# Product market regulation, innovation and productivity.

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**Abstract**

This paper analyses the innovation-productivity relationship at the industry-level for a sample of OECD manufacturing industries. We pay particular attention to the influence of product market regulation (PMR) on the innovative process and its consequences on productivity. We test for a differentiated effect of PMR depending on whether countries in a given industry and time period are technological leaders or laggards. Usual policy claims positing innovation boosting effects of deregulation policies at the leading edge are not supported by the data.

# 1 Introduction

A recent literature has investigated the relationship between product market competition (PMC) and growth (Aghion and Griffith, 2005). Several efficiency-promoting effects of competition have been considered, which are all related to the simple idea that more intense competition would lead firms to seek a higher efficiency in order to maintain their respective market positions. Competitive pressure would also spur firms to allocate resources more efficiently and "trim fat". Following the emergence of the innovation-based endogenous growth theory (Aghion and Howitt, 1998), the importance of competition as an engine of growth through its innovation-inducing effects has been stressed in several theoretical and applied contributions (Aghion et al. 1997; 2005). These themes have been incorporated in the policy debates linking competition policy or the extent of regulation in product markets to competitiveness and growth, and indeed '[t]he view that competition and entry should promote efficiency and prosperity has now become a common wisdom worldwide' (Aghion and Griffith, 2005, p.1). The most accepted view in policy circles is that a more intense competition should be promoted through the implementation of a less stringent product market regulation (PMR).[1] Besides, the importance of competition

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[1]For instance: the European Council recommendations in the context of Europe 2020 growth strategy (Official Journal of the European Union, 2011/C 217/05), OECD (2007), IMF (2010).

as a driver of innovation and growth should be expected to be greater for economies that compete at or near the leading edge of technology since innovation would matter more than imitation close to the frontier (Acemoglu et al. 2003, 2006) and the growth- and innovation-enhancing impact of innovation-inducing factors would increase with the proximity to the technological frontier (Vandenbussche et al., 2006). The aim of this paper is to provide an empirical assessment of such claims.

An empirical assessment on this matter is important since, contrary to the received argument, theoretical works studying the way in which market structure shapes the incentives to innovate leave little room for an unambiguous positive (resp. negative) relationship between product market competition (resp. regulation) and innovation or growth. The "traditional" economic view is indeed one in which PMC has a negative impact on innovation as competition erodes innovation rents (Schumpeter 1911, 1934). Such a negative link is featured in most endogenous growth models following the lines of Romer (1990), Segerstrom et al. (1990), Grossman and Helpman (1991) or Aghion and Howitt (1992). By way of contrast, the managerial literature has provided arguments highlighting the role of competition as a slack reducing device (Machlup, 1967; Porter 1990). When considering optimal (and not just satisfying) behaviour, arguments mainly rely on the idea that PMC may reduce inefficiencies stemming from principal-agent governance-related problems. However, the resulting link between PMC and firm efficiency is usually ambiguous (Scharfstein; 1988; Hermalin, 1992; Schmidt, 1997; Raith, 2003).

When innovation occurs step-by-step, that is when laggards must catch-up with the technological leader before overtaking it, the above-mentioned Schumpeterian argument can be used to reverse the negative relationship between PMC and innovation in some industries. When laggards catch-up with the leader and both type of firms compete in a neck-and-neck fashion, firms will innovate in order to escape competition. However, at the same time, laggards' innovation will be discouraged by competition as they anticipate lower post innovation profits. This is the underlying rationale of Aghion et al. (1997, 2005). Using this argument, the latter paper suggests that the relationship between PMC and innovation is hump-shaped and that the peak of this curve is 'larger and occurs at a higher degree of competition in more neck-and-neck industries', that is to say in industries where firms compete at the same technological level. That is behind the idea that the benefits of increasing competition through lowering regulation should be higher near the world technological frontier, whereas they could be nil or even negative far from that frontier.

The nonlinearity of the relationship between competition and innovation is more generally analysed by Boone (2001), who axiomatically defines the intensity of competition in order to encompass different standard parametrisations. Considering heterogenous competitors, Boone (2001) shows that the value of innovation changes with the identity of the innovator, which in turn depends on the level of competition itself. No general form of nonlinearity can be inferred without specifying the market structure in more details. Details therefore matter and it is not surprising to find contradicting claims when one goes further into the industrial organisation literature. For instance, within the context of Cournot competition with product differentiation, Tishler and Milstein (2009) show that strategic behaviour in what they call R&D wars leads to a U-shaped relationship.

As it is clear from Boone (2001), the possibility of innovation by technology leaders is key to understanding the effect of PMC. Leaders may have some advantages that allow them to innovate despite the implied destruction of own rents (the so-called 'Arrow effect').

One special form of leader's advantage is the one given by its position as an incumbent that moves first (Gilbert and Newberry, 1982). In that case, entry becomes endogenous and, contrary to traditional schumpeterian models, leaders innovate and may remain in the market durably. Competition *for* the market can then be a substitute for competition *in* the market (Etro, 2007). The main idea is that the presence of an active monopoly can actually hide an intense competition threat. Amable et al. (2010) show that even in a framework similar to Aghion et al. (2005), introducing the possibility for the technological leader to innovate in order to make the follower's innovation more difficult leads to a reversal of the relationship between competition and innovation in the so-called neck-and-neck industries: competition may become detrimental to innovation, even more so as one moves closer to the technological frontier. Moreover, the relationship between PMR and market structure is also affected by these strategic interactions in a non trivial way. Ledezma (2013) shows that, if the persistence of leadership relies on technology advantages strategically acquired by leaders in the process of innovation, PMR may in some cases reduce such advantages and induce firm and innovation dynamics through Schumpeterian leapfrogging. PMR may in fact, purposely or not, induce knowledge standardisation and this can be so even if PMR is allowed to increase the costs of innovation, as long as it forces leaders to stay, qualitatively, within the boundaries of the current good.

Implications of endogenous entry and strategic interactions render visible the weakness of outcome measures of competition. Empirical assessments at the industry level using regulation policy measures are then useful to analyse the received argument. There exists a non negligible body of literature that follows this approach which usually relies on time varying industry level data on developed countries. As in this paper, these works use PMR indicators constructed by the OECD, which tabulates detailed surveys on regulatory practices (see section 2.2. below). The scope of those practices is generally economy-wide or related to network service sectors. As a way to obtain more time-variability across countries and industries, the OECD provides regulatory impact indicators that seek to measure the so-called "knock-on" effects of PMR. This is done by connecting regulatory practices in key input sectors accordingly to their use in each industry. Hence, regulatory impact indicators capture the extent to which upstream regulation restrict activities in downstream industries. This type of restrictiveness is generally highly correlated with other aspects of PMR measured by economy-wide indicators (Amable et al. 2010). Studies at the industry level are then able to perform estimations on PMR data presenting a panel structure where individuals are country-industry couples.

In general, estimations seek to explain economic performances as the outcome of PMR in a reduced form equation. The latter usually include a measure of the gap vis-à-vis the technology frontier and a term interacting this technology gap with the proxy of PMR. In many cases, the technology gap variable is in fact a measure of closeness to the technology frontier as the productivity of a country in a given industry and year is expressed relative to that of the best performing country (in the same industry and year). The interaction term indicates then how the marginal effect of PMR on the performance measure vary with the closeness to the technology frontier. This type of specification is related to one of the conclusions of Aghion et al. (2005) who state that competition is a source of incentives to innovate for firms operating at the leading edge whereas for those lagging behind the opposite is true, an argument that has been transposed to policy-oriented debates advocating for deregulation in European markets.[2]

Contradicting these predictions, results of Amable et al. (2010) show that the marginal effect of PMR on patenting intensity tends to be positively growing with the closeness to the technological frontier. Furthermore, at the leading edge this marginal effect is significantly positive for several specifications. Although this result is not the rule in the related empirical literature it is by no means the exception. In practical terms, it comes from a positive estimated coefficient of the interaction term. The same positive sign has also be found by Nicoletti and Scarpetta (2003) and Conway et al. (2006) with PMR proxies highlighting economy-wide aspects of PMR and productivity growth as a measure of economic performance. Interpretations are however different: that positive sign in an error-correction model of multifactor productivity growth is seen as a slowing down effect of PMR on the natural catching-up process of laggards. On the other hand, Bourlès et al. (2010) do report a negative effect of PMR, which grows stronger the closer to the technology frontier. Their sample consider both manufacturing and service industries. Nicoletti and Scarpetta (2003) and Inklaar et al. (2008) highlight the specificities of both type of sectors, something that could explain differences in estimates. Arnold et al. (2008) merge industry-level regulation data with firm-level information. They also seek to identify a differentiated effect of PMR on productivity, but this time defined on whether firms are above the productivity median at the national level. The estimated coefficient of this differently specified interaction term is negative.

What all these papers have in common is that estimations are based on reduced form equations incorporating either inputs (i.e. innovation) or outputs (i.e. productivity) measures of technical progress. In this paper we seek to relate PMR to both aspects in an integrated framework. We follow a large body of empirical work, starting from that of Griliches (1979, 1992, 1994, 2000) to recent studies derived from Crépon et al. (1998) who proposed a conceptual and analytical framework relating R&D, innovation and productivity at the firm level. Differing from this literature, our empirical application is performed at the industry level. It relies on a sample of 13 manufacturing industries for 17 OECD countries during the 1977-2005 period for which we have information on multifactor productivity, innovation, skill composition of labour and regulatory impact. There are several reasons for this approach. Firstly, the industry-level scope is more likely to capture information on equilibrium relationships and, thereby, relevant to measure a bottom-line aggregate impact stemming from, a priori, contradicting mechanisms induced by competition. Secondly, it also facilitates the empirical implementation since at this level we do not face selection issues that are common in firm-level data on R&D. Moreover, industry-level data allows to exploit the variability of different PMR regimes. This helps to reduce the risk of endogeneity as compared with observed measures of competition such as profitability. At the same time interpretations are more easily related to policy.

On the other hand, we keep the idea of testing a structural specification able to identify how PMR influences technical progress. We restrict our attention to the innovation-productivity relationship and use patenting intensity as the measure of innovative performance, which in turn explains productivity. Taking into account relative performances in terms of productivity we test for a differentiated impact of the regulatory environment depending on whether national industries are leader or followers at the international level. In this new wider approach and using recently issued data, results are consistent with pre-

[2]See for instance the policy brief of Aghion (2006).

vious findings contradicting the idea that technical progress at the leading edge should be grounded on deregulation policies.

The rest of the paper is organised as follows. The following section exposes the methodology, data and empirical strategy. Section 3 presents the main results and a brief conclusion closes the paper.

# 2 Methodology

## 2.1 The data

### 2.1.1 Sources

We use three main sources of industry-level (time-series) data. From the EU KLEMS database, provided by the Groningen Growth and Development Centre (GGDC), we draw information on output, input and productivity measures. This information has been completed with data on patenting from EUROSTAT and with PMR indicators constructed by the OECD. We focus on manufacturing activities for which there exists available information on the main variables in our specifications. This leads to an unbalanced panel of 17 countries, 13 industries spanning from 1977-2005, which leads to 5694 observations.

A descriptive analysis of the sample is given in appendix. Appendix A.1 presents the details of the sample. Tables A1 and A2 show the lists of countries and industries and Table A3 reports on aggregate descriptive statistics (mean, dispersion and number of non-missing observations) at the country level. In appendix A.2 we take a closer look on the sample heterogeneity related to country, industry and time dimensions and complete the evidence with reduced-form estimates linking productivity growth and PMR.

### 2.1.2 The main variables

**Multi factor productivity levels and closeness to the world technology frontier** Multi factor productivity (MFP) levels were obtained combining two publicly available databases provided by the GGDC: (i) the EU KLEMS database, which proposes measures of MFP *growth* relative to the base year 1995[3], and (ii) the Productivity Levels (PL) database, which contains MFP measures in *levels,* but only for the year 1997 and with MFP indexes being relative to that of the United States.[4] Since MFP levels need to be comparable over time and across countries and industries, a specific deflation procedure is performed by the GGDC to construct MFP in levels. This namely imposes heavy data requirements in order to construct purchasing power parities (PPP) at the industry level. For this reason the PL database proposes measures in levels only for the benchmark year 1997, which is the best documented year for such a purpose.

Using both EUKLEMS and PL databases it is possible, however, to reproduce MFP series in levels for our full sample period. This amounts to apply the so called constant-PPP approach (see Inklaar and Timmer, 2008). More precisely, let be $G_b(c,i,t)$ the MFP growth index of country $c$, industry $i$ at time period $t$ for the year base $b$, and $MFP_{US}(c,i,t)$ the MFP level index, relative to the US. In this notation, what the EU

[3]November 2009 release (March 2011 update), http://www.euklems.net/. A complete description on EU KLEMS can be found in O'Mahony and Timmer (2009).

[4]http://www.rug.nl/feb/Onderzoek/Onderzoekscentra/GGDC/data/levels

KLEMS and LP databases provide are, respectively, $G_{1995}(c,i,t) = \frac{MFP(c,i,t)}{MFP(c,i,1995)}$ and $MFP_{US}(c,i,1997) = \frac{MFP(c,i,1997)}{MFP(US,i,1997)}$. MFP measures in levels for the full sample span are then obtained (after adjustment of the year base of the MFP growth index to 1997) as:

$$MFP_{US}(c,i,t) = MFP_{US}(c,i,1997)\,\frac{G_{1997}(c,i,t)}{G_{1997}(US,i,t)} = \frac{MFP(c,i,t)}{MFP(US,i,t)} \tag{1}$$

With MFP levels at hand we construct a measure of closeness to the world technology frontier (WTF) as the MFP of a country in a given industry and time period relative to the highest MFP level observed in the sample for that industry and year (i.e. the WTF in the industry that year). Formally the WTF of each industry $i$ at year $t$ is defined as

$$WTF_{it} = MFP_{US}(c^*,i,t) \qquad where\ c^* = \arg\max_c \{MFP_{US}(c,i,t)\} \tag{2}$$

and the closeness to the WTF $CL_{cit}$ of each country $c$ in a given industry $i$ and time period $t$ is given by

$$CL_{cit} = \frac{MFP_{US}(c,i,t)}{WTF_{it}}. \tag{3}$$

This measure of closeness to the WTF will then be used in our regressions to split the sample into "leader" and "follower" country-industries.

**Innovation** Innovation is measured as patent intensity (PI), the number of patents divided by hours worked. Patent statistics relates to patent applications to the European Patent Office (EPO) by sector of economic activity (EUROSTAT, Sciences & Technology database). Thanks to an unweighted concordance matrix between international patent classification (IPC) and NACE classification of economic activity (Rev 1.1), the statistics of patent applications can be distributed across industries for a given country (See Schmoch et al. 2003). Because of this distribution and the size-normalisation (through hours worked) we have a variable that is no longer an integer but a continuous aggregate indicator of innovation intensity.

**Skill composition of labour** Although for productivity we rely on the 2009 EU KLEMS release, we use detailed information on labour inputs offered in the previous release (2008). From this we can get the share of hours worked by skill-, medium- and high-skilled persons engaged. We aggregate medium- and high-skilled shares in order to control for the skill composition of labour as a determinant of innovation and productivity.

**Product market regulation** PMR is measured through the regulation impact (henceforth REGIMP) indicator constructed by the OECD. We use the 2008 updated release (see Conway and Nicoletti (2006) for the methodology details).[5] REGIMP measures the knock-on effect of regulation in key non-manufacturing (NM) input sectors on the rest of the economy. These input sectors include network services such as energy (electricity and gas), transport (air, rail, road transport) and communications (post and telecommunications) - in acronyms, the ETCR regulation; retail distribution and professional services - in acronyms, the RBSR regulation; and finance. Regulation in these activities

[5] www.oecd.org/economy/pmr.

is measured as an aggregate average composite of scores constructed upon qualitative information about regulatory practices in several important areas. For ETCR regulation those areas cover entry, public ownership, vertical integration, price controls and market structure. Information here is available for the 1975-2007 period (. For RBSR regulation, regulatory areas consider more specific restrictions on entry and conduct. These data present information for 1998, 2003 and 2008. Information on the financial sector has the lowest coverage (only for 2003). Scores in all indicators of NM regulation are coded accordingly to an increasing schedule (from 0 to 6) reflecting the restrictiveness imposed by regulatory provisions.

REGIMP seeks to capture the impact of these NM regulatory provisions on all economic sectors. For each 2-digit ISIC industry, REGIMP is computed as a weighted sum of NM regulation indicators, where weights reflect the use of the respective NM sector as input.[6] The requirements of NM sectors in each industry are in turn obtained from harmonised input/output matrices. PMR in a NM sector will have a stronger impact on a specific industry if it is heavily used in production. Given this vertical linkage, REGIMP is usually interpreted as associating regulation in "upstream" industries with operation "downstream", although it should be kept in mind that not all downstream industries are final goods and that not all NM sector output is used in production activities. Moreover inter-industry manufacturing relationships also exist. That said, an important share of NM sector output is used for production in other sectors. Conway and Nicoletti (2006), based on the input/output tables, report shares ranging from 50 to 80% so that REGIMP does give a measure about the degree of restrictiveness imposed to manufacturing activities due to PMR in key sectors of the economy.

A key advantage is that REGIMP presents a panel variability compatible with our set of variables. At the same time, it remains strongly correlated with other measures capturing more directly regulatory practices, but that have the drawback of being economy-wide indicators with scarce variability in both time and cross-section dimensions (see for instance PMR indicators used in Nicoletti and Scarpetta, 2003). The latest release of the REGIMP series also offers series restricted to regulatory areas (sub-indicators) of public ownership (henceforth RPO) as well as series excluding public ownership (henceforth RWPO). We use these additional two recently issued series as alternative PMR indicators in our robustness checks.

## 2.2 Empirical Strategy

We test a two-equation system that links PMR, Innovation (PI) and MFP growth. In the first-stage equation, patent intensity of country $c$ industry $i$ at time period $t-1$ ($\ln PI_{cit-1}$) is explained by lagged PMR ($\ln PMR_{cit-1}$), the skill composition of labour, proxied by the share of hours worked by medium- and high-skilled workers ($\ln HMS_{cit-1}$) and its own autoregressive process. In the second-stage equation, the log-difference of the MFP is explained by these three lagged variables without autoregressive process of innovation.

[6] NM regulation indicators must be mapped to a 2-digit ISIC classification which implies in some cases a simple average of sub-indicators of regulation (e.g. the average of regulation in Post and regulation in Telecomunication for the ISIC sector 64 Post and telecomunication).

Formally,

$$\begin{aligned}
\Delta \ln MFP_{cit} &= \beta_0 + \beta_1 \ln PMR_{cit-1} + \beta_2 \ln HMS_{cit-1} + \beta_3 \ln PI_{cit-1} \\
&\quad + \eta_{ci} + \eta_t + \varepsilon_{cit} \\
\ln PI_{cit-1} &= \alpha_0 + \alpha_1 \ln PMR_{cit-1} + \alpha_2 \ln HMS_{cit-1} + \textstyle\sum_{\tau=k}^{m} \gamma_\tau \ln PI_{cit-1-\tau} \\
&\quad + \delta_{ci} + \delta_{t-1} + \xi_{cit-1}
\end{aligned} \tag{4}$$

where $\eta_{ci}, \delta_{ci}$ are individual (country-industry) unobserved fixed effects; $\eta_t$ and $\delta_t$ are time specific unobserved fixed effects; and finally $\varepsilon_{cit}$ and $\xi_{cit}$ the idiosyncratic disturbances, supposed to be identically distributed conditionally on the regressors. In our regressions $\tau$ spans between 3 and 5. We use an instrument variable (IV) and GMM approaches to estimate (4). In both cases we take into account the unobserved intrinsical heterogeneity by exploiting the panel data structure.

In order to take into account a differentiated effect of PMR according to the "neck-and-neckness" of the technological competition, our estimations consider two kind of subsamples : leaders and followers. Leaders are defined as those country-industry couples performing above a certain percentile of the sample distribution of closeness to the world technology frontier (WTF), defined by eqs. (2) and (3). We refer to the percentile identifying leaders and followers as the threshold of the WTF and consider in our regressions the 50th, 60th and 75th percentiles in order to consider different definitions of relative performances. In each case, we allow our parameter estimates to differ in each subsample.

By using this estimation strategy we can identify how PMR affects MFP directly as well as indirectly, through innovation, and how its effect may vary according to the technology lead of a country in a given industry and time period. The most received argument discussed above suggests that one should expect (at least) in the first stage equation $\alpha_1 < 0$ for leaders and $\alpha_1 > 0$ for followers, provided that $\beta_3 > 0$.

# 3 Results

Estimation results are presented in Tables 1 to 6. The tables present results for leaders or for followers defined for different sample splits: 50th, 60th or 75th percentile of the relative MFP level. All Tables present in the first stage (the patenting equation) in the upper panel and the second stage (the MFP growth equation) in the second panel. Table 1 for instance give results of the estimations for leaders. Columns (1) to (3) present estimations of the same model for a sample split at the 50th, 60th and 75th percentile respectively. Columns (4) and (5) give the results of models extended with additional lags and a technological externality (the frontier level of MFP) for a sample split at the 75th percentile estimated with the GMM two-step estimator.[7] The same structure is kept for the following tables.

The first estimations are made with the REGIMP indicator and the results are documented in Table 1 for the leaders and Table 2 for the followers. The impact of PMR at the first stage (innovation) is unambiguously positive for the leaders. Besides, this positive impact grows significantly when one narrows the definition of the leaders or, to put it differently, when one goes near to the technology frontier: the elasticity jumps from 0.145 at the 50% split to 0.224 at the 60% level and 0.563 at the 75% level. Therefore,

[7]For models exactly identified, IV and GMM estimations coincide.

contrary to the common wisdom, PMR has a positive and growing impact on innovation. As expected, skilled labour also favourably influences innovation, which is also positively affected by past innovation performance. On the other hand, the productivity externality term is not significantly different from zero. At the second stage (productivity), innovation is seen to positively influence productivity growth, with an elasticity that does not vary significantly with the definition of the leader/follower split. The introduction of the productivity externality term , which gives a significantly positive coefficient, augments significantly the value of the innovation elasticity. The skilled labour elasticity turns out to be significantly negative in the productivity equation, which may point to a possible overestimation of the contribution of this factor in the MFP computations or that the importance of this factor is more crucial at the innovation than at the production stage.

The results for the followers are documented in Table 2. the elasticity of PMR at the first stage is significantly negative for every sample split, and less negative at the 75% cut-off level than at the 50% or 60% levels. Combining this with the results obtained for the leaders, one obtains a significantly negative influence of PMR far from the technological frontier that gradually turns into a significantly positive impact that grows when one gets near the technological frontier. This is exactly the opposite of the relationship postulated by the "common wisdom". the other elasticities in the innovation equation are in conformity with expectations: a significantly positive influence of skilled labour and past innovation. The world productivity frontier is here again not significant. At the second stage, one can see that the influence of innovation on productivity is not as high as with industry leaders, which is what one could have expected. The term for elasticity of productivity with respect to innovation is only significant at the 10% level at the 50% cutoff level (column (1)) and always less than 50% of the elasticity for leaders in other models. PMR has a significant positive impact on the productivity growth of followers, and the elasticity is twice as high as for leaders.

To sum up, PMR has been found to be a positive influence on leaders' innovation and a negative one on followers'. This is the opposite of the received view about the merits of deregulation policy for the innovation performance, but this is in accord with the results of Amable et al. (2010). PMR has a positive influence on productivity growth for both leaders and followers, which again contradicts the "common wisdom".

Table 1

**Innovation equation** (first-stage estimates).
Dependent variable: patenting intensity (PI) in natural logs (lag 1)
**Leaders**

| Closeness to the WTF split | Q50 | Q60 | Q75 | Q75 | Q75 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ln(REGIMP t-1) | 0.145** | 0.224*** | 0.563*** | 0.436*** | 0.330*** |
| | (0.073) | (0.085) | (0.110) | (0.108) | (0.118) |
| ln(HMS t-1) | 0.468*** | 0.483*** | 0.431*** | 0.363*** | 0.306*** |
| | (0.044) | (0.048) | (0.061) | (0.061) | (0.069) |
| ln(PI t-4) | 0.451*** | 0.419*** | 0.369*** | 0.316*** | 0.275*** |
| | (0.013) | (0.015) | (0.019) | (0.029) | (0.057) |
| ln(PI t-5) | | | | 0.129*** | 0.180*** |
| | | | | (0.024) | (0.060) |
| ln(PI t-6) | | | | | 0.063* |
| | | | | | (0.037) |
| ln(WTF t-1) | | | | -0.032 | -0.027 |
| | | | | (0.035) | (0.037) |
| Year dummies | Yes | Yes | Yes | Yes | Yes |
| Number of Obs | 2528 | 2018 | 1262 | 1216 | 1169 |
| Adjusted R2 | 0.87 | 0.87 | 0.85 | 0.84 | 0.84 |
| Individuals | 150 | 130 | 87 | 85 | 84 |

**Productivity equation** (second-stage estimates).
Dependent variable: MFP growth in natural logs

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| ln(PI t-1) | 0.180*** | 0.158*** | 0.162*** | 0.243*** | 0.273*** |
| | (0.022) | (0.027) | (0.040) | (0.042) | (0.061) |
| ln(REGIMP t-1) | 0.237*** | 0.428*** | 0.380*** | 0.325*** | 0.324*** |
| | (0.058) | (0.067) | (0.095) | (0.095) | (0.116) |
| ln(HMS t-1) | -0.308*** | -0.251*** | -0.195*** | -0.245*** | -0.271*** |
| | (0.039) | (0.043) | (0.055) | (0.056) | (0.068) |
| ln(WTF t-1) | | | | 0.113*** | 0.104*** |
| | | | | (0.029) | (0.040) |
| year dummies | Yes | Yes | Yes | Yes | Yes |
| Number of Obs | 2528 | 2018 | 1262 | 1216 | 1169 |
| Sargan/Hansen p | | | | 0.751 | 0.386 |
| Individuals | 150 | 130 | 87 | 85 | 84 |

Note: Standard errors in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$. See eq. (4) for specification details.

Table 2

**Innovation equation** (first-stage estimates).
Dependent variable: patenting intensity (PI) in natural logs (lag 1)
**Followers**

| Closeness to the WTF split | Q50 | Q60 | Q75 | Q75 | Q75 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ln(REGIMP t-1) | -0.273*** | -0.300*** | -0.195*** | -0.209*** | -0.234*** |
| | (0.077) | (0.069) | (0.060) | (0.059) | (0.056) |
| ln(HMS t-1) | 0.533*** | 0.467*** | 0.482*** | 0.380*** | 0.271*** |
| | (0.052) | (0.047) | (0.038) | (0.039) | (0.046) |
| ln(PI t-4) | 0.387*** | 0.405*** | 0.428*** | 0.393*** | 0.353*** |
| | (0.014) | (0.013) | (0.011) | (0.016) | (0.035) |
| ln(PI t-5) | | | | 0.125*** | 0.116*** |
| | | | | (0.014) | (0.035) |
| ln(PI t-6) | | | | | 0.083*** |
| | | | | | (0.026) |
| ln(WTF t-1) | | | | -0.004 | -0.017 |
| | | | | (0.014) | (0.012) |
| Year dummies | Yes | Yes | Yes | Yes | Yes |
| Number of Obs | 2328 | 2843 | 3603 | 3478 | 3356 |
| Adjusted R2 | 0.83 | 0.83 | 0.86 | 0.85 | 0.84 |
| Individuals | 162 | 182 | 197 | 197 | 196 |

**Productivity equation** (second-stage estimates).
Dependent variable: MFP growth in natural logs

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| ln(PI t-1) | 0.069* | 0.084** | 0.117*** | 0.145*** | 0.169*** |
| | (0.041) | (0.035) | (0.027) | (0.027) | (0.031) |
| ln(REGIMP t-1) | 0.665*** | 0.652*** | 0.542*** | 0.553*** | 0.553*** |
| | (0.088) | (0.076) | (0.063) | (0.064) | (0.103) |
| ln(HMS t-1) | -0.111 | -0.178*** | -0.246*** | -0.281*** | -0.308*** |
| | (0.069) | (0.058) | (0.046) | (0.047) | (0.050) |
| ln(WTF t-1) | | | | 0.013 | 0.010 |
| | | | | (0.016) | (0.020) |
| year dummies | Yes | Yes | Yes | Yes | Yes |
| Number of Obs | 2328 | 2843 | 3603 | 3478 | 3356 |
| Sargan/Hansen p | | | | 0.554 | 0.223 |
| Individuals | 162 | 182 | 197 | 197 | 196 |

Note: Standard errors in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$. See eq. (4) for specification details.

Tables 3 and 4 present estimations performed with the RPO indicator of regulation. the impact of PMR follows the same pattern as that observed using the REGIMP indicator. the significantly positive influence of RPO on leaders' innovation increases with the proximity to the technological frontier. the impact of RPO on followers is non significantly different from zero. Therefore, the slope of the curve linking the PMR-elasticity of innovation to the proximity to the technological frontier is here again positive, and not negative as the common wisdom would have it. Innovation has a significantly positive influence on leaders' productivity growth, and a weaker or non significant one for followers. The impact of skilled labour is positive for leaders' and followers' innovation, almost always significantly, and negative or nil for productivity growth. PMR has a positive direct impact on followers' productivity growth, but not always for leaders, where the elasticity is sometimes non significantly different from zero. The world technological frontier externality has a positive impact on followers' productivity, but not with leaders.

The tests are then performed with RWPO and the results are featured in Tables 5 and 6 for leaders and followers respectively. As with the other PMR indicators, the impact of RWPO on innovation is significantly positive and increases with the proximity to the technological frontier. PMR has a significantly negative influence on innovation with followers. The impact of PMR on productivity growth is mostly insignificant. The impact of the other variables is similar to what was obtained with REGIMP and RPO: positive influence of innovation on productivity growth, of skilled labour on innovation, etc.

Therefore, the estimations made with the other indicators of PMR confirm the results obtained with REFIMP. Product market regulation has a positive influence on innovation and, in many cases, directly on productivity growth as well. Besides, the relationship between the impact of PMR and the distance to the technological frontier that one can isolate from the previous results contradicts the received view: PMR's beneficial effects are stronger for industries close to the frontier.

Table 3

**Innovation equation** (first-stage estimates).
Dependent variable: patenting intensity (PI) in natural logs (lag 1)

**Leaders**

| Closeness to the WTF split | Q50 | Q60 | Q75 | Q75 | Q75 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ln(RPO t-1) | 0.255*** | 0.346*** | 0.534*** | 0.329*** | 0.175* |
| | (0.061) | (0.072) | (0.094) | (0.096) | (0.095) |
| ln(HMS t-1) | 0.523*** | 0.568*** | 0.366*** | 0.209** | 0.118 |
| | (0.050) | (0.057) | (0.089) | (0.093) | (0.142) |
| ln(PI t-4) | 0.459*** | 0.420*** | 0.391*** | 0.305*** | 0.270*** |
| | (0.014) | (0.016) | (0.021) | (0.031) | (0.069) |
| ln(PI t-5) | | | | 0.170*** | 0.188*** |
| | | | | (0.026) | (0.072) |
| ln(PI t-6) | | | | | 0.083* |
| | | | | | (0.043) |
| ln(WTF t-1) | | | | -0.028 | -0.026 |
| | | | | (0.038) | (0.042) |
| Year dummies | Yes | Yes | Yes | Yes | Yes |
| Number of Obs | 2277 | 1795 | 1075 | 1037 | 999 |
| Adjusted R2 | 0.87 | 0.86 | 0.83 | 0.82 | 0.81 |
| Individuals | 145 | 124 | 83 | 81 | 80 |

**Productivity equation** (second-stage estimates).
Dependent variable: MFP growth in natural logs

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| ln(PI t-1) | 0.205*** | 0.190*** | 0.250*** | 0.321*** | 0.357*** |
| | (0.025) | (0.031) | (0.047) | (0.049) | (0.071) |
| ln(RPO t-1) | 0.090* | 0.170*** | -0.030 | -0.056 | -0.049 |
| | (0.053) | (0.064) | (0.093) | (0.095) | (0.103) |
| ln(HMS t-1) | -0.394*** | -0.380*** | -0.468*** | -0.491*** | -0.554*** |
| | (0.047) | (0.056) | (0.081) | (0.087) | (0.122) |
| ln(WTF t-1) | | | | 0.086** | 0.076 |
| | | | | (0.034) | (0.048) |
| year dummies | Yes | Yes | Yes | Yes | Yes |
| Number of Obs | 2277 | 1795 | 1075 | 1037 | 999 |
| Sargan/Hansen p | | | | 0.529 | 0.207 |
| Individuals | 145 | 124 | 83 | 81 | 80 |

Note: Standard errors in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$. See eq. (4) for specification details.

Table 4

**Innovation equation** (first-stage estimates).
Dependent variable: patenting intensity (PI) in natural logs (lag 1)
**Followers**

| Closeness to the WTF split | Q50 | Q60 | Q75 | Q75 | Q75 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ln(RPO t-1) | -0.028 | -0.037 | 0.063 | -0.003 | -0.065 |
| | (0.072) | (0.063) | (0.054) | (0.053) | (0.051) |
| ln(HMS t-1) | 0.597*** | 0.517*** | 0.551*** | 0.424*** | 0.292*** |
| | (0.055) | (0.050) | (0.040) | (0.042) | (0.051) |
| ln(PI t-4) | 0.390*** | 0.411*** | 0.425*** | 0.390*** | 0.355*** |
| | (0.015) | (0.014) | (0.012) | (0.017) | (0.038) |
| ln(PI t-5) | | | | 0.130*** | 0.142*** |
| | | | | (0.015) | (0.039) |
| ln(PI t-6) | | | | | 0.062** |
| | | | | | (0.027) |
| ln(WTF t-1) | | | | -0.011 | -0.024* |
| | | | | (0.014) | (0.012) |
| Year dummies | Yes | Yes | Yes | Yes | Yes |
| Number of Obs | 2224 | 2709 | 3436 | 3316 | 3198 |
| Adjusted R2 | 0.84 | 0.84 | 0.86 | 0.86 | 0.85 |
| Individuals | 160 | 180 | 196 | 196 | 195 |

**Productivity equation** (second-stage estimates).
Dependent variable: MFP growth in natural logs

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| ln(PI t-1) | 0.014 | 0.029 | 0.079*** | 0.108*** | 0.135*** |
| | (0.044) | (0.037) | (0.029) | (0.029) | (0.034) |
| ln(RPO t-1) | 0.601*** | 0.535*** | 0.408*** | 0.428*** | 0.443*** |
| | (0.084) | (0.071) | (0.059) | (0.059) | (0.086) |
| ln(HMS t-1) | -0.021 | -0.086 | -0.177*** | -0.214*** | -0.243*** |
| | (0.079) | (0.067) | (0.052) | (0.053) | (0.059) |
| ln(WTF t-1) | | | | 0.010 | 0.004 |
| | | | | (0.016) | (0.020) |
| year dummies | Yes | Yes | Yes | Yes | Yes |
| Number of Obs | 2224 | 2709 | 3436 | 3316 | 3198 |
| Sargan/Hansen p | | | | 0.380 | 0.305 |
| Individuals | 160 | 180 | 196 | 196 | 195 |

Note: Standard errors in parentheses.* $p<0.10$, ** $p<0.05$, *** $p<0.01$. See eq. (4) for specification details.

Table 5

| **Innovation equation** (first-stage estimates). Dependent variable: patenting intensity (PI) in natural logs (lag 1) **Leaders** | | | | | |
|---|---|---|---|---|---|
| Closeness to the WTF split | Q50 | Q60 | Q75 | Q75 | Q75 |
| | (1) | (2) | (3) | (4) | (5) |
| ln(RWPO t-1) | 0.120** | 0.153** | 0.370*** | 0.357*** | 0.362*** |
| | (0.060) | (0.070) | (0.088) | (0.085) | (0.094) |
| ln(HMS t-1) | 0.445*** | 0.462*** | 0.399*** | 0.345*** | 0.303*** |
| | (0.042) | (0.046) | (0.059) | (0.059) | (0.067) |
| ln(PI t-4) | 0.455*** | 0.425*** | 0.388*** | 0.332*** | 0.282*** |
| | (0.013) | (0.015) | (0.018) | (0.029) | (0.062) |
| ln(PI t-5) | | | | 0.132*** | 0.183*** |
| | | | | (0.024) | (0.062) |
| ln(PI t-6) | | | | | 0.072* |
| | | | | | (0.038) |
| ln(WTF t-1) | | | | -0.040 | -0.037 |
| | | | | (0.034) | (0.037) |
| Year dummies | Yes | Yes | Yes | Yes | Yes |
| Number of Obs | 2398 | 1917 | 1196 | 1154 | 1112 |
| Adjusted R2 | 0.87 | 0.87 | 0.85 | 0.85 | 0.85 |
| Individuals | 146 | 126 | 82 | 80 | 79 |
| **Productivity equation** (second-stage estimates). Dependent variable: MFP growth in natural logs | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| ln(PI t-1) | 0.182*** | 0.180*** | 0.211*** | 0.298*** | 0.328*** |
| | (0.023) | (0.027) | (0.039) | (0.041) | (0.060) |
| ln(RWPO t-1) | -0.036 | 0.102* | 0.106 | 0.071 | 0.064 |
| | (0.047) | (0.055) | (0.074) | (0.075) | (0.093) |
| ln(HMS t-1) | -0.348*** | -0.331*** | -0.268*** | -0.318*** | -0.347*** |
| | (0.037) | (0.041) | (0.053) | (0.055) | (0.066) |
| ln(WTF t-1) | | | | 0.105*** | 0.097** |
| | | | | (0.030) | (0.040) |
| year dummies | Yes | Yes | Yes | Yes | Yes |
| Number of Obs | 2398 | 1917 | 1196 | 1154 | 1112 |
| Sargan/Hansen p | | | | 0.806 | 0.440 |
| Individuals | 146 | 126 | 82 | 80 | 79 |

Note: Standard errors in parentheses.* p<0.10, ** p<0.05, *** p<0.01. See eq. (4) for specification details.

Table 6.

| **Innovation equation** (first-stage estimates). Dependent variable: patenting intensity (PI) in natural logs (lag 1) **Followers** | | | | | |
|---|---|---|---|---|---|
| Closeness to the WTF split | Q50 | Q60 | Q75 | Q75 | Q75 |
| | (1) | (2) | (3) | (4) | (5) |
| ln(RWPO t-1) | -0.196*** | -0.215*** | -0.150*** | -0.111** | -0.097* |
| | (0.065) | (0.059) | (0.052) | (0.051) | (0.053) |
| ln(HMS t-1) | 0.585*** | 0.513*** | 0.514*** | 0.412*** | 0.298*** |
| | (0.051) | (0.046) | (0.038) | (0.039) | (0.046) |
| ln(PI t-4) | 0.376*** | 0.396*** | 0.416*** | 0.380*** | 0.337*** |
| | (0.014) | (0.013) | (0.011) | (0.016) | (0.036) |
| ln(PI t-5) | | | | 0.128*** | 0.110*** |
| | | | | (0.014) | (0.036) |
| ln(PI t-6) | | | | | 0.100*** |
| | | | | | (0.027) |
| ln(WTF t-1) | | | | -0.003 | -0.015 |
| | | | | (0.015) | (0.012) |
| Year dummies | Yes | Yes | Yes | Yes | Yes |
| Number of Obs | 2263 | 2749 | 3474 | 3358 | 3244 |
| Adjusted R2 | 0.83 | 0.83 | 0.85 | 0.85 | 0.84 |
| Individuals | 162 | 181 | 197 | 197 | 196 |
| **Productivity equation** (second-stage estimates). Dependent variable: MFP growth in natural logs | | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| ln(PI t-1) | 0.018 | 0.033 | 0.071*** | 0.099*** | 0.136*** |
| | (0.040) | (0.034) | (0.027) | (0.027) | (0.031) |
| ln(RWPO t-1) | 0.026 | 0.059 | 0.033 | 0.050 | 0.079 |
| | (0.069) | (0.062) | (0.052) | (0.052) | (0.049) |
| ln(HMS t-1) | -0.165** | -0.228*** | -0.284*** | -0.317*** | -0.357*** |
| | (0.066) | (0.056) | (0.044) | (0.045) | (0.048) |
| ln(WTF t-1) | | | | 0.005 | -0.001 |
| | | | | (0.015) | (0.019) |
| year dummies | Yes | Yes | Yes | Yes | Yes |
| Number of Obs | 2263 | 2749 | 3474 | 3358 | 3244 |
| Sargan/Hansen p | | | | 0.201 | 0.065 |
| Individuals | 162 | 181 | 197 | 197 | 196 |

Note: Standard errors in parentheses.* p<0.10, ** p<0.05, *** p<0.01. See eq. (4) for specification details.

# 4 A reduced form

As mentioned before, the relationship between growth and PMR is often tested under a reduced form, where PMR directly influences productivity growth, without the consideration of intermediate steps involving innovation. For instance, Bourles et al. (2010) test the following form:

$$\begin{aligned}\Delta \ln MFP_{cit} &= \alpha_1 \Delta \ln MFP_{Fit} + \alpha_2 gap_{ci,t-1} + \alpha_3 gap_{ci,t-1} + \alpha_4 PMR_{cit-1} \cdot gap_{ci,t-1} \\ &\quad + \eta_i + \eta_{ct} + \varepsilon_{cit}\end{aligned} \tag{5}$$

The interaction term between PMR and the technology gap allows to compute the marginal effect of PMR on productivity according to the distance to the technological frontier. One specificity of Bourles et al. (2010)'s specification is the introduction of country-specific time dummies, along with industry dummies, but no consideration of country-sector specific fixed effects. Considering the structure of the data, a more conventional specification would involve time dummies along with country-industry fixed effects, i.e. the specification adopted in our previous estimations. For the sake of comparison with our own results, we reproduce the estimation of Bourles et al.'s model in Table7 (column (1)) along with several other specifications: a simple model with country, industry and time effects (column (2)), a fixed effect (country-industry) estimation with year dummies (column (3)) and a fixed effect with country-specific time dummies (column (4)). For each specification, the marginal effect of PMR[8] (i.e. $\alpha_3 + \alpha_4 \cdot gap$) is computed for five different values of the gap: the minimum value (i.e. the technological frontier), the mean less one standard deviation, the mean, the mean plus one standard deviation and the maximum level.

The estimation of the same model as in Bourles et al. (2010) delivers results in conformity with the "common wisdom" (column (1)): the impact of PMR on productivity growth is everywhere negative, and all the more so that one is near the technological frontier (i.e. when the gap is at its minimum level). Changing the specification to include separately country, industry and year dummies (column (2)) alters slightly the results. PMR is no longer detrimental to productivity growth whatever the distance to frontier, but only when the productivity level is higher than the mean. Nevertheless, the general message of the "common wisdom" is preserved, PMR hampers productivity growth near the frontier. Results change considerably when one adopts a specification that takes account of the panel structure of the data. The estimation of the fixed-effect model with year dummies (column (3)) gives a positive effect of PMR everywhere, growing with the proximity to frontier, i.e. the same type of result as those obtained with the two-equation models of the previous section. This result is also obtained when one adopts the same country-specific pattern for year effects as in Bourles et al. (2010) in a fixed-effect model (column (4)). the positive effect of PMR is even larger, and increases, albeit slightly, with the proximity to frontier. Therefore, the results obtained by Bourles et al. (2010) with a reduced-form model are not robust to specification changes. The conclusion drawn from the estimations of the two-equation models of the previous section, in contrast, can also be derived from a reduced-form model estimated with panel estimators.

Table 7. Estimation results for the reduced-form model

[8] We keep the log specification adopted previously.

| | Dependent variable: $\Delta \ln MFP_{cit}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta \ln MFP_{Fit}$ | -0.069* | -0.066* | -0.075** | -0.070** |
| | (0.037) | (0.038) | (0.031) | (0.030) |
| $gap_{ci,t-1}$ | 0.052 | 0.084 | -0.205*** | -0.124* |
| | (0.053) | (0.054) | (0.070) | (0.068) |
| $PMR_{ci,t-1} \cdot gap_{ci,t-1}$ | 0.016 | 0.030 | -0.099*** | -0.067** |
| | (0.022) | (0.022) | (0.029) | (0.028) |
| $PMR_{ci,t-1}$ | -0.246*** | -0.193** | 1.061*** | 2.347*** |
| | (0.083) | (0.084) | (0.126) | (0.178) |
| Effects | | | | |
| year | no | yes | yes | no |
| industry | yes | yes | no | no |
| country | no | yes | no | no |
| country-year | yes | no | no | yes |
| country-industry | no | no | yes | yes |
| number of observations | 5298 | 5298 | 5298 | 5298 |
| number of individuals | | | 220 | 220 |
| Marginal effect of PMR according to the gap value | | | | |
| min | -0.210*** | -0.123*** | 0.832*** | 2.192*** |
| | (0.043) | (0.042) | (0.073) | (0.156) |
| mean - 1 std dev | -0.194*** | -0.093*** | 0.735*** | 2.126*** |
| | (0.034) | (0.032) | (0.061) | (0.155) |
| mean | -0.185*** | -0.076** | 0.677*** | 2.088*** |
| | (0.035) | (0.033) | (0.060) | (0.156) |
| mean + 1 std dev. | -0.176*** | -0.058 | 0.620*** | 2.049*** |
| | (0.040) | (0.037) | (0.063) | (0.159) |
| max | -0.174*** | -0.054 | 0.607*** | 2.040*** |
| | (0.041) | (0.039) | (0.065) | (0.160) |

Note: Standard errors in parentheses.* p<0.10, ** p<0.05, *** p<0.01. See eq. (5) for specification details.

# 5 Conclusion

The aim of this paper was to analyse the impact of PMR on the innovative process and its further consequences on productivity. Our empirical strategy was designed to test the impact of PMR on the innovation-productivity relationship, which, according to most received claims, should be negative, especially so in national industries competing at the leading edge. To do so, we have split our industry-level sample in order to consider leader and follower industries at different levels of the relative multi-factor productivity.

Our estimations find no evidence supporting a negative impact of product market regulation on industries operating at the leading edge of technology. On the contrary, most estimations made with leaders show a significantly positive impact of PMR on productivity channelled through the innovative process. Country-industry specificities are important in explaining these results compared to other works in the related literature. Overall, our findings are reminiscent of the well-documented theoretical ambiguities in the relationship between product market competition and innovation as well as of the non trivial consequences of regulation in vertically-related industries.

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# A Appendix

## A.1 Sample Details

Table A1. List of industries (2-digit Nace)

| Code | Description |
|---|---|
| 15t16 | Food , beverages and tobacco |
| 17t19 | Textiles, textile , leather and footwear |
| 20 | Wood and of wood and cork |
| 21t22 | Pulp, paper, paper , printing and publishing |
| 23 | Coke, refined petroleumm and nuclear fuel |
| 24 | Chemicals and chemecal |
| 25 | Rubber and plastic |
| 26 | Other non-metallic mineral |
| 27t28 | Basic metals and fabricated metal |
| 29 | Machinery, nec |
| 30t33 | Electrical and optical equipment |
| 34t35 | Transport equipment |
| 36t37 | Manufacturing nec, recycling |

Table A2. List of countries

| Code | Country |
|---|---|
| AUS | Austria |
| AUT | Austria |
| BEL | Belgium |
| CZE | Czech Republic |
| DNK | Denmark |
| ESP | Spain |
| FIN | Finland |
| FRA | France |
| GER | Germany |
| HUN | Hungary |
| IRL | Ireland |
| ITA | Italy |
| JPN | Japan |
| NLD | Netherlands |
| SWE | Sweden |
| UK | United Kingdom |
| USA | United States |

Table A3. Descriptive statistics on main variables

| Country | | MFP growth | REGIMP | Patent Intensity | High &Medium Skill share | Closeness to the WTF |
|---|---|---|---|---|---|---|
| AUS | Mean | 101.16 | 0.08 | 0.36 | 3.91 | 38.75 |
| | SD | 18.15 | 0.02 | 0.62 | 0.06 | 20.84 |
| | N | 338 | 429 | 403 | 312 | 338 |
| AUT | Mean | 103.17 | 0.12 | 0.89 | 4.24 | 35.84 |
| | SD | 33.04 | 0.02 | 1.46 | 0.12 | 16.67 |
| | N | 364 | 429 | 403 | 338 | 364 |
| BEL | Mean | 100.59 | 0.18 | 0.76 | 3.78 | 66.51 |
| | SD | 19.16 | 0.03 | 1.10 | 0.32 | 28.79 |
| | N | 351 | 429 | 403 | 338 | 351 |
| CZE | Mean | 122.01 | 0.13 | 0.06 | 4.48 | 31.12 |
| | SD | 54.31 | 0.03 | 0.12 | 0.03 | 20.86 |
| | N | 169 | 429 | 169 | 143 | 169 |
| DNK | Mean | 115.76 | 0.07 | 1.20 | 4.02 | 45.84 |
| | SD | 107.43 | 0.02 | 2.26 | 0.23 | 26.14 |
| | N | 364 | 429 | 403 | 338 | 364 |
| ESP | Mean | 95.30 | 0.13 | 0.14 | 3.27 | 45.03 |
| | SD | 14.20 | 0.03 | 0.25 | 0.53 | 23.78 |
| | N | 364 | 429 | 403 | 338 | 364 |
| FIN | Mean | 88.78 | 0.10 | 0.88 | 3.98 | 50.49 |
| | SD | 42.18 | 0.02 | 1.41 | 0.31 | 26.39 |
| | N | 494 | 429 | 403 | 468 | 403 |
| FRA | Mean | 102.03 | 0.10 | 0.94 | 4.11 | 52.12 |
| | SD | 38.86 | 0.02 | 1.47 | 0.18 | 24.40 |
| | N | 364 | 429 | 403 | 338 | 364 |
| GER | Mean | 111.24 | 0.11 | 1.23 | 4.25 | 48.69 |
| | SD | 39.49 | 0.02 | 2.00 | 0.07 | 20.20 |
| | N | 221 | 429 | 403 | 195 | 221 |
| HUN | Mean | 138.26 | 0.12 | 0.07 | 4.35 | 34.25 |
| | SD | 67.26 | 0.02 | 0.12 | 0.04 | 24.19 |
| | N | 169 | 429 | 208 | 143 | 169 |
| IRL | Mean | 104.84 | 0.08 | 0.27 | 4.44 | 56.52 |
| | SD | 23.85 | 0.02 | 0.44 | 0.06 | 28.45 |
| | N | 260 | 396 | 403 | 234 | 260 |
| ITA | Mean | 84.95 | 0.15 | 0.37 | 4.58 | 56.30 |
| | SD | 23.25 | 0.02 | 0.55 | 0.02 | 31.61 |
| | N | 494 | 429 | 403 | 468 | 403 |

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Table A3. Descriptive statistics on main variables (continued)

| Country | | MFP growth | REGIMP | Patent Intensity | High &Medium Skill share | Closeness to the WTF |
|---|---|---|---|---|---|---|
| JPN | Mean | 93.11 | 0.13 | 0.66 | 4.14 | 42.01 |
| | SD | 28.48 | 0.02 | 1.21 | 0.30 | 23.57 |
| | N | 442 | 429 | 390 | 468 | 390 |
| NLD | Mean | 97.98 | 0.07 | 1.28 | 4.41 | 44.62 |
| | SD | 21.79 | 0.02 | 1.95 | 0.09 | 31.98 |
| | N | 377 | 429 | 403 | 351 | 377 |
| SWE | Mean | 130.03 | 0.08 | 1.13 | 4.20 | 43.37 |
| | SD | 114.41 | 0.02 | 1.55 | 0.17 | 26.69 |
| | N | 195 | 429 | 403 | 325 | 195 |
| UK | Mean | 90.13 | 0.09 | 0.52 | 4.06 | 56.81 |
| | SD | 24.87 | 0.03 | 0.76 | 0.34 | 27.86 |
| | N | 494 | 429 | 403 | 468 | 403 |
| USA | Mean | 101.92 | 0.06 | 0.51 | 4.33 | 57.53 |
| | SD | 41.74 | 0.01 | 0.85 | 0.18 | 28.18 |
| | N | 403 | 429 | 403 | 468 | 403 |
| Total | | 101.51 | 0.11 | 0.60 | 4.09 | 48.12 |
| | | 47.51 | 0.04 | 1.57 | 0.45 | 27.49 |
| | | 6019 | 9106 | 9299 | 7162 | 5694 |

## A.2 Sample heterogeneity

We complete here our main econometric analysis with a brief discussion on patterns arising from the three-dimensional structure of our data (country, industry and time). Figure 1 and 2 present descriptive statistics for our main variables. Central tendency and dispersion of each variable are presented using box-plots organised by each of these dimensions. This allows to visually analyse how the specificities in each of them structure data patterns. It appears, for instance, that the country dimension is key for understanding variations in our proxy of regulation REGIMP (Panel (a)) and that the industry dimension plays an important role in variations of the closeness to the WTF (Panel (e)). Things are less clear for MFP growth. In each panel a number outliers appear, with typically more than one country (resp. industry) presenting extreme values when box-plots follow an industry (resp.country) categorisation. As shown by Figure A2, this feature still shows up in a filtered sample obtained after dropping extreme values such as Hungary, Czech Republic as well as industries 23 (Coke, refined petroleum and nuclear fuel), 30t33 (Electrical and optical equipment) and 36t37 (Manufacturing n.e.c., recycling).

Figure A1

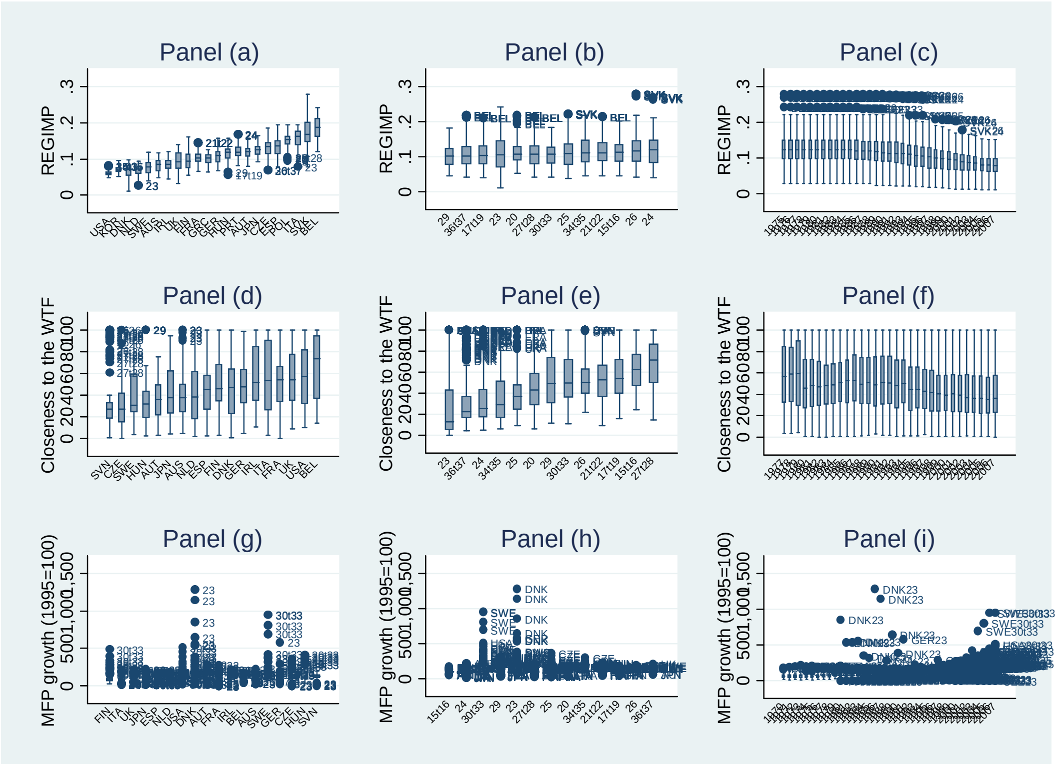
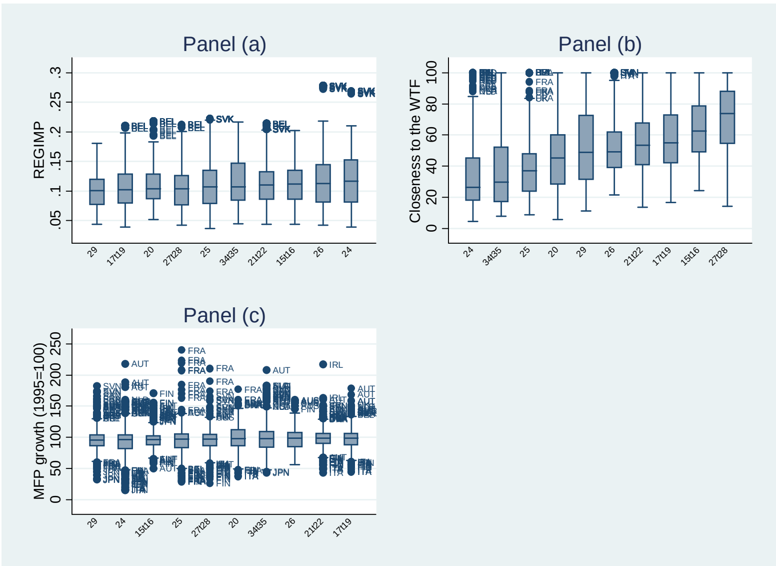



Figure A2




This descriptive evidence suggests country-industry specificities explaining MFP growth. We test more directly this by estimating reduced-form regressions which seek to explain the log difference in MFP by the log of our proxy of product market regulation (REGIMP) and a set of dummies. In column (1) the specification considers country, industry and year dummies and points out a significantly negative elasticity of REGIMP. This results still holds and with higher magnitude (in absolute value) when the specification considers a full set of interactions between country and time dummies (i.e. controlling for national-level trends). Column (3) and (4) are individual fixed-effect specifications. Results are within-group estimations where the Fisher test indicates that we can reject at any conventional risk the null of no-join effect of individual intrinsic characteristics. In both of these regressions the elasticity of REGIMP is significantly positive. This elasticity becomes even larger after the inclusion of country-time dummies. Hence, controlling for unobserved time-invariant heterogeneity matters otherwise country-industry specific factors not taken into account by (but correlated with ) our regulation proxy (particular institutional architectures, initial conditions, spillovers, etc.) may bias the results if only industry characteristics common to all countries are considered.

Table A4. MFP growth regressions
Dependent variable: log-difference in MFP

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ln(REGIMP) | -0.084*** | -0.199*** | 0.701*** | 2.144*** |
| | (0.031) | (0.034) | (0.058) | (0.149) |
| Cons | 4.040*** | 3.619*** | 5.714*** | 8.917*** |
| | (0.092) | (0.181) | (0.131) | (0.351) |
| Individual fixed-effect | No | No | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes |
| Industry dummies | Yes | Yes | No | No |
| Country dummies | Yes | Yes | No | No |
| country year dummies | No | Yes | No | Yes |
| Number of Obs | 5622 | 5622 | 5622 | 5622 |
| adjusted R2 | 0.18 | 0.21 | 0.16 | 0.24 |
| individuals | | | 220 | 220 |
| F-test (p-value) | | | 0.000 | 0.000 |