and robustness tests of this model. Section 6 discusses the theoretical argument relating innovation with competition and sheds light on a possible explanation of our results: the inclusion of innovative leaders into the Aghion et al.'s (2005) model makes the relationship between the innovation-fostering effect of competition and distance to frontier more complex. A brief conclusion follows.

2 Empirical strategy

2.1 Dynamic issues

Our purpose is to test the impact of competition on innovation with a time-series-cross-section data at the industry level for OECD countries. This structure has two particularities. First, information on innovation is aggregated and belongs to individuals which represent different activities performed in different countries. Second, a plausible model of the innovation process should exploit this panel structure and allow for a dynamics in which past innovations help to explain current ones. These particularities imply a non-negligible unobserved heterogeneity among individuals that will be present in both past and current innovation. More specifically let p_{it} be our proxy of innovation activity in natural log and summarise, for the moment, our explanatory covariates (in log) on the vector x_{it}. Our problem can be formulated as the estimation of the following dynamic multivariate model:

$$p_{it} = \alpha p_{it-1} + \beta x_{it} + \epsilon_{it} \tag{1}$$

Where $\epsilon_{it} = \eta_i + \mu_{it}$

The main issue is that the past realisation of our dependent variable is endogenous to the fixed effect in the error term. In this framework, the estimates of α provided by OLS are upward biased and those coming from the Within-group estimator are downward biased (Bond 2002; Benavente et al. 2005). While the former neglects the unobserved time-invariant heterogeneity η_i, which is the source of correlation between p_{it-1} and ϵ_{it}, the latter includes past values of p_{it} since it subtracts the mean to eliminate η_i. Although these estimators are biased, they are useful because they give an interval in which a consistent estimation of α should lie.

Several strategies can be adopted to face these dynamic concerns. They go from the estimation of the model in differences, by instrumenting $\Delta p_{it-1}$with p_{it-2} using a two stage least squares (Andersen and Hsiao, 1981), to different techniques based on the generalised method of moments (GMM). GMM-based methods improve efficiency by exploiting the moment conditions that relate deeper lags of the dependent variable, some times transformed, to the error term. Among GMM techniques we are particularly interested in the one suggested by Arellano and Bover (1995) and fully developed by Blundell and Bond (1998), usually called system GMM (S-GMM). The difference GMM (D-GMM) proposed by Arellano and Bond (1991), which applies a transformation in differences and uses the orthogonality conditions of available lags of p_{it-1}, is augmented by S-GMM under the assumption that first differences of the instrumenting variables are uncorrelated to the error in levels. Thanks to this assumption, one can include the original equation in levels and use Δp_{it-2} and deeper as instruments for p_{it-1}. The transformed equation and the one in levels make a system in which more instruments can be exploited.

The use of a new set of instruments in differences improves efficiency as it deals with the problem of weak instruments of D-GMM in persistent series. Note that equation (1) is equivalent to state $\Delta p_{it} = (\alpha - 1)\, p_{it-1} + \beta x_{it} + \epsilon_{it}$. Hence Δp_{it} is weakly correlated with p_{it-1} if α is close to 1. Intuitively, in the case of a process close to a random walk, past values will not predict current changes as good as past changes can predict current values. In that sense, one can expect that instrumenting p_{it-1} with Δp_{it-s} $(s = 2..T)$ should give more accurate estimates. On the other hand, the inclusion of the equation in levels will be useful to keep the information of variables that do not change too much during time. This is namely the case of our proxies of regulation.

It should be stressed that our measure of innovation is based on the aggregation of patents at the country level and distributed at the industry level according to a transformation matrix linking technology and industry classification. In addition, to take into account fixed effects related to size and economic activity we normalize this measure dividing by the hours worked. In this context, it seems reasonably to treat this aggregated normalised measure of innovation as a continuous variable rather than counts coming from independent experiments.

2.2 Specifying regressors x_{it}

One advantage of GMM techniques is that they allow the other regressors x_{it} to be predetermined (explained by their past realisations) or endogenous (explained by current and past realisations of other variables and by their own autoregressive process). In our basic estimation, we consider as explanatory variables x_{it} the closeness to the frontier cl_{it}, the product market competition proxy mc_{it} and their interaction $mc_{it} * cl_{it}$. As elemental controls we also include in all regressions the capital intensity kl_{it} and the externalities ex_{it} arising from the innovative activity of the same industry in the rest of the world. The interaction term will capture the extent to which product market competition influences the innovative process conditional to the proximity to the technological frontier. We also include year dummies d_t in order to control for macroeconomic shocks homogeneous across individuals. The following baseline model is estimated:

$$p_{it} = \alpha\, p_{it-1} + \beta_1\, cl_{it} + \beta_2\, mc_{it} * cl_{it} + \beta_3\, mc_{it} + \beta_4\, kl_{it} + \beta_5\, ex_{it} + \beta_6\, d_t + \epsilon_{it} \quad (2)$$

Even though the S-GMM estimator deal with the potential endogeneity of the regressors, as a robustness check, to reduce the risk of reverse causality, we also estimate the model considering the explicative variables lagged once:

$$p_{it} = \alpha\, p_{it-1} + \beta_1\, cl_{it-1} + \beta_2\, mc_{it-1} * cl_{it-1} + \beta_3\, mc_{it-1} + \beta_4\, kl_{it-1} + \beta_5\, ex_{it-1} + \beta_6\, d_t + \epsilon_{it} \quad (3)$$

Aiming at getting further insights about the concavity of the effect of competition, we augment the reduced form of the interaction and include the squares terms of the closeness to the frontier and product market competition:

$$p_{it} = \alpha p_{it-1} + \beta_1 cl_{it} + \beta_2 mc_{it} * cl_{it} + \beta_3 mc_{it} + \beta_4 kl_{it} + \beta_5 ex_{it} + \beta_7 cl_{it}^2 + \beta_8 mc_{it}^2 + \beta_6 d_t + \epsilon_{it} \quad (4)$$

This specification is equivalent to consider a translog approximation of a constant elasticity function between both variables that can be more precise to capture an eventual complementarity between them. A similar equation is also estimated for the model with all regressor in lag 1. Finally, we test an extended version of (2) and (4), including further controls such as import penetration, financial deepness and labour market regulation.

In all S-GMM regressions the set of instruments is composed of the dependent variable p_{it}, the closeness to the frontier cl_{it}, the product market competition mc_{it}, and their interaction $mc_{it} * cl_{it}$, all in lag two or deeper. We also use as instrument the externalities ex_{it} in lag 1 (or deeper) as we can exploit its expected exogeneity. Since the Sargan-Hansen test for overidentifying restriction, which tests the exogeneity of instruments, becomes less rigorous as the number of instruments increases, the recommendation is to have less instruments than individuals (Roodman, 2006), a rule that is in line with evidence provided by simulation (see Windmeijer 2005). Since the number of instrument is quadratic in time dimension and S-GMM generates not only a set of instrument for the transformed equation but also for the equation in levels, this rule, for our sample size, is some what constraining. We overcome this difficulty by using limited lags, by considering most informative instruments and by collapsing in some cases the matrix of an instrumenting variable into a vector. The latter strategy is equivalent to sum up independent moment conditions in one equation. Examples of this strategy are Calderon et al. (2002) or Beck and Levine (2004). In each case, the main criterion to accept the instrumentation strategy is the Sargan-Hansen test and its version in difference which allows to test a subset of instruments. In addition, we pay special attention to the autocorrelation of the error term, a crucial assumption for the validity of instruments in lag 2. To do so, use is made of the Arellano-Bond test for serial correlation in differences. Since by construction first order correlation is expected we only focus on the test for second order correlation in difference, which relates ϵ_{it-1} with ϵ_{it-2} by looking at the correlation between $\Delta\epsilon_{it}$ and $\Delta\epsilon_{it-2}$.

2.3 The marginal effect of competition on innovation

Since we have included an interaction term between product market competition and the closeness to technological frontier ($mc_{it} * cl_{it}$), the assessment concerning the expected overall effect of product market competition mc_{it} needs the computation of its marginal effect conditional on specific values of the closeness to technological frontier cl_{it} (Braumoeller 2004):

$$\frac{\partial E(p_{it}/x_{it})}{\partial mc_{it}} = \widehat{\beta}_2 cl_{it} + \widehat{\beta}_3 \tag{5}$$

For the translog version:

$$\frac{\partial E(p_{it}/x_{it})}{\partial mc_{it}} = \widehat{\beta}_2 cl_{it} + \widehat{\beta}_3 + 2\widehat{\beta}_8 mc_{it} \tag{6}$$

Similar expressions hold for (3) and the lagged version of (4). It is easy to see, for instance, that a positive and significant $\widehat{\beta}_2$ means nothing but that competition increases innovation activity *only* for an individual completely far away the technological frontier ($cl_{it} = 0$). That is for the unrealistic case of zero labour productivity. Notice that for the augmented version (4), the calculation of the marginal effect of competition depends on the level of competition itself mc_{it} in (6).

As each of these linear combinations is computed using the estimated values of β_2,β_3 and β_8, one still needs to determine their significance, which in turn will depend on the variance of estimates and the value at which cl_{it} is evaluated (Friedrich 1982). For the (5), this significance is given by the ratio

$$\frac{\widehat{\beta}_2 cl_{it} + \widehat{\beta}_3}{\sqrt{\widehat{\sigma}_{\widehat{\beta}_3\widehat{\beta}_3} + cl_{it}^2 \widehat{\sigma}_{\widehat{\beta}_2\widehat{\beta}_2} + 2cl_{it}^2 \widehat{\sigma}_{\widehat{\beta}_2\widehat{\beta}_3}}}$$

Where $\widehat{\sigma}_{\gamma\delta}$ is the sample covariance between γ and δ. Hence, statistically insignificant coefficients may combine to produce statistically significant conditional effects. In our regression we evaluate the marginal effect and its significance for the minimum, one deviation under the mean, the mean, one deviation over the mean and the maximum sample values of cl_{it}. For the translog version we take the mean value of mc_{it}.

2.4 Testing for unit root

The validity of lagged differences as instruments for levels depends on whether this lagged differences are uncorrelated with the error term. Blundell and Bond (1998) state this assumption in terms of the stationarity of the initial conditions of the autoregressive process. Let us consider the reduced AR(1) version of our model:

$$p_{it} = \alpha p_{it-1} + \epsilon_{it} \qquad \epsilon_{it} = \eta_i + \mu_{it} \tag{7}$$

If the initial conditions do not deviate systematically from their long term stationary value $E\left[\left(y_{i1} - \left(\frac{\eta_i}{1-\alpha}\right)\right)\eta_i\right] = 0$, it follows that the deviation itself will be uncorrelated with the fixed effect. Thus, for the second period onwards the difference of the dependent variable will be also uncorrelated with the fixed effect. In other words, under this assumption, a first difference transformation of the instrument will be enough to purge η_i. If there is no serial correlation of μ_{it}, then $E\left[\Delta p_{it-1}\epsilon_{it}\right] = 0$.

As a consequence, we verify the risk of unit root of our main time series variables by the means of the Fisher test developed by Maddala and Wu (1999) for panel data. Alternative tests such as Levin, Lin and Chu (2002) and Im, Pesaran and Shin (2003) seem less convenient for our case. First, Levin, Lin and Chu (2002) consider the strong assumption that all units have the same autoregressive coefficient. This assumption constraints the alternative hypothesis to posit that all series are stationary. Second, the single statistic of the Fisher test, resuming the significance of all individual unit root test, has an exact χ^2 distribution. On the contrary, Im, Pesaran and Shin (2003) consider the mean of the t-statistic of each Augmented Dickey-Fuller individual test, whose normality is asymptotic. Finally, as both tests assume that the sample period is the same for all cross-section units, they need a balanced panel data. This reduces the size of the sample and the efficiency of the test.

Results of these tests are reported in Table 13 (appendix). In order to allows for serial correlation in the error term we consider one and two lags of Δy_{it} for each individual Augmented Dickey-Fuller test. We do not take a risk rejecting the null hypothesis of non stationary for all series when the autoregressive model considers a constant (drift). This specification is consistent with our regressions.

3 Data

We collected information for 17 OECD countries and 15 manufacturing industries at two-digit ISIC-Rev3 from 1979 to 2003 (Table 8). Original data come from OECD-STAN, GGDC-ICOP project[2] and EUROSTAT databases. From OECD-STAN we use trade indicators and investment series. Starting from OECD-STAN, the GGDC-ICOP data complete the information with surveys and their own estimations, consistent with national accountings.[3] This data is our original source for value added series, implicit deflators and hours worked. Patent series were obtained from EUROSTAT, which distribute by industries the number of patents granted according to a matrix relating technology and industry classification.

3.1 Distance to frontier

Labour productivity (value added per hour worked) is used as the main measure of efficiency. The technological frontier is defined as the most productive available technology for each ISIC-Rev3 Industry at every period. The individual (country-industry couple) having the maximum labour productivity among all countries in a given year is identified as the technological leader for that year. The closeness to the frontier is measured as the ratio of labour productivity relative to that of the frontier.[4] For instance, the closeness to the frontier of Spain in chemical industry in 1994 is the labour productivity

[2] The International Comparisons of Output and Productivity (ICOP) project of the Groningen Growth & Development Centre (GGDC)

[3] GGDC-ICOP estimate OECD-STAN missing information going to alternative sources and applying different estimation methods. However, the resulting dispersion is considerably bigger (See GGDC rows in Table 3.9 in appendix). We drop GGDC-ICOP estimations of industry 30 (office machinery) because of its high dispersion and keep the OECD-STAN values for GGDC-ICOP outliers when OECD information exists. The global dispersion considerably diminishes (Filtered Data). With this filter we get 6098 observation instead of 4129, with series quite comparable to those available in OECD-STAN.

[4] The distance to frontier is the inverted ratio.

of the Spanish chemical industry in 1994 divided by the highest labour productivity level for chemicals among all countries in that year. We consider a moving average of three year in order to smooth the series.

All nominal series were deflated to 1997 in their national currency. However, in order to make an international comparison at the industry level, we need to take into account price differences among countries at the industry level (cross section deflation). This is particularly important for value added series since we base our productive measure on them. Use is made of the industry purchasing power parities (I-PPPs) provided by Timmer, Ympa and van Ark (2006) for 1997. The authors consider a mix between purchasing power parities based on two points of the productive process: consumer expenditure and production. Expenditure PPPs are computed from ICP index and production PPPs from average producer prices, which are calculated at the industry level dividing output values by quantities. While the former includes only final goods and must be adjusted for taxes, distribution margins and trade costs, the latter needs to face the problem of matching varieties of goods that may differ in quality and product definition among countries. The selected PPPs measure (adjusted-expenditure or production) depends on the specificity of each industry. The authors propose a harmonised dataset of purchasing power parities disaggregated at the industry level (I-PPPs) for a wide sample of developing countries. Aiming at getting comparable series, they apply the multilateral weighted aggregation method proposed by Elteto and Koves (1964) and Szulc (1964) (EKS). This method allows to obtain transitivity in multilateral comparisons starting from binary comparisons.

Table 10 (appendix) shows the average labour productivity of each country for the full sample period and compares the values whether one uses the standard (non-adjusted) expenditure PPPs at the country level or the industry-PPP computed by Timmer, Ympa and van Ark (2006). Table 11 (appendix) presents similar figures at the industry level (world sample average). At the country level the average of labour productivity for the full sample period seems similar among countries. However, the variation induced by both measures increases if one considers the industry level. This issue is important because the hierarchy in terms of productivity and namely the identification of the frontier level might change.

3.2 Innovation

As a proxy of innovation we consider the number of patents. At the industry level, they are provided by EUROSTAT. In this database the applications at the European Patents Office (EPO) are linked to industry standard classifications by the means of a detailed matrix of weights. This matrix builds on firm data allowing to relate ISIC industries to the subclasses of International Patent Classification (IPC) categories. The US counterpart of the EPO is the United States Patents and Trademarked Office (USPTO). Both series are not directly comparable since the EPO system informs about applications and the USPTO about patent granted. We consider the EPO system as it is more representative for the countries present in our sample. Aiming at controlling for market size effects, patents are normalised by the hours worked of the industry. At the end we get a continuous aggregated measure of innovation that enables international comparisons at the industry level.

Information on R&D expenditure, disaggregated at the industry level, is available from the OECD ANDBERD database. Nevertheless, the intersection between R&D information and the availability of the rest of variables leads to a significant reduction of the number of observations (mainly Austria, Greece, Ireland and Portugal) and R&D data is only available from 1987.

3.3 Competition and regulation measures

Five indicators have been selected to capture product market competition. On order to capture the extent of competition, we use both input (*de jure*) and output (*de facto*) measures of the competitive environment. Within the first group of proxies, we consider four indicators of market regulation: (1) the global product market regulation PMR provided by the OECD and documented by Conway, Janod and Nicoletti (2005); (2) the size of the public enterprise sector PMR(public), a component of PMR that focuses on state control; (3) the regulatory provisions in non-manufacturing sectors (telecoms, electricity, gas, post, rail, air passenger transport, and road freight) summarised by the REGREF indicator, also provided by the OECD (Conway and Nicoletti, 2006) and (4) the corresponding effect of these regulatory provisions on the manufacturing sector given by the REGIMP indicator, which is also documented by (Conway and Nicoletti, 2006). REGIMP is based on an input/output matrix defining the use of non-manufacturing sectors as inputs in manufacturing. Thus, it aims at capturing the "knock-on" effet of regulation in selected non-manufacturing sectors on manufacturing.

On the other hand, we also consider a measure of the outcome of competition, namelly the number of firms per value added (N-FIRMS/VA), which is a proxy of market atomicity (or the inverse of the average size), usually expected to be the result of the reduction of market barriers.

The scope of these indicators is as follow. REGIMP and N-FIRMS/VA are consistent with our time-series-cross-section data structure. REGREF is a time series at the country level reflecting the evolution of the economy-wide competitive environment. Finally, PMR and PMR(public) are computed at the country level for two point times (1998 and 2003). They have been distributed for two periods: before and after 2000. Since PMR is based on a collection of private and governmental practices, this distribution should be in line with the evolution of European market reforms. Figure 1 gives a picture of the hierarchy of countries depending on their regulatory environments.

Figure 1. Hierarchy of regulatory environments

3.4 Controls

We use two elemental controls: capital intensity and innovation spillovers. Capital series were constructed using investment series and the standard Perpetual Inventory Method (PIM). This method uses the dynamic rule by which current capital stock equals the stock of the preceding period after depreciation plus current investment. To compute the initial stock, the PIM method supposes that pre-sample investment grows at a constant rate. Under the assumption of steady state this rate equals the one of value added. After applying this result to the dynamic rule, the initial stock becomes a function of initial investment, the global depreciation rate and the steady state growth rate of value added. We proxy the latter with the mean of the sample period and use a depreciation rate of 7.5%, the standard assumption. To capture innovation spillovers, we consider patenting activity of the rest of the world in the same manufacturing industry (the number of patents per hour worked produced by the same industry in the rest of the world).

As additional controls, we also include indicators of foreign competition, labour market regulation and financial deepness: the import penetration ratio MPEN available in OECD-STAN at the industry level, the employment protection indicator EPLBLD proposed by Amable, Demmou and Gatti (2007) at the country level, which updates the EPL indicator of the OECD, and the financialisation ratio defined as the total assets of institutional investors relative to GDP. Table 12 (appendix) summarises the main descriptive statistics.

4 Results

4.1 OLS and Within-group regressions

Table 1 presents OLS and Within-group estimates of the effects of competition on patenting using *de facto* and *de jure* measures of competition: the number of firms relative to value added (N-FIRMS/VA in columns [1] to [3]) the "knock-on" effect of regulation in non-manufacturing sectors (REGIMP in columns [4] to [6]), the indicator of competition in non-manufacturing sectors (REGREF in columns [7] to [9]), the economy-wide indicator of product market regulation (PMR in [10] to [12]) and the indicator for public sector (PMR(Public) in [13] to [16]). The models differ with the inclusion of the lagged dependent variable and the estimator: OLS or Within-group panel estimator. Models [3], [6], [9], [12] and [15] are first difference equations with no lagged dependent variable. This amounts to forcing the coefficient of the lagged dependent variable in level to be equal to one.

As expected, the coefficient on the lagged dependent variable differs greatly between the OLS and fixed-effect estimator, being greater for the former model. Also the signs of the coefficients for the externality effect and the capital/labour ratio are mostly significantly positive. For each regression, the lower panel of the Table presents the estimated marginal effects of the competition indicator for different levels of the relative productivity level (the closeness to the frontier). The first line of the lower panel gives the value of the marginal effect when the relative technological level is at its minimum (min), i.e. when the distance to frontier is at its maximum. The last lines give the marginal effects and standard errors when the relative productivity level is at the maximum of the sample, i.e. at the technology frontier. Marginal effects coefficients are also presented for the mean value of the relative technological level, the mean value minus one standard deviation and plus one standard deviation. Therefore, reading a column of the lower panel of the Table shows how the marginal effect of competition changes as the distance to the technological frontier decreases and vanishes.

The interpretation of the marginal effect for regressions [1] to [3], with the relative number of firms indicator, differs from the interpretation for the other indicators. A higher relative number of firms is a direct measure competition since it informs about the number of competitors that share the same market. It can also be interpreted as an inverse measure of the average firms' size in the industry, related to the level of concentration in the industry. If competition is more favourable to innovation near the technological frontier, the marginal effects should increase as the relative technological level augments from its minimum to its maximum. Indeed, if one follows strictly the predictions of Aghion et al. (2005), Aghion (2006), one should expect a negative marginal effect of competition far from the technological frontier (the Schumpeterian effect) and a positive effect close to the frontier (the 'escape competition' effect). Results reported in Table 1 show that, while the relative number of firms is positively correlated with innovation in laggard industries, its effect decreases as the industry moves closer to the technological frontier. At the leading edge the effect of competition given by this indicator loses its significancy. Having a less concentrated industry seems to matter more when the industry is far from the leading edge than when it is near. This result is true whatever the estimator or specification, only the magnitude of the effects and their significance change. This result could be compared with the positive size effect found in many micro studies of innovation. If the firm size is a positive influence on innovation, one may suppose that it will be all the more important that the technological competition is fierce, i.e. that the industry is close to the leading edge.

Using a proxy for size or concentration in the industry is subject to the usual limitations: it measures the outcome of the competition process, not so much the competitive environment. In this respect, the use of indicators of regulation will make it possible to avoid ambiguous interpretations of the results. The interpretation of the marginal effects of regulation according to the proximity to thefrontier is straightforward. Again, if competition is good for innovation, product market regulation should exert a negative influence on patenting, all the more so that the distance to frontier diminishes. Indeed, for Conway, Janod and Nicoletti (2005) and Conwayand Nicoletti (2006), these regulation proxies reflect ant-competitive market barriers. Following Aghion et al.'s (2005) predictions, regulation could be good when the industry is far from the frontier, but should gradually become detrimental as the distance to frontier is reduced. One observes contrasted results in regres-

Dependent Variable: Patenting (patents decomposition /hours worked) **- OLS and Within Group Estimators**

Regressions for Competition ([1] to [3]) and Regulation ([4] to [15])

	N-FIRMS/VA			REGIMP			REGREF			PMR			PMR(Public)		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]
Patenting (t-1)	0.974***	0.328***		0.961***	0.557***		0.960***	0.599***		0.961***	0.637***		0.944***	0.596***	
	(0.009)	(0.072)		(0.006)	(0.032)		(0.006)	(0.029)		(0.007)	(0.029)		(0.007)	(0.030)	
Closeness to Frontier	-0.030	-0.096*	0.003	0.026	-0.181	-0.077	-0.021	-0.001	0.062	0.001	0.013	0.068*	0.028	0.082**	0.027
	(0.027)	(0.056)	(0.054)	(0.089)	(0.161)	(0.151)	(0.042)	(0.045)	(0.048)	(0.029)	(0.038)	(0.038)	(0.038)	(0.039)	(0.043)
Closeness × Competition (Regulation)	-0.010	-0.089***	-0.006	0.012	-0.075	-0.043	0.023	-0.011	-0.047	-0.027	-0.069	-0.131*	-0.007	-0.084***	-0.013
	(0.016)	(0.028)	(0.026)	(0.042)	(0.078)	(0.069)	(0.034)	(0.041)	(0.047)	(0.052)	(0.071)	(0.079)	(0.030)	(0.032)	(0.037)
Competition (Regulation)	0.059	0.402***	0.060	-0.024	-0.514	0.568*	-0.026	-0.138	0.187	0.228	0.322	1.070***	0.114	0.064	0.573*
	(0.065)	(0.117)	(0.107)	(0.174)	(0.348)	(0.312)	(0.142)	(0.189)	(0.219)	(0.220)	(0.341)	(0.358)	(0.125)	(0.285)	(0.333)
Externalities	0.032***	0.330***	-0.066	0.039***	0.419***	-0.021	0.041***	0.351***	0.005	0.038***	0.306***	0.013	0.057***	0.327***	0.011
	(0.009)	(0.088)	(0.100)	(0.006)	(0.065)	(0.062)	(0.006)	(0.061)	(0.062)	(0.007)	(0.059)	(0.059)	(0.007)	(0.060)	(0.061)
Capital Intensity	0.011	0.537***	0.103	0.002	0.254***	0.087**	0.002	0.246***	0.082**	0.000	0.233***	0.082**	0.004	0.249***	0.081**
	(0.011)	(0.083)	(0.072)	(0.009)	(0.031)	(0.036)	(0.009)	(0.031)	(0.036)	(0.009)	(0.031)	(0.036)	(0.009)	(0.031)	(0.035)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs	1352	1352	1352	2646	2646	2646	2646	2646	2646	2521	2521	2521	2646	2646	2646
Individuals		133	133		148	148		148	148		134	134		148	148
Estimator	OLS	Within	Within	OLS	Within	Within	OLS	Within	Within	OLS	Within	Within	OLS	Within	Within

Marginal Effect of Competition ([1] to [3]) and Regulation ([4] to [15])

	N-FIRMS/VA			REGIMP			REGREF			PMR			PMR(Public)		
Closeness (sample values)	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]
Minimum	0.039	0.233***	0.048	-0.001	-0.655***	0.487**	0.016	-0.158	0.099	0.176	0.190	0.820***	0.101	-0.094	0.549*
	(0.035)	(0.064)	(0.059)	(0.095)	(0.219)	(0.195)	(0.078)	(0.116)	(0.134)	(0.123)	(0.224)	(0.226)	(0.069)	(0.245)	(0.280)
Mean less one standard deviation	0.021**	0.080***	0.037**	0.019	-0.781***	0.415***	0.054**	-0.177***	0.020	0.127***	0.066	0.586***	0.089***	-0.236	0.527**
	(0.010)	(0.019)	(0.018)	(0.028)	(0.137)	(0.118)	(0.026)	(0.061)	(0.068)	(0.037)	(0.145)	(0.140)	(0.020)	(0.216)	(0.240)
Mean	0.017***	0.043***	0.035***	0.025	-0.815***	0.395***	0.065***	-0.182***	-0.001	0.117***	0.039	0.535***	0.086***	-0.274	0.522**
	(0.006)	(0.013)	(0.012)	(0.017)	(0.130)	(0.110)	(0.018)	(0.052)	(0.057)	(0.025)	(0.138)	(0.135)	(0.010)	(0.211)	(0.231)
Mean plus one standard deviation	0.013*	0.006	0.032**	0.030	-0.849***	0.376***	0.075***	-0.187***	-0.022	0.106***	0.013	0.485***	0.083***	-0.312	0.516**
	(0.007)	(0.016)	(0.015)	(0.022)	(0.133)	(0.110)	(0.022)	(0.049)	(0.052)	(0.027)	(0.135)	(0.136)	(0.014)	(0.206)	(0.222)
Maximum	0.011	-0.008	0.031*	0.032	-0.859***	0.370***	0.078***	-0.188***	-0.028	0.102***	0.002	0.465***	0.082***	-0.323	0.514**
	(0.009)	(0.019)	(0.017)	(0.026)	(0.136)	(0.112)	(0.025)	(0.049)	(0.052)	(0.031)	(0.136)	(0.138)	(0.017)	(0.204)	(0.220)

Note: Hubert-White corrected standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01; All variables in log

Table 1.

sions using the REGIMP indicator (columns [4] to [6] in Table 1), which is provided in panel-data-like structure (times-series-cross-section data). The OLS regression gives marginal effects non significantly different from zero, i.e. no impact of product market regulation on innovation whatever the distance to frontier. The fixed effect regression gives a statistically negative impact of regulation, which is increasing with the relative technological level. On the other hand, considering the model without the lagged dependent variable gives significant positive marginal effects of regulation.

Looking at the results documented in Table 1 (columns [4] to [15]), three configurations emerge. The most frequent case is that of a positive impact of regulation policy, which is decreasing as the industry approaches the technological frontier but remains significantly positive even at the frontier([6], [10],[12],[13] and [15]). In regression [7], this positive marginal effect appears on the contrary to increase as the industry moves closer to the frontier. On the other hand, regulation policy turns out to have a negative significant marginal effect in regressions [5] and [8]. Although this effect is decreasing with the closeness to the frontier, it appears significantly negative for laggard industries. Furthermore, in some cases regulation turns out to have non significant marginal effects, no matter what the distance to the frontier is ([4],[9],[11] and [14]). Interestingly, even if these regressions do not allow to conclude to a single pattern of the relationship between competition and innovation, none of them reproduce the predictions of the baseline model.

4.2 Addressing dynamics (System-GMM regressions)

As argued in the previous Section, OLS and Within-group estimators may not be appropriate for the problem considered here. The use of the S-GMM estimator will allow us to deal with the lagged dependent variable bias and the potential endogeneity of several of the regressors. One may indeed suppose that the competition indicators taken into account here are endogenous. For instance, lagging firms or industries may pressure for protection from competition in exchange for political support, whereas the support for regulation would be less pronounced in the vicinity of the technological frontier. Other variables may also be endogenous to the growth process itself. For these reasons, the competition indicators and the capital/labour ratio will be considered as endogenous in the S-GMM estimations.

Dependent Variable: Patenting (patents decomposition /hours worked) **- System-GMM Estimations**
Regressions for Competition ([1]) and Regulation ([2] to [5])

	N-FIRMS/VA [1]	**REGIMP [2]**	**REGREF [3]**	**PMR [4]**	**PMR (Public) [5]**
Patenting (t-1)	0.896***	0.903***	0.843***	0.922***	0.887***
	(0.064)	(0.032)	(0.049)	(0.022)	(0.033)
Closeness to Frontier	-0.013	1.924**	-0.284	0.003	0.046
	(0.126)	(0.972)	(0.230)	(0.053)	(0.129)
Closeness × Competition (Regulation)	-0.113*	0.936**	0.494**	0.020	0.068
	(0.067)	(0.469)	(0.198)	(0.114)	(0.096)
Competition (Regulation)	0.509*	-3.794**	-1.926**	0.257	-0.144
	(0.280)	(1.909)	(0.823)	(0.450)	(0.397)
Externalities	0.177*	0.116**	0.219***	0.084***	0.114***
	(0.105)	(0.046)	(0.064)	(0.024)	(0.036)
Capital Intensity	0.032	-0.032	0.122	-0.041	0.118**
	(0.057)	(0.041)	(0.079)	(0.039)	(0.055)
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of Obs	1352	2646	2646	2521	2646
Sargan-Hansen p	0.387	0.164	0.117	0.187	0.224
AR(2)p	0.522	0.908	0.919	0.654	0.946
Instruments	122	136	131	106	142
Individuals	133	148	148	134	148
Estimator	SY_GMM	SY_GMM	SY_GMM	SY_GMM	SY_GMM

Marginal effect of competition ([1]) and Regulation ([2] to [5])

Closeness (sample values)	**N-FIRMS/VA [1]**	**REGIMP [2]**	**REGREF [3]**	**PMR [4]**	**PMR (Public) [5]**
Minimum	0.294*	-2.033**	-0.997**	0.294	-0.017
	(0.153)	(1.027)	(0.455)	(0.264)	(0.217)
Mean less one standard deviation	0.100**	-0.451*	-0.162	0.330*	0.098
	(0.045)	(0.240)	(0.150)	(0.175)	(0.063)
Mean	0.053*	-0.028	0.061	0.338*	0.128***
	(0.028)	(0.062)	(0.105)	(0.183)	(0.038)
Mean plus one standard deviation	0.006	0.395**	0.284**	0.345*	0.159***
	(0.035)	(0.200)	(0.125)	(0.199)	(0.052)
Maximum	-0.012	0.516**	0.348**	0.348*	0.167***
	(0.042)	(0.258)	(0.141)	(0.208)	(0.062)

Note: Hubert-White corrected standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01; All variables in log

Table 2.

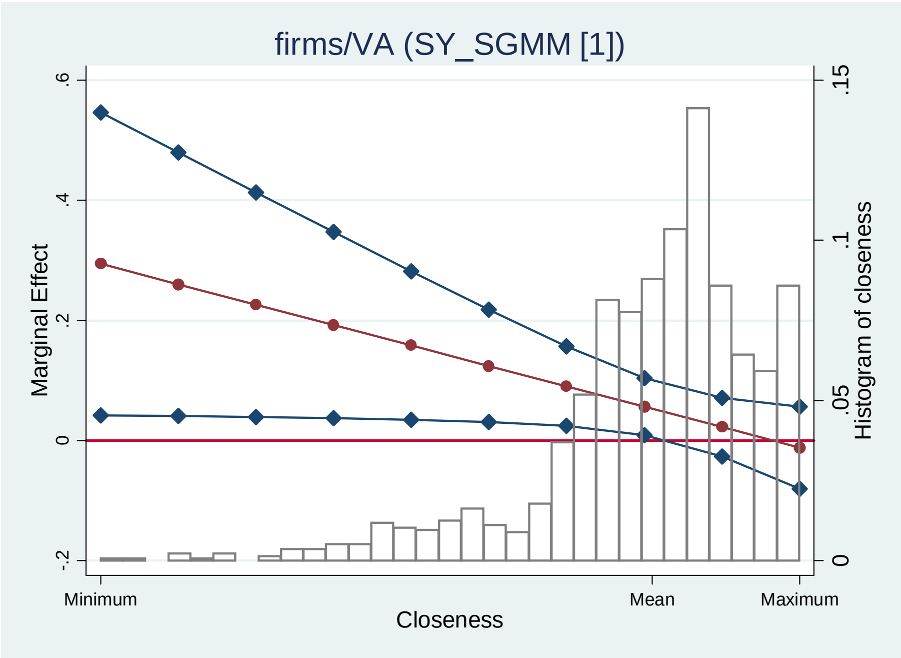

Figure 2. Marginal effect of N-Firms/VA on patenting

Table 2 presents the S-GMM estimations of the effects of competition on innovation. As in our previous results, the number of firms plays a positive role for innovation, but only when industries are far from the technological frontier (Column [1]). This effect vanishes once the relative productivity level rises above the mean. Figure 2 presents the plot of the marginal effect against the closeness to the technological frontier. As one notices clearly with the confidence intervals, a significant innovation-boosting effect exists only for industries under the mean relative productivity. The Figure displays also the histogram of the relative productivity levels. One notices that only a limited number of industry laggards are likely to benefit from increased competition while the bulk of the industries would benefit very little if anything.

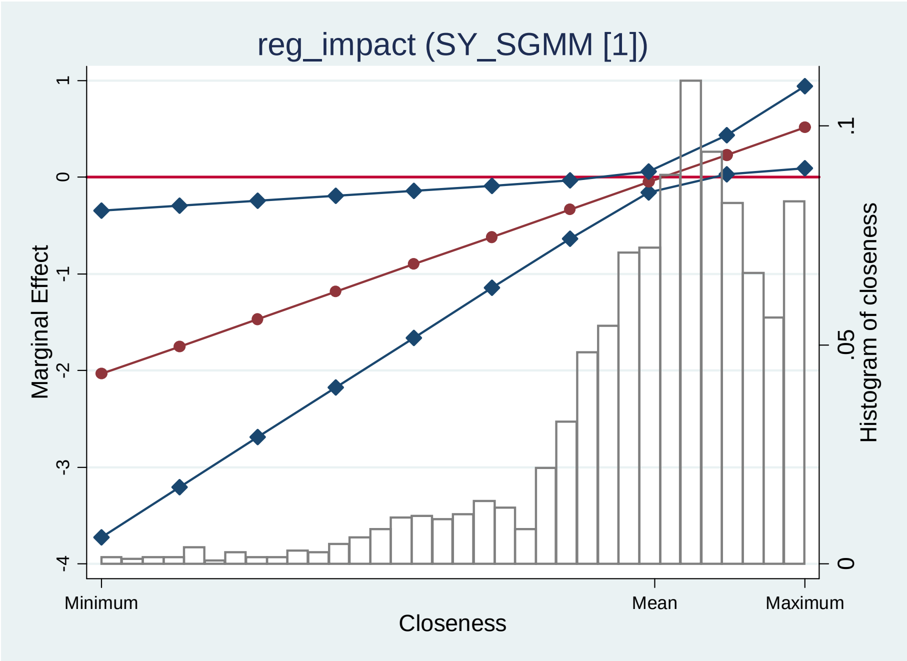

Figure 3. Marginal effect of REGIMP on patenting

This effect of competition is broadly confirmed by the results obtained using the indicators of regulation. For the regulation impact (Column [2] and Figure 3) and regulation in non-manufacturing activities (Column [3] and Figure 4) indicators, competition regulation has a negative impact on innovation far from the frontier. This effect becomes gradually positive as the relative productivity level increases above the mean and turns out to be significantly positive at the frontier. The results for the economy-wide product market regulation indicators (Columns [4] and [5], Figures 5 and 6) are in line with those just mentioned. Product market regulation has no impact on innovation far from the frontier, and an increasingly positive effect as the productivity level rises.

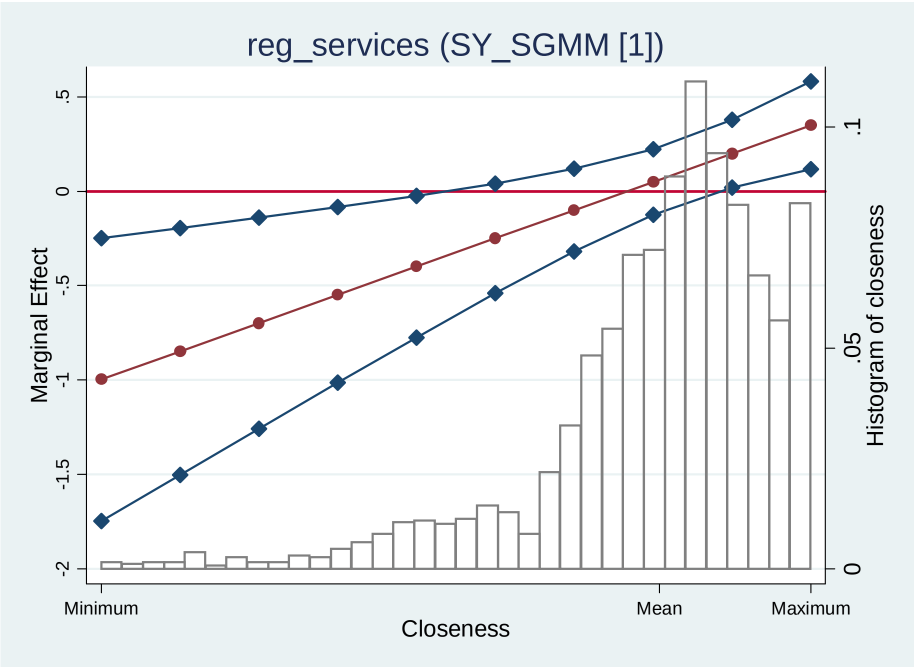

Figure 4. Marginal effect of REGREF on patenting

On the whole, the use of an estimator well-suited to a dynamic specification allows to depict a clearer picture about the marginal effect of competition and regulation according to the proximity to the technological frontier: product market regulation has an increasingly positive impact on innovation as the industry moves closer to the frontier, i.e. the marginal effects of regulation indicators display a positive slope. The findings with the relative number of firms as a proxy for the outcome of market competition are consistent with this result. The next Section checks the robustness of these results by considering alternative specifications under system GMM.

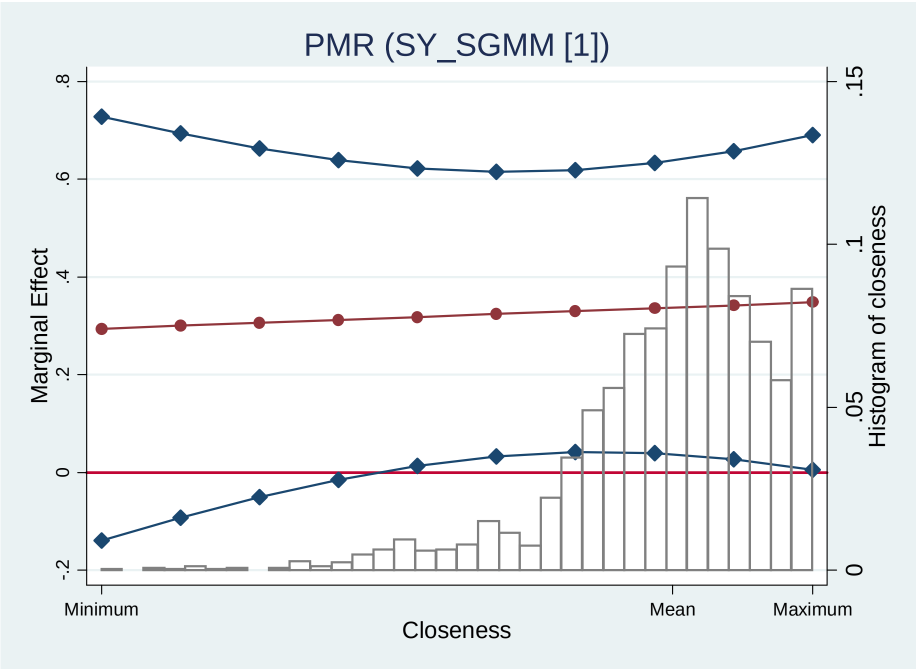

Figure 5. Marginal effect of PMR on patenting

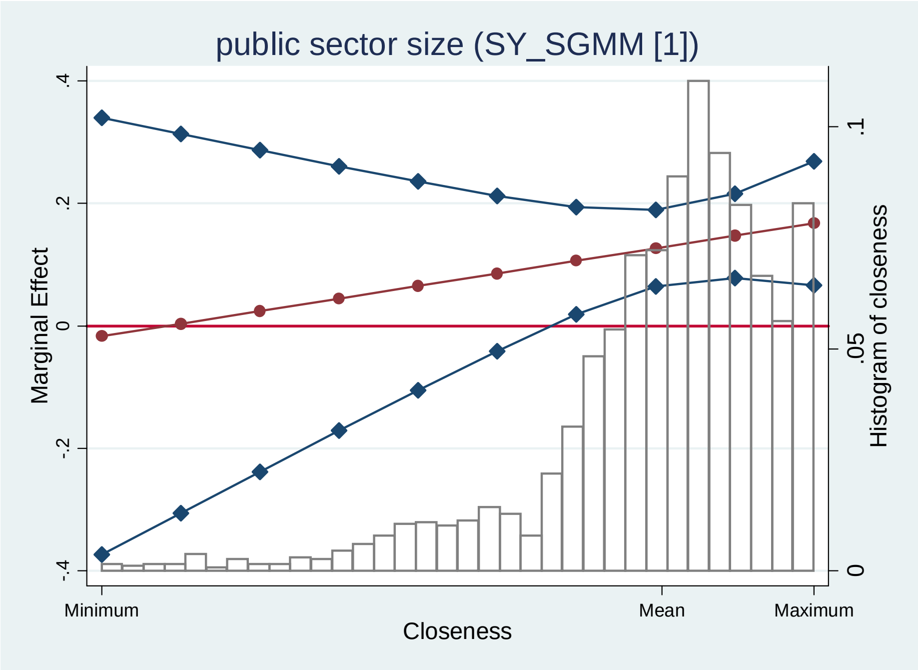

Figure 3.9. Marginal effect of PMR(Public) on patenting

5 Robustness tests

5.1 Additional controls

The model considered in the preceding Section is now extended to include other variables. The competition indicators considered previously referred to the domestic situation only. However competition from foreign firms can be important in some industries. In order to control for this effect, the import penetration ratio is included in the regressions. Other institutional variables may have an influence too. The literature on competition and innovation refers particularly to labour and financial markets (Aghion, 2006). More labour market flexibility is supposed to favour restructuring and hasten the decline of sunset industries, allowing factors to be transferred to sunrise industries (Saint-Paul, 2002). Also, more developed financial markets are expected to boost innovative investment since credit-constrained firms may not be able to finance the fixed costs necessary to develop new product or processes. For these reasons, two variables were introduced in the regression: a measure of employment protection and the ratio of total financial assets of institutional investors to GDP (OECD). Results for the extended models are presented in Table 3.

Import penetration turns out to have significant coefficients for models [1] and [4]. Each time, the coefficient is positive, which means that the innovation-boosting effect of foreign competition is present. However, changing the competition indicator leads to non significant coefficients in models [2], [3] and [5]. The labour market legislation (employment protection) variable obtains significant coefficients with all regulation indicators. However, the impact is negative with the economy-wide product market regulation indicators ([4] and [5]) but positive with the non-manufacturing regulation indicators ([2] and [3]). One cannot therefore conclude to the existence of an innovation-hindering effect of employment legislation. Finally, the financial variable obtains significant, positive, coefficients with the economy-wide indicators ([4] and [5]).

The extension of the model with the three variables do not significantly change the results concerning the marginal effect of product market regulation or competition. The magnitude of the effect is sometimes changed (for instance with the "knock-on" effect of non-manufacturing regulation REGIMP) but the positively-sloped relationship of the regulation effect with the relative productivity level is maintained. The same applies for the negative slope of the marginal effect of the relative number of firms ([1]) The only change worth mentioning takes place with the REGREF indicator([3]), usually used as proxy of the evolution of regulation at the national level. Using this indicator, regulation now fails to have a positive impact on innovation even at the frontier. However, since REGIMP seems more suited to the industry-level data used in the estimations, the results of model [2] are supposed to be more accurate. One can also note that the positive impact of the PMR variable restricted to the Public Sector [5] turns now significant far from the technological frontier whereas it was not the case in the baseline model (Table 2, column [5]).

We also consider a translog-like specification to test the effect of the interaction between competition and proximity to the frontier. To this effect, quadratic terms for the distance to frontier and the competition indicators were introduced in the regressions. This more flexible function should make it possible to estimate more accurately the effects of regulation. Results are presented in Table 4. Once again, nothing substantial is altered in comparison with the results in Tables 2 or 3. The slopes of the marginal effects remain the same and the magnitude of the effects is not changed very much. However, this time, regulation fails to have a positive innovation effect at the frontier even with the REGIMP indicator.

Dependent Variable: Patenting (patents decomposition /hours worked) **- System-GMM Estimations**
Regressions for Competition ([1]) and Regulation ([2] to [5]) (Full set of controls)

	N-FIRMS/VA [1]	**REGIMP [2]**	**REGREF [3]**	**PMR [4]**	**PMR (Public) [5]**
Patenting (t-1)	0.919***	0.857***	0.840***	0.835***	0.693***
	(0.027)	(0.044)	(0.044)	(0.051)	(0.082)
Closeness to Frontier	-0.125	1.411***	-0.031	-0.117	-0.027
	(0.133)	(0.516)	(0.125)	(0.106)	(0.111)
Closeness × Competition (Regulation)	-0.104	0.665***	0.065	0.265	0.059
	(0.069)	(0.257)	(0.115)	(0.163)	(0.086)
Competition (Regulation)	0.469	-2.814***	-0.780	-0.010	0.775
	(0.289)	(1.067)	(0.551)	(0.927)	(0.485)
Externalities	0.061*	0.156***	0.152***	0.106*	0.282***
	(0.035)	(0.041)	(0.043)	(0.062)	(0.086)
Capital Intensity	0.168**	-0.069	0.033	0.015	0.119**
	(0.070)	(0.074)	(0.054)	(0.063)	(0.057)
Import Penteration	0.109*	-0.054	0.015	0.239**	0.052
	(0.062)	(0.047)	(0.060)	(0.118)	(0.092)
Labour Market Regulation	-0.045	0.118*	0.169*	-0.444**	-0.278*
	(0.033)	(0.069)	(0.098)	(0.207)	(0.153)
Financial Assets/GDP	-0.019	-0.001	-0.012	0.293**	0.518**
	(0.051)	(0.060)	(0.055)	(0.117)	(0.207)
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of Obs	1154	2110	2110	2110	2110
Sargan-Hansen p	0.378	0.148	0.125	0.128	0.117
AR(2)p	0.823	0.920	0.885	0.900	0.873
Instruments	99	122	93	75	106
Individuals	125	126	126	126	126
Estimator	SY_GMM	SY_GMM	SY_GMM	SY_GMM	SY_GMM

	Marginal effect of Competition ([1]) and Regulation ([2] to [15])				
Closeness (sample values)	**N-FIRMS/VA [1]**	**REGIMP [2]**	**REGREF [3]**	**PMR [4]**	**PMR (Public) [5]**
Minimum	0.232*	-1.425***	-0.644*	0.545	0.899**
	(0.134)	(0.534)	(0.341)	(0.673)	(0.394)
Mean less one standard deviation	0.086**	-0.349**	-0.538**	0.974*	0.994***
	(0.042)	(0.142)	(0.222)	(0.545)	(0.371)
Mean	0.045*	-0.104	-0.513**	1.072**	1.016***
	(0.024)	(0.091)	(0.209)	(0.531)	(0.373)
Mean plus one standard deviation	0.004	0.142	-0.489**	1.171**	1.038***
	(0.029)	(0.119)	(0.204)	(0.522)	(0.377)
Maximum	-0.012	0.248*	-0.479**	1.213**	1.047***
	(0.037)	(0.150)	(0.205)	(0.521)	(0.380)

Note: Hubert-White corrected standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01; All variables in log

Table 3.

Dependent Variable: Patenting (patents decomposition /hours worked) **- System-GMM Estimations**
Regressions for Competition ([1]) and Regulation ([2] to [5]) (Translog Model)

	N-FIRMS/VA [1]	**REGIMP [2]**	**REGREF [3]**	**PMR [4]**	**PMR (Public) [5]**
Patenting (t-1)	0.918***	0.836***	0.865***	0.913***	0.880***
	(0.031)	(0.041)	(0.033)	(0.024)	(0.031)
Closeness to Frontier	0.891*	0.385	0.674	0.115	0.301
	(0.479)	(0.681)	(0.846)	(0.580)	(0.298)
Closeness × Competition (Regula	-0.061	0.396*	0.505**	0.042	0.052
	(0.038)	(0.218)	(0.242)	(0.096)	(0.089)
Competition (Regulation)	0.295**	-1.248	-4.420***	1.001*	-0.132
	(0.147)	(1.070)	(1.406)	(0.514)	(0.345)
Externalities	0.102**	0.191***	0.180***	0.095***	0.119***
	(0.047)	(0.051)	(0.042)	(0.026)	(0.035)
Capital Intensity	0.037	0.011	0.014	-0.033	0.103***
	(0.046)	(0.041)	(0.038)	(0.043)	(0.036)
Closeness to Frontier^2	-0.139**	-0.099	0.078	-0.014	-0.037
	(0.064)	(0.113)	(0.082)	(0.084)	(0.041)
Competition^2 (Regulation^2)	0.013	-0.095	-0.553***	-0.533***	0.087
	(0.010)	(0.201)	(0.161)	(0.169)	(0.111)
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of Obs	1352	2646	2646	2521	2646
Sargan-Hansen p	0.556	0.185	0.211	0.288	0.117
AR(2)p	0.524	0.950	0.904	0.651	0.958
Instruments	121	142	144	106	143
Individuals	133	148	148	134	148
Estimator	SY_GMM	SY_GMM	SY_GMM	SY_GMM	SY_GMM

Marginal effect of Competition ([1]) and Regulation ([2] to [15])

Closeness (sample values)	**N-FIRMS/VA [1]**	**REGIMP [2]**	**REGREF [3]**	**PMR [4]**	**PMR (Public) [5]**
Minimum	0.178**	-0.765*	-1.180**	0.485*	0.152
	(0.076)	(0.429)	(0.542)	(0.286)	(0.263)
Mean less one standard deviation	0.073***	-0.096	-0.327**	0.560**	0.240
	(0.021)	(0.132)	(0.147)	(0.234)	(0.160)
Mean	0.048**	0.082	-0.098	0.576**	0.263*
	(0.020)	(0.137)	(0.074)	(0.238)	(0.148)
Mean plus one standard deviation	0.022	0.261	0.130	0.592**	0.286**
	(0.030)	(0.198)	(0.115)	(0.247)	(0.145)
Maximum	0.013	0.312	0.195	0.598**	0.293**
	(0.034)	(0.221)	(0.141)	(0.252)	(0.147)

Note: Hubert-White corrected standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01; All variables in log

Table 4.

The two above-mentioned extensions can be combined to obtain a translog model with the full set of controls. Table 5 presents the estimations of this model with the various competition or regulation indicators. The results concerning the marginal effects are basically unchanged. The main result, i.e. the non existence of a significant negative effect of product market regulation at the technological frontier, is preserved. However, it should be also noticed that, relatively to the simple translog model, the extended one provides a better assessment of the impact of regulation. While in the previous table (Table 4, columns [2] and [3]) the marginal effects of regulation in services and their impact on industries were only significant far from the frontier, they are now significant for a larger interval. Concerning the effects of additional controls, results are not substantially modified. The positive effects of labour market legislation obtained with the regimpact and REGREF indicators now turn out to be insignificant (columns [2] and [3]) while the negative impact obtained with the economy-wide regulation indicators is maintained. The financial assets variable only obtains a significant coefficient with the PMR variable restricted to the Public sector (column [5]).

Besides some changes in the significance and magnitude of the marginal effect of regulation, the picture depicted in the system-GMM regressions (Table 2) remains qualitatively unchanged after this first robustness test. Indeed, most of the time, regulation policy improves innovative performances as one moves closer to the leading edge of technology (columns [2][4][5], Tables 2, 3 and 4). Only the model with additional institutional controls using the regulation in services indicator (column [3], Tables 3 and 5) delivers divergent results. Product market regulation turns out significantly detrimental to innovative performances near the frontier only in regression [3] in Table 3. Nevertheless, this adverse impact of services regulation is weaker the closer to the frontier an industry is.

Dependent Variable: Patenting (patents decomposition /hours worked) **- System-GMM Estimations**
Regressions for Competition ([1]) and Regulation ([2] to [5]) (Full set of controls; Translog Model)

	N-FIRMS/VA [1]	REGIMP [2]	REGREF [3]	PMR [4]	PMR (Public) [5]
Patenting (t-1)	0.920***	0.950***	0.814***	0.927***	0.688***
	(0.023)	(0.031)	(0.053)	(0.040)	(0.076)
Closeness to Frontier	0.344	1.632	1.495	-0.520	0.791
	(0.825)	(1.103)	(1.148)	(0.599)	(0.817)
Closeness × Competition (Regulation)	-0.101	0.565**	0.401	0.101	0.075
	(0.066)	(0.276)	(0.246)	(0.143)	(0.076)
Competition (Regulation)	0.462*	-4.143**	-1.016	0.850	0.814
	(0.274)	(2.003)	(0.860)	(0.951)	(0.529)
Externalities	0.066**	0.062**	0.165***	0.025	0.292***
	(0.033)	(0.029)	(0.052)	(0.036)	(0.080)
Capital Intensity	0.154**	0.006	0.087	0.032	0.127**
	(0.064)	(0.103)	(0.058)	(0.053)	(0.061)
Import Penteration	0.099*	-0.023	0.073	0.205**	0.032
	(0.054)	(0.069)	(0.061)	(0.104)	(0.094)
Labour Market Regulation	-0.031	-0.026	0.058	-0.276*	-0.308*
	(0.036)	(0.077)	(0.093)	(0.161)	(0.177)
Financial Assets/GDP	-0.000	-0.021	-0.017	0.088	0.490**
	(0.050)	(0.060)	(0.061)	(0.092)	(0.204)
Closeness to Frontier^2	-0.062	-0.046	-0.249	0.064	-0.113
	(0.107)	(0.103)	(0.182)	(0.093)	(0.116)
Competition^2 (Regulation^2)	0.008	-0.421	-0.391**	-0.416	-0.057
	(0.011)	(0.300)	(0.189)	(0.429)	(0.159)
Year dummies	Yes	Yes	Yes	Yes	Yes
Number of Obs	1154	2110	2110	2110	2110
Sargan-Hansen p	0.294	0.137	0.219	0.231	0.210
AR(2)p	0.815	0.928	0.893	0.920	0.889
Instruments	103	95	88	77	110
Individuals	125	126	126	126	126
Estimator	SY_GMM	SY_GMM	SY_GMM	SY_GMM	SY_GMM

Marginal effect of Competition ([1]) and Regulation ([2] to [15])

Closeness (sample values)	N-FIRMS/VA [1]	REGIMP [2]	REGREF [3]	PMR [4]	PMR (Public) [5]
Minimum	0.233*	-1.222**	-1.250*	0.596	0.846**
	(0.125)	(0.578)	(0.651)	(0.501)	(0.348)
Mean less one standard deviation	0.091**	-0.308*	-0.601**	0.759*	0.967***
	(0.038)	(0.187)	(0.284)	(0.448)	(0.351)
Mean	0.052**	-0.099	-0.453**	0.796*	0.995***
	(0.023)	(0.150)	(0.216)	(0.452)	(0.357)
Mean plus one standard deviation	0.013	0.109	-0.305*	0.833*	1.022***
	(0.031)	(0.175)	(0.172)	(0.462)	(0.366)
Maximum	-0.003	0.199	-0.241	0.849*	1.034***
	(0.039)	(0.201)	(0.164)	(0.468)	(0.370)

Note: Hubert-White corrected standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01; All variables in log

Table 5.

5.2 The model with lagged regressors

To test further the robustness of the results, regressors are now included with a lag. This specification allow to further reduce the risk of reverse causality. Results for the base and for the translog models are presented in Tables 6 and 7 and are compared with those of the contemporaneous model (Tables 2 and 4).

Concerning the base model for the S-GMM estimates, two main differences arise. First, while the contemporaneous model account for a positive significant impact of regulation close to the frontier (Table 2, columns [2] and [3]), regulation policy in the lagged model does not have a significant impact near the frontier (Table 6, columns [2] and [3]). In contrast, the economy-wide regulation indicator for the Public sector turns out now to have a significant and positive impact for laggard industries , while they were non significant in the baseline model (Table 2 and 6, columns [4] and [5]). For all regulation indicators the main result obtained with system-GMM estimations is confirmed, i.e. a positively-sloped relationship for the marginal effect of regulation as the distance to the frontier decreases. Also, one should note that the negative slope for the relative number of firms is preserved.

Results for the translog model estimations are given in Table 7. Two main remarks can be made. First, for the impact of service regulation (REGREF) and Public sector indicators (PMR(public), the magnitude of the marginal effect is higher in the translog lagged model than in contemporaneous one (see Tables 4 and 7). Second, the adverse impact of the REGREF and REGIMP indicators ([2] and [3] appear significant for a wider interval, at least up to the mean value of the relative productivity level, whereas this effect was only significant for small values in the translog contemporaneous model (Table 4). Most importantly, the upward slope of the marginal effect is still observed.

One should stress that here again the most interesting result is not substantially modified: there is no evidence of an adverse impact of regulation near the frontier and the marginal effects of regulation display a positively-sloped relationship against the relative productivity level of the industry. Similarly, the marginal effect of the number of firms per value added on patenting is significantly positive for laggard industries and decreases with the productivity gap, becoming non significant at the frontier.

6 A possible explanation

Recent works have undertaken the attempt to reconcile the traditional Schumpeterian view of a negative effect of competition on innovation and the idea according to which competition may push firms to reduce their inefficiencies in order to keep their market position. Aghion et al. (2005) present a theoretical basis enabling to encompass both arguments. The rationale consists in considering that innovation is carried out by incumbents that take into account not only post-innovations rents but the difference between post- and pre- innovation rents. The inclusion of positive and negative effects of competition leads to the inverted U-shape pattern depicting the relationship between competition and innovation.

One important prediction of Aghion et al. (2005) is that, for those firms competing at the leading edge, it is the pro-innovation effect of competition that dominates. We show in this Section that the validity of this prediction depends on the extent to which leaders are absents in the R&D contest. Results are different if leaders do carry out R&D and, by doing so, they can make more difficult the catching-up process of laggards. For a sake of presentation, we slightly modify the Aghion et al.'s (2005) model to include this possibility.

6.1 The baseline setup

Consider Aghion et al.'s (2005) economy composed of a unit mass of identical consumers. Each consumer supplies a unit of labour inelastically and has a logarithmic instantaneous utility function $u(y_t) = \ln y_t$ with a constant discount rate of r. The consumption good is produced with intermediate goods according to the following production function:

$$\ln y_t = \int_0^1 \ln x_{jt} dj \tag{8}$$

In each industry j, there are two duopolists, A and B. At each date, the final consumption good needs, as inpunt, an aggregate good of each industry with the form $x_j = x_{Aj} + x_{Bj}$. Because of the utility function's specification (8), each individual spends the same amount on each good. Total spending is normalised to unity, so that the budget constraint is $p_{Aj}x_{Aj} + p_{Bj}x_{Bj} = 1$.

Each intermediate firm produces with constant returns to scale using labour as the only input. Denoting k the technology level of the duopoly firms in industry j, one unit of labour generates an output flow equal to:

$$A_i = \gamma^{k_i} \qquad i = A, B \tag{9}$$

The baseline model assumes that, in any intermediate industry, the largest gap between the leader and the follower is one technological step because of knowledge externalities. If the leader innovate, the follower immediately moves one step up the quality ladder so that the relative positions of the two firms is not altered.

At any point in time, there will be two types of sectors in the economy: leveled industries where both firms are at the same technological level and unleveled industries where the technological leader is one quality step above its competitor. Thus, three type of firms are possible $i \in \{-1, 0, 1\}$: the follower ($i = -1$); the firm in a level sector ($i = 0$), the leader firm ($i = 1$). Depending on innovation firms A and B transit among these different states.

Product market competition is modelled in the following way. The degree of collusion ϵ of the two firms in a leveled industry will measure the degree of product market competition. Firms do not collude when the industry is unleveled. In this case, the leader applies a limit pricing rule, setting a price equal to the marginal cost of the laggard. The latter makes then zero profit while the leader makes a profit equal to one minus its production cost (wages are normalised to 1):

$$\pi_{-1} = 0 \qquad \pi_1 = 1 - \frac{1}{\gamma} \tag{10}$$

In a leveled industry, if firms do not collude, Bertrand competion brings profits to zero. At a maximum level of collusion, firms split the leader profits between themselves (one half for each). Thus the model summarises in $\Delta = 1 - \epsilon$ $(0 \leq \epsilon \leq 1/2)$ the degree of competition. Profits in leveled sectors are then given by:

$$\pi_0 = (1 - \Delta)\, \pi_1 \tag{11}$$

If a firm moves one technological step ahead at a Poisson hazard rate of n it incurs in a R&D cost $\frac{c\, n^2}{2}$. The follower can move one step ahead at a hazard rate h even without spending anything on R&D. One note n_0 the R&D intensity of each firm in leveled industries, n_{-1} that of the follower firm and n_1 that of a leading firm in an unleveled industry. A particular characteristic of the baseline model is that $n_1 = 0$ since the leading firm has no incentive to innovate because of the knowledge externality assumption. It is this feature that we modify.

6.2 A leader reducing knowledge diffusion

The assumption of a non-innovative technological leader appears to contradict casual evidence in a large number of activities.[5] We therefore slightly modify the baseline setup exposed above to allow for leader innovation. We keep the assumption restricting the maximum sustainable productivity gap to be one step. As before, in an industry in which the leader has succeeded in innovating, its rival will immediately be upgraded one step. However, we consider that the leader's R&D effort n_1 makes it more difficult for the follower to innovate and move one step ahead, i.e. it reduces the catch-up probability to $h - \lambda n_1$, with λ a parameter capturing the ability of the leader

[5] One may for instance check the R&D expenditure of industry leaders given in Table 1 of Segerstrom (2007).

to influence the R&D difficulty of the follower. This type of effect is supported by the empirical evidence provided by Crépon and Duguet (1997): in narrow defined industries, they find a negative externality of R&D between competitors. One may suppose that the engagement of the leader in a new discovery induces a change in the technological paradigm. Even if the quality difference is still one step, the leader's innovation makes this last step harder to climb for the follower.[6].

The steady state Bellman equations can be expressed as:

$$rV_1 = \pi_1 + (n_{-1} + h - \lambda n_1)(V_0 - V_1) + n_1 (V_1 - V_1) - \frac{cn_1^2}{2} \tag{12}$$

$$rV_{-1} = \pi_{-1} + (n_{-1} + h - \lambda n_1)(V_0 - V_{-1}) - \frac{cn_{-1}^2}{2} \tag{13}$$

$$rV_0 = \pi_0 + n_0 (V_1 - V_0) + \overline{n}_0 (V_{-1} - V_0) - \frac{cn_0^2}{2} \tag{14}$$

Where V_i is the value of each type of firm $i \in \{-1, 0, 1\}$. The R&D effort of the competitor in a leveled sector is denoted by $\overline{n}_0$. In a symmetric Nash equilibrium both R&D intensity are equal. Hence, the baseline model of Aghion et al. (2005) might be interpreted as a particular case in which $\lambda = 0$. Using the maximum principle, first order conditions on the right-hand-side lead to:

$$cn_1 = \lambda (V_1 - V_0) \tag{15}$$

$$cn_{-1} = V_0 - V_{-1} \tag{16}$$

$$cn_0 = V_1 - V_0 \tag{17}$$

Recalling that $\pi_0 = (1 - \Delta)\pi_1$ and solving for n_1 and n_{-1} leads to the reduced system:

$$0 = \Delta\pi_1 - \frac{\rho c n_1}{\lambda} + \frac{cn_1^2}{2}\left(1 - \frac{1}{\lambda^2}\right) \tag{18}$$

[6] The very closely related quality ladder model of Grossman and Helpman [1991] also assumes that leaders do not innovate. Rewards of a new improvement in quality are not profitable enough to incitate the leader to engage in R&D. Nevertheless, as pointed out in Chapter 4, Footnote 4, leaders might have other reasons, namely to deter the innovation of their rivals. This case is excluded in the standard quality ladder framework.

$$0 = -\left(1-\Delta\right)\pi_1 - \frac{1}{\lambda^2}\frac{cn_1^2}{2} + \left(\rho + n_1\left[\frac{1}{\lambda} - \lambda\right]\right)cn_{-1} + \frac{cn_{-1}^2}{2} \tag{19}$$

Where $\rho \equiv h + r$. These equations give the solution for the leader R&D effort n_1 and for that of the follower n_{-1}, respectively. The following propositions analyse the properties of stationary R&D efforts in this jump-stochastic process.

Proposition 1. *The possibility of two stationary R&D effort of the **leader firm** depends on λ.*

(a) *For $\lambda < 1$ there is one relevant stationary strategy for the leader:*

$$n_{1a} = \lambda\frac{\rho c - \sqrt{D_1}}{c\left(\lambda^2 - 1\right)} \tag{20}$$

Where $D_1 \equiv \rho^2c^2 - 2c\left(\lambda^2 - 1\right)\Delta\pi_1$. For this strategy, competition increases R&D effort.

(b) *For $\lambda > 1$ and $\lambda^2 - 1 < \frac{\rho^2 c}{2\Delta\pi_1}$ there exists two relevant stationary strategies for the leader: n_{1a}* and

$$n_{1b} = \lambda\frac{\rho c + \sqrt{D_1}}{c\left(\lambda^2 - 1\right)} \tag{21}$$

For stratgey n_{1b}, competition discourages R&D effort.

Proof. This results relies on the possibility of one or two positive roots of (18). First, we solve the quadratic equation (18). This gives n_{1a} and n_{1b}. For $\lambda < 1$ the coefficient multiplying the squared term in (18) is negative: $\frac{c}{2}\left(1 - \frac{1}{\lambda^2}\right) < 0$. The discriminant D_1 is positive when $\lambda^2 - 1 < \frac{\rho^2 c}{2\Delta\pi_1}$, which is allways ensured for $\lambda < 1$. Hence the function first increases and then decreases (inverted U-shape). The intercept is positive ($\Delta\pi_1$), so only one solution is positive. Clearly, for $\lambda < 1$ the term $\left(\lambda^2 - 1\right) < 0$ so that n_{1a} is the positive root in this case. One immediatley verifies that for $\frac{\partial n_{1a}}{\partial\Delta} < 0$ (innovation-inducing effect of competition). A similar reasoning applies for $\lambda > 1$. The coefficient multiplying the squared term in (18) is now positive:$\frac{c}{2}\left(1 - \frac{1}{\lambda^2}\right) > 0$. Since the intercept is positve, for $\lambda^2 - 1 < \frac{\rho^2 c}{2\Delta\pi_1}$ D_1 is also positive and the curve depicted by (18) intercepts twice the n_1 axis in the positive side. These roots are given by n_{1a} and n_{1b}. For $\lambda > 1$ one immediatley verifies that for $\frac{\partial n_{1b}}{\partial\Delta} < 0$ (innovation-deterring effect of competition). ■

Proposition 2. *The possibility of two stationary R&D effort of a* ***leveled firm*** *depends on* λ.

(a) *For* $\lambda < 1$ *there is one relevant stationary strategy for a leveled firm:*

$$n_{0a} = \frac{\rho c - \sqrt{D_1}}{c\left(\lambda^2 - 1\right)} \tag{22}$$

Where $D_1 \equiv \rho^2 c^2 - 2c\left(\lambda^2 - 1\right)\Delta\pi_1$. *For this strategy competition increases R&D effort.*

(b) *For* $\lambda > 1$ *and* $\lambda^2 - 1 < \frac{\rho^2 c}{2\Delta\pi_1}$ *there exists two relevant stationary strategies for a leveled firm:* n_{0a} and

$$n_{0b} = \frac{\rho c + \sqrt{D_1}}{c\left(\lambda^2 - 1\right)} \tag{23}$$

For stratgey n_{0b} *competition discourages R&D effort.*

Proof. This result follows inmediately from Proposition 2 and the first order conditions (15) and (17) by which one deduces $n_1 = \lambda n_0$.■

Proposition 2. *For any value of* λ, *competition discourages the stationary R&D effort of the* ***follower firm****. The follower's stationary strategy is given by:*

$$n_{-1} = \frac{\left(-\left(\rho + n_1\left[\frac{1}{\lambda} - \lambda\right]\right)c + \sqrt{D_{-1}}\right)}{c} \tag{24}$$

Where $D_{-1} \equiv \left[\left(\rho + n_1\left[\frac{1}{\lambda} - \lambda\right]\right)c\right]^2 + 2c\left[\left(1 - \Delta\right)\pi_1 + \frac{1}{\lambda^2}\frac{cn_1^2}{2}\right]$.

Proof. This result comes from the solution of the quadratic equation (19). The coefficient multiplying the squared term in (19) is positive:$\frac{c}{2} > 0$. The discriminant D_{-1} is allways positive too. Thus, the polynomial function first decreases and then increases (U-shape). Since its intercept is negative $\left(-\left(1 - \Delta\right)\pi_1 - \frac{1}{\lambda^2}\frac{c(n_1)^2}{2} < 0\right)$ one solution lies on the negative side of the n_{-1} axis and the other on the positive one. Therefore, only the latter is relevant and is given by (24).■

The two possible stationary strategies of the leader will imply two type of equilibrium since n_0 and n_{-1} are functions of n_1. As in Aghion et al. (2005), the steady state equilibrium is defined in terms of the structure of the sector. If μ_1 is the probability in steady state of being in an unleveled sector, the probability that a sector moves from an unleveled state to a leveled one is then $\mu_1 (n_{-1} + h - \lambda n_1)$. The transition in the opposite direction is made with probability $2\mu_0 n_0$, where μ_0 denotes the steady-state probability of being in a leveled sector. The steady state equilibrium is given by equalising inward- and outward-flows:

$$\mu_1 (n_{-1} + h - \lambda n_1) = 2\mu_0 n_0 \tag{25}$$

Where the condition $\mu_1 + \mu_0 = 1$, of course, must hold . This implies:

$$\mu_1 = \frac{2n_0}{[(n_{-1} + h - \lambda n_1) + 2n_0]} \tag{26}$$

$$\mu_0 = 1 - \mu_1 \tag{27}$$

The R&D effort of the leader does not change the structure of the industry, but it contributes to the aggregate flow of innovation, which can be expressed as:

$$I = \mu_1 (n_{-1} + h - \lambda n_1 + n_1) + 2\mu_0 n_0 \tag{28}$$

The implication of the stationary R&D effort of the leader n_{1b} is that the the steady state proportion of unleveled sectors can be important, because the leader innovates and the follower has a lower probability to catch-up. In this type of sectors, if n_{1b} applies, both leader's and follower's R&D are deterred by competition. Thus, the aggregate effect of competition may be in fact negative. This is what Figures 7 to 9 show. For the sake of brevity, only numerical simulations are reported. The Figures display the aggregate flow of innovation I as function of competition Δ. Figure 7 considers the stationary strategy n_{1a} for $\lambda < 1$, which is the only possible outcome in this case. With use a value of λ very close to 0 ($\lambda = 0.001$). As expected, for very low values of λ, the model reproduces the standards results: the effects of competition on innovation are given by an inverted U-shape pattern.

In Figure 8 we consider the stationary strategy n_{1a} for $\lambda > 1$. Since for this case ($\lambda > 1$) there is also a second stationary strategy, Figure 9 plots aggregate innovation when the optimal R&D effort of firms at the leading edge is given by n_{1b}. Hence, when the ability of the leader to reduce knowledge diffusion is important enough ($\lambda > 1$) one has two possible equilibriums. When the stationary strategy of the leader is given by n_{1a}, the inverted U-shape no longer holds and innovation appears as monotonically increasing with competition. On the other hand, when the leader innovates at the (numerically) higher rate n_{1b} exactly the opposite occurs: competition is uniformly *detrimental* to innovation. As $n_{1b} > n_{1a}$ one might interpret this results as the outcome of fierce rivalry in high technology industries.

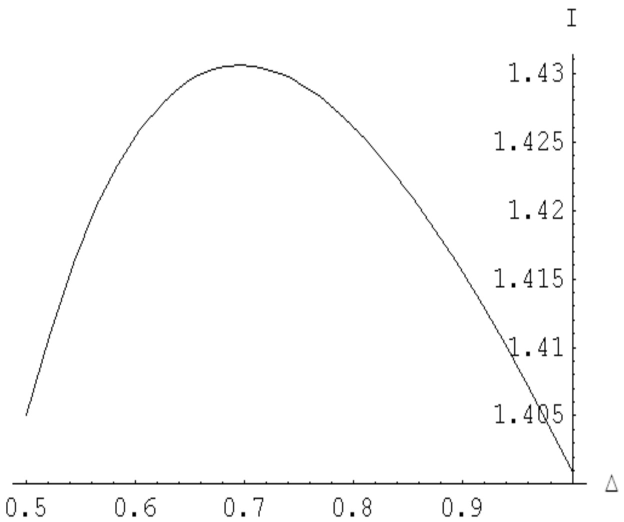

Figure 7. The effect of competition (Δ) on aggregate flow of innovation (I) using n_{1a}

$$h = 0.5,\ r = 0,\ c = 0.5,\ \pi 1 = 0.8, \lambda = 0.001$$

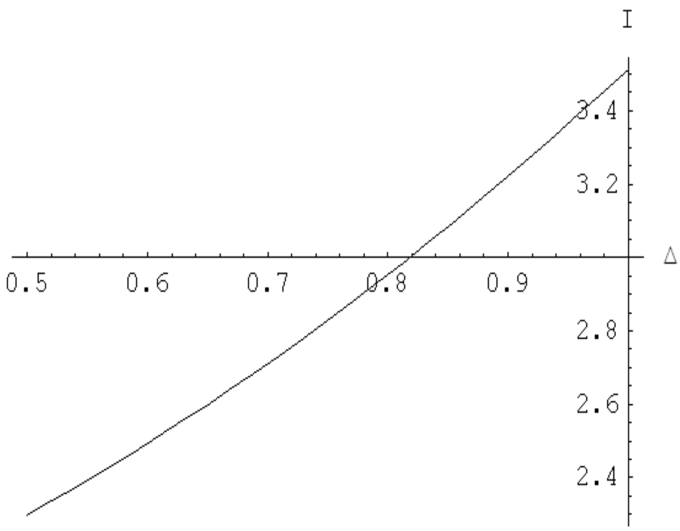

Figure 8. The effect of competition (Δ) on aggregate flow of innovation (I) using n_{1a}

$$h = 0.5; r = 0; c = 0.5; \pi 1 = 0.8; \lambda = 1.01$$

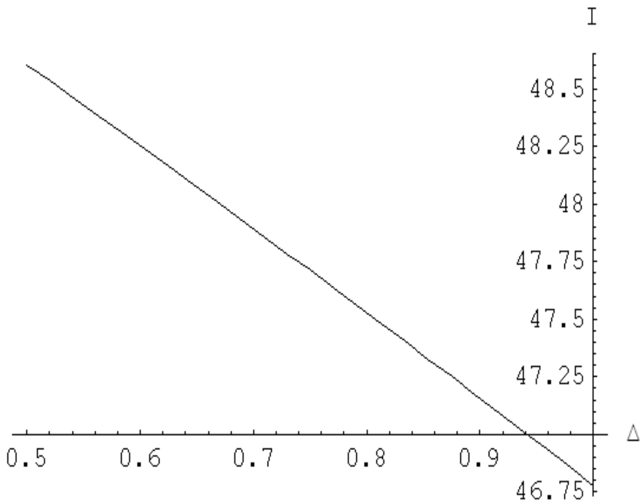

Figure 9. The effect of competition (Δ) on aggregate flow of innovation (I) using n_{1b}

$h = 0.5; r = 0; c = 0.5; \pi 1 = 0.8; \lambda = 1.01$

Thus, this modification of the baseline model shows that the prediction of a boosting effect of competition on innovation in industries that are close to the technological frontier is not the only possible equilibrium. Namely, if leaders has enough influences on laggard's innovation the outcome of competition may be detrimental for innovation.

7 Conclusion

This paper has examined the proposition according to which the impact of competition on innovative performance depends on the distance to the technological frontier. Basically, this proposition states that competition discourages innovation for laggard firms or industries but represents a major incentive to innovate as the economy moves closer to the technological frontier. This is consistent with the idea of an inverted U-shaped relationship between competition and innovation that is stepper for economies at the leading edge of technology. To test the empirical validity of this proposition we used a panel of industries for OECD countries.

The outcome of the estimations presented in this paper do not support the existence of an innovation-bolstering effect of product market competition at the technological frontier. Concerning regulation, two main results arise depending on specifications and proxies. In the first case, regulation has a positive effect whatever the distance to the frontier and the magnitude of its impact is higher the closer the industry is to the frontier. This is the case when one considers the economy-wide indicators. In the second configuration, which is representative of time-varying indicators of regulation, the effect of regulation is negative far from the frontier and vanishes or becomes positive when the technology gap decreases. Based on these estimates, regulation, if anything, might foster innovation at the leading edge. Regarding the measure of the outcome of competition given by the relative number of firms, results reveals that the positive effect of competition is only observed for laggard industries and is non-significant at the top technological level.

These results, though contradicting the recent belief in the positive effects of competition on innovation, are compatible with previous theoretical work and micro empirical studies that emphasised the existence of a Schumpeterian effect or even a size effect in innovation. Similarly, results concerning the positive impact of the public sector on innovation are also consistent with arguments highlighting the suboptimality of the market equilibrium in the presence of technological externalities. At the end, the lack of evidence supporting the benefits of market competition when industries come close to the technology frontier raises important questions concerning economic policy. Namely, strategies, such as those adopted in the Lisbon Agenda, strongly relying on a positive effect of product market deregulation on innovation seem weakly supported by the data. Competition policy does not seem to be a substitute for science and technology policy. A possible explanation of our results, briefly illustrated in the theoretical Section, put forward the active presence of leaders in the innovative process.

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9 Appendix

	Industry	Country list
15-16	Food products, beverages and tobacco	Austria
17-19	Textiles, textile products, leather and footwear	Belgium
17	Textiles	Denmark
18	Wearing apparel, dressing and dyeing of fur	Finland
19	Leather, leather products and footwear	France
20	Wood and products of wood and cork	Germany
21-22	Pulp, paper, paper products, printing and publishing	Greece
24	Chemicals and chemical products	Ireland
25	Rubber and plastics products	Italy
26	Other non-metallic mineral products	Japan
27	Basic metals	Netherland
28	Fabricated metal products, except machinery and equipment	Norway
29	Machinery and equipment, n.e.c.	Portugal
30	Office, accounting and computing machinery	Spain
31	Electrical machinery and aPPPratus, nec	Sweden
32	Radio, television and communication equipment	UK
33	Medical, precision and optical instruments, watches and clocks	US
34	Motor vehicles, trailers and semi-trailers	

Table 8. List of industries and countries

Sample	**N**	**mean**	**Std. Dev.**	**min**	**max**
OECD-STAN	4129	28,73	19,68	2,82	309,13
GGDC	6345	37,58	216,74	-12,21	12233,91
GGDC Industry 30	423	198,40	818,60	-12,21	12233,91
Final Filtered Data	6099	25,73	23,85	0,02	581,73

Table 9. Descriptive statistics of labour productivity in I-PPPs for different samples

Country	**Mean I-PPPs**	**CV I-PPPs**	**Mean PPPs**	**CV PPPs**
Austria	23,19	0,80	25,98	0,60
Belgium	33,27	0,66	32,30	0,71
Denmark	23,44	0,55	23,60	0,46
Finland	26,87	0,73	25,86	0,76
France	28,01	0,99	29,79	0,88
Germany	28,61	0,74	28,19	0,85
Greece	12,24	0,66	13,51	0,68
Ireland	30,35	1,99	32,34	2,03
Italy	29,17	0,63	26,49	0,71
Japan	24,05	1,28	22,54	1,14
Netherland	31,84	0,63	32,86	0,44
Norway	25,42	0,49	26,64	0,45
Portugal	14,03	0,79	15,86	0,70
Spain	25,77	0,49	24,25	0,52
Sweden	27,98	0,58	26,88	0,52
UK	22,74	0,68	25,44	0,62
US	30,86	0,60	30,86	0,60
Total	25,73	0,93	26,07	0,91

Table 10. Mean values and coefficient of variation of Labour Productivity by country

Industry	**Mean I-PPPs**	**CV I-PPPs**	**Mean PPPs**	**CV PPPs**
Basic metals	29,21	0,39	28,36	0,38
Chemicals and ch	54,73	0,94	45,16	0,78
Electrical machi	22,93	0,47	25,00	0,45
Fabricated metal	20,53	0,42	19,50	0,36
Food products, b	24,20	0,44	25,41	0,37
Machinery and eq	23,02	0,36	23,57	0,32
Medical, precisi	19,97	0,50	24,08	0,46
Motor vehicles,	18,92	0,70	26,81	0,47
Office, accounti	29,69	1,49	27,68	1,41
Other non-metall	30,97	0,36	25,28	0,34
Pulp, paper, pap	26,80	0,35	28,27	0,34
Radio, televisio	26,20	1,78	35,74	1,90
Rubber and plast	32,02	0,44	23,26	0,35
Textiles, textil	12,89	0,39	15,64	0,35
Wood and product	16,25	0,43	18,25	0,37
Total	25,73	0,93	26,07	0,91

Table 11. Mean values and coefficient of variation of Labour Productivity by industry

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Labor productivity	6099	25,73	23,85	0,02	581,73
Closeness to the frontier (%)	6099	56,89	24,07	1,93	100
Patents over hour worked	6345	0,00165	0,00939	0,00000	0,39679
Capital intensity	2785	0,05	0,03	0,00	0,20
REGREF	6375	4,19	1,31	1,05	6,00
REGIMP	6375	0,13	0,04	0,05	0,22
PMR	5760	1,80	0,44	0,92	2,78
PMR (Public)	6375	3,01	1,28	0,00	4,61
N-FIRMS/VA	2599	2,06	3,67	0,00	37,70

Table 12. Global descriptive statistics

Variable	**Model**	χ**2**	**p-value**
p_{it}	AR(1)	770.384	0.000
p_{it}	AR(1)+trend	451.852	0.970
p_{it}	AR(1)+drift	1810.240	0.000
cl_{it}	AR(1)	897.568	0.000
cl_{it}	AR(1)+trend	811.743	0.000
cl_{it}	AR(1)+drift	1809.637	0.000
kl_{it}	AR(1)	268.474	0.855
kl_{it}	AR(1)+trend	320.743	0.136
kl_{it}	AR(1)+drift	608.019	0.000
ex_{it}	AR(1)	565.012	0.046
ex_{it}	AR(1)+trend	217.560	1.000
ex_{it}	AR(1)+drift	1615.682	0.000
p_{it}	AR(2)	615.627	0.001
p_{it}	AR(2)+trend	284.219	1.000
p_{it}	AR(2)+drift	1593.648	0.000
cl_{it}	AR(2)	542.291	0.083
cl_{it}	AR(2)+trend	433.096	0.984
cl_{it}	AR(2)+drift	1334.333	0.000
kl_{it}	AR(2)	255.967	0.947
kl_{it}	AR(2)+trend	640.608	0.000
kl_{it}	AR(2)+drift	526.042	0.000
ex_{it}	AR(2)	311.474	1.000
ex_{it}	AR(2)+trend	188.493	1.000
ex_{it}	AR(2)+drift	1244.758	0.000

Table 13. Unit Root Test Maddala and Wu (1999) (Ho: Non Stationary)