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Product market regulation, innovation, and productivity☆

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ABSTRACT

Several recent policy and academic contributions consider that liberalising product markets would foster innovation and growth. This paper analyses the innovation–productivity relationship at the industry-level for a sample of OECD manufacturing industries. We pay particular attention to the vertically-induced influence of product market regulation (PMR) of key input sectors of the economy on the innovative process of manufacturing and its consequences on productivity. We test for a differentiated effect of this type of PMR depending on whether countries are technological leaders or laggards in a given industry and for a given time period. Contrary to the most widespread policy claims, the innovation-boosting effects of liberalisation policies at the leading edge are systematically not supported by the data. These findings question the relevance of a research and innovation policy based on product market liberalisation.

1. Introduction

The interest in policies aiming at fostering innovative activity through framework conditions has grown in Europe over the last decade, if only because restrictions on public spending have reduced the funding of more traditional research and innovation policies (Blind, 2012). The regulatory framework has been at the centre of economic policy debates and the most accepted view in economic policy circles, particularly in Europe, is that a more intense competition should be promoted through the implementation of a less stringent product market regulation (PMR).[1] Explaining the contribution of competition policy to Europe 2020, Alexander Italianer, Director-General of DG Competition declared in 2010 that competition was the key to ensure that the vision of growth and dynamism carried by Europe 2020 comes true: '*Effective competition pushes companies to innovate. They have to come up with new and better products to retain existing customers and gain new ones... Competition encourages companies to allocate their resources in the most efficient way, leading companies to offer more choice and better quality at lower prices. As a result competition boosts productivity, growth and job creation.*'[2]

This view is not devoid of academic grounding. Following the emergence of the innovation-based endogenous growth theory (Aghion and Howitt, 1998), the importance of product market competition (PMC) as an engine of growth through its efficiency- and innovation-inducing effects has been stressed in some theoretical and applied contributions (e.g. Aghion et al., 1997, 2005, 2014; Aghion and Griffith, 2005). This theme has been incorporated in the policy debates linking competition policy (or the extent of regulation in product markets) to competitiveness and growth. 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). Moreover, the importance of competition as a driver of innovation and growth is expected to be greater for economies that compete at or near the leading edge of technology (Acemoglu et al., 2003, 2006; Vandenbussche et al., 2006). This literature has led European policy-makers to base their innovation-promoting efforts on the aforementioned less stringent PMR. This makes for a minimal technology and industrial policy, which primarily consists in lifting regulations as much as possible to ensure

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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/C217/05), OECD (2007), IMF (2010).

[2] *Competition Policy in support of the EU 2020 policy objectives. Speech at the Vienna Competition Conference 2010 'Industry vs. Competition?'*

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a fair competition. However, putting too much emphasis on this "common wisdom" might in the end prove inefficient for innovation and growth, leading to a neglect of dedicated science and innovation policies.

Meanwhile, the deregulation process is going on, more markedly in some industries than in others. In fact, since the 1980s (and mostly during the 1990s in Europe), network industries such as electricity, gas, rail, airlines, post and telecommunications have experienced an important process of market reform. The influence of PMR in network industries is likely to impact the technological and competitive processes of the rest of the economy through vertical linkages. Thus, the transformation in the regulation of these industries has been seen as a wider liberalisation trend in developed economies. Some applied works have concluded that this type of reforms has boosted productivity growth. This link is widely perceived as robust and has recently been presented as evidence of the aforementioned theoretical predictions (e.g. Bourlès et al., 2013). The underlying rationale is that the lack of dynamism in key input sectors of the economy becomes an impediment for firms to implement their innovative strategies in their own markets, especially when they compete neck-and-neck with their rivals and seek to escape competition.

This paper critically examines the robustness of such claims, which have clear policy implications. Indeed, they are at the root of recommendations that advocate the liberalisation of product markets as an innovation-boosting policy. The contribution of our critical examination is twofold. We first start by recalling the theoretical ambiguities of the relationship between competition and innovation. These go beyond the mechanisms isolated in models à la Aghion et al. (2005), such as the "escape competition" effect. A review of the related empirical literature also reveals that results are fairly less clear-cut than what the "common wisdom" presumes. We then provide a systematic empirical assessment of the vertically-induced impact of non-manufacturing regulation (mainly in network sectors) on innovation and productivity in manufacturing industries. Besides challenging the "common wisdom", this paper goes one step further in the empirical identification of the impact of regulatory reforms on technical progress. Most papers on this topic perform estimations based on reduced-form equations taking productivity (or, less frequently, innovation) measures as the dependent variable. Here, we seek to add more structure to the econometric model by relating productivity to innovation, and the latter to PMR in an integrated framework.

We take inspiration from a large body of empirical work, starting from 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 and our main estimations focus on the innovation-productivity nexus only. We rely 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 indicators.

There are several reasons for performing our test at this level of aggregation. First, the industry-level scope is more likely to capture information on equilibrium relationships. Thereby, this level of analysis is more relevant to measure the bottom-line aggregate impact on innovation and productivity of the (a priori) contradictory economic mechanisms induced by the competitive process. Second, it also facilitates the empirical implementation since at this level of analysis we do not face the selection issues that plague most firm-level data on R&D. Moreover, internationally comparable industry-level data allows us to exploit the variability of different PMR regimes. This helps us reduce the risk of endogeneity as compared with observed measures of competition. Interpretations are more easily related to policy.

We consider the same PMR indicators used in the related empirical literature. They are constructed by the OECD in order to capture the so-called "knock-on" effects of non-manufacturing regulation on the rest of the economy. In the literature, these PMR indicators are used to measure the restrictiveness and low-competition environment supposedly induced by PMR. Our measure of innovative performance is patenting intensity, which in our model is affected by PMR and in turn explains productivity. Using measures of relative performances in total factor productivity, we also construct a measure of the closeness to the world technology frontier and split our sample into two unbalanced panels of national industries, depending on whether they perform near (leaders) or far from (followers) the leading edge. This allows us to test for a differentiated impact of the regulatory environment on the technological change of each type of industry. In this new and extended approach, using recently issued data, results are consistent with previous findings contradicting the idea that technical progress at the leading edge should be grounded on liberalisation policies (e.g. Amable et al., 2010, 2011).

The paper is organised as follows. Section 2 summarises the current debate and findings of the related literature. Section 3 exposes the empirical strategy followed in the paper. Section 4 discusses the estimation results. Section 5 presents an extended model including R&D. Section 6 discusses the policy implications of the results and concludes.

2. PMC, PMR, innovation and productivity

In order to better understand the policy debate on these issues, as well as our own critical contribution, it is worth making a selective synthesis of the main arguments analysing the link between market structure and technological performances. We begin by focusing the discussion on PMC as a theoretical concept and introduce PMR as the applied policy counterpart. It should be kept in mind, however, that the link between both remains far from trivial.[3]

2.1. Theoretical issues

Although the contemporary "common wisdom" states that liberalising product markets should foster innovation and productivity growth, theoretical contributions studying the way market structure shapes the incentives to innovate do not deliver an unambiguous positive relationship between PMC on the one hand and innovation or growth on the other (Amable and Ledezma, 2015). The "traditional" economic view is indeed one in which PMC has a negative impact on innovation as competition erodes innovation profits (Schumpeter, 1934, 1942). 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).

When innovation occurs step-by-step, that is when laggards must catch-up with the technological leader before overtaking it, the aforementioned 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

[3] It is fair to say that the gap between *de jure* and *de facto* aspects of competition has been largely neglected in the applied macro-level policy oriented literature on PMR and growth. See Armstrong and Sappington (2006, 2007), for a review on these issues.

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*' (Aghion et al., 2005, Proposition 5), that is to say in industries where firms compete at the same technological level. This has given rise to 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.[4]

The nonlinearity of the relationship between competition and innovation is more generally analysed within the industrial organisation literature. A key contribution providing some degree of generality is that of Boone (2001), who axiomatically defines the intensity of competition in order to encompass different standard parametrisations. Considering heterogeneous 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 further. Details therefore matter. For instance, within the context of Cournot competition and product differentiation, Tishler and Milstein (2009) show a (non-inverted) U-shaped relationship between the intensity of competition, as measured by the degree of substitutability, and R&D.

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 their own rents (the so-called 'Arrow effect'). One special form of the leader's advantage is that given by its position as an incumbent that moves first (Gilbert and Newbery, 1982). In that case, entry becomes endogenous and, contrary to traditional innovation-based growth 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 here is that the presence of an active monopoly can actually hide an intense competition threat. Amable et al. (2010) consider the possibility for the technological leader to innovate in order to make the follower's innovation more difficult within a framework similar to Aghion et al. (2005). Such an interaction may reverse the relationship between competition and innovation predicted by Aghion et al. (2005) 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 itself is also affected by these strategic interactions in a non-trivial way. Ledezma (2013) shows that, if the persistence of leadership relies on technological 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 theoretically allowed to increase the costs of innovation, as long as it forces leaders to stay, qualitatively, within the boundaries of the current good.

2.2. Industry-level tests

Implications of endogenous entry and strategic interactions render visible the weakness of outcome measures of competition or market concentration and explain the widespread use of regulatory indicators in the applied literature and its focus on aggregate (mostly industry-level) outcomes. Some contributions estimate the impact of PMR on innovation or productivity without taking into account the proximity to the technological frontier. Blind (2012) distinguishes several regulatory indicators derived from business opinion surveys and tests their impact on the patenting intensity at the macro-level for a panel of 21 countries between 1999 and 2004. His findings display a diversity of influences according to the indicators. While restrictive price regulation has a negative impact on patenting, competition legislation has no impact, and product and service legislation, taken to deter business activity, actually has a positive influence on a country's innovative performance. Barbosa and Faria (2011) focus on 10 EU countries and 22 2-digit manufacturing industries. Their cross-section estimates for the period 2002–2004 show a weakly significant negative effect of regulation on the proportion of innovative firms within an industry. However, they use a macroeconomic indicator of PMR, common to all industries of a given country. Empirical assessments at the industry-level using regulation policy measures are then useful to analyse the relevance of the received argument about the positive effect of liberalisation on innovation and productivity growth.

A fairly large body of empirical literature follows this approach (see, e.g., Nicoletti and Scarpetta, 2003; Conway et al., 2006; Bourlès et al., 2013). It usually relies on time-varying industry-level data for developed countries. As in this paper, these works use PMR indicators constructed by the OECD, which tabulates detailed surveys on regulatory practices (see Section 3.1.2). The scope of these practices is generally economy-wide or related to the experience of PMR in network services sectors. As a way to obtain more insights on the effect of this type of reforms on the rest of the economy, the OECD constructs "regulatory impact" indicators that measure the so-called "knock-on" effects of non-manufacturing regulation. This is done by connecting the regulatory practices in key non-manufacturing input sectors to the use of these sectors' output in each industry of the economy. This is why regulatory impact indicators are usually presented as capturing the extent to which upstream regulation restrict activities in downstream industries. The resulting index of regulation is generally highly correlated with other aspects of PMR measured by economy-wide indicators (Amable et al., 2010) and at the same time allows for more time-variability across countries and industries. This makes it possible to perform estimations on PMR data presenting a panel structure where individuals are country-industry couples (national industries).

In general, estimations seek to measure the impact of PMR on economic performance (captured by a measure of innovation or, more often, productivity) in a reduced-form econometric equation. The latter usually includes a measure of the gap vis-à-vis the technology frontier and a term interacting this technology gap with the PMR proxy. 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 economic performance) varies with the closeness to the technology frontier. This type of specification seeks to measure the policy-oriented interpretation of Aghion et al. (2005) whereby liberalisation reforms would boost innovation activity.[5]

[4] The managerial literature also highlights a positive impact of competition on innovation, the former being a device that reduces organisational slack (Machlup, 1967; Porter, 1990). When considering maximising (and not just satisficing) 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 still usually ambiguous (Scharfstein, 1988; Hermalin, 1992; Schmidt, 1997; Raith, 2003).

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

Contradicting these predictions, results of Amable et al. (2010), which rely on similar specifications, 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 between PMR and the closeness to technology frontier. The same positive sign has also been found in Nicoletti and Scarpetta (2003) and Conway et al. (2006) with PMR indicators highlighting economy-wide aspects of PMR and productivity growth used as a proxy for technical progress/economic performance. These authors, however, emphasise the slowing down effect of PMR on the catching-up process of laggards rather than the positive effect close to the frontier. On the other hand, Bourlès et al. (2013) do report a negative effect of PMR, which grows stronger the closer to the technology frontier. Their sample consider both manufacturing and service sectors. Nicoletti and Scarpetta (2003) and Inklaar et al. (2008) highlight the specificities of both type of sectors, something that could explain the differences in estimates across studies. 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 interacted with a dummy variable indicating if firms are above the productivity median at the national level. The estimated coefficient of this differently specified interaction term is negative.

What emerges from this snapshot of the related literature is that the relationship between PMC, PMR, innovation and productivity growth can fairly be considered as an open question, at least to the point of tempering the optimism of mainstream policy recommendations.[6]

3. Methodology

From the review of the related literature we can grasp some lessons for improving the empirical identification. A first conclusion is that the specificities of national industries matter. It is then important to provide further empirical scrutiny by fully exploiting the "panel" structure of the data. We show that adopting an individual fixed-effect structure (i.e. for country-industry pairs) in the econometric model is key to control for unobserved heterogeneity of national industries.

A second line of improvement relates to the measures of PMR. They are composite indicators of several dimensions of the regulatory environment. One important element is the scope of government participation in network industries. Full privatisation was not always the strategy adopted for unbundling and this may have had consequences for the rest of the economy. We consider in our robustness checks different "sub-indicators" of regulatory impact, including, excluding or isolating the scope of government implication.

Last, but not least, the above-discussed empirical literature has focused separately on productivity and innovation. However, both are linked stages of the same process of technical progress. Consequently, within a system estimation we test how PMR affects the innovation-productivity nexus. In our robustness checks the model is extended to include R&D as part of the process.

Hence, relative to the existing empirical literature at the industry-level, we propose a more careful account of panel unobserved heterogeneity within a system equation in which causality is more rigorously tested and where more economic channels can be accounted for. The detail of this analysis is presented in what follows.

3.1. The data

3.1.1. Sources

We use three main sources of industry-level time-series data. From the EU KLEMS database constructed by the Groningen Growth and Development Centre (GGDC), we draw information on labour inputs and multifactor productivity (MFP) 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 more than five thousand potentially exploitable observations. Sample details are given in Appendix. Tables A1 and A2 present the lists of countries and industries. Aggregate descriptive statistics (mean, dispersion and number of non-missing observations) at the country level are reported in Table A3.

3.1.2. Main variables

MFP growth, MFP levels and closeness to the world technology frontier. We rely on measures of MFP growth relative to the base year 1995, available in the EU KLEMS database (March 2011 update of the November 2009 release). The use of EU KLEMS data on MFP growth is preferred to specific calculations for several reasons. Methods and data are publicly available and continuously updated so that our analysis share a common accessible basis with other related studies. National Accounts are systematically considered in EU KLEMS and completed with cross-checked micro level surveys, which increases information availability. At the same time the underlying methodology ensures conceptual consistency between variables and different scopes of aggregation. Improved availability is also gained in terms of detailed series on capital and labour inputs, which allows for a more precise growth accounting. Details on these and other features of the EU KLEMS database can be found in O'Mahony and Timmer (2009).[7]

Our empirical strategy also requires MFP *levels* in order to construct an indicator of the closeness to the world technology frontier (WTF) which shall be used in our regressions to split the sample into "leader" and "follower" national industries. MFP levels were obtained combining (i) the MFP growth measures of EU KLEMS and (ii) the Productivity Levels (PL) database, also provided by the GGDC.[8] The latter contains MFP indexes in levels relative to the United States only for the year 1997. This constraint is imposed by the need of offering information comparable over time and across countries and industries. To this aim, a specific deflation procedure is performed, which imposes heavy data requirements for constructing 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 period for such a purpose. In addition, the resulting information on MFP levels also offers a double deflation scheme for value added.

Using both the EUKLEMS and PL databases it is possible, however, to reproduce MFP series in levels for the full sample period.

[6] We have focused here on industry-level empirical tests. The mixture of results also appears in microeconomic country-specific studies on PMC and innovation (e.g. Cohen, 2010). Case study evidence on services liberalisation also adds to a less optimistic view on the supposed innovation-boosting effects (see Section 6).

[7] For the data and further documentation see http://www.euklems.net/index.html and the numerous EU KLEMS publications dealing with particular applications as well methodological issues. O'Mahony and Timmer (2009) also present statistical comparisons with the OECD STAN database.

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

This amounts to apply the so called constant-PPP approach (see Inklaar and Timmer, 2008). More precisely, for a given country c, industry i and time period t let $MFPG^{b}_{c,i,t}$ be the MFP growth index relative to the year base b, MFP_{cit} the MFP level index and MFP^{US}_{cit} that relative to the United States. In this notation, what the EU KLEMS and PL databases provide are, respectively

$$MFPG^{95}_{cit} = \frac{MFP_{cit}}{MFP_{ci95}}; \quad MFP^{US}_{ci97} = \frac{MFP_{ci97}}{MFP_{USi97}}$$

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:

$$MFP^{US}_{cit} = MFP^{US}_{ci97}\frac{MFPG^{97}_{cit}}{MFPG^{97}_{USit}} = \frac{MFP_{cit}}{MFP_{USit}} \tag{1}$$

With MFP levels at hand we define our measure of closeness to the WTF as follows. For a given industry and year we first identify the WTF as the highest MFP level observed in the sample, i.e. that of the leader country in the industry for that year. Formally,

$$WTF_{it} = MFP^{US}_{c^*it} \quad where\, c^* = arg\max_{c}\left\{MFP^{US}_{cit}\right\} \tag{2}$$

For each country c in a given industry i and time period t, the closeness to the WTF, CL_{cit}, is then defined as its MFP level relative to that of the WTF:

$$CL_{cit} = \frac{MFP^{US}_{cit}}{WTF_{it}} = \frac{MFP_{cit}}{MFP_{c^*it}} \tag{3}$$

As the last equality makes clear, the MFP level of the United States does not participate in the definition of CL_{cit}.

In our regressions, $MFPG^{95}_{cit}$ is used as the dependent variable and WTF_{it} belongs to the set of explanatory variables. The constructed indicator of CL_{cit} is not part of the set of covariates in the regressions. It is only used to identify among national industries the subsamples of leaders and followers.

Innovation. Innovation is measured as patenting intensity (PI), that is to say 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 a concordance matrix between the international patent classification (IPC) and the 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 (with 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 the March 2011 update of the 2009 EU KLEMS release provides information on labour inputs and labour compensation, the details on skill composition is only available in the previous release (2008). We extract from this latter source the share of hours worked by high-skilled persons in order to include it in our regressions as a potential determinant of innovation. As a result, the main estimations do not consider the years 2006 and 2007 for which we have no information on skill composition. However, reduced form estimates shown in the preliminary analysis performed in Section 3.1 do exploit the full length of the sample for the main variables and deliver consistent conclusions.

Product market regulation. There is an abundant literature, inspired by Pavitt (1984) that has dealt with intersectoral linkages, particularly between the service and manufacturing sectors. Laursen and Meliciani (2000) explored the role of such linkages for innovation and external competitiveness and found that R&D imported from other sectors through upstream and downstream linkages had a significant positive effect on competitiveness in scale-intensive and specialised-supplier types of industries. Guerrieri and Meliciani (2005) found that knowledge-intensive industries were the main users of producer services. For Castellacci (2008), the interaction between – not necessarily symmetrical (Park and Chan, 1989) – technologically advanced manufacturing and service industries is a key to competitiveness. At a more aggregate level, Windrum and Tomlinson (1999) show that economies with strong, mutually beneficial, links between services and manufacturing are likely to benefit the most from a transition towards a service economy.[9]

A particular type of linkage is considered here, through the measure of regulatory pressures. PMR is measured by the regulation impact (henceforth REGIMP) indicator constructed by the OECD. We use the 2008 updated release (see Conway and Nicoletti (2006) for the details of the methodology).[10] 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: (i) network services such as energy (electricity and gas), transport (air, rail and road transport) and communications (post and telecommunications) – the regulation of which is captured by the ETCR indicator; (ii) retail distribution and professional services – the regulation of which is captured by the RBSR indicator; and (iii) finance.

Regulation in each of these activities is measured as an average composite of scores constructed upon qualitative information about regulatory practices in several important “regulatory areas”. For ETCR, these areas cover entry, public ownership, vertical integration, price controls and market structure. Information here is available for the 1975–2007 period. For RBSR regulation, areas consider more specific restrictions on entry and conduct, and the data contains 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.[11] 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 manufacturing industries are final goods and that not all NM sector output is used in production activities. 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.

As previously mentioned, a key advantage of REGIMP is its panel variability, which is 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

[9] Their argument relies on a parallel between the first Industrial Revolution and the contemporary pattern of structural change. Progress in agriculture and manufacturing reinforced each other in the former case, and a similar situation seems to exist between services and manufacturing in the latter.

[10] http://www.oecd.org/economy/pmr.

[11] 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).

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 REGIMP data also offers series restricted to the regulatory area of public ownership (henceforth the RPO indicator) as well as series excluding this dimension (henceforth RWPO). We use these additional series as alternative PMR indicators in our robustness checks.

3.2. Empirical strategy

Our main estimations rely on a two-equation model that allows us to identify (i) the determinants of innovation and (ii) those of MFP (which include innovation itself).[12] Among these determinants, the vertically-induced effects of non-manufacturing PMR (henceforth PMR for brevity) is expected to play a crucial role, which may depend on whether national industries compete far from or close to the WTF. In the first-stage equation, patent intensity of country c, in industry i at time period $t-1$, $\ln PI_{cit-1}$, is explained by its own autoregressive process, the level of PMR, $\ln PMR_{cit-1}$, the share of hours worked by high-skilled workers, $\ln HS_{cit-1}$, and the MFP level exhibited by the WTF, $\ln WTF_{it-1}$. In the second-stage equation, the dependent variable is the log-difference of MFP relative to the base year 1995, viz. $\ln MFPG_{cit}^{95} = \ln MFP_{cit} - \ln MFP_{ci95}$, which is explained by PMR, patent intensity and the MFP level of the WTF. Neither the autoregressive process of innovation nor the share of high-skilled labour is assumed to directly influence the log-difference of MFP (recall that the productivity accounting allowing to compute MFP as a residual has already taken into account input factors). Formally,

$$\begin{aligned}
\ln MFPG_{cit}^{95} &= \beta_1 \ln PMR_{cit-1} + \beta_2 \ln PI_{cit-1} + \beta_3 \ln WTF_{it-1} + \eta_{ci} + \eta_t + \varepsilon_{cit} \\
\ln PI_{cit-1} &= \alpha_1 \ln PMR_{cit-1} + \alpha_2 \ln WTF_{it-1} + \alpha_3 \ln HS_{cit-1} + \sum_{\tau=k}^{m} \gamma_\tau \ln PI_{cit-1-\tau} + \delta_{ci} + \delta_{t-1} + \xi_{cit-1}
\end{aligned} \tag{4}$$

where η_{ci}, δ_{ci} are individual (country-industry) unobserved fixed effects; η_t and δ_t are time specific unobserved fixed effects; and finally ε_{cit} and ξ_{cit} the idiosyncratic disturbances.

In our regressions we consider alternatively $\tau = 3$, 4 and 5. We use instrumental variable (IV) and GMM approaches to estimate (4). In both cases we take into account the unobserved individual time-invariant heterogeneity by exploiting within-group variance. This implies that the productivity equation will in fact be estimated in levels (i.e. the term $\ln MFP_{ci95}$ in $\ln MFPG_{cit}^{95} = \ln MFP_{cit} - \ln MFP_{ci95}$, at the left-hand side, will be eliminated by the within-group transformation). In estimating (4) we also consider the possibility of arbitrary heteroskedasticity and autocorrelation.

In order to identify a differentiated effect of PMR accordingly 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 the closeness to the world technology frontier, CL_{cit}, defined by Eq. (3). We consider in our regressions the 50th, the 60th and the 75th percentiles of the CL_{cit} as alternative cutoff levels for the sample splitting. In each case, we allow our parameter estimates to differ in each subsample. The MFP level featured at WTF, $\ln WTF_{it-1}$, is introduced as an explanatory variable in both equations in order to control for technological externatilities.

By letting PMR participate in both equations, we can identify how PMR affects MFP through patented innovation as well as through other type of non-patented innovative activity. With the sample splitting we can test how its influence 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 in the first stage equation $\alpha_1 < 0$ for leaders and $\alpha_1 > 0$ for followers, provided that $\beta_2 > 0$. As a robustness check, in Section 5 we extend the model to include R&D as a third equation.

4. Results

4.1. Preliminary analysis

The three-dimensional structure of our data implies the presence of different sources of unobserved specificities explaining MFP differences across national industries. We start therefore our analysis by estimating reduced-form regressions which seek to explain the log difference of MFP by the log of our indicator of PMR (REGIMP) and a set of dummies controlling for time, country and industry fixed effects, as well as their plausible interactions. Formally, we test:

$$\ln MFPG_{cit}^{95} = \lambda_0 + \lambda_1 \ln PMR_{cit-1} + \mu_{cit} \tag{5}$$

where μ_{cit} is composed of an intrinsical disturbance ν_{cit} and several fixed effects, the specific form of which depends on the hypotheses regarding the underlying unobserved heterogeneity. Results are presented in Table 1. In column (1) the specification considers country, industry and time fixed effects, i.e. $\mu_{cit} = \mu_c + \mu_i + \mu_t + \nu_{ict}$ and yields a significantly negative elasticity of REGIMP. This result still holds and with increased magnitude (in absolute value) when the specification includes country-specific time fixed effects, i.e. $\mu_{cit} = \mu_c + \mu_i + \mu_t + \mu_{ct} + \nu_{ict}$, which seeks to control for national-level shocks. This type of dummy structure, controlling for national trends, is close to that assumed by Bourlès et al. (2013).

Columns (3) and (4) report on specifications considering this time individual (country-specific industry) fixed-effects. Regression in column (3) includes also time fixed effects, i.e. $\mu_{cit} = \mu_{ci} + \mu_t + \nu_{ict}$ whereas country-specific time fixed effects are added in the regression reported in column (4), i.e. $\mu_{cit} = \mu_{ci} + \mu_{ct} + \mu_t + \nu_{ict}$. Both of these specifications are estimated using the within-group transformation. The Fisher test here indicates that we can reject at any conventional risk the null hypothesis of no-joint effect of individual (country-industry) intrinsic characteristics. In both of these regressions the elasticity of REGIMP is significantly positive. This elasticity increases after the inclusion of country-time dummies, as in column (2). Hence, controlling for unobserved time-invariant individual heterogeneity matters.

[12] This model is directly comparable to the econometric specifications that appear in the key studies mentioned in Section 2.2. Some use patents as the dependent variable, and others use MFP. Our model takes things further by examining the effect of regulation on both variables. Another possible specification would consist in including a lag of R&D intensity in the patenting equation in lieu of (or alongside) the lag of patenting intensity. We do not adopt it here because it would be less comparable to those prevalent in the aforementioned literature (which pays surprisingly little heed to R&D). In addition, our patenting equation already includes some degree of control for R&D in the form of the share of highskill labour (R&D expenditures primarily consist in the wages of R&D personnel). Last but not least, the long-term effects of R&D are already partly controlled for by the lagged value of patenting intensity (since the latter results from past R&D efforts). In Section 5, we propose an alternative model with an additional R&D equation (note that adding country-industry R&D series to our sample slightly reduces its time dimension, since information on R&D expenditures is only available over a shorter time span).

Table 1
Reduced-form regressions.

Dependent variable: MFP growth relative to 1995, $\ln MFPG^{95}_{cit}$				
	(1)	(2)	(3)	(4)
$\ln(REGIMP_{cit})$	−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)
Fixed-effects	μ_c, μ_i, μ_t	$\mu_c, \mu_i, \mu_{ct}, \mu_t$	μ_{ci}, μ_t	$\mu_{ci}, \mu_{ct}, \mu_t$
Number of obs.	5622	5622	5622	5622
Adjusted R^2	0.18	0.21	0.16	0.24
Individuals			220	220
F-test (p-value)			0.000	0.000

Note: Standard errors in parentheses. μ_c, μ_i, μ_t, μ_{ci} and μ_{ct} stand for, resp., country, industry, time, country-specific industry and country-specific time fixed effects.
* $p<0.10$.
** $p<0.05$.
*** $p<0.01$.

Unobserved determinants of MFP tied to national industry-level specificities and correlated with our regulation proxy (e.g. institutions, initial conditions, technology-based R&D propensity, etc.) may lead to biased estimations if only industry characteristics common to all countries and/or country characteristics common to all industries are controlled for.

4.2. Two-step estimates

The results of the two-step analysis are presented in Tables 2–7. These tables report the estimation of Eq. (4) for a subsample of leaders or followers national industries, defined differently depending on whether they are respectively above or below the 50th, the 60th or the 75th percentile of our measure of closeness to the WTF (see Section 2). All Tables show for a given type of individual (leader or follower) and regulation indicator (REGIMP, RWPO or RPO) the first-stage estimates (the patenting equation) in the upper panel and the second stage (the MFP equation) in the bottom panel. Columns (1) to (3) present estimations of the same model for a sample split at the 50th, 60th and 75th percentile respectively. Here, the lag of patenting intensity is instrumented by its own third lag. Columns (4) to (6) consider an additional scrutiny for the regressions of column (3). The definition of the closeness to WTF in these regressions is the strictest one. This definition corresponds to a particularly interesting sample split as it captures differentiated effects of PMR on what can be called the leading-edge of technology. These alternative regressions also consider deeper autoregressive processes for patenting intensity. All models consider individual (i.e. country-industry) and time fixed effects. In all regressions also, statistics are robust to arbitrary heteroskedasticity as well as to arbitrary autocorrelation through kernel-based estimations. Column (6) reports the results obtained from estimations implementing two-step efficient generalised method of moments (GMM).

The rows at the end of each table give a summary of tests on instruments as well as on identification. These consist of (i) the Hansen test on the validity of overidentifying restrictions, (ii) a rank test for underidentification based on a Lagrangean multiplier version of the Kleibergen and Paap (2006) *rk* statistic, which amounts to generalise the Anderson canonical correlation rank statistic to the non-i.i.d. case; (iii) a weak identification test which is a “robust” analogue of the weak identification IV test for the i.i.d. case (Stock and Yogo, 2005), based on the Kleibergen–Paap *rk* statistics; and finally (iv) a weak-identification-robust inference test (i.e. a test on the structural significance of the endogenous regressors) based on Anderson and Rubin (1949), here also considering heteroskedasticity-robust statistics.[13] Although changing the regulation proxy or the sample of national industries amounts to changing the scope of the regulatory provisions being considered and their expected impact on innovation and productivity, we keep the same specification of instruments for the sake of comparison. The same structure of presentation is then kept in all tables.

The first estimations are made with the REGIMP indicator and the results are documented in Table 2 for the leaders and Table 3 for the followers. The impact of PMR, measured by this proxy, is generally positive for leaders at both the innovation and the productivity stage. Interestingly, the point elasticity of PMR in the first stage (innovation) is positive but the parameter estimated is not significantly different from zero when we use broad definitions of leaders (i.e. national industries above the 50th and the 60th percentile of closeness to the WTF). However, this positive impact becomes significant and significantly higher when one narrows the definition of the leaders or, to put it differently, when one goes nearer to the technology frontier: The elasticity jumps from 0.080 at the 50% split to 0.486 at the 75% level. Even in the fully instrumented model (columns (5) and (6)) the estimated elasticity is more than four times higher at the 75th percentile split. The instrumentation strategy is also validated for the 60% and the 75% threshold.[14] Therefore, contrary to the common wisdom, these estimations show that PMR has a positive impact on innovation, which grows with the proximity to the WTF. As expected, skilled labour also favourably influences innovation, which is also positively affected by past innovation performance. On the other hand, spillovers stemming from the WTF appear to not significantly affect innovation for leader national industries. In the second stage (productivity), innovation is seen to positively influence productivity in all regressions, with an elasticity that does not vary significantly with the definition of the leader/follower split in the basic regressions. The positive impact of patents on productivity should dispel any doubts one might have had about the relevance of that variable for representing significant innovations. The introduction of the productivity externality term appears with a significantly positive coefficient, but only at the vicinity of the WTF. For this

[13] Whereas for the Hansen test we would like to fail to reject the null hypothesis that orthogonality conditions are valid, for the rest of the tests the rejection of the respective null hypothesis is evidence of proper specification.

[14] The higher p-values, yet still small, for the Anderson–Rubin tests are the consequence of the joint hypothesis tested: the coefficient of the endogenous regressor in the structural equation is equal to zero, and, in addition, the overidentifying restrictions are valid. As can be seen in Table 2, the coefficients of the lagged patenting intensity is itself significant at least at the 10% level.

Table 2

Leaders – Innovation equation (first-stage estimates) – **REGIMP indicator**
Dependent variable: patenting intensity, $\ln(PI_{cit-1})$

WTF split	Q50 (1)	Q60 (2)	Q75 (3)	Q75 (4)	Q75 (5)	Q75 (6)
$\ln(REGIMP_{cit-1})$	0.080	0.100	0.486***	0.406***	0.331**	0.331**
	(0.101)	(0.127)	(0.152)	(0.145)	(0.143)	(0.143)
$\ln(WTF_{cit-1})$	−0.030	−0.015	−0.022	−0.039	−0.033	−0.033
	(0.030)	(0.039)	(0.053)	(0.048)	(0.045)	(0.045)
$\ln(PI_{cit-4})$	0.491***	0.459***	0.393***	0.339***	0.299***	0.299***
	(0.023)	(0.028)	(0.034)	(0.050)	(0.057)	(0.057)
$\ln(PI_{cit-5})$				0.135***	0.186***	0.186***
				(0.047)	(0.063)	(0.063)
$\ln(PI_{cit-6})$					0.064	0.064
					(0.040)	(0.040)
$\ln(HS_{cit-1})$	0.126***	0.124***	0.108**	0.135***	0.147***	0.147***
	(0.039)	(0.043)	(0.048)	(0.045)	(0.043)	(0.043)
Adjusted R^2	0.86	0.86	0.84	0.84	0.84	0.84

Leaders – Productivity equation (second-stage estimates) – **REGIMP indicator**
Dependent variable: MFP growth relative to 1995, $\ln MFPG^{95}_{cit}$

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(PI_{cit-1})$	0.120***	0.109**	0.135*	0.199**	0.221***	0.171**
	(0.040)	(0.045)	(0.071)	(0.078)	(0.081)	(0.075)
$\ln(REGIMP_{cit-1})$	0.341***	0.546***	0.453***	0.436***	0.441***	0.480***
	(0.108)	(0.126)	(0.156)	(0.157)	(0.159)	(0.157)
$\ln(WTF_{cit-1})$	-0.062	0.008	0.117**	0.113**	0.105*	0.117**
	(0.041)	(0.043)	(0.054)	(0.054)	(0.055)	(0.054)
Number of obs.	2528	2018	1262	1216	1169	1169
Individuals	150	130	87	85	84	84
Tests of instruments and identification						
Overidentifying restrictions (Hansen test)						
p-Value (J statistic)	0.004	0.108	0.484	0.595	0.211	0.211
Under identification (Kleibergen–Paap rank test)						
p-Value (LM statistic)	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification (Kleibergen–Paap based, for non-i.i.d errors)						
Wald F statistic	233.18	140.327	71.818	62.053	54.231	54.231
Endogenous regressors (Anderson–Rubin test)						
p-Value (chi-2 test)	0.001	0.034	0.173	0.086	0.028	0.028

Note: Standard errors in parentheses. See Eq. (4) for details on the IV specification. All estimations consider a constant term, individual (country-industry) fixed effects and year dummies. Statistics are robust to arbitrary heteroskedasticity and also to arbitrary autocorrelation through kernel-based estimations. Column (6) reports two-step efficient generalised method of moments (GMM) estimations.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

subsample the value of the innovation elasticity is higher. The productivity equation also shows that PMR positively impacts productivity by other channels than innovative patented activity. Although in this stage the associated elasticity of PMR is significantly positive and sizeable everywhere, it is also larger at the leading edge.

The results for followers are documented in Table 3. The elasticity of PMR at the innovation stage is significantly negative for every sample split, and less negative at the 75% cutoff level than at the 50% or the 60% cutoff levels. Combining this with the results obtained for leaders, one obtains a significantly negative influence of PMR far from the technology frontier that gradually turns into a significantly positive impact that grows when one gets near the technology frontier. This is exactly the opposite of the relationship postulated by the “common wisdom”. Our results are nevertheless in accordance with those of Amable et al. (2010), Nicoletti and Scarpetta (2003) and Conway et al. (2006).[15] The fact that these results differ from what is generally seen as “common wisdom” illustrates how ambiguous the relationship between PMR, innovation and growth can be. Depending on the proxies and econometric methodologies used, there is scope for some variety in the results. For instance, most empirical studies in the literature fail to develop suitable controls for unobserved individual heterogeneity, heteroskedasticity and autocorrelation in the models from which they derive their results. In the present study, we not only use a carefully-constructed measure of MFP, we also implement an econometric methodology that controls for the above-mentioned biases (which may typically plague large panels in which the time dimension is long).

Going back to our other results, we find that 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 here again does not exert any significant impact. In the second stage, as expected, the influence of innovation on productivity is not as high as with industry leaders. The estimate of the elasticity of productivity with respect to innovation is only significant at 10% for the 50% and 60% cutoff levels (columns (1) and (2)) and, when significant, less than a half of the innovation elasticity for leaders in comparable models. Interestingly also, contrary to what happens in the innovation stage, in the productivity equation PMR has a significantly positive impact on the productivity of followers, and the elasticity is generally higher than that estimated for leaders. This suggests

15 As we mentioned, interpretations may be radically different.

Table 3

Followers – Innovation equation (first-stage estimates) – **REGIMP indicator**
Dependent variable: patenting intensity, $\ln(PI_{cit-1})$

WTF split	Q50 (1)	Q60 (2)	Q75 (3)	Q75 (4)	Q75 (5)	Q75 (6)
$\ln(REGIMP_{cit-1})$	−0.353***	−0.368***	−0.254***	−0.240***	−0.250***	−0.250***
	(0.096)	(0.087)	(0.076)	(0.072)	(0.072)	(0.072)
$\ln(WTF_{cit-1})$	−0.021	−0.020	0.001	−0.007	−0.020	−0.020
	(0.020)	(0.018)	(0.017)	(0.016)	(0.015)	(0.015)
$\ln(PI_{cit-4})$	0.436***	0.449***	0.481***	0.423***	0.370***	0.370***
	(0.029)	(0.025)	(0.021)	(0.031)	(0.034)	(0.034)
$\ln(PI_{cit-5})$				0.150***	0.130***	0.130***
				(0.027)	(0.034)	(0.034)
$\ln(PI_{cit-6})$					0.097***	0.097***
					(0.026)	(0.026)
$\ln(HS_{cit-1})$	0.030	0.038	0.089**	0.096***	0.079**	0.079**
	(0.048)	(0.039)	(0.036)	(0.034)	(0.034)	(0.034)
Adjusted R^2	0.82	0.83	0.85	0.85	0.84	0.84

Followers – Productivity equation (second-stage estimates) – **REGIMP indicator**
Dependent variable: MFP growth relative to 1995, $\ln MFPG^{95}_{cit}$

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(PI_{cit-1})$	0.058	0.054	0.069**	0.083**	0.093**	0.093***
	(0.050)	(0.043)	(0.034)	(0.036)	(0.037)	(0.034)
$\ln(REGIMP_{cit-1})$	0.676***	0.673***	0.577***	0.591***	0.604***	0.508***
	(0.223)	(0.185)	(0.148)	(0.150)	(0.152)	(0.130)
$\ln(WTF_{cit-1})$	0.107***	0.071**	0.025	0.013	0.010	−0.003
	(0.038)	(0.032)	(0.027)	(0.026)	(0.027)	(0.025)
Number of obs.	2328	2843	3603	3478	3356	3356
Individuals	162	182	197	197	196	196
Tests of instruments and identification						
Overidentifying restrictions (Hansen test)						
p-Value (J statistic)	0.015	0.056	0.130	0.161	0.123	0.123
Under identification (Kleibergen–Paap rank test)						
p-Value (LM statistic)	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification (Kleibergen–Paap based, for non-i.i.d errors)						
Wald F statistic	117.62	157.084	252.284	249.726	190.421	190.421
Endogenous regressors (Anderson–Rubin test)						
p-Value (chi-2 test)	0.026	0.077	0.044	0.012	0.010	0.010

Note: Standard errors in parentheses. See Eq. (4) for details on the IV specification. All estimations consider a constant term, individual (country-industry) fixed effects and year dummies. Statistics are robust to arbitrary heteroskedasticity and also to arbitrary autocorrelation through kernel-based estimations. Column (6) reports two-step efficient generalised method of moments (GMM) estimations.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

the presence of important non-patented innovative activity in this sub-sample.

To sum up, with the widely-used REGIMP indicator, 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 innovation performance at the leading edge, but this is in accord with previous results discussed above (specially those by Amable et al. (2010)) and also with standard Schumpeterian mechanisms. Moreover, PMR has also a positive influence on productivity and this time for both leaders and followers, which again contradicts the "common wisdom".

As explained in Section 2, the regulation proxy REGIMP is an aggregate index that summarises all areas of regulation covered in each sub-index of regulatory practices in network services, retail and finance. In order to disentangle different channels by which product market provisions in these sectors affect the rest of the economy, the OECD provides alternative indicators that either exclude the public ownership dimension (the aforementioned RWPO indicator), or isolate it (the aforementioned RPO indicator). We use these as alternative measures of regulatory pressures shaping the innovative activity of national industries.

Tables 4 and 5 present estimations performed with the RWPO indicator of regulation, respectively for leaders and followers. Regressions using this alternative indicator are interesting in that they help to identify whether the positive impact of PMR on innovation and productivity presented above relates to provisions shaping market structure (and thus the incentives to engage in innovative activities), or conversely to the presence of the State, which may have a particularly higher propension to engage in R&D investments (motivated for instance by wider public policies integrating the positive externalities of the innovation process). Measured by this indicator, PMR appears to impact innovation in a broadly similar fashion to that observed above using the REGIMP indicator. The significantly positive influence of RWPO on leaders' innovation also appears in the vicinity of the WTF. The impact of RWPO on followers' innovation is mainly negative but less so as one moves closer to the leading edge. Therefore, here again, the elasticity of innovation with respect to PMR increases with the proximity to the technological frontier and does not decrease, as the common wisdom would have it. Regarding the other regressors of the first stage, we observe that the impact of the share of skilled labour is also similar to those obtained previously: positive for leaders' innovation and lower and less significant for followers' innovation. Likewise, in this stage, spillovers stemming from the world technology leader

Table 4

Leaders – Innovation equation (first-stage estimates) – **RWPO indicator**
Dependent variable: patenting intensity, $\ln(PI_{cit-1})$

WTF split	Q50 (1)	Q60 (2)	Q75 (3)	Q75 (4)	Q75 (5)	Q75 (6)
$\ln(RWPO_{cit-1})$	0.076	0.074	0.329***	0.342***	0.368***	0.368***
	(0.081)	(0.100)	(0.121)	(0.115)	(0.113)	(0.113)
$\ln(WTF_{cit-1})$	−0.039	−0.032	−0.032	−0.049	−0.045	−0.045
	(0.030)	(0.039)	(0.055)	(0.049)	(0.046)	(0.046)
$\ln(PI_{cit-4})$	0.493***	0.463***	0.409***	0.354***	0.308***	0.308***
	(0.024)	(0.029)	(0.036)	(0.055)	(0.064)	(0.064)
$\ln(PI_{cit-5})$				0.136***	0.189***	0.189***
				(0.050)	(0.067)	(0.067)
$\ln(PI_{cit-6})$					0.073*	0.073*
					(0.042)	(0.042)
$\ln(HS_{cit-1})$	0.076**	0.087**	0.085*	0.116***	0.139***	0.139***
	(0.037)	(0.043)	(0.049)	(0.045)	(0.043)	(0.043)
Adjusted R^2	0.87	0.86	0.85	0.84	0.84	0.84

Leaders – Productivity equation (second-stage estimates) – **RWPO indicator**
Dependent variable: MFP growth relative to 1995, $\ln MFPG^{95}_{cit}$

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(PI_{cit-1})$	0.121***	0.124**	0.182**	0.254***	0.273***	0.238***
	(0.042)	(0.048)	(0.073)	(0.079)	(0.083)	(0.079)
$\ln(RWPO_{cit-1})$	0.022	0.187*	0.158	0.145	0.144	0.151
	(0.092)	(0.110)	(0.135)	(0.134)	(0.135)	(0.132)
$\ln(WTF_{cit-1})$	−0.069*	−0.004	0.109**	0.106**	0.098*	0.109**
	(0.042)	(0.044)	(0.054)	(0.054)	(0.055)	(0.053)
Number of obs.	2398	1917	1196	1154	1112	1112
Individuals	146	126	82	80	79	79
Tests of instruments and identification						
Overidentifying restrictions (Hansen test)						
p-Value (J statistic)	0.025	0.205	0.679	0.742	0.220	0.220
Under identification (Kleibergen–Paap rank test)						
p-Value (LM statistic)	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification (Kleibergen–Paap based, for non-i.i.d errors)						
Wald F statistic	204.263	124.064	68.257	57.501	52.506	52.506
Endogenous regressors (Anderson–Rubin test)						
p-Value (chi-2 test)	0.002	0.023	0.042	0.013	0.003	0.003

Note: Standard errors in parentheses. See Eq. (4) for details on the IV specification. All estimations consider individual (country-industry) fixed effects and year dummies. Statistics are robust to arbitrary heteroskedasticity and also to arbitrary autocorrelation through kernel-based estimations. Column (6) reports two-step efficient generalised method of moments (GMM) estimations.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

are not significantly different from zero. As for the productivity equation, innovation has a significantly positive influence on leaders' productivity, and this time a non-significant one for followers, which is consistent with the large p-values in the corresponding Anderson–Rubin tests. Using the RWPO indicator, PMR has almost no direct impact on followers' or on leaders' productivity. The world technological frontier externality has a positive impact on leaders especially when the threshold of closeness to the WTF is restricted to 75%. Estimations using the RWPO indicator yield then a similar pattern regarding the innovation stage but a fairly weaker one regarding the productivity stage. This is especially true for follower industries, to which the model seems less well suited than it is for leaders. Instrumentation is validated in terms of orthogonality and identification for leading-edge estimates.

Estimations are then performed with RPO which considers only the public ownership dimension. The results are featured in Tables 6 and 7 for leaders and followers respectively. As it was the case with the other PMR indicators, the impact of RPO on innovation is significantly positive and increases with the proximity to the technological frontier. PMR presents here also a significantly negative influence on followers' innovation. Among leaders, innovation also presents a sizeable positive and significant impact on productivity, although it should be kept in mind that the same instrumenting strategy used in the previous tests in the productivity equation of leaders is not validated here by the test of exogeneity of the instruments. The results of the innovation equation as a single equation, and namely the sign of the elasticities of the PMR indicator, are of course not concerned by this. For the productivity equation of followers when the sample is split at the 75th percentile, the exogeneity of instruments is broadly validated, especially in the full specification. Here again, as in the case of REGIMP, PMR appears to positively influence productivity for followers, even though it is negatively associated with their patenting intensity. Overall, even if weaker in light of orthogonality conditions in the two-equation model for leaders, the evidence suggested by the RPO indicator by no means gives support to the postulate of a negative influence of larger upstream public ownership on leading-edge technical progress. Indeed, the opposite can be concluded from the single innovation equation.

Therefore, the estimations made with the other indicators of vertically-induced PMR broadly confirm the results obtained with REGIMP. Regulation has a positive influence on innovation at the leading edge and, in several cases, directly on productivity as well. Besides, the relationship between the impact of PMR and the distance to the technological frontier that one can draw from the previous results contradicts the received view: PMR's

Table 5

Followers – Innovation equation (first-stage estimates) – **RWPO indicator**
Dependent variable: patenting intensity, $\ln(PI_{cit-1})$

WTF split	Q50 (1)	Q60 (2)	Q75 (3)	Q75 (4)	Q75 (5)	Q75 (6)
$\ln(RWPO_{cit-1})$	−0.222**	−0.236***	−0.167**	−0.111*	−0.093	−0.093
	(0.088)	(0.080)	(0.069)	(0.067)	(0.067)	(0.067)
$\ln(WTF_{cit-1})$	−0.010	−0.016	0.001	−0.005	−0.016	−0.016
	(0.021)	(0.019)	(0.018)	(0.016)	(0.015)	(0.015)
$\ln(PI_{cit-4})$	0.432***	0.446***	0.473***	0.416***	0.358***	0.358***
	(0.030)	(0.026)	(0.022)	(0.032)	(0.035)	(0.035)
$\ln(PI_{cit-5})$				0.155***	0.126***	0.126***
				(0.028)	(0.035)	(0.035)
$\ln(PI_{cit-6})$					0.113***	0.113***
					(0.026)	(0.026)
$\ln(HS_{cit-1})$	0.037	0.039	0.069*	0.080**	0.058*	0.058*
	(0.050)	(0.043)	(0.037)	(0.034)	(0.032)	(0.032)
Adjusted R^2	0.82	0.82	0.85	0.84	0.83	0.83

Followers – Productivity equation (second-stage estimates) – **RWPO indicator**
Dependent variable: MFP growth relative to 1995, $\ln MFPG^{95}_{cit}$

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(PI_{cit-1})$	−0.008	−0.012	0.008	0.021	0.035	0.050
	(0.048)	(0.041)	(0.034)	(0.035)	(0.036)	(0.034)
$\ln(RWPO_{cit-1})$	0.030	0.060	0.038	0.053	0.070	0.090
	(0.100)	(0.085)	(0.071)	(0.070)	(0.070)	(0.069)
$\ln(WTF_{cit-1})$	0.090**	0.059*	0.016	0.005	0.000	−0.006
	(0.037)	(0.031)	(0.027)	(0.027)	(0.027)	(0.026)
Number of obs.	2263	2749	3474	3358	3244	3244
Individuals	162	181	197	197	196	196
Tests of instruments and identification						
Overidentifying restrictions (Hansen test)						
p-Value (J statistic)	0.295	0.318	0.500	0.106	0.080	0.080
Under identification (Kleibergen–Paap rank test)						
p-Value (LM statistic)	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification (Kleibergen–Paap based, for non-i.i.d errors)						
Wald F statistic	108.934	143.801	223.719	219.13	172.072	172.072
Endogenous regressors (Anderson–Rubin test)						
p-Value (chi-2 test)	0.571	0.595	0.744	0.103	0.067	0.067

Note: Standard errors in parentheses. See Eq. (4) for details on the IV specification. All estimations consider a constant term, individual (country-industry) fixed effects and year dummies. Statistics are robust to arbitrary heteroskedasticity and also to arbitrary autocorrelation through kernel-based estimations. Column (6) reports two-step efficient generalised method of moments (GMM) estimations.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

beneficial effects are stronger for industries that are closer to the frontier.

5. Sensitivity analysis and further identification

5.1. PMR and the incentives to invest in R&D

The previous regressions consider an output measure of the innovation process. Although they show that a statistically significant positive impact of PMR on innovation indeed appear close to the leading edge, we do not know whether this impact is related to the R&D effort deployed within each national industry or to the features of the "technology" of innovation transforming this effort into new (patented) ideas. The mainstream argument associating upstream services liberalisation with increased downstream manufacturing innovation insists on the *incentives* to innovate. Over-regulated services industries are supposed to create administrative burden and inappropriate vertical rent sharing, which in turn lessens the incentive to invest in R&D. The existing empirical literature has focused on reduced-form regressions incorporating mainly productivity measures as the dependent variable or, in some cases, output-based innovation measures such as patents (e.g. Amable et al., 2010), without addressing the question of the incentive to invest in R&D. Consequently, in this section we go further in the empirical identification by extending the previous econometric model in order to consider R&D, innovation and productivity in an integrated framework.

We follow here the conceptual framework proposed by Crépon et al. (1998), hereafter CDM. CDM-type estimations typically relate a measure of productivity to a measure of innovation output, and the latter to a measure of R&D expenditures, using firm-level data (which implies correcting for various selectivity biases in addition to endogeneity biases). Our panel of industries allows us to estimate a simplified version of the CDM framework in which all equations are linear and include the same previous set of key variables. We use R&D stock measures provided by the EU KLEMS linked database, which relies on OECD ANBERD data. As in the case of patenting activity, we consider for each country industry and time period, an indicator of R&D stock normalised by hours worked, RD_{cit} (henceforth, R&D intensity). In order to take into account the time it takes for an R&D investment to pay off in terms of innovation output, we introduce our R&D variable with a three-year lag, as is often done in the literature when data allows.

As in the previous estimations, we model patenting intensity as an autoregressive process, the outcome of which is also explained

Table 6

Leaders – Innovation equation (first-stage estimates) – **RPO indicator**
Dependent variable: patenting intensity, $\ln(PI_{cit-1})$

WTF split	Q50 (1)	Q60 (2)	Q75 (3)	Q75 (4)	Q75 (5)	Q75 (6)
$\ln(RPO_{cit-1})$	0.153*	0.176*	0.489***	0.342***	0.212**	0.212**
	(0.080)	(0.104)	(0.106)	(0.103)	(0.107)	(0.107)
$\ln(WTF_{cit-1})$	−0.022	0.001	−0.028	−0.037	−0.028	−0.028
	(0.030)	(0.039)	(0.054)	(0.049)	(0.048)	(0.048)
$\ln(PI_{cit-4})$	0.512***	0.478***	0.412***	0.311***	0.273***	0.273***
	(0.024)	(0.030)	(0.036)	(0.055)	(0.063)	(0.063)
$\ln(PI_{cit-5})$				0.178***	0.189**	0.189**
				(0.050)	(0.075)	(0.075)
$\ln(PI_{cit-6})$					0.087**	0.087**
					(0.044)	(0.044)
$\ln(HS_{cit-1})$	0.130***	0.123***	0.102**	0.112**	0.104**	0.104**
	(0.040)	(0.044)	(0.049)	(0.047)	(0.047)	(0.047)
Adjusted R^2	0.86	0.86	0.83	0.82	0.81	0.81

Leaders – Productivity equation (second-stage estimates) – **RPO indicator**
Dependent variable: MFP growth relative to 1995, $\ln MFPG^{95}_{cit}$

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(PI_{cit-1})$	0.115***	0.100**	0.172**	0.230**	0.259**	0.183*
	(0.043)	(0.049)	(0.082)	(0.094)	(0.103)	(0.101)
$\ln(RPO_{cit-1})$	0.243***	0.356***	0.162	0.144	0.145	0.177
	(0.075)	(0.085)	(0.115)	(0.121)	(0.125)	(0.120)
$\ln(WTF_{cit-1})$	−0.073	0.001	0.118*	0.115*	0.110*	0.114*
	(0.046)	(0.049)	(0.062)	(0.062)	(0.062)	(0.062)
Number of obs.	2277	1795	1075	1037	999	999
Individuals	145	124	83	81	80	80
Tests of instruments and identification						
Overidentifying restrictions (Hansen test)						
p-Value (J statistic)	0.000	0.004	0.015	0.029	0.009	0.009
Under identification (Kleibergen–Paap rank test)						
p-Value (LM statistic)	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification (Kleibergen–Paap based, for non-i.i.d errors)						
Wald F statistic	237.382	134.879	67.345	50.004	36.444	36.444
Endogenous regressors (Anderson–Rubin test)						
p-Value (chi-2 test)	0.000	0.004	0.008	0.008	0.003	0.003

Note: Standard errors in parentheses. See Eq. (4) for details on the IV specification. All estimations consider a constant term, individual (country-industry) fixed effects and year dummies. Statistics are robust to arbitrary heteroskedasticity and also to arbitrary autocorrelation through kernel-based estimations. Column (6) reports two-step efficient generalised method of moments (GMM) estimations.

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

by the skill intensity of the labour force. In addition, this time the R&D intensity of the national industry explicitly enters as a key input of the innovation process, which in turn is explained by regulatory pressures.[16] The model also supposes that productivity is increased by the output of the innovation process and technological externalities stemming from the world technology frontier of the industry. We include in each equation individual and time fixed effects. Hence, as before, any time-invariant unobserved variable specific to each industry in a given country, as well as any common time shock is being controlled for in all equations.

Formally, we test the following three-equation system

$$\begin{aligned}
\ln MFPG^{95}_{cit} &= \beta_1 \ln PI_{cit-1} + \beta_2 \ln WTF_{it-1} + \eta_{ci} + \eta_t + \varepsilon_{cit} \\
\ln PI_{cit-1} &= \alpha_1 \ln PI_{cit-4} + \alpha_2 \ln PI_{cit-5} + \alpha_3 \ln HS_{cit-1} \\
&\quad + \alpha_4 \ln RD_{cit-4} + \delta_{ci} + \delta_{t-1} + \xi_{cit-1} \\
\ln RD_{cit-4} &= \theta_1 \ln PMR_{t-4} + \upsilon_{ci} + \upsilon_{t-4} + \varsigma_{cit-4}
\end{aligned} \tag{6}$$

Table 8 presents three-stage least-square estimates of Eq. (6) for the thresholds of sample splitting previously used. Hence, country-industry leaders are defined alternatively as those country-industry pairs performing in a given year above the 50th, 60th, and 75th percentiles of the closeness to the WTF. In each case, followers are the complementary sub-sample. The results obtained with our CDM-type framework are consistent with those of our previous two-stage estimates. For leaders, the regulation proxy has a positive impact on R&D intensity, which positively impacts patenting intensity, which in turns raises productivity growth. In the "leaders" equations, all the elasticities associated to PMR, R&D, innovation, and productivity are significant at 1%. More importantly, the above-mentioned positive effects become stronger as the definition of the WTF gets narrower. This is especially the case for the regulation proxy, the elasticity of which ranges from 0.72%, in a sample split where leaders are the 50% closest to the WTF, to an elasticity

[16] Our main findings in the previous regressions are also robust to two other possible specifications. The first one includes the STAN indicator of export share of production, time-varying for each country-industry pair. This helps to control for international demand-pull channels of technical progress and scale-economies driven by foreign markets. The second alternative specification includes R&D intensity as an additional regressor in the innovation equation of our main econometric model (Eq. (4)). Although this could be a simple way to control for the input of the innovation process, we find that this alternative specification is not as well theoretically grounded as our Eq. (6), which makes much more sense as a structural model. Both of these series of alternative sensitivity analyses yield qualitatively similar conclusions (full table of estimates are available upon request).

Table 7

Followers – Innovation equation (first-stage estimates) – **RPO indicator**
Dependent variable: patenting intensity, $\ln(PI_{cit-1})$

WTF split	Q50 (1)	Q60 (2)	Q75 (3)	Q75 (4)	Q75 (5)	Q75 (6)
$\ln(RPO_{cit-1})$	−0.192**	−0.169**	−0.072	−0.100	−0.131**	−0.131**
	(0.095)	(0.083)	(0.069)	(0.064)	(0.062)	(0.062)
$\ln(WTF_{cit-1})$	−0.028	−0.024	−0.002	−0.011	−0.025	−0.025
	(0.020)	(0.019)	(0.018)	(0.016)	(0.016)	(0.016)
$\ln(PI_{cit-4})$	0.454***	0.468***	0.494***	0.426***	0.376***	0.376***
	(0.030)	(0.026)	(0.022)	(0.034)	(0.036)	(0.036)
$\ln(PI_{cit-5})$				0.160***	0.157***	0.157***
				(0.030)	(0.037)	(0.037)
$\ln(PI_{cit-6})$					0.078***	0.078***
					(0.025)	(0.025)
$\ln(HS_{cit-1})$	0.044	0.051	0.096**	0.098***	0.071**	0.071**
	(0.050)	(0.041)	(0.038)	(0.035)	(0.035)	(0.035)
Adjusted R^2	0.83	0.83	0.85	0.85	0.85	0.85

Followers – Productivity equation (second-stage estimates) – **RPO indicator**
Dependent variable: MFP growth relative to 1995, $\ln MFPG^{95}_{cit}$

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(PI_{cit-1})$	0.023	0.016	0.042	0.056	0.067*	0.074**
	(0.049)	(0.042)	(0.034)	(0.036)	(0.036)	(0.035)
$\ln(RPO_{cit-1})$	0.605***	0.558***	0.458***	0.490***	0.521***	0.445***
	(0.177)	(0.145)	(0.113)	(0.116)	(0.120)	(0.106)
$\ln(WTF_{cit-1})$	0.105***	0.069**	0.019	0.008	0.003	−0.012
	(0.040)	(0.034)	(0.028)	(0.028)	(0.028)	(0.027)
Individuals	160	180	196	196	195	195
Tests of instruments and identification						
Overidentifying restrictions (Hansen test)						
p-Value (J statistic)	0.016	0.063	0.118	0.105	0.116	0.116
Under identification (Kleibergen–Paap rank test)						
p-Value (LM statistic)	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification (Kleibergen–Paap based, for non-i.i.d errors)						
Wald F statistic	116.259	156.729	251.93	262.204	193.284	193.284
Endogenous regressors (Anderson–Rubin test)						
p-Value (chi-2 test)	0.038	0.150	0.129	0.037	0.032	0.032

Note: Standard errors in parentheses. See Eq. (4) for details on the IV specification. All estimations consider a constant term, individual (country-industry) fixed effects and year dummies. Statistics are robust to arbitrary heteroskedasticity and also to arbitrary autocorrelation through kernel-based estimations. Column (6) reports two-step efficient generalised method of moments (GMM) estimations.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

slightly larger than 1% at the very leading edge (i.e. the 75th percentile of sample split). This large positive impact at the vicinity of the WTF is more conducive to higher productivity than in the other regressions since both R&D and innovation also present their larger impact here.

The other variables in the leaders' innovation equation present the expected sign. Interestingly, comparing the broadest definition of leaders (50%) to the narrowest (50%) reveals that innovation tends to rely increasingly on R&D, somewhat less on past innovation and definitively less on skill intensity. This is consistent with the view that at the leading edge innovation relates more to the discovery of new ideas than to the absorption and "packaging" of past discoveries.[17] This conjecture may explain why a more institutionally coordinated environment (what others call "administrative burden") is associated to more R&D investment since such an environment may be less risky than a competitively coordinated one. As stated in Pavitt (1984)'s seminal article, innovation is by essence largely specific to the firm where it occurs, and that makes it also path-dependent: To innovate, firms depend on the stock of specific technological knowledge acquired in the course of their past R&D and innovation efforts. Putting this knowledge to its best use may be easier in a less competitive environment, which gives time and resources to explore alternative options building on the available specific knowledge stock. By contrast, increased competitive pressure is unlikely to push firms into exploring alternative options (to which they do not easily have access anyway), but rather into shutting them down in order to cut costs.

The results obtained in "followers" industries somehow reveal the opposite patterns. PMR presents a negative impact on the cumulative R&D effort, which is larger (in absolute value) and more significant the narower the definition of followers. Whether this translates ultimately into a negative impact on productivity is unclear. Patenting intensity is weakly associated to productivity here. It is only when followers are defined as performing below the 75% of the proximity to the WTF that patenting intensity is significantly associated to productivity, although with a considerably smaller elasticity than that estimated for leaders. For this particular subsample, however, PMR has no significant impact on R&D effort.

5.2. Vertical linkages

Our PMR indicator exploits cross-section differences in input-output tables to obtain industry-level measures of vertically-induced regulatory pressures in network industries. It is then

[17] Hölzl and Janger (2014) test the validity of the distance to the frontier argument for innovation in Europe and show that firms close to the technological frontier increasingly rely on the creation of own knowledge for their innovation-based growth strategies.

Table 8

R&D equation
Dependent variable: R&D intensity $\ln(RD_{cit-3})$

WTF split	Q50 Leaders	Q50 Followers	Q60 Leaders	Q60 Followers	Q75 Leaders	Q75 Followers
$\ln(REGIMP_{cit-3})$	0.722***	−0.344***	0.873***	−0.114	1.012***	0.123
	(0.092)	(0.115)	(0.103)	(0.104)	(0.119)	(0.095)

Innovation equation
Dependent variable: patenting intensity $\ln PI_{cit-1}$

WTF split	Q50 Leaders	Q50 Followers	Q60 Leaders	Q60 Followers	Q75 Leaders	Q75 Followers
$\ln(PI_{cit-4})$	0.274***	0.438***	0.238***	0.457***	0.155***	0.415***
	(0.036)	(0.041)	(0.038)	(0.042)	(0.047)	(0.034)
$\ln(PI_{cit-5})$	0.202***	0.200***	0.215***	0.188***	0.213***	0.192***
	(0.032)	(0.039)	(0.033)	(0.035)	(0.048)	(0.028)
$\ln(HS_{cit-1})$	0.165***	0.063	0.168***	0.075	0.089**	0.094***
	(0.032)	(0.061)	(0.034)	(0.048)	(0.038)	(0.030)
$\ln(RD_{cit-4})$	0.480***	−0.305**	0.481***	−0.331**	0.513***	−0.087
	(0.117)	(0.152)	(0.119)	(0.142)	(0.143)	(0.117)

Productivity equation
Dependent variable: MFP growth relative to 1995 $\ln MFPG^{95}_{cit}$

WTF split	Q50 Leaders	Q50 Followers	Q60 Leaders	Q60 Followers	Q75 Leaders	Q75 Followers
$\ln(PI_{cit-1})$	0.188***	0.059*	0.218***	0.043	0.351***	0.053**
	(0.024)	(0.033)	(0.028)	(0.030)	(0.043)	(0.023)
$\ln(WTF_{it-1})$	−0.079***	0.077***	−0.029	0.037*	0.114***	−0.010
	(0.022)	(0.022)	(0.026)	(0.019)	(0.034)	(0.016)
Number of obs.	2094	1790	1681	2203	1034	2850

Note: The table presents three-stage least-square estimates. See Eq. (6) for details on the system specification. Standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Table 9

Innovation equation (first stage)
Dependent variable: patenting intensity, $\ln PI_{cit-1}$

WTF split Marginal effect of $\ln REGIMP_{cit-1}$	Q50 (1)	Q60 (2)	Q75 (3)	Q75 (4)	Q75 (5)	Q75 (6)
- for SD industries	−0.095*	−0.091	−0.064	−0.072	−0.059	−0.059
	(0.056)	(0.064)	(0.081)	(0.083)	(0.083)	(0.083)
- for PRI industries	0.138**	0.157**	0.206**	0.174**	0.145*	0.145*
	(0.066)	(0.073)	(0.092)	(0.087)	(0.083)	(0.083)
- for SB industries	0.046	0.028	0.037	0.069	0.065	0.065
	(0.077)	(0.089)	(0.109)	(0.103)	(0.100)	(0.100)
Adjusted R^2	0.98	0.97	0.97	0.98	0.98	0.98

Productivity equation (second stage)
Dependent variable: MFP growth relative to 1995, $\ln MFPG^{95}_{cit}$

WTF split Marginal effect of $\ln REGIMP_{cit-1}$	Q50 (1)	Q60 (2)	Q75 (3)	Q75 (4)	Q75 (5)	Q75 (6)
- for SD industries	0.312***	0.343***	0.422***	0.440***	0.447***	0.462***
	(0.064)	(0.070)	(0.089)	(0.090)	(0.094)	(0.092)
- for PRI industries	0.285***	0.332***	0.451***	0.462***	0.464***	0.468***
	(0.070)	(0.076)	(0.097)	(0.098)	(0.101)	(0.100)
- for SB industries	−0.018	−0.078	−0.045	−0.021	−0.018	−0.013
	(0.101)	(0.122)	(0.134)	(0.138)	(0.142)	(0.142)
Adjusted R^2	0.38	0.39	0.47	0.47	0.47	0.47
Number of observations	2535	2025	1266	1222	1174	1174

Note: Standard errors in parentheses. The econometric model has a similar structure than Eq. (4) but with the PMR variable interacted with dummies for Supplier-Dominated (SD) industries, Production-Intensive (PRI) industries and Science-Based (SB) industries (see Footnote 18 for details on the classification of industries). Statistics are robust to arbitrary heteroskedasticity and also to arbitrary autocorrelation through kernel-based estimations. Column (6) reports two-step efficient generalised method of moments (GMM) estimations.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

interesting to discuss our main result, namely the positive impact of PMR on leaders' innovation process, in the light of the literature on vertical linkages mentioned in Section 3. To do so, we interacted indicators of a taxonomy *à la* Pavitt (1984) with our measure of PMR in our main econometric model. The taxonomy distinguishes between Supplier-Dominated (SD) industries, Production-Intensive (PRI) industries and Science-Based (SB) industries. It follows the application of Pavitt's taxonomy to industries adopted in Amable and Verspagen (1995).[18] Taking SD industries as the category of reference, we re-estimated Eq. (4) with our PMR indicator interacted with the remaining two industry categories.[19]

Table 9 presents the marginal effects of PMR by category of industry (SD, PRI and SB). We find an overall positive effect of the PMR variable (measured by REGIMP) on both innovation and productivity among leading PRI industries, and an overall direct positive effect of PMR on the productivity of leading SD industries. By contrast, PMR presents mostly a statistically non-significant impact on our innovation measure in SD industries. All this is consistent with Pavitt (1984)'s insights. Innovation in SD industries is mostly process innovation drawn from other sectors (where suppliers operate). In that perspective, if regulation in upstream network sectors does lead to more innovation therein, it will be embodied in the services used in SD industries and lead to productivity gains. The regulatory environment will not necessarily increase innovation in SD industries, since innovation is actually conducted in external upstream sectors. On the contrary, in PRI industries, Pavitt (1984) suggests that innovation primarily stems from "production engineering" and "process engineering" departments within firms. In that respect, more regulation in upstream sectors could allow innovators in production intensive industries to develop stable relationships with network-services providers. The latter would in turn benefit from a market environment allowing for scales economies, thereby contributing to construct a suitable knowledge base for production. As we highlight in our broader discussion below (Section 6), case studies provide evidence of detrimental effects of liberalisation policies on innovation in network industries such as telecoms and electricity.

Last but not least, the absence of any statistically significant effect of REGIMP among science-based industries could be explained by the fact that innovation in these industries occurs mostly through cooperation with (and closeness to) science and basic research. Therefore, the degree of regulation in upstream sectors may matter very little for those industries. Moreover, while science-based industries (such as the semiconductors industry) keep their design, engineering and development activities in their country of origin, production is often conducted offshore in order to cut costs. Hence, the amount of regulation in upstream sectors will matter little for those industries, as cost considerations have already been taken care of through offshoring.

6. Discussion and conclusion

The negative effect of product market regulation on innovation and growth is often taken for granted in many policy-making circles. Key EU policy initiatives, such as the Lisbon Agenda after 2005 or Europe 2020, rely on a couple of simple ideas. The first is that liberalisation would open markets to competition, allowing new entrants to bring new ideas and to challenge incumbents. The second is that this competitive pressure would stimulate innovation because companies facing competition would constantly need better products and services in order to maintain or gain market share (Ellersgaard Nielsen et al., 2013). The web page presenting the action of the DG for economic and financial affairs of the European Commission[20] for product market competition states that '*[w]ell-functioning product markets ensure that EU consumers benefit from lower prices and a wider choice of goods and services by guaranteeing increased competition [...] They also favour the entry of new companies with new products or brands to bring onto the market, and boost the incentives for all firms to innovate and create new goods or services.*' The contribution of the European Commission at the 2014 G20 meeting insisted that '*[r]igidities in [...] product markets have hindered [...] productivity growth [...] Areas for enhanced implementation of existing EU internal market rules have been identified (those with the largest potential): services, financial services, transport, digital market and energy*' (European Commission, 2014, p. 6) and it recommended '*structural reforms in product and labour markets*' because '*[r]eforms improving competition in product markets [...] can boost growth*' (European Commission, 2014, p. 9). The European Central Bank is also in favour of '*[m]easures aimed at increasing services market competition [...which] would support a higher level and growth rate of labour productivity in the services sector and promote a more dynamic economy*' (ECB, 2006, p. 8). The OECD constantly remind countries that '*[i]ncreasing competition by reducing burdens on [...] businesses would stimulate innovation, increase productivity and support growth*' (OECD, 2015, p. 100).

Yet, the results presented above question the "common sense" underlying such policy recommendations. We have shown that contrary to the expectation that product market regulation should be detrimental to innovation and productivity when one is close to he technological frontier, one finds a positive effect of regulation which grows when one gets closer to that frontier.[21]

This result may defy the "common sense", but it should not be considered as that surprising considering the theoretical ambiguities linking competition and innovation mentioned in Section 2. The strength of the "escape competition" effect, crucial in Aghion et al. (2005)'s conclusion regarding the beneficial effect of competition on innovation, may be lessened by a variety of factors: industry leaders's advantage in research or innovation, endogenous entry, etc. The more traditional Schumpeterian effect according to which competition is detrimental to innovation may therefore be stronger than what the theoretical models underlying the "common sense" position may lead to believe.

The above-cited innovation-based endogenous growth models also suppose that the only way for a firm to escape competition is to innovate. In reality, many other possibilities are open to firms: cutting wages schedules in order to gain price competitiveness, relocate part of their activities in low wage regions, innovating defensively in order to prevent imitation and knowledge diffusion,

[18] See Appendix Table A1 in Laursen and Meliciani (2000) for a comparison between the different applications of Pavitt's taxonomy using sectoral data.

[19] Following the 2-digit NACE classification given in Table A1, PRI industries are industries 25, 27t28, 29, 34t35, 36t37; SB are industries 25 and 30t33; and SB the rest of industries.

[20] http://ec.europa.eu/economy_finance/structural_reforms/product/index_en.htm.

[21] Using data from the Innovation survey for Norway, Castellacci (2011) estimated an extended CDM model aiming at identifying positive and negative influences of competition on innovation. Despite the differences in the type of data (firm-level for a single country) and measure of competition (PMR in our case, Herfindahl index for Castellacci, 2011), the ambivalence of the results is worth mentioning. Castellaci found that more concentrated industries have both a greater likelihood to invest in R&D and larger R&D outlays than less concentrated ones. Interestingly, the positive effect of market concentration on R&D investment grows with the proximity to the frontier. On the other hand, the impact of R&D on innovation and productivity was found to be larger in less concentrated industries, a result that could be related to the lower proportion of innovative firms in the author's interpretation. It is worth noting that, contrary to dedicated indicators such as "regimp", indices of market concentration are a fuzzy measure of State regulation, since market concentration may stem from "natural" causes (e.g., natural monopoly).

etc. In fact, if competition increases the uncertainty surrounding the firm's activity, it may not be optimal to engage in risky activities such as innovation. As previously mentioned, firms' innovation depend on specific technological knowledge which they can more easily exploit in a less competitive environment. A lower competitive pressure can allow firms to devote time and resources to the exploration of various technological strategies based on whatever specific knowledge is available to them. By contrast, in a more competitive environment, firms may well choose to rely on cost-cutting options, as a safer alternative to innovation. By cutting cost or "trimming fat", they may in fact shut down the innovation tap. Moreover, even if a firm chooses to innovate in a context of increased competition, it may prefer to look for safer incremental (rather than radical) innovation, with more limited effects on productivity improvements as a result.

Some case studies have indeed shown that liberalisation in network industries have led firms to cut down expenditure on research. Calderini and Garrone (2003) have found privatisation in telecoms has led former monopolies to decrease their scientific publication activities. Jamasb and Pollitt (2011) have studied the impact of liberalisation in the electricity sector in the UK and found that it has led to reduction in R&D spending. Similar evolutions have been found in the US and Japan (Cohen and Sanyal, 2009; Jamasb and Pollitt, 2008).

Another point is that the link between regulation and competition may be more complex than the simple negative relationship posited in the bulk of the literature. Regulation may not be systematically hostile to competition, as it is of course recognised by the promotion of "pro-competitive" regulation. However it is difficult in practice to label some provisions as anticompetitive once we get into the economics of market failures, and labeling State-designed rules and State's presence as signs of low-quality institutions is even more dubious in a second-best context. Indeed, some provisions not benefiting from a "pro-competitive" label may in fact orient competition in a specific direction: security, health, quality, environmental constraints, educational requirement in professional activities, stability of working hours, etc. and actually foster the innovative activity of firms by pushing them to avoid cost-cutting or defensive strategies.[22] More generally, the focus on the incentives to innovate given to the private entrepreneur is at best a simplified view of the innovation process. It conveys a vision centered on a private firm the innovation effort of which would be hindered by the regulative activity of a State whose role should be confined to correcting market failures. This vision is contradicted by our results with the indicator of the regulatory area of public ownership, which show that the involvement of the State can be beneficial to innovation close to the technological frontier.

Mazzucato (2014) showed the leading role of the State in the major innovations of the last decades (internet, biotech, nanotechnologies, green technologies, etc.). This role is not limited to investment in basic research or to subsidising private firms in order to correct market failures that lead to a sub-optimal level of R&D. The State created new technologies and markets and made possible the later investment of private firms on those markets. Often, the most radical innovations cannot come from private entrepreneurs because they have neither the means nor the will to take the implied risks and make the necessary investments.

[22] A specific example of innovation-inducing regulation is that of environmental standards, which, according e.g. to Porter and van der Linde (1995), may spur both innovation and productivity, and the more so the stricter they are. Although this hypothesis has led to an ongoing controversy, it has also found at least partial empirical support. For instance, Mohnen and van Leeuwen (2013) find that environmental regulation leads to an increase in innovation performance, but not in productivity.

If it is unlikely that *any* regulation can act as a stimulus to innovation, it is equally dubious that *every* regulation is detrimental to technological improvements.[23]

Appendix A. Sample details and descriptive statistics

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 petroleum and nuclear fuel
24	Chemicals and chemical
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 (1995 = 100)	REGIMP	Patent intensity	High skill share	Closeness to the WTF
AUS	Mean	101.16	0.08	0.36	8.40	38.75
	SD	18.15	0.02	0.62	2.50	20.84
	N	338	429	403	312	338
AUT	Mean	103.17	0.12	0.89	4.02	35.84
	SD	33.04	0.02	1.46	2.05	16.67
	N	364	429	403	338	364
BEL	Mean	100.59	0.18	0.76	7.63	66.51
	SD	19.16	0.03	1.10	3.14	28.79
	N	351	429	403	338	351
CZE	Mean	122.01	0.13	0.06	6.23	31.12
	SD	54.31	0.03	0.12	1.57	20.86
	N	169	429	169	143	169
DNK	Mean	115.76	0.07	1.20	2.94	45.84

[23] See Pelkmans and Renda (2014) on the differentiated effects of regulation on innovation.

Table A3 (*Continued*)

Country		MFP (1995 = 100)	REGIMP	Patent intensity	High skill share	Closeness to the WTF
	SD	107.43	0.02	2.26	3.12	26.14
	N	364	429	403	338	364
ESP	Mean	95.30	0.13	0.14	8.06	45.03
	SD	14.20	0.03	0.25	4.25	23.78
	N	364	429	403	338	364
FIN	Mean	88.78	0.10	0.88	17.63	50.49
	SD	42.18	0.02	1.41	7.11	26.39
	N	494	429	403	468	403
FRA	Mean	102.03	0.10	0.94	5.91	52.12
	SD	38.86	0.02	1.47	2.29	24.40
	N	364	429	403	338	364
GER	Mean	111.24	0.11	1.23	6.87	48.69
	SD	39.49	0.02	2.00	3.26	20.20
	N	221	429	403	195	221
HUN	Mean	138.26	0.12	0.07	9.41	34.25
	SD	67.26	0.02	0.12	3.24	24.19
	N	169	429	208	143	169
IRL	Mean	104.84	0.08	0.27	9.35	56.52
	SD	23.85	0.02	0.44	3.53	28.45
	N	260	396	403	234	260
ITA	Mean	84.95	0.15	0.37	3.00	56.30
	SD	23.25	0.02	0.55	3.06	31.61
	N	494	429	403	468	403
JPN	Mean	93.11	0.13	0.66	13.10	42.01
	SD	28.48	0.02	1.21	6.96	23.57
	N	442	429	390	468	390
NLD	Mean	97.98	0.07	1.28	3.84	44.62
	SD	21.79	0.02	1.95	1.79	31.98
	N	377	429	403	351	377
SWE	Mean	130.03	0.08	1.13	7.44	43.37
	SD	114.41	0.02	1.55	6.11	26.69
	N	195	429	403	325	195
UK	Mean	90.13	0.09	0.52	5.89	56.81
	SD	24.87	0.03	0.76	4.00	27.86
	N	494	429	403	468	403
USA	Mean	101.92	0.06	0.51	16.11	57.53
	SD	41.74	0.01	0.85	9.09	28.18
	N	403	429	403	468	403
Total		101.51	0.11	0.60	8.76	48.12
		47.51	0.04	1.57	6.77	27.49
		6019	9106	9299	7162	5694

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