Product market regulation, knowledge frontier and efficiency

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Abstract

This paper estimates efficiency in knowledge production across OECD industries by means of a Stochastic Frontier Approach (SFA), and investigates the role of upstream product market regulation (PMR). PMR is found to influence R&D efficiency not directly, but only with second-order effects, i.e. by interacting with the functioning of the technology, labour and the financial market. High levels of PMR are associated with poor efficiency performance where intellectual property protection is strong, whilst they are beneficial in the presence of scarcely regulated financial markets and stringent employment protection. In this sense, PMR appears to channel frictions arising from the regulation of other markets.

Keywords: R&D, knowledge production, efficiency, product market regulation
JEL classification: O31, O41, O42.

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1 Introduction

In recent years, large attention has been paid to the determinants of productivity (or technology) leadership and to the factors that enable technological catch up or leapfrogging across countries and industries. Particular emphasis has been placed upon innovation and human capital (Griffith et al., 2004, Cameron, 2005).

According to the recent developments in the endogenous growth literature, knowledge production at the frontier is crucial to grow and compete in the global market. This holds both for advanced countries, that can thus maintain their technological lead, and for laggards which can ultimate the catch-up process through imitation of frontier innovation. An increasing number of studies have investigated the key factors for knowledge production and the forces shaping innovation frontier. This interest was triggered by the advent of the second-generation theories of R&D-based endogenous growth (Madsen, 2008).

Although the development of empirical studies on productivity dynamics and innovation frontier have proceeded almost parallel, a non-negligible difference still persists between these two branches of the literature. Indeed, they differ for the consideration given to efficiency in resource management: i.e., to what extent countries or industries achieve different economic outcomes despite similar endowments, as some exploit efficiently available resources, and some use them inefficiently. Whereas it is well documented that a large portion of productivity differentials can be ascribed to how countries (or industries) manage production inputs, and which factors are behind international efficiency gaps, it remains almost unexplored how countries (or industries) efficiently perform innovation activity. This is the object of the present paper.

We study efficiency levels in knowledge production focusing on the role played by the institutional framework regulating the functioning of upstream markets, i.e. regulation pertaining those (upstream) markets that sell inputs to innovating (downstream) firms. Our key idea is that if intermediate input markets are imperfect –due to administrative barriers, licensing, etc.– innovating firms are likely to reach sub-optimal efficiency levels, falling behind the innovation frontier. This occurs as upstream regulation may create entry barriers in downstream markets, raising the market power of incumbents. Furthermore, when business environment prevents from properly allocating factor inputs among production tasks, companies cannot focus on core activities and outsource marginal tasks. To investigates all these issues, we carry out a stochastic frontier analysis (SFA) on innovation data for fifteen manufacturing industries of ten OECD economies between 1990 and 2002 which, as widely documented, was period of intense market reforms and widespread pro-competition initiatives (Conway and Nicoletti, 2006,Griffith et al., 2010). We estimate a knowledge production function controlling for heterogeneity, omitted variables' problem, and looking at how (upstream) product market regulation interplays with the institutional profile of the other markets (technology, labour and finance). Our results show that upstream regulation does not influence directly innovation efficiency but has second-order effects. A higher upstream regulation turns out to be detrimental when the degree of intellectual property rights' protection is similar across countries, and be beneficial when associated with high levels of either employment protection or financial development.

Our study extends the literature on innovation and institutional factors in several respects. First, it identifies a new effect through which market regulation shapes innovation output, i.e. by changing efficiency in research inputs' management. Second, our evidence supports the view that looking at anti-competitive practices within the industry misses a relevant determinant of innovation, and that a multifaceted assessment of anti-competition legislation, which also considers the between-industry (upstream) effects of regulation, is necessary. Third, in examining the latter dimension of regulation impact, we draw an outline on efficiency levels of innovation activity exploiting cross-country, cross-industry data variation; it contrasts with most existing works which instead rely upon only one dimension of the data.

The remainder of the paper is the following. Section 2 surveys the literature on the determinants of knowledge production and innovation efficiency, paying attention to the role of market regulation. Section 3 defines the analytical framework by first discussing the econometric methodology (sect. 3.1) and then presenting data (3.2). The empirical section 4 presents both descriptive and regression results (sect. 4.1 and 4.2). Section 5 concludes.

2 Background

2.1 Innovation, efficiency and productivity growth

There is large consensus that endogenous technological change is the main channel to raise productivity levels and improve living standards (Aghion and Durleauf, 2009). Recently, the empirical literature on innovation and economic growth has taken a twofold direction. Following the developments in the distance-to-frontier growth theories, a first strand of studies have examined the role of innovation for shifting technology frontier, and for enabling convergence towards the frontier through imitation and absorption of foreign knowledge (Griffith et al., 2004). Another body of works, motivated by the emergence of the scale invariant R&D-based growth theory (see Jones, 1995), have looked at how the effect of R&D on productivity or knowledge growth, and the forces hampering the success of innovation. Either product proliferation associated with demographic change or the increasing technological complexity of innovation are found to lower returns to R&D (Madsen, 2008, Ang and Madsen, 2011, Venturini, 2012a, and 2012b).[1]

Rather arguably, all these studies assume that firms exploit R&D inputs to the same extent, even when located in different industries or countries. However, innovation is by nature an uncertain and risky activity, which relies upon scarcely available resources. Moreover, best practices may derive from the learning associated with research failures and successes, or arise with the entry into the market of high-tech start-up. These factors, if coupled with certain institutional settings, may influence conditions under which research inputs are managed. In summary, very different innovation outcomes may be achieved even when a similar amount of resources is devoted to R&D.

Several analyses have shown how input usage translates into productivity benefits, and the pivotal role played by R&D in the creation of knowledge and its dispersion (Kneller and Stevens, 2006, Henry et al., 2009). Only more recently, a rising body of studies has examined at the efficiency performance in research and patenting. These works can be grouped into those using the deterministic approach of data envelopment analysis (DEA), and those using the non-deterministic approach based on the Stochastic Frontier Analysis (SFA), which is the methodology employed in this paper. Among them, Wang (2007) examines the technical efficiency in research across 23 OECD

[1] An empirical analysis conjugating these two lines of research can be found in Madsen et al. (2010).

and 7 non-OECD countries, finding large disparities in R&D efficiency scores. These can be largely explained by cross-country differentials in technology endowments and open-market institutional settings. In a similar vein, Fu and Yang (2009) find that countries may rank differently in terms of innovation capacity (patenting frontier) and innovation (in)efficiency. The former is positively correlated with the share of high-tech industries while innovation efficiency is affected positively by the degree of economic development, the share of business research, and the strength of intellectual property protection. By means of a two-stage non-parametric DEA approach, Cullmann *et al.* (2012) study R&D efficiency differences among OECD countries over the period 1995-2004, focusing on the role of regulatory environment.

2.2 Product market regulation and innovation

Regulation is motivated on the basis of market failures such as monopoly conditions, externalities and asymmetric information. However, when excessive, it lowers market competition by raising barriers to entry, placing restrictions on product choices or firm operations, or protecting incumbents. Regulation may also prevent firms to outsource marginal tasks and allocate efficiently factor inputs among activities. It is on this basis that barriers to product market competition may reduce firms' ability and incentives to efficiently manage R&D resources. On the other side, research consists of complex tasks, characterised by learning-by-doing and long periods of trials. It means that dynamic economies of scale may be at work in technologically advanced sectors, and that incumbents may be more efficient than new comers in research. This effect may be reinforced by the strategic profile of innovation in most industries where, due to the oligopolistic or monopolistic competition nature of the markets, innovating firms use patents as a means to block new comers and preserve their market power.

In this paper, we look at cross-industry (cross-country) variation in knock-on effects of product market regulation, i.e. how regulation in upstream sectors (services) influences innovation efficiency of downstream (manufacturing) firms that purchase factor inputs from the former. Although this kind of anti-competitive laws pertains only the tertiary sector, its effects spread throughout the economy with the intense inter-industry intermediate transactions. Because of barriers to entry, licensing, etc., service inputs may be sold at higher prices or at a lower quality with respect to a market without frictions; moreover, downstream firms may be obliged to negotiate with service providers to obtain better contract conditions (Bassanini and Ernst, 2002). Imperfections in intermediate input markets have been acknowledged to slow productivity growth at various levels of data aggregation. Bourlès *et al.* (2012) document that upstream regulation has negative impact on TFP growth, which increases the closer industry to the technological frontier; this effect has increased since the mid-1990s with the deepening of globalization and the ICT diffusion.[2]

In contrast to productivity literature, it is nearly unexplored how the institutional setting of intermediate input markets reverberates on innovation performance downstream. Also, there is no evidence on the effect of this factor on the research efficiency. Furthermore, the scarce evidence on upstream regulation and patenting contrasts with the mainstream literature on the relationship between competition (or market power) and innovation. Using a distance-to-frontier approach, Amable *et al.* (2009) indeed show that imperfections in the intermediate input markets are negatively associated with patenting of laggard industries, but this effect changes sign and becomes positive moving closer to the frontier. Griffith et al. (2010) link the analysis on the role of regulation for innovation to that of regulation on productivity. Exploiting information on the Single Market Programme's reforms carried out within the EU during the 1990s, these authors show that lower regulation increased industry competition and lowered the rate of profitability; this raises incentives to carry out R&D which, in turn, spurred productivity growth. Findings reported by Blind (2012) fall in between to those of the previous studies. This author studies the effect regulation on compliance costs on the availability of R&D resources and incentives to perform innovation. Restrictions to product market competition are found to have a positive impact on patenting, but this effect vanishes when several dimensions of regulation policy are taken into account (competition legislation, price control, environmental laws).

Overall, these findings conform to the predictions of distance-to-frontier

[2] Arnold *et al.* (2011) carry out a similar analysis using firm-level data. Conway *et al.* (2006) show that service regulation reduces the speed with which laggard countries catch up the productivity frontier. Using a SFA approach, Fioramanti (2011) shows that tight upstream regulation depresses production efficiency in most OECD industries. In a more comprehensive analysis, Barone and Cingano (2011) document that lower service regulation significantly raises the growth rate of value added, productivity and exports in downstream service-intensive industries. See Bourlès *et al.* (2012) for an extended survey of such a literature.

theory on the non-linear relationship between competition (or regulation) and innovation. It depends on the race between two opposite forces. The first one is the escaping-competition effect which leads firms to innovate in order to prevail over their close competitors. The second force is the typical Schumpeterian effect for which R&D engagement is higher for bigger firms. The prevailing force change with the nature of the sectors. In 'neck-to-neck' industries, firms are very close technologically, and hence competition is likely to encourage innovation as firms expect to catch-up and become the market leader. In 'unlevelled' industries, the technological base of the firms is more unequal and the Schumpeterian effect is expected to dominate (i.e. greater competition reduces innovation incentives), as the probability to win a R&D race, and dominate the market, is low. From this perspective, the evidence provided by Amable *et al.* (2009) at country level would confirm that the escape-competition effect is prevalent in the proximity of the innovation frontier, whereas the Schumpeterian effect dominates far behind it. In essence, the relationship between competition and innovation would be U-shaped, in contrast to what found by earlier empirical works (Aghion *et al.*, 2005).

3 Analytical framework

3.1 Econometric issues

We adopt a stochastic frontier analysis (SFA) approach to investigate differentials in efficiency levels in innovation activity of OECD manufacturing industries, and how this aspect is influenced by the regulatory framework of upstream markets to which innovating firms relate to. The two issues are contemporaneously addressed by implementing a one-step estimation procedure that we will detail below.

Our knowledge production function relates a measure of innovative output to a measure of the effort made in knowledge generation, a temporal pattern in the ability of transforming input into innovative output and a stochastic term. The latter consists of two elements: a symmetric-noise component, and a negative asymmetric component.

$$I_{ij,t} = A \cdot RD_{ij,t}^{\beta} \cdot e^{\sum \lambda_t} \cdot e^{v_{ij,t} - u_{ij,t}}, \qquad (1)$$

where $I_{ij,t}$ is the number of patents introduced by sector ith, belonging to country jth in the tth time period, A is a constant, $RD_{ij,t}$ is the R&D capital stock which refers to the same sector/country in the same period of time, $\sum \lambda_t$ is a set of time dummies which capture year-specific shocks in the production of innovative ideas and $v_{ij,t}$ and $u_{ij,t}$ are the stochastic terms of the equation. In particular, $v_{ij,t}$ captures random departures from the predicted-by-the-model output (either due to unobserved observation-specific random shocks in the patenting activity, or measurement errors in $I_{ij,t}$), while the $u_{ij,t}$ captures departures from the knowledge production frontier which are due to a sub-optimal use of the input, i.e. inefficiency (we are adopting the framework first proposed by Aigner et al. , 1977; Meeusen and van den Broeck , 1977, by applying it to the knowledge production function).

In log-linear form, the stochastic frontier model may be re-written as:

$$\ln I_{ij,t} = \alpha + \beta \cdot \ln RD_{ij,t} + \sum \lambda_t + v_{ij,t} - u_{ij,t}, \tag{2}$$

where the the $v_{ij,t}$ component is assumed to be normally distributed, and the $u_{ij,t}$ component follows a half-normal distribution, and $v_{ij,t}$ is assumed to be independently distributed of $u_{ij,t}$.[3]

Given that the purpose of this work is also to investigate how product market regulation affects the degree of efficiency of different sectors across countries, a viable empirical strategy of modeling efficiency as a function of market regulation is needed; however, Wang and Schmidt (2002) showed that recovering the inefficiency scores in a first-step regression of Equation 2 and, then, regressing them on other observed characteristics of the units under analysis is not an option, because of issues related to omitted variable biases and inconsistency in the first step of the analysis. As Schmidt (2011) has pointed out the two step procedure is faulted as the second stage requires efficiency terms to be independently and identically distributed but in the first stage they may be a function of some country specific factors leading to conclude that they are not identically distributed.
Thus, they a coherent way of estimating a knowledge production function through SFA is to directly specify the distribution parameters of the inefficiency terms $u_{ij,t}$ as functions of country/sector degree of regulation, $PMR_{ij,t}$, then estimating all parameters in the model (the α and β parameter in Equation 2 plus the parameter relating to the effect of $PMR_{ij,t}$

[3]Comparative results suggest that estimates of inefficiency are robust to the assumed distribution, thus the choice of the distribution can be considered a function only of computational tractability.

on $u_{ij,t}$) via maximum likelihood (ML), by means of a one-step procedure. A possibility is that of modeling the variance of the inefficiency distribution as a function of the country/sector degree of PMR, which is both a way of including 'third-variables' in the efficiency analysis and taking into account heteroskedasticity in the error components(Kumbhakar and Lovell , 2000)[4].

In a formal way:

$$v_{ij,t} \sim N(0, \sigma_v), \tag{3}$$

$$u_{ij,t} \sim N^+(0, \sigma_{u_{ij,t}}), \tag{4}$$

where, employing an exponential functional form for modeling the variance of $u_{ij,t}$,

$$\sigma^2_{u_{ij,t}} = exp\left(c \cdot PMR^{\delta}_{ij,t}\right), \tag{5}$$

which in log-linear form becomes:

$$\ln \sigma^2_{u_{ij,t}} = (\gamma + \delta \cdot \ln PMR_{ij,t}). \tag{6}$$

The model is heteroskedastic in the $u_{ij,t}$ components, thus allowing the (variance of the) inefficiency term to be a function of the degree of regulation affecting the sector in a specific country.

The specification in Equations 2, however, does not take into account the panel nature of the data, and treats them much as a pooled set of observations. This raises an important point: when differences among observations are confined to $\ln RD_{ij,t}$ and year-specific shocks, the u_{it} elements in Equation 2 are intended to capture all and only the time-variant inefficiency associated to a specific sector in a given country; conversely, if there are country/sector-specific time invariant effects —which may be correlated to the R&D input— and they are not tackled in the model, this fact would lead to biased estimates in the β parameter. This 'pure' heterogeneity would thus affect overall residuals $v_{ij,t} - u_{ij,t}$, leading to an incorrect statement of technical inefficiency (Greene , 2008, see)[5]. Greene (2005) proposed a

[4]Consequences of neglected heteroscedasticity in stochastic frontier models have been addressed in several papers using Monte Carlo simulations: Caudill and Ford (1993) pointed out that heteroscedasticity in the one-sided term lead to overestimation of the intercept and underestimation of the slope coefficient in a single-factor Cobb-Douglas frontier production function. The authors extended the analysis in another paper (Caudill et al. , 1995) in order to look at the consequences on inefficiency estimates, which resulted to be overestimated for small firms and underestimated for large firms.

[5]This issue is much like the heterogeneity (omitted variable) bias problem in standard

stochastic frontier model which contemplate both unobserved heterogeneity and time-variant inefficiency, the 'true' fixed effects (TFE) model, which can be written as

$$\ln I_{ij,t} = \alpha_{ij,t} + \beta \cdot \ln RD_{ij,t} + \sum \lambda_t + v_{ij,t} - u_{ij,t}, \tag{7}$$

where, as above,

$$v_{it} \sim i.i.d.\ N(0, \sigma_v^2),\ \ , u_{it} \sim i.i.d.\ N^+(0, \sigma^2_{u_{ij,t}}), \tag{8}$$

and $\alpha_{ij,t}$ is a vector of country/sector dummies which should capture time-invariant unobserved heterogeneity, separating it from the 'pure' time-variant inefficiency.

3.2 Data description

The data used to study efficiency levels achieved in innovation refer to fifteen manufacturing industries observed between 1990 and 2002 in ten OECD countries.[6]

Innovation output is measured by the number of patent applications at the US Patent and Trademark Office (USPTO). Patent counts are distinguished by the application year, industry and nationality of the assignee.[7] Research input, X, is alternatively measured by R&D expenditure, $RDexp$ (expressed at constant prices), or their cumulative value over time, $RDstock$. Research capital stock is constructed with the perpetual inventory method and geometrical depreciation, i.e. $RDstock_t = RDexp_t + (1 - \delta)RDexp_{t-1}$. For all countries and industries, the depreciation rate is set to 15%. The value of the stock at the initial year is obtained with the Hall and Mairesse (1995)'s formula, $K_0 = R_0/(\delta + g)$, where g represents the rate of change of $RDexp$ observed over the examined period. Industry deflators for gross output are

panel data models.

[6]Industry list: Food, beverage and tobacco; Chemicals; Pharmaceuticals; Rubber and plastics; Other non-metallic minerals; Basic metals; Fabricated metal products; Machinery; Office machinery; Electrical eq. and apparatus; Communication eq.; Medical and scientific instruments; Motor vehicles; Other transport eq.; Other manufacturing. Country list: Australia, Canada, Germany, France, Italy, Japan, Netherlands Sweden, UK , US.

[7]We follow the concordance table between ISIC and IPC patent classes provided by Schmock *et al.* (2003).

used to convert current prices expenditure into constant prices values; these have been then translated into US PPP dollars (at 1995 prices). Research input X is one-year lagged with respect to patenting indicator to control for the administrative time lag to initiate a legal application. To control for heterogeneity in the quality of innovation output, we also use the number of patent counts weighted with the forward citations received singly by each of them; this scaling factor is normalized on the manufacturing (yearly) mean to correct for citation truncation (Hall *et al.*, 2001).

Patent statistics are taken from NBER USPTO patent data files[8], R&D expenditure from OECD ANBERD database 2002 and 2009, industry accounts data EU KLEMS data March 2007. The latter source is used for labour quality series, which will be employed in the regression analysis as a control variable in the knowledge production function. As further controls (to be discussed below), we also rely upon the following set of institutional variables: OECD indicators of Employment Protection, the bank credit to GDP ratio (Beck and Demirgü-Kunt, 2009), the Ginarte and Park (1997) index of intellectual property protection.

Data on regulation impact are extracted from OECD Product Market Regulation dataset 2011 (see Conway *et al.*, 2006 for details). This indicator gauges how anti-competitive legislation in the tertiary sector, namely energy, transport and communications, and the retail and the professional services industries, reverberate on downstream sectors through inter-industry intermediate input-output transactions. The index is built as: $PMR_{it} = \sum_i R_{kt}\omega_{ik}$ (country j subscript omitted). R_{kt} is a qualitative score of anti-competitive regulation in any single non-manufacturing industry k listed above at time t. The weights ω_{ik} measure the total input requirement of the (manufacturing) industry i for intermediate inputs from sector k. These weights have been derived from OECD input-output tables, and benchmarked to the year 2000 to hold the input-output structure constant over time, and reduce simultaneity issues.

The indicator of regulation impact has some valuable properties. Firstly, it is available at time-, country-, industry-varying levels, in contrasts to most institutional variables used in the literature which are instead available only at a nationwide level. Secondly, the regulation impact indicator accounts for the competition from outside firms whilst measures of market concentration based on average levels of profitability reflect only the functioning of the

[8]Retrieved from Bronwyn Hall's homepage; release March 2006.

market where the firm operates. Thirdly, it is less influenced by endogeneity with respect to the indicators of market concentration, provided that it reflects administrative barriers, licensing, etc. (Schiantarelli, 2010).

4 Empirical analysis

4.1 Descriptive statistics

First of all, some descriptive statistics are shown in Table 1 in which we can observe how countries rank with respect to input (R&D) and output(Patents). With regard to the latter, the two most effective countries are the US and Japan, both in terms of adjusted and unadjusted patent series. The same is true with respect to the innovation inputs: the US and Japan are the leading countries and Germany is the most effective European country.

Table 1: Average value by Country (1990-2002)

	Patent counts	Quality adjusted counts	R&D expenses	R&D stock	PMR
Australia	33.8	54.7	95.3	484.0	7.6
Canada	131.0	226.0	309.1	1,421.6	7.0
France	219.7	364.5	1,014.4	5,781.4	10.2
Germany	568.6	945.1	1,809.7	9,608.2	10.4
Italy	80.8	134.3	399.1	2605.2	15.9
Japan	2,102.7	3,622.5	3,698.2	17,027.0	11.6
Netherlands	75.7	119.6	193.7	1,240.1	6.9
Sweden	79.3	133.3	306.7	1,470.0	6.5
UK	148.9	250.1	798.64	5171.9	8.7
US	4,365.4	7,751.1	7,571.9	40,475.1	5.7

This innovation profile is reinforced when we consider separately high and low tech sectors. By looking at Tables 2 and 3 we can notice that US, Japan and Germany stand out both with respect to low and high tech sectors. Indeed,the amount of inputs devoted to the innovation process is higher

Table 2: Average value by Country (1990-2002) in High-Tech Sectors

	Patent counts	Quality adjusted counts	R&D expenses	R&D stock	PMR
Australia	46.01	74.67	99.80	517.14	7.50
Canada	182.83	321.34	442.31	1987.59	7.13
Germany	835.93	1397.07	2774.80	14616.36	10.60
France	311.18	518.75	1501.53	8645.45	9.95
Italy	112.84	188.05	609.12	3957.26	16.05
Japan	3156.59	5501.45	5223.54	23507.56	11.58
Netherlands	111.88	177.20	278.12	1844.39	6.69
Sweden	116.62	198.99	466.55	2152.82	6.18
UK	216.93	368.50	1228.64	7874.38	8.91
US	6391.93	11505.68	11665.68	62016.95	5.59

Table 3: Average value by Country (1990-2002) in Low-Tech Sectors

	Patent counts	Quality adjusted counts	R&D expenses	R&D stock	PMR
Australia	15.54	24.77	88.55	434.32	7.69
Canada	53.17	83.05	109.19	572.52	6.83
Germany	167.60	267.07	362.07	2096.09	10.18
France	82.42	133.23	283.77	1485.22	10.52
Italy	32.72	53.59	84.11	577.04	15.77
Japan	521.83	803.99	1410.25	7306.04	11.75
Netherlands	21.46	33.17	66.99	333.83	7.09
Sweden	23.33	34.77	66.92	445.78	6.86
UK	46.85	72.61	153.47	1118.24	8.48
US	1325.67	2119.13	1431.25	8162.25	5.81

for high-tech sectors in all countries, and the same trend can be observed considering the patent series.

4.2 Estimation results

The econometric analysis will be developed in a threefold step. First, we estimate a baseline innovation function where we assess the sensitivity of the results to the measurement of innovation variables and to their heterogeneous time profile. Second, we include control variables into knowledge production function and among the institutional determinants of (in)efficiency. Third, we examine whether the results are robust to the sample composition, i.e. across country and industry groupings.

Table 4 shows our baseline estimates. R&D capital stock is used as main proxy for research input, as it is able to capture inter-temporal knowledge spillovers of R&D, i.e. how past research efforts contribute to the current innovation output. In col. (1), we use row patent counts as innovation output, and find an elasticity of 0.23 for R&D input. This coefficient falls in the range of values obtained in previous studies (see among others Fu and Yang, 2009 and Ang and Madsen, 2011). When we look at the determinants of research inefficiency, we find a negative coefficient for PMR, -0.06 (significant at 1%). It suggests that the Schumpeterian effect described above would be prevalent for this dimension of innovation performance: the larger the regulation in upstream sectors, the higher the degree of innovation efficiency downstream. Because of lower market entry or larger incentives to better manage own resources, incumbent innovators may benefit from the strong learning effects associated with R&D, and the related (dynamic) increasing returns. In col. 2, we include country- and industry-specific time trends. The former would account for nation-specific institutional changes that may be confounded with the deregulation waves concerning the product markets; the latter would capture changes in structural characteristics of innovation. This check yields a lower coefficient for R&D capital but leaves unchanged the estimated impact of PMR. In col. (3), we re-estimate the baseline specification using quality-adjusted patents, obtaining largely consistent findings. The last two regressions of Table 4 replicate the analysis using R&D expenses combined with row and quality-adjusted patent data. Apart from the lower effect found for research input, the negative impact of PMR on inefficiency is broadly confirmed.

Table 5 examines robustness of the previous results to the inclusion of covariates that may influence knowledge generation and innovation inefficiency. In col. 2, we estimate knowledge frontier considering a measure of cross-industry knowledge spillovers, an industry-specific measure of labour

Table 4: Baseline estimates and sensitivity checks on innovation variables

	1	2	3	4	5
	Coef./se	Coef./se	Coef./se	Coef./se	Coef./se
RDstock	0.23***	0.08***	0.20***		
	(0.03)	(0.03)	(0.03)		
RDexp				0.07***	0.06***
				(0.02)	(0.02)
cons	4.68***	119.3***	5.01***	6.36***	6.45***
	(0.28)	(21.1)	(0.28)	(0.17)	(0.17)
Quality adjustment	NO	NO	YES	NO	YES
Industry and country trend	NO	YES	NO	NO	NO
$ln\sigma_v^2$	-3.30***	-3.80***	-3.13***	-3.43***	-3.17***
	(0.20)	(0.13)	(0.14)	(0.27)	(0.16)
PMR	-0.06***	-0.06***	-0.05**	-0.07***	-0.06**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
cons	-1.51***	-1.76***	-1.72***	-1.24***	-1.56***
	(0.23)	(0.18)	(0.24)	(0.21)	(0.23)
Log-likelihood	-328.9	48.9	-360.2	-355.2	-380.2
N	1950	1950	1950	1950	1950

***,**,* denote significance at the 1%, 5%, 10% level, respectively.

quality, and a country-wide index of financial development.

It is widely documented that international technology spillovers are relevant either for productivity growth or knowledge generation (see among others Mancusi, 2008). To control for this effect, we include the sum of patent stock applied in the same industry by the other countries. This un-weighted measure of knowledge spillovers has been earlier used by Bottazzi and Peri (2007). It reflects the idea that, once patented, new knowledge flows freely without any particular conduit (trade, technology movements, etc.), influencing firms involved in similar activities. Labour quality is defined as the output share of high-skilled workers.[9] The rationale to control for it is that innovation output might depend on a larger set of skills than those captured by R&D statistics; indeed, the latter reflect only researchers' abilities and to

[9]It is inferred weighting the contribution of each group of employees, distinguished by age, gender, tenure, etc., with their wage bill, assumed to be a proxy for worker productivity.

the extent to which they are accounted for by their wage rate. Potentially, it may leave unexplained an important portion of patent variability. Consistent with the predictions of Schumpeterian theory, an increasing body of studies have shown that financial factors raise the ability to innovate and patent (Maskus et al., 2012 and Ang and Madsen, 2012.). For this reason, we include the ratio between private bank credit to GDP, as a control for the accessibility of external funds to carry out research.[10] In col. 2, we obtain parameters for control variables which are consistent with earlier evidence. There is indeed a positive and significant influence on innovation output by the credit-to-GDP ratio and cross-industry patent spillovers. On the other hand, labour quality has a very limited negative impact which, however will disappear in subsequent regressions (cf. Venturini, 2012b). In this specification, taken in absolute terms, the parameter size of both R&D input and PMR are lower (0.11 and -0.02).

Next, we consider the role of other institutional factors which to various extents may determine efficiency levels of research. First, we consider the strength of patent protection, relative to the US levels (IPP). This is done to capture whether firms located in countries with legal protection system more prone to innovation are able to patent more through a better resource management. This argument appears to be supported by the data as the coefficient of IPP amounts to -0.09. Second, to control for the extent of financial regulation, we consider the bank credit-to-GDP ratio (in percentage values) as a the determinant of inefficiency. It is indeed known that such a factor indirectly reflects the degree of regulatory restrictiveness of the financial market. Since the early 1990s most countries engaged in liberalisation programs, and this resulted in higher levels of bank credit. As we can see, this variable is found to promote innovation efficiency, even though its effect is only weakly significant from a statistical point of view (-0.47). Third, we specifically address the issue of whether the effect of PMR does overlap to that of labour market institutions (EPL). Evidence on the relationship between innovation and employment protection is rather wide, but there is no consensus on the mechanisms at work.[11] For instance, examining a sample of large multinational firms, Griffith and Macartney (2010) document that more restrictive labour market settings are usually associated with incremental in-

[10] Alternative country-level measures of financial development (private bond or stock market capitalization to GDP) were used providing results similar to those shown below.

[11] See Menezes-Filho and Van Reenen (2003) for a survey.

novations, whilst less restrictive legislations with radical innovations. The first effect would result from the increasing firm-specific human capital and job security of employees, the latter from the possibility to easily re-allocate labour towards the most promising lines of research and business.[12] In our estimates, the second type of effect seems to prevail: the higher employment protection, the higher research inefficiency (0.59). It should be observed from col. 3 that, when we control for other institutional factors, the positive effect of PMR turns out to be higher (-0.15 vs -0.02 of col. 2).

At this point it is interesting to see whether the regulatory setting of the upstream product markets interplays with the functioning of the market for technology, credit and labour. In col. 4 we interact country-level institutional controls with industry-specific time-varying series on PMR. Some important points are in order. PMR has no longer a direct impact on research efficiency, but only indirectly in association with the functioning of the other markets. Severe restrictions in the product markets are associated with lower levels of research efficiency when the legal discipline of patent protection is similar across countries (0.009). This means that a more vis-a-vis technology competition, which is not hampered by imperfect matching between national systems of legal protection, increases research efficiency if combined with lower administrative barriers on the product market. On the other hand, regulation is associated with better efficiency performance in the presence of less regulated financial market (i.e. characterized by a higher credit intensity), but more stringent protection of employment protection. The former effect would be dominant over the positive impact found for the credit-to-GDP ratio taken as single variable (see col. 3). The latter effect would be consistent with the view expressed above that greater job stability, raising firm-specific human capital and company investment, allows innovating firms to achieve higher efficiency levels.

One might be concerned that the evidence in favour of second-order effects of PMR reflects the nature of the interaction terms, which are obtained multiplying country- and industry-level variables. Such interactions might therefore take the heterogeneous response of each sector to nation-wide regulation in the technology, labour or financial markets, rather than capturing the transmission of imperfections between these and the product market. To

[12] In this paper, we consider the overall indicator of employment protection as the results remain qualitatively unchanged even when we distinguish between regulation on dismissals of regular contract workers and the discipline on temporary workers.

Table 5: Sensitivity checks to control variables

	1	2	3	4	5
	Coef./se	Coef./se	Coef./se	Coef./se	Coef./se
RDstock	0.23***	0.11***	0.11***	0.07***	0.13***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Spillovers		1.16***	0.89***	0.85***	0.74***
		(0.06)	(0.05)	(0.05)	(0.06)
Labour quality		-0.001**	-0.004	-0.004	-0.001
		(0.00)	(0.000)	(0.00)	(0.00)
Credit		0.23***	0.10**	0.05	-0.02
		(0.05)	(0.05)	(0.04)	(0.03)
cons	4.68***	-2.77***	-0.94**	-0.28	-0.04
	(0.28)	(0.46)	(0.43)	(0.38)	(0.43)
$ln\sigma_v^2$	-3.30***	-4.26***	-4.17***	-4.05***	-5.69***
	(0.20)	(0.36)	(0.31)	(0.09)	(0.22)
PMR	-0.06***	-0.02**	-0.15***	0.50	0.09
	(0.02)	(0.01)	(0.03)	(0.34)	(0.29)
IPP			-0.09***	-0.15***	-0.12***
			(0.01)	(0.03)	(0.27)
Credit			-0.47*	9.05***	3.26***
			(0.25)	(1.01)	(0.89)
EPL			0.59***	2.26***	1.68***
			(0.09)	(0.21)	(0.21)
PMR × IPP				0.009**	0.006**
				(0.004)	(0.003)
PMR × Credit				-1.26***	-0.63***
				(0.14)	(0.06)
PMR × EPL				-0.22***	-0.12***
				(0.02)	(0.02)
cons	-1.51***	-1.51***	6.94***	1.14	4.04
	(0.23)	(0.19)	(1.01)	(2.98)	(2.57)
Controls × industry dummies	NO	NO	NO	NO	YES
Log-likelihood	-328.9	-135.4	-19.4	82.9	296.8
N	1950	1860	1860	1860	1860

***,**,* denote significance at the 1%, 5%, 10% level, respectively.

Table 6: Sensitivity checks to sample composition

	1	2	3	4
	Coef./se	Coef./se	Coef./se	Coef./se
RDstock	0.05**	0.08**	0.04	0.14***
	(0.03)	(0.03)	(0.03)	(0.05)
Spillovers	0.86***	0.99***	0.84***	0.46***
	(0.05)	(0.06)	(0.05)	(0.14)
Labour quality	-0.02***	-0.04***	-0.002	-0.02***
	(0.00)	(0.01)	(0.00)	(0.01)
Credit	0.07	0.46***	0.08	-0.05
	(0.04)	(0.11)	(0.05)	(0.05)
cons	-5.01***	-6.55***	-5.04***	2.28**
	(0.60)	(0.80)	(0.65)	(1.05)
$ln\sigma_v^2$	-3.87***	-3.49***	-3.82***	-4.84***
	(0.11)	(0.09)	(0.11)	(0.22)
PMR	0.48	1.75	0.31	0.94
	(0.35)	(1.45)	(0.43)	(0.61)
IPP	-0.15***	0.04	-0.19***	-0.07
	(0.04)	(0.13)	(0.05)	(0.05)
Credit	9.08***	10.8***	10.8***	6.97***
	(1.13)	(1.53)	(1.53)	(1.13)
EPL	2.31***	5.36***	2.71***	2.05***
	(0.25)	(0.96)	(0.33)	(0.30)
PMR × IPP	0.010**	0.004	0.014***	0.002
	(0.004)	(0.013)	(0.005)	(0.006)
PMR × Credit	-1.31***	-1.68***	-1.56***	-0.96***
	(0.15)	(0.22)	(0.22)	(0.14)
PMR × EPL	-0.23***	-0.45***	-0.28***	-0.19***
	(0.03)	(0.09)	(0.04)	(0.04)
cons	1.14	-25.8*	3.10	-4.20
	(3.16)	(14.46)	(3.88)	(5.21)
Country	NO USA	ONLY EU	ALL	ALL
Industries	ALL	ALL	HIGH-TECH	LOW-TECH
Log-likelihood	-35.0	-4.83	4.52	118.5
N	1665	1080	1116	744

***,**,* denote significance at the 1%, 5%, 10% level, respectively.

exclude this possibility, in the last column of Table 4 we interact between IPP, EPL, the credit ratio and industry-specific dummies.

Finally, we perform some robustness checks to the sample composition (Table 6). First, we remove the US to control for the home bias associated with the usage of USPTO data. In col. 2, we focus on the EU member countries only, as they have relatively similar institutional characteristics. In the last two columns, the analysis is restricted to the group of high and high-and-medium tech industries, and to low and low-and-medium tech ones (see OECD, 2005 for details on this classification). Looking at knowledge frontier, we observe that bank credit is significant only for the EU country group. For high-tech industries, knowledge spillovers, as measured by sum of patent stocks of the partner countries in the industry, is the dominant factor in explaining innovation output. Turning to the determinants of the efficiency, evidence on second-order effects of PMR is fully confirmed across specifications. As an exception, the combination of strong protection in the product and technology markets turns out to be insignificant for the EU countries and low-tech industries. On average, in Europe the first-order EPL effect is decisively stronger.

5 Concluding remarks

As acknowledged by R&D endogenous growth theories, knowledge creation is one of the crucial force for a developed country to expand at a stable rate. However, the ability to manage R&D resources efficiently, and therefore to achieve better growth performance, cannot be taken for granted.

The novelty of our paper is that of applying the stochastic frontier approach to estimate a knowledge production function and assess the role of (upstream) product market regulation for R&D efficiency in OECD industries. We have singled out some interesting findings. First, patenting is significantly raised by research effort, knowledge spillovers and an easy access to credit. Second, PMR is found to influence R&D efficiency not directly, but only with second-order effects, i.e. by interacting with the functioning of the technology, labour and the financial market. Regulation in the product market is associated with lower levels of efficiency in contexts where intellectual property protection is strong, whilst seems benefical in the presence of less regulated financial markets and stringent employment protection. Third, these results are shown to be robust to the measurement of innovation variables, the presence of omitted factors, as well as to various country or industry groupings.

Our evidence enriches the exiting literature in several respects. It confirms that imperfections in intermediate input (service) markets may have positive effects on manufacturing innovation, supporting thus the view that Schumpeterian effect dominates the escape-competition effect. However, according to our findings, non-linearity found in earlier works is likely to derive from amplification of frictions between the product market and the rest of the economy. In this sense, product market regulation reinforces, or weakens, the impact of the other forms of regulation, rather having an own direct effect on research efficiency.

Our results can be of great relevance also from a policy perspective: if we consider R&D as one of the most crucial elements in fostering economic growth, it is particularly relevant to understand which institutional factors may lead a country to use or not R&D resources efficiently. Indeed, if research is performed inefficiently, policies aimed at fostering investment in this area are unlikely to achieve the expected outcome of encouraging economic growth over the long run.

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