Does deregulation drive innovation intensity? Lessons learned from the OECD telecommunications sector

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Abstract

The channel between innovation and industry regulation constitutes a non-lasting debate among the economists and researchers within the recent years. Despite the significant contributions on this field, mostly made from the empirical standpoint, the existing literature is still incomplete. This might be attributed to the fact that existing studies fail to combine a strong theoretical framework with the empirical scrutiny in order to exemplify and decompose the relationship between regulation intensity and innovation activity. We attempt to shed light on this limitation by theoretically modeling the telecommunications sector, in which access regulation impacts the non-separable activity in process and product innovation. We then empirically test our model by deploying an efficient panel threshold technique along the lines of Hansen (1999). Our balanced panel dataset comprises of 32 OECD countries over the period 1995-2012. The empirical results unveil a non-monotonic relationship of an "*inverted V-shaped*" form between regulation and innovation. We argue that beyond certain thresholds increasing the regulatory stringency further results in decreasing sector innovation. Our findings survive robustness checks after the inclusion of two alternative threshold variables (market structure and entry regulation) incurring significant implications for the policy makers and government officials.

JEL classification: L51; L96; L80; D43; C24

Keywords: Innovation; Regulation; Telecommunications, Market structure; Panel threshold model.

1. Introduction

In many network industries, such as electricity, gas, rail and telecommunications, the existing demand and cost conditions lead to significant market failures. In particular, their natural monopolistic structure, combined with high levels of vertical integration and network externalities, results in the inability of market forces to achieve the desirable competitive outcome (Buckley, 2003; Economides, 2005). In such cases, sector-specific regulators establish the conditions under which firms compete for and in the market, thus affecting market structure, firms' profits and industry performance. It is therefore imminent that regulation dictates the intensity of competition, which in turn determines the market performance in terms of static and dynamic efficiency (Laffont and Tirole, 2000; Röller, and Waverman, 2001).

Static efficiency is related to the short-run regulatory goal of promoting productive efficiency (i.e., existing assets are utilized efficiently) and allocative efficiency (i.e., existing resources are efficiently allocated to the economy). On the contrary, dynamic efficiency concerns the long-run goal of encouraging product innovation (which reflects a quality-upgrading activity) and process innovation (which reflects a cost-reducing activity). Although it is widely acknowledged that perfectly competitive markets achieve static efficiency, the impact of competition intensity on firms' incentives to invest in innovation has been one of the most fiercely debated topics among economists, academics and policy makers.

The beginning of this dispute dates back in early 1940s, when Schumpeter (1942) argued that innovation activity is positively correlated with large firms and market power since competition stifles innovation profits. This statement calls for a short-run legal protection as a reward for successful innovation. On the other hand, Arrow (1962) has pointed out that market power provides firms with disincentives to innovate as they mainly focus on protecting the status quo rather than engaging in developing costly disruptive technologies. Arrow's argument implies a clear policy for opening competition as a means to foster innovation. Although there is a sizeable literature studying the link between market structure and innovation, no clear consensus has been reached by combining the findings of theoretical and empirical works.[1]

This inconclusive relationship is highlighted by Motta (2004) who suggests a "*middle ground*" environment to spur innovation, where a sufficient degree of competition is combined with high enough market power coming from the innovative activities. In a similar vein, Shapiro (2012) concludes that innovation is spurred if the market is contestable. As a result, it is not clear whether more stringent regulation (which usually leads to more concentrated markets) or more light regulation (which usually results in more intense competition) stimulates higher levels of innovation initiatives (see, for instance, Blind, 2012; Amable et al, 2016).

This paper introduces the novel theory of non-separable activity in process and product innovation into a simple theoretical framework in order to explain the time-evolving relationship between regulation and innovation activity in the telecommunications sector. We contribute the literature in many fronts. First and foremost, we are the first to unravel a statistically significant relationship between

[1] See Wörter et al. (2010) for an excellent review of this literature.

regulatory stringency and innovation for both above and below the optimal level of regulatory intensity. For this reason, we rely on a suitable econometric methodology along the lines of Hansen (1999) to precisely estimate the threshold parameter, which in most of the other studies is arbitrarily given (see among others Marino et al, 2019; Papaioannou, 2017). Moreover, we build and combine a theoretical framework along with the empirical findings to analyse the causal link between deregulatory stringency and innovation activity.

The main finding of this paper is that the impact of regulation on innovation is *a priori* ambiguous. In particular, when the overall innovation activity results in more (less) product innovation than process innovation, more strict regulation increases (decreases) the level of innovation activity. A suitable application of this finding to the telecommunications sector unveils an inverse V-shaped relationship between regulation and innovation. This non-monotonic relationship is empirically tested by using non-parametric techniques within a panel threshold framework of the OECD countries over the period 1995-2012. The theoretical and empirical findings well explain the descriptive impact of regulation on innovation activity in the OECD telecommunications sector.

The rest of this paper is organized as follows. Section 2 describes the deregulatory process in the telecommunications sector among OECD countries, while Section 3 discusses their innovation activity trying to link regulatory stringency with patent intensity. Sections 4 and 5 present the theoretical model and the applied empirical methodology, respectively. Section 6 discusses the empirical findings of the study and performs the necessary robustness checks. Finally, Section 7 concludes the paper.

2. The deregulatory process in the OECD telecommunications sector

The telecommunications sector in the OECD countries has undergone substantial regulatory and institutional reforms. In the early 1980s most OECD telecommunications sectors were still governed by state-owned vertically integrated operators, the so-called "*incumbents*" (see, among others, Li and Lyons, 2012; Jeanjean and Houngbonon, 2017). These monopoly firms were legally protected and subject to strict retail price regulation (see, among others, Gruber and Koutroumpis, 2013; Agiakloglou and Polemis, 2018) to meet social and macroeconomic goals (Boylaud and Nicoletti, 2001).

Policy actions facilitating market liberalization and privatization were implemented in the United States (US) and United Kingdom (UK) in the early 1980s and in Europe in the 1990s. These actions were dictated by the conventional wisdom that competition and private incentives improve allocative and productive efficiency (Aghion and Griffith, 2005; Peitz, 2003).

The first wave of the deregulation process focused on privatizing national operators and changing the form of price regulation from rate-of-return to more flexible incentive-based regulations, such as price-cap regulation. The building block of these initiatives lies in the view that privatization and incentive-based regulations improve on the weak incentives for cost efficiency in rate-of-return regulation of monopoly operators.

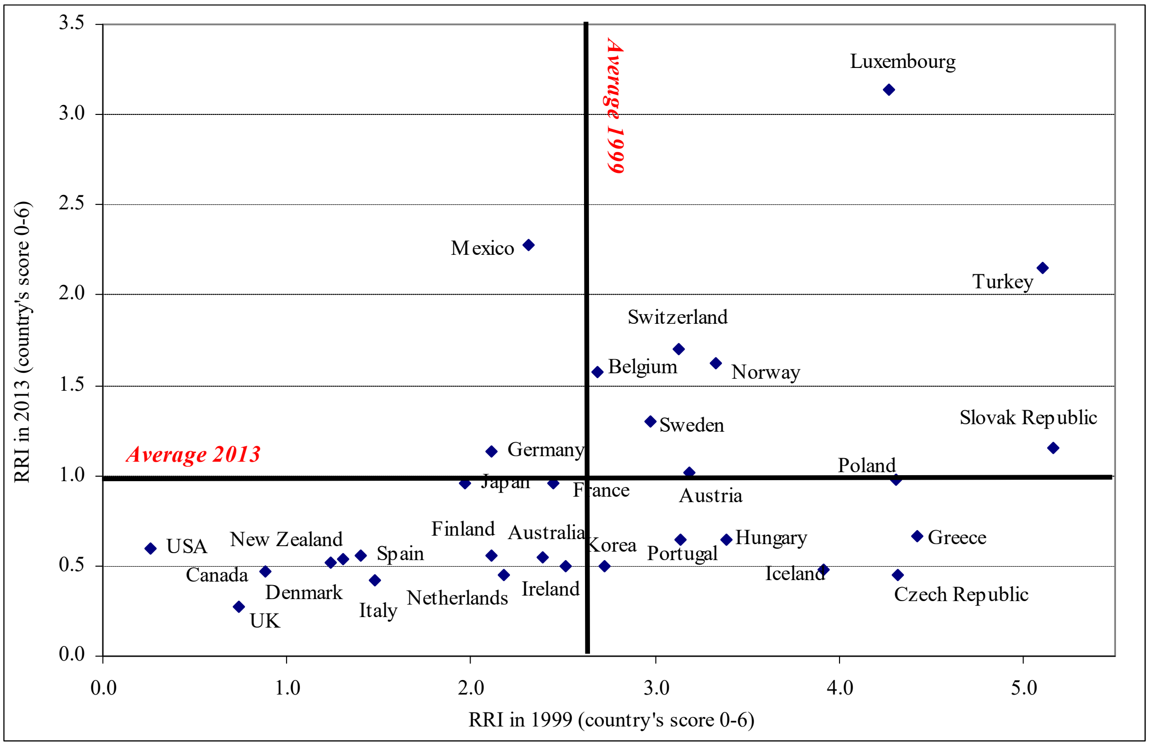
In the second wave of deregulation, governments authorized entry by alternative operators, the so-called "*new entrants*", and the provision of new services (e.g., mobile services and value-added services) into the market. In order to facilitate efficient entry, sector-specific National Regulatory Authorities (NRAs) were established with the responsibility of regulating, supervising and monitoring the market.

The third wave of deregulation concerns the full liberalization of the market, implying the end of the exclusivity period of the incumbent operators. The promotion of service-based competition was achieved by mandating incumbents to grant entrants with access to their metallic local loops at regulated prices. This form of regulation is widely known as Local Loop Unbundling (LLU), which implies that the incumbents' essential access network is separated from its overall core facilities and downstream operations in order to allow for commercial wholesale supply of this upstream input (De bijl and Peitz, 2002). It is thus obvious that policy makers and government officials were challenged to reform the telecommunications industry due to inefficiencies identified in its vertically integrated segments (Paleologos and Polemis, 2013).

However, as competition rises and new entrants are competing effectively with the incumbent operator, the goal of regulation is shifting towards more deregulatory policies which promote sustainable facilities-based competition, thus creating a "level playing field" between the incumbent and entrants.

Figure 1 presents a scatter graph of the intensity of telecommunications regulation in each OECD country one year and fifteen years after the full liberalization of the market in most of OECD countries. The stringency of regulation is captured by the OECD overall regulatory reform index for telecommunications (Telecommunications Reform Index - TRI). Lower (higher) values of the TRI index reflects a less (more) stringent regulation.

Figure 1: Changes in the TRI (1999 and 2013).



Note: The vertical solid line dividing the graph's plot area represents the non-weighted average for the beginning of the regulatory period (2.7), while the horizontal one denotes the non-weighted average for the end of the sample period (1.0).

Source: OECD International regulation database

The figure is split into four quadrants. Countries located in the South-West quadrant have consistently adopted deregulatory schemes. Countries located in the North-East quadrant are characterized by an above-average regulatory intervention, although they have moved towards less strict regulatory schemes. Countries placed in the North-West quadrant perform a moderate deregulation, whereas countries placed in the South-East quadrant have experienced a drastic deregulation process.

We can thus conclude that all OECD countries (except US) have decreased the regulatory restrictions imposed to the telecommunications sector, although the rate of deregulatory process varies significantly among countries. Such variations can be mainly explained by the fact that the timing of entry liberalization in each of the three telecommunications market segments (long distance network or trunk services, international and mobile telephony services) is quite different among OECD countries (see Table 1).

Table 1: Regulation of entry

Country	**Year of liberalization**		
	Trunk	***International***	***Mobile***
Australia	1991	1991	1992
Austria	1998	1998	1995/1996
Belgium	1998	1998	1996
Canada	1990	1992	-
Czech Republic	2000	2000	-
Denmark	1996	1996	Prior to 1992
Finland	1993	1993	Prior to 1992
France	1998	1998	1989
Germany	1998	1998	1991
Greece	2001	2001	1993
Hungary	2002	2002	n/a
Ireland	1998	1998	n/a
Italy	1998	1998	1994
Japan	1986	1987	1987
Korea	1996	1996	n/a
Luxembourg	1998	1998	1998
Mexico	1996	1996	n/a
Netherlands	1997	1997	1995
New Zealand	1990	1990	n/a
Norway	1998	1998	1992
Poland	n/a	n/a	n/a
Portugal	2000	2000	1991
Spain	1998	1998	1994
Sweden	1994	1992	1986
Switzerland	1998	1998	1998
Turkey	2006	2006	1997/1998
United Kingdom	1985	1986	1984
United States	1984	1984	1983

Notes: n/a = not available.

Source: OECD International Regulation Database and Boylaud and Nicoletti, (2001).

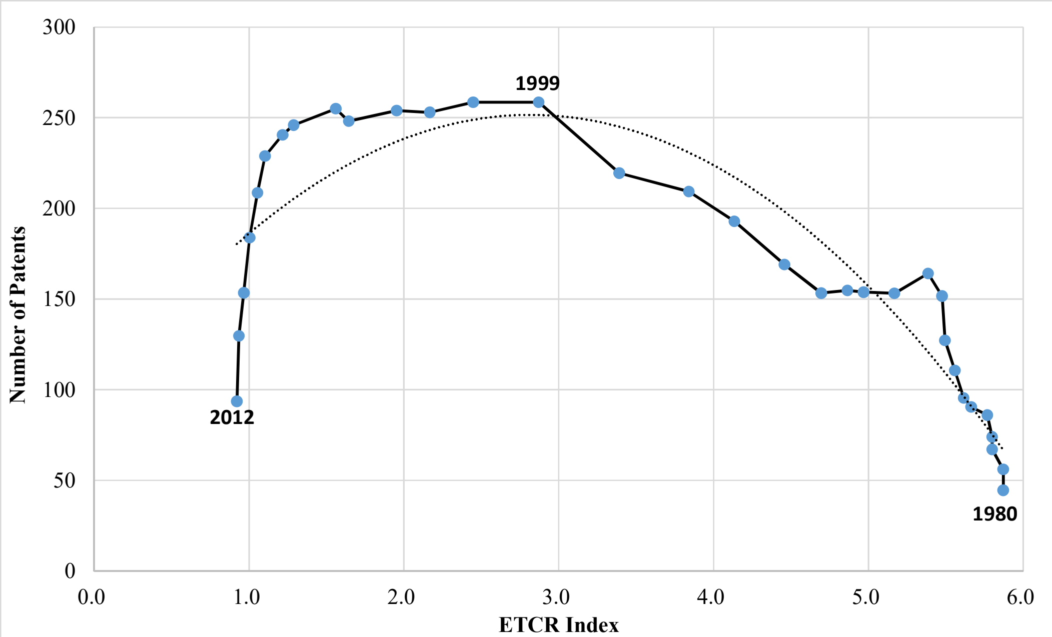
3. Innovation activity in the OECD telecommunications sector

The previous section made it clear that the liberalization of the telecommunications market that took place in the OECD countries was a crucial step towards establishing effective competition in sectors previously monopolized by state-owned firms. As we have discussed in Section 1, although there is an indisputable positive effect of less strict regulation on competition intensity, the impact of promoting competition, through lessening regulatory restrictions, on firms' innovation activity is quite ambiguous.

This paper contributes to the ongoing debate concerning the relationship between regulation and innovation by studying the impact of regulatory stringency on the innovation activity in the OECD telecommunications market. Figure 2 correlates the average number of telecommunications-related patent grants in the OECD countries with the average level of the Telecommunications Reform Index (TRI) in a yearly basis from 1980 to 2012.

From the inspection of Figure 1, we can deduce that there is an inverted-U relationship between regulation and innovation in the OECD telecommunications sector. The interpretation of this link is closely related to the impact of competition on firms' incentives to innovate. In order to elaborate on this link, we have to analyze the evolution of the OECD telecommunications market during the studying period.

Figure 2: Patent grants and regulatory stringency in the OECD telecommunications sector (1980-2012).



Note: The figure denotes the OECD average value of the number of patent grants to the EPO and the regulatory reform index for telecoms (TRI) per year. The dashed curve denotes the trend line.

Source: OECD TRI Data Regulation and OECD Patent Grants

In the early 1980s, strict legal restrictions had induced the state-owned incumbent operators to monopolize the telecom market. The absence of competition and the rate-of-return regulation were deterring factors for undertaking costly innovation initiatives. The first wave of liberalization gave incumbent operators incentives to innovate. Ai and Sappington (2002) find that changing the regulatory standard from rate-of-return regulation to more flexible incentive-based regulations leads to an increase in process innovation.

During the second wave of liberalization, new entrants could enter more and more segments of the market. The incumbent firms were reacting to the increasing competition by undertaking innovation activities to protect their dominant position. Such initiatives were focusing in process innovation to reduce their production cost since the former state-owned operators were quite inefficient compared to new entrants. In addition, the provision of new services, such as mobile telephony, led both incumbent and entrants to invest in product innovation.

This positive relationship between less strict regulation and innovation was prevailing until the late 1990s. Most OECD countries fully liberalized the telecommunications market in 1998, while continuing to withdraw regulatory restrictions with the goal of further increasing competition. However, just one year after the full liberalization of the telecommunications market, firms started to decrease their innovation rate as a reaction to the increased competition level. As the LLU prices were moving towards the incumbents' cost of providing the access with the goal of cancelling any advantage of such vertically integrated firms, the innovation incentives of both incumbents and entrants were decreasing.

In particular, the technological progress in digital transmission and packet switching allowed for product innovation. However, incumbents were not willing to heavily invest in quality knowing that they would be mandated to provide access to their upgraded networks at cost-based prices (Cave and Prosperetti, 2001). Therefore, entrants preferred to avoid the cost of product innovation as they could free-ride on the incumbents' networks at such low access prices (Valletti, 2003). In addition, a sufficiently high level of productive efficiency had been reached, thus giving room for only marginal process innovations.

The negative relationship between competition and innovation in the liberalized telecommunications sector has been proven both theoretically and empirically.[2] Therefore, telecom regulators have to deal with the common trade-off between promoting static and dynamic efficiency (Bouckaert et al., 2010).

The inverted-U relationship between regulation and innovation is therefore explained by studying the innovation incentives related to higher competition levels stem from less strict regulation. There is a sizeable literature stream verifying a non-monotonic "inverted U-shaped" relationship between competition and innovation (see, for instance, Aghion et al., 2005, Amable et al., 2010).

The paper closest to ours is that of Marino et al. (2019) who study the relationship between innovation and regulation in the OECD electricity sector from 1985 to 2010. They find descriptive evidence of an inverted U-shaped relationship between the average number of patents and the sectoral regulatory index depicting the average regulation intensity. Combining the descriptive evidence from the telecommunications and the electricity sectors in the OECD area, we conclude that a significant reform in such network industries triggers the regulatory trade-off between static and dynamic efficiency.

A crucial difference between the two sectors is that, according to the descriptive evidence, the optimal degree of regulatory intensity in telecommunications in terms of innovation activity lies almost in the middle of full regulation and full deregulation (3/6), whereas the same degree in the electricity sector is closer to full regulation (4/6).

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[2] Cambini and Jiang (2009) and Tselekounis et al. (2014) provide an extensive review of this literature.

The estimation of such optimal levels should be the main goal of the theoretical and empirical studies focusing on interpreting the relationship between regulation and innovation in network industries. Contrary to Marino et al. (2019) who do not empirically derive such optimal regulatory level, we build on a threshold model which succeeds in estimating the degree of regulatory intensity that maximizes innovation incentives. In addition, Marino et al. (2019) lacks of a strong theoretical framework, whereas we develop a theoretical model that succeeds in describing the evolving relationship between regulation and innovation in the telecommunications market.

4. Theoretical Framework

In this section, we present a theoretical modeling setup which well describes the relationship between regulation and innovation in the telecommunications market. We then characterize the equilibrium of the game which is solved backwards. Last, we draw some policy implications based on the main findings of our analysis.

4.1. The Model

We consider an unregulated downstream market in which a vertically integrated incumbent (firm *I*) and a new entrant (firm *E*) compete for providing a homogeneous final telecommunications service to consumers. The two firms compete á la Cournot, meaning that they choose their quantities (q_I and q_E, respectively) simultaneously and independently. This type of competition well reflects the telecommunications sector since it is characterized by significant capacity constraints.

The provision of one unit of the final service requires one unit of an upstream input owned by the incumbent. Therefore, the entrant has to pay a per-unit wholesale price $w \geq 0$ to the incumbent in order to have access to this critical input (e.g., the access network). The production of the upstream input incurs a per-unit cost $c \geq 0$ regardless of whether the critical input is used by the incumbent or the entrant. Any other production and distribution costs are normalized to zero. It is reasonable to assume that $w \geq c$ in order to ensure that the incumbent's profit from its upstream activity is non-negative.

The quality of the final service, which is positively affected by the incumbent's activity in product innovation, increases the valuation of consumers for telecommunications services. However, as Vareda (2010) points out, in most cases the innovation activity does have an impact on both demand (increasing the quality of the services allowing better communication experience) and cost (decreasing marginal costs due to the use of more sophisticated equipment).

As a result, the incumbent is incapable of separating its innovation activity between product innovation and process innovation. This means that an overall innovation activity δ translates into: (i) a final product of better quality which increases the initial reservation price of the final service A by $\rho\delta$; and (ii) a more efficient production technology which decreases the marginal cost of producing the upstream input by $(1-\rho)\delta$. The cost of innovating is given by $\kappa\delta^2/2$, where κ denotes the rate at which the overall innovation activity becomes marginally more expensive.

Given the above setting, the profit functions of the incumbent and the entrant are given, respectively, by

$$\pi_I = (P-C)q_I + (w-C)q_E - \frac{\kappa}{2}\delta^2 \tag{1}$$

and

$$\pi_E = (P - w)q_E \tag{2}$$

where P is the retail price of the final service given by the inverse demand function $P = A + \rho\delta - b(q_I + q_E)$ and C is the marginal cost of producing the upstream input given by $C = c - (1-\rho)\delta$. Parameter b reflects the slope of the inverse demand function.

Firms play a two-stage game. In stage one, the incumbent chooses the level of the non-separable activity in process and product innovation. In stage two, the downstream firms make their optimal quantity choices. In order to study the impact of regulation on innovation activity in the telecommunications market, we assume that the wholesale price w is exogenously set by the sector-specific regulator at the beginning of the game.[3] Higher levels of w signify a more strict regulation which favors the dominant incumbent firm, whereas lower levels of w are related to more intense competition in the downstream market.

4.2. Equilibrium analysis

Taking the first-order conditions of Eqs. (1) and (2) with respect to q_I and q_E , respectively, gives the reaction functions of firm *I* and *E*:[4]

$$q_I = \frac{A - c + \delta}{2b} - \frac{q_E}{2} \tag{3}$$

and

[3] This means that innovation activities are undertaken under regulatory certainty. See Tselekounis and Varoutas (2013) for the impact of regulatory uncertainty on investment incentives.

[4] It is easy to show that the second-order conditions for profit-maximization always hold.

$$q_E = \frac{A - w + \rho\delta}{2b} - \frac{q_I}{2} \tag{4}$$

It is interesting to point out that q_I and q_E are strategic substitutes and that the former is positively affected by the overall innovation activity of the incumbent, whereas the latter only positively depends on the part of the incumbent's innovation that improves the quality of the product. This is reasonable since both product and process innovation make the incumbent better off, whereas the entrant is only benefited by the spillover effect of quality-enhancing innovation. Solving the system of Eqs. (3) and (4) with respect to q_I and q_E yields the optimal quantity chosen by each firm:

$$q_I = \frac{A - 2c + w + \delta(2 - \rho)}{3b} \tag{5}$$

and

$$q_E = \frac{A - 2w + c - \delta(1 - 2\rho)}{3b} \tag{6}$$

From the inspection of the retail equilibrium, we can deduce that the wholesale price and the marginal cost of providing access affect the optimal choices of the two firms in completely different directions. Most significantly, the level of innovation activity always affect the incumbent's quantity in a positive way, whereas its impact on the entrant's quantity is positive if and only if more than half of the non-separable innovation activity proves to be quality-enhancing.

Substituting the retail equilibrium outcomes in the incumbent's profit function given by Eq. (1) and then take its first-order condition with respect to δ gives the level of innovation activity that maximizes the profit of the incumbent:

$$\delta = \frac{A(7-5\rho)-c(2+5\rho)+5w(2\rho-1)}{9b\kappa+10\rho^2-10\rho-2} \quad (7)$$

Given that the second-order condition of π_I with respect to δ requires the denominator of Eq. (7) to be positive, the incumbent's optimal level of innovation activity is always positive provided that both firms are active in the downstream market.

Equation (7) gives the level of non-separable innovation activity chosen by the incumbent. It is obvious that this privately-optimal level of innovation depends on the wholesale price of the critical input. Since this price is usually set by the regulator, we can study the effect of regulation on the overall innovation activity from a theoretical perspective.

Interestingly enough, the impact of regulation on the incumbent's incentives to innovate is *a priori* ambiguous. In particular, when $\rho \in [0, 0.5)$, more strict regulation is related to less innovation activity. On the contrary, when $\rho \in (0.5, 1]$, the impact of regulation on innovation activity is positive. In other words, when the incumbent's innovation activity results in more (less) product innovation than process innovation, more strict regulation increases (decreases) the incentives of the incumbent to innovate. Finally, when the quality-enhancing and the cost-reducing effects are equal (i.e., when $\rho = 0.5$), the regulation of the upstream market does not affect the innovation activity.

The above analysis of the relationship between regulation and innovation activity explains the evolution of the average number of telecommunications-related patent grants in the OECD countries. Before market liberalization, the monopolistic structure of the market was fully protected by the regulatory policy. After market liberalization, the deregulation process has been implemented by gradually relaxing the entry barriers associated with the regulatory framework, as well as by ensuring a level-playing field between the active operators. This (de)regulatory policy can be reflected by a decreasing TRI index as shown in Figure 2. In our modeling setup, the main goal of such policies can be captured by a decreasing wholesale price w. To put it differently, the TRI index and the parameter w reflect the level of regulatory stringency.

As we have discussed in Section 3, in the early stages of market liberalization, most innovation activities made by the incumbent operators would result in more process than product innovations. The reason is that, at these stages, the state-owned incumbents were quite inefficient operators, meaning that most innovation activities could be more easily transformed into cost-reducing rather than quality-enhancing innovations. This liberalization period is related to low levels of ρ, implying a negative relationship between regulation and innovation activity. In other words, as the wholesale price decreases from significantly high levels (thus reflecting significant barriers to entry), the incentives for undertaking innovation activities increase. This effect is also present in Figure 1, since a decrease in the TRI index from a high initial level results in an increase in the average number of telecommunications-related patent grants in the OECD countries.

On the contrary, when the market competitiveness has exceeded a sufficiently high competitive structure (denoting by $\rho = 0.5$), the innovation activities are more likely to result in new products rather than in processes that reduce the production cost. Indeed, more symmetric firms strive to differentiate themselves by offering products of higher quality. However, when the wholesale price is set close to the cost of providing the critical input, the incumbent does not have significant incentives to lower its upstream cost.

In our modeling setup, this tendency translates into high levels of ρ, implying a positive relationship between regulation and innovation activity. This means that as the wholesale price further decreases, the incentives for undertaking innovation activities decrease as well. This result is in line with the impact of a decrease in the TRI index on the number of patents when this index has reached its optimal level in terms of innovation incentives.

This optimal level reflects a turning point since a marginal increase or decrease in its value reverses the relationship between regulation and innovation. In our theoretical framework, this turning point is captured by the level of ρ which makes the cost-reducing and the quality-enhancing effects equal (i.e., $\rho = 0.5$). For $\rho \in [0, 0.5)$, a decrease in w leads to an increase in δ and for $\rho \in (0.5, 1]$, a decrease in w leads to a decrease in δ . However, if we consider that the value of ρ increases during the deregulation process captured by a decreasing w, we derive an inverted-V relationship between regulatory stringency and incentives to innovate. This relationship is not only present in Figure 1 which shows the analysis of the real data, but also derived from the empirical analysis that follows.

As a result, we can deduce that our theoretical framework succeeds in describing the evolving relationship between regulation and innovation in the telecommunications sector. We should point out that this non-monotonic relationship drawn by our modeling setup is derived due to the novel use of the non-separability nature of innovation activities. It is obvious that process innovation or product innovation alone would result in a monotonic relationship, thus failing to satisfactorily explain the descriptive evidence depicted in Figure 1.

4. Data and Methodology

This section describes the data that we used, while providing and analysing the descriptive statistics for the sample variables. Moreover, we discuss and analyse the estimation strategy and the econometric methodology applied (parametric and threshold model) to empirically estimate the relationship between regulation and incentives to innovate.

4.1 Data and variables

We use a yearly balanced panel data set for 32 OECD countries (N=32) over the period 1995 to 2012 (T=17). The reason we restricted our sample to this time span was strictly dictated by severe data discrepancies in most of the sample variables. However, since our main goal is to empirically investigate the effect of deregulation on innovation, this choice could not raise any issue regarding the sample selection since little reform of the telecommunications sector occurred before 1995 (see also Figure 2).

The panels used in this study comprise 20 EU countries (e.g. Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, Netherlands, Poland, Portugal, Slovakia, Spain, Sweden and the United Kingdom), while the rest fall outside the EU market (i.e. Australia, Canada, Chile, Iceland, Japan, Korea, Mexico, New Zealand, Norway, Switzerland, Turkey and the United States).

Our dependent variable is the number of patents (PAT) granted by the European Patent Office (EPO) in the ICT technology domain, which includes four distinct categories (telecommunications, consumer electronics, computers-office machinery and other ICT). In order to have a representative sample, we isolate the telecommunications IPC codes from the rest patent categories.[5] The data for this variable are publicly available from the OECD patent database.[6] Despite some limitations such as secrecy, lead time, comparison deficiencies that are raised when patents are used as proxy for innovation activity (see Marino et al, 2019), they are regarded by the existing literature as reliable and efficient measure of innovation (see for example Marino et al, 2019; Drivas et al, 2016; Drivas et al, 2017; Deltas and Karkalakos, 2013).

To capture the effect of regulatory intensity on innovation, we used three measures of upstream product market regulation for the telecommunications sector obtained by the OECD.[7] Firstly, we used the overall regulatory index of the sector (TRI) as our main regime-dependent variable (threshold variable). We also used two other regulatory indexes namely STRUCT and ENTRY which are components of the TRI. These measures capture regulatory conditions in terms of market structure (e.g (market share of new entrants in the trunk, international and mobile telephony market) and entry characteristics (i.e legal conditions of entry into trunk, international and mobile telephony market) in the specific sector (see Marino et al, 2019; Polemis and Stengos, 2017). All

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[5] The IPC codes that are included in the telecommunications category of the EPO are the following: G01S, G08C, G09C, H01P, H01Q, H01S3/025,043,063,067,085,0933,0941,103,133,18,19,25), H01S5, H03B, H03C, H03D, H03H, H03M, H04B, H04J, H04K, H04L, H04M, H04Q.

[6] https://stats.oecd.org/Index.aspx?DataSetCode=PATS_IPC

[7] https://stats.oecd.org/index.aspx?DataSetCode=PMR

these regulatory measures fall within the interval [0 – 6]. A high (low) score is awarded to countries characterized by increased (decreased) regulated sector (Conway and Nicoletti, 2006). The reason that justifies the use of the specific OECD regulatory measures instead of other proxies of upstream product market regulation (i.e. Telecommunications Regulatory Governance Index, Fraser index, etc) is attributed to the fact that these indexes "[…] *capture regulatory management practices that are imposed on network telecommunications sector, by measures of the governance of the bodies that design, implement and enforce these regulations*" (Agiakloglou and Polemis, 2018), while on the other hand are broadly used by the empirical literature (see for example Li and Lyons, 2012; Paleologos and Polemis, 2013; Amamble et al, 2016; Agiaklogou and Polemis, 2018).

Lastly, we supplement our analysis with the use of three other variables namely GDP, EXP and IMP to control for macroeconomic fluctuations or trade shocks (Marino et al, 2019). GDP accounts for the annual percentage growth rate of GDP at market prices based on constant 2010 USD dollars. EXP denotes the exports of goods and services as percentage of GDP. Specifically, EXP includes the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services, while it excludes compensation of employees and investment income and transfer payments. Lastly, IMP, denotes the imports of goods and services and is expressed as percentage of GDP. The data are drawn from the World Development

Indicators (WDI) database provided by the World Bank.[8]. The following table presents the descriptive statistics of the sample variables.

Table 2: Summary statistics of the sample variables

Variables	**Observations**	**Mean**	**Standard deviation**	**Min**	**Max**
TRI	576	2.141	1.558	0.429	6
ENTRY	576	1.400	1.880	0	6
STRUCT	576	2.472	1.302	0.888	6
PAT	576	217.7	458.5	0	2,774
GDP (%)	576	2.771	3.163	-14.72	11.80
IMP (%)	576	42.16	22.79	7.708	156.4
EXP (%)	576	44.15	27.11	8.972	187.1
ln(PAT)	576	2.627	3.770	-6.908	7.928
ln(TRI)	576	0.498	0.741	-0.843	1.792
ln(STRUCT)	576	0.796	0.444	-0.118	1.792
ln(ENTRY)	576	-3.397	3.958	-6.908	1.792
ln(TRI) × GDP	576	2.040	3.589	-9.762	19.49
ln(TRI) × EXP	576	22.70	43.87	-74.65	226.1
ln(TRI) × IMP	576	21.82	39.86	-62.61	191.2
ln(STRUCT) × GDP	576	2.663	3.489	-10.17	19.35
ln(STRUCT) × EXP	576	35.77	31.90	-3.509	226.1
ln(STRUCT) × IMP	576	34.56	29.22	-3.743	191.2
ln(ENTRY) × GDP	576	-5.634	19.00	-76.77	101.7
ln(ENTRY) × EXP	576	-158.9	232.9	-1,293	226.1
ln(ENTRY) × IMP	576	-149.1	211.8	-1,081	191.2

Source: OECD and World Bank.

4.2 Preliminary testing for cross-section dependence and stationarity

One of the additional complications that arise when dealing with panel data compared to the pure time-series case, is the possibility that the variables or the random disturbances are correlated across the panel dimension. The early literature on unit root and cointegration tests adopted the assumption of cross-sectional independence (see Pesaran 2015). However, it is common for macro level data to violate this assumption

[8] https://datacatalog.worldbank.org/dataset/world-development-indicators.

which will result in low power and size distortions of tests that assume cross-section independence. For example, cross-section dependence in our data may arise due to common unobserved effects triggered by differences in the regulatory framework among the OECD countries. Therefore, before proceeding to unit root and cointegration tests we test for the existence of cross-section independence.

For this reason, we use the cross-section dependence test (CD test) developed by Pesaran (2004). As it is evident from Table 3 the relevant test strongly rejects the null hypothesis of cross-section independence (P-values = 0.000). In face of this evidence we proceed to test for unit roots using tests that are robust to cross-section dependence (i.e second generation tests for unit roots in panel data).

Table 3: Cross section dependence test results

Variable	**CD test**	**P-value**	**Correlation**	**Absolute (correlation)**
ln(PAT)	26.25***	0.000	0.278	0.391
ln(TRI)	80.56***	0.000	0.853	0.853
ln(ENTRY)	76.74***	0.000	0.817	0.817
ln(STRUCT)	77.78***	0.000	0.823	0.823
GDP	52.02***	0.000	0.550	0.553
EXP	48.07***	0.000	0.509	0.578
IMP	50.40***	0.000	0.533	0.643
ln(TRI) × GDP	45.62***	0.000	0.483	0.528
ln(TRI) × EXP	72.80***	0.000	0.771	0.797
ln(TRI) × IMP	74.28***	0.000	0.786	0.799
ln(STRUCT) × GDP	57.46***	0.000	0.608	0.610
ln(STRUCT) × EXP	63.02***	0.000	0.667	0.694

ln(STRUCT) × IMP	64.69***	0.000	0.685	0.717
ln(ENTRY) × GDP	35.04***	0.000	0.371	0.428
ln(ENTRY) × EXP	56.67***	0.000	0.600	0.682
ln(ENTRY) × IMP	59.36***	0.000	0.628	0.696

Notes: Under the null hypothesis of cross-sectional independence the CD statistic is distributed as a two-tailed standard normal. Results are based on the test of Pesaran (2004). The p-values are for a one-sided test based on the normal distribution. Correlation and Absolute (correlation) are the average (absolute) value of the off-diagonal elements of the cross-sectional correlation matrix of residuals. ***significant at 1%.

To examine the stationarity properties of the sample variables we use two second generation panel unit root tests namely the "*CIPS*" and the "*PESCADF*" test both accounting for cross section dependence (Im. et al, 2003; Pesaran, 2003 and Pesaran, 2007). The latter runs the t-test for unit roots in heterogenous panels with cross-section dependence proposed by Pesaran (2003), while the former reports the p-value of the Lagrange multiplier (LM) test on the Breusch-Godfrey serial correlation of each individual regression (see Pesaran, 2007). The null hypothesis assumes that all series are homogeneous nonstationary, while rejection of the null implies that the series do not contain a unit root (stationarity). To eliminate the cross section dependence, the standard Dickey Fuller (DF) regressions are augmented with the cross section averages of lagged levels and first-differences of the individual series (see Lewandowski, 2006).

It is worth emphasizing that other unit root tests that allow for cross section dependence (see for example Breitung and Das, 2005) collapse if it is assumed that cross-correlation is due to common factors, while the "*CIPS*" test remains valid (see Pesaran, 2015; Halkos and Polemis, 2017; Polemis and Stengos 2019). As it is evident from the inspection of Table 3, the "*CIPS*" test provides mixed results. However, the

"*PESCADF*" test in both specifications (i.e. with an intercept and with a linear trend) provides sufficient evidence that all the series contain a unit root. Since this test has more power than "*CIPS*" test we assume that all of the sample variables are integrated of order one (I-1).

Table 4: Panel unit root test results.

Variable	***Pesaran CIPS with an intercept***	***Pesaran CIPS with an intercept and a linear trend***	***Pesaran CADF with an intercept***	***Pesaran CADF with an intercept and a linear trend***
ln(PAT)	-2.487^{***}	-3.310^{***}	-1.614 [0.740]	-2.266 [0.553]
ln(TRI)	-2.077	-2.260	-2.106^{**} [0.018]	-2.091 [0.867]
ln(STRUCT)	-2.494^{***}	-2.744	-1.585 [0.790]	-2.039 [0.920]
ln(ENTRY)	-1.743	-1.792	-1.773 [0.406]	-1.782 [0.998]
GDP	-2.786^{***}	-2.898^{***}	-1.797 [0.354]	-2.164 [0.759]
EXP	-1.266	-1.395	-1.432 [0.951]	-1.557 [0.999]
IMP	-1.728	-1.764	-1.916 [0.151]	-2.093 [0.865]
ln(TRI) × GDP	-2.861^{***}	-3.298^{***}	-1.033 [0.999]	-1.909 [0.984]
ln(TRI) × EXP	-2.073	-2.361	-1.582 [0.794]	-2.113 [0.839]
ln(TRI) × IMP	-2.134	-2.464	-1.543 [0.850]	-2.000 [0.948]
ln(STRUCT) × GDP	-3.277^{***}	-3.199^{***}	-1.471 [0.924]	-2.164 [0.760]
ln(STRUCT) × EXP	-2.137	-2.434	-1.610 [0.747]	-2.294 [0.490]
ln(STRUCT) × IMP	-2.311^{**}	-2.419	-1.722 [0.518]	-2.155 [0.776]
ln(ENTRY) × GDP	-2.468^{***}	-2.644^{*}	-1.618 [0.733]	-1.993 [0.952]
ln(ENTRY) × EXP	-2.178^{*}	-2.206	-1.464 [0.930]	-1.164 [0.999]
ln(ENTRY) × IMP	-2.108	-2.093	-1.539 [0.856]	-1.186 [0.999]

Notes: Rejection of the null hypothesis indicates stationarity in at least one country. The null hypothesis is that of a unit root. The number of lags is determined by the Bayesian Information Criterion (BIC). The numbers in square brackets denote the P-values. Significant at ***1%, **5% and *10% respectively.

Having identified the order of integration in the model variables, we proceed with the panel cointegration testing. In other words, we are interested to find a long-run structural relationship among the sample variables. For this reason, we rely on three powerful panel cointeration tests namely the Pedroni's (1999) ADF-based and PP-based cointegration tests, the Kao's (1999) ADF-based tests and the Westerlund (2007) test. The latter is also suitable to examine if a cointegration relationship exists among a set of variables that do not necessarily have the same order of integration (see Pesaran, 2015).

It is worth mentioning that all the above tests allow for cross-section dependence but only the latter requires a balanced panel, while the two former tests (Pedroni and Kao) can be applied for unbalanced panel data as well (see Pedroni, 2000; 2001). The Westerlund (2007) test represents an error-correction approach to testing for cointegration that is based on the statistical significance of the error correction term. The intuition behind this approach is that if a long run relationship between the variables in our model exists, we can write a regression that allows us to estimate the error-correcting terms which reflect the response of the system to random shocks that "*pushes*" the system towards its long-run equilibrium point. If the error-correction terms are significantly different from zero across cross-sections, then there is evidence in favor of the existence of a long-run relation.

The results of the tests are presented in Table 5. As it is evident, all tests lead to the rejection of the null hypothesis of no cointegration. In other words, cointegration statistics provide sufficient evidence to support the existence of a structural relationship between the sample variables in each of the three models (see Columns 1-3).

Table 5: Panel cointegration test results

Test	**(1) Model I**	**(2) Model II**	**(3) Model III**
Pedroni – Modified PP	3.2661^{***} [0.0005]	3.9449^{***} [0.000]	3.3115^{***} [0.0005]
Pedroni – PP	-6.8819^{***} [0.000]	-5.5831^{***} [0.000]	-7.2864^{***} [0.000]
Pedroni - ADF	-6.3851^{***} [0.000]	-5.1318^{***} [0.000]	-5.8675^{***} [0.000]
Kao – Modified DF	-3.3098^{***} [0.0005]	-3.3672^{***} [0.0004]	-3.2381^{***} [0.0006]
Kao –DF	-6.2831^{***} [0.000]	-6.3717^{***} [0.000]	-6.1912^{***} [0.000]
Kao - ADF	-1.6446^{*} [0.050]	-1.8168^{**} [0.0346]	-1.7281^{**} [0.0420]
W-T	-1.7595^{**} [0.0393]	-1.8686^{**} [0.0308]	-1.7278^{**} [0.0420]

Notes: Model I includes the ln(TRI) as the threshold variable. Model II includes the ln(STRUCT) as the threshold variable and Model III includes the ln(ENTRY) as the threshold variable. Pedroni-ADF, Pedroni-PP, Kao-ADF, stand for Pedroni (1999). ADF-based and PP-based, and Kao (1999) ADF-based cointegration tests, respectively. W-T stands for the Westerlund (2007) cointegration test. The null hypothesis assumes that there is no co-integration. The numbers in parentheses denote the p-values. Significant at ***1% and **5% respectively.

4.3 The baseline model

Our simple baseline parametric model that will be contrasted with the threshold model (TR) described below takes the following form:

$$\ln(PAT_{it}) = a_0 + a_1 \ln(TRI_{it}) + a_2 \ln(TRI_{it})^2 + a_3 GDP_{it} + a_4 EXP_{it} + a_5 IMP_{it} + X'_{it}\psi + \mu_i + \theta_t + \mu_i * \delta_t + \varepsilon_{it} \quad (8)$$

where logged patent intensity ($\ln PAT_{it}$) of country i in time t is regressed on the logged value of upstream product market regulation expressed in levels ($\ln TRI_{it}$) and its squared (non-linear) term $(\ln TRI_{it})^2$. Moreover, GDP denotes the annual percentage of GDP in USD dollars at the country-year level. EXP and IMP denote the exports and imports of country i at year t as a percentage of GDP. The vector X'_{it} includes the interaction terms (cross-terms), to account for possible non-linearities, while ψ denotes the relevant estimated coefficients. To account for unobserved heterogeneity, we include μ_i which stands for the (time invariant) country-specific residual (country FE) that differs between countries but remains constant for any particular country (unobserved country FE). Moreover, θ_t is the time variant effect (year FE) and therefore differs across years but is constant for all countries in a specific year. The reason we account for time dummies (year FE) in our model is that we are able to trace the co movement of the variables due to external shocks (Polemis and Stengos, 2019; Asimakopoulos and Karavias, 2016). Our model also incorporates country∗year dummies (FE) to control for omission biases related to specific unobserved factors such as rate of technical change, sector's productivity, etc (Papaioannou, 2017). Finally ε_{it} denotes the idiosyncratic i.i.d disturbance term.

4.4 The threshold model[9]

The TR model is expressed by the following equations:

[9] The description of the TR model follows closely the study of Polemis and Stengos, (2017).

$$y_t = x_t^T \beta_1 + \varepsilon_t,\ q_t \leq \gamma \tag{9}$$

$$y_t = x_t^T \beta_2 + \varepsilon_t,\ q_t > \gamma \tag{10}$$

These equations describe the relationship between the variables of interest in each of the two regimes (high and low deregulation) and q_t stands for the threshold variable with γ being the unknown sample split (threshold) value that needs to be estimated. The threshold variable may, but has not to be an element of x_t^T, the k-dimensional vector of exogenous regressors (see Hansen, 1999 and Bick, 2010). We assume for simplicity that the error term ε_t is independent and identically distributed (i.i.d) with mean zero and finite variance σ_v^2, although one can also allow for a conditional heteroskedastic error structure and weak dependence. The approach that we employ here does not rely on a known γ. In other words the parameter γ needs to be estimated along-side the other unknown parameters of the model. However, the method is based on first testing for the presence of a threshold effect. Once we reject the null of no threshold we proceed in the estimation of the model that includes the estimation of the threshold and allows for the sample split. The method is based on a CLS technique that splits the model into the two regimes, whereby there is a full interaction of all the variables with the (estimated) threshold.

By introducing a dummy variable $d_t(\gamma) = I(q_t \leq \gamma)$, we can write the model above in a single expression (Hansen, 1999, Savvides and Stengos, 2000):

$$y_t = x_t^T \beta + x_t^T(\gamma)\mathrm{K} + \varepsilon_t \tag{11}$$

where $\beta = \beta_2$ and $\mathrm{K} = \beta_1 - \beta_2$. For testing that there is no threshold the null hypothesis is simply that H_0: K=0 or H_0: $\beta_1 = \beta_2$. That allows for the comparison between the TR model and the simple linear benchmark without a threshold. It is worth noting that the parameter γ (threshold parameter) is not identified under the null hypothesis of no threshold (K=0) and usual test statistics have non-standard distributions (Hansen, 2000; Kourtellos et al, 2015). Based on the above, our threshold model takes the following algebraic form:

$$\ln(PAT_{it}) = \mu_i + \theta_t + \beta_1' x_{it} I(\ln TRI_{it} \leq \gamma) + \beta_2' x_{it} I(\ln TRI_{it} > \gamma) + \varepsilon_{it} \qquad (12)$$

where x_{it} is the vector of exogenous control variables with regime independent slope coefficients. *I (·)* is the indicator function taking the value one when the condition in the parenthesis is satisfied and zero otherwise. The latter also, represents the regime defined by each threshold variable (lnTRI, lnSTRUCT and lnENTRY), and the threshold value γ that needs to be estimated within the model.

5. Results and discussion

This section presents the empirical findings of the study. We first present the results of the benchmark parametric model and compare these estimates with the threshold model. In addition, we perform the necessary robustness checks by using two alterative specifications of regulatory intensity accounting for the market structure and entry conditions.

5.1. Parametric regression estimates

Table 6 presents the results from the benchmark parametric (linear and quadratic) regressions. Columns 1-3 portray the OLS-FE estimates, while the instrumental variable (IV) FE estimates are displayed in columns 4-6. The reason for not using pooled OLS estimators is that they do not allow for possible dependence between the time varying regressors and the individual-specific effects (Pesaran, 2015). As it is observed, the estimates presented in the second column of Table 2 clearly exhibit an inverted-U relationship between patents and regulatory stringency which in turn we try to rationalize in the subsequent section.

Table 6: Parametric regression results

Dependent variable: ln(PAT)	**(1)** **OLS-FE**	**(2)** **OLS-FE**	**(3)** **OLS-FE**	**(4)** **IV-FE**	**(5)** **IV-FE**	**(6)** **IV-FE**
ln(TRI)	0.394 (0.412)	0.689* (0.434)	2.200*** (0.583)	-0.257 (0.326)	0.727*	4.618*** (0.705)
ln(TRI)^2	-	-0.447** (0.215)	-1.174** (0.470)	-	-0.872***	-1.677*** (0.0501)
GDP	0.00337 (0.0388)	-0.0139 (0.0395)	-0.454 (0.738)	0.00466 (0.0292)	-0.0226	0.227*** (0.0146)
EXP	-0.0329 (0.0284)	-0.0347 (0.0283)	-0.249*** (0.0613)	-0.0356 (0.0282)	-0.0432	0.158*** (0.0119)
IMP	0.0232 (0.0349)	0.0184 (0.0348)	0.290 (0.794)	0.0224 (0.0338)	0.0189	0.0651*** (0.0149)
ln(TRI) × GDP	0.0789** (0.0349)	0.0943*** (0.0355)	0.268*** (0.0521)	0.0533 (0.0332)	0.0914***	0.0197 (0.0307)
ln(TRI) × EXP	0.0975*** (0.0206)	0.0849*** (0.0215)	0.302*** (0.0389)	0.0913*** (0.0207)	0.0705***	-0.532*** (0.0237)
ln(TRI) × IMP	-0.129*** (0.0237)	-0.116*** (0.0244)	-0.388*** (0.0502)	-0.113*** (0.0236)	-0.0959***	0.355*** (0.0260)
Constant	1.916*** (0.704)	2.740*** (0.806)	3.760*** (0.418)	-	-	-
Country FE	*Yes*	*Yes*	*No*	*Yes*	*Yes*	*No*
Year FE	*Yes*	*Yes*	*No*	*No*	*No*	*No*
Country × Year FE	*No*	*No*	*Yes*	*No*	*No*	*Yes*
Observations	576	576	576	576	576	576
Countries	32	32	32	32	32	32
R^2-within	0.181	0.188	0.172	0.106	0.142	0.999
F-statistic	4.78***	4.79***	4.88***	9.11***	11.13***	40.32***

	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Notes: OLS-FE stands for the OLS with fixed effects regressions. IV-FE is for the instrumental variable regression models. The numbers in parentheses and square brackets denote the standard errors and the p-values respectively. Instruments for the IV models (column 2 and 4) include the lagged set of the covariates. F-statistics are reported for OLS- FE and IV-FE regressions. Significant at ***1%, **5% and *10% respectively.

Both the linear influence of regulation on patents' activity and its squared coefficient estimate are statistically significant alternating their signs starting from positive (0689) to negative (-0.477). It is interesting to note that in the linear specification under the absence of country*year FE (see Column 1), there is a positive but not statistically significant (even at 10%) relationship between patents and regulation implying that a non-linear model better explains the correlations between the main variables. This findings is reinforced by the existence of statistically significant coefficient estimates for all the reported interaction terms (see Columns 2 and 3). Surprisingly, the rest of the covariates (GDP, EXP, IMP) do not expose a statistically significant relationship with the dependent variable (lnPAT). However, when we account for the quadratic specification with (see column 3) and without country * year FE (see column 2), we verify that the impact of squared regulation on innovation (proxied by the lnPAT) is significantly negative (2.2 and 0.689 respectively), while its linear term is also statistically significant and positive (-1.174 and 0.447 respectively).

We must stress though that estimating Eq. 8 with OLS may be problematic due to the fact that patent activity in the telecommunications sector can be endogenously affect the level of regulatory intensity in the sector. This may occur either for macroeconomic (i.e common trends across the OECD telecommunications sectors) or microeconomic reasons (e.g telecommunications demand conditions driven by other sectors). Similarly with other empirical studies (see for example Dagoumas and Polemis, 2019;

Papaioannou, 2017; Dai et al, 2014; Fabra and Requant, 2014), we address this concern of reverse causality, by adopting the instrumental variable (IV) approach and the 2SLS.

In the first stage, we predict the values of ln(TRI) and ln(TRI)^2 while in the second stage we perform the regressions by using the lagged once covariates as instruments (see Chen et al, 2018). In this case, we notice that without the inclusion of the quadratic term the effect of product market regulation (PMR) appears to be not statistically significant (see Column 4). However, if the effect of regulatory stringency on innovation exhibits a concave curve, its marginal effect will be positive before reaching a threshold and become negative afterward. This may result in an overall zero effect if we force a monotonic relationship (Dai et al, 2014; Chen et al, 2018). We notice though that with an inclusion of an additional quadratic term, the estimated effects of regulation on sector's patent activity become statistically significant and their estimate coefficients alternate their signs starting from positive to negative. Specifically, when we account for country FE only (see column 5) the relevant estimates of the linear and its squared term are statistically significant and equal to 0.727 and -0.872 respectively. This suggests a non-monotonic relationship in a form of an inverted U-shaped curve. The main difference here in relation to the previous OLS-FE specifications, is the positive and statistically significant coefficient estimate of the GDP variable (0.227), implying that as expected an increase (decrease) in the level of economic growth leads to an increase (decrease) of the level of patent activity expressed in natural logarithm.

All in all, we argue that our results are in alignment with other theoretical and empirical studies (see among others Arrow, 1962; Aghion et al, 2005; Van Reenen, 2011; Correa and Ornaghi, 2014; Polemis and Tzeremes, 2019) that give sufficient ground on the validity of an inverted U-shaped relationship between product market competition and innovation. We argue though that the decreasing part of the curve can be attributed to the fact that regulatory stringency increases post entry monopoly rents, eliminating the number of entrants in the medium term. This leads to a decrease in the level of effective competition, which in turn reduces the number of patents granted by the EPO in the telecommunications sector. On the contrary, in the increasing part of the curve, a strengthening of deregulation generates an "*escape competition effect*". This means that when deregulation prevails in the sector and firms do not differ substantially in terms of their technological level, a firm tries to innovate by increasing the number of patents granted to escape competition from the rival firms since profits from being a leader are higher than profits from being a follower (see Hashmi, 2013).

Moreover, our empirical findings differ significantly from the recent study of Papaioannou (2017) in which it is argued that a U shaped relationship is present between regulation and Information and Communication Technology (ICT) investment across eleven EU countries and the US. One reason for this discrepancy, might be attributed to the different specification of the model since we use extra covariates and not only regulatory index and its squared term. Another explanation for the different findings obtained in both studies arises from the different econometric technique that is used in each of them. Specifically, the study of Papaioannou (2017) uses a semiparametric regression approach where no assumption for the functional form between the sample variables is needed compared to our study. We must stress though, that the traditional semiparametric local polynomial smooth formulation treats the variables that enter the (unknown) nonlinear part of the model as nuisance variables. Therefore, it does not allow for the explicit estimation of the marginal effects of these non-linear components on the dependent variable (Robinson, 1988; Stengos and Liang, 2005). Lastly, the different dependent variable that was used in the other study (ICT investment compared to telecom patents) may also justify the different findings.

5.2 Threshold regression estimates

In this section, we portray the estimates of the threshold regression model (TR), where three logged regulatory stringency indexes (TRI, STRUCT and ENTRY) serve as threshold variables that classify the sample OECD countries into two regimes (i.e. regulatory and de-regulatory regime).[10]

However, before we proceed with the relevant estimates, we must first determine the number of thresholds (K) in each model since it is possible to obtain multiple sorting point estimates (see for example Hansen, 1999). The F-statistics, along with their bootstrap p-values, are presented in the following table. We observe that the null hypothesis of no single threshold (K=0) is rejected in all of the three models (see Table 7, Columns 1-3) since the bootstrap p-values are equal to zero.

Table 7: Threshold test results

Test for single threshold *Statistical Hypotheses:* H_0 *: No threshold (K=0)* H_1 *: At most one threshold (K=1)*	**(1)** **Threshold variable ln(TRI)**	**(2)** **Threshold variable ln(STRUCT)**	**(3)** **Threshold variable ln(ENTRY)**

[10] The estimations of all the threshold regression models were performed in STATA ver. 15 using the "xthreg" command developed by Wang, (2015).

Threshold estimate $\hat{\gamma}_1$	**0.9764** **(2.65)**	**1.3965** **(4.04)**	**1.0989** **(3.00)**
95% confidence interval	[0.9162 , 0.9789]	[1.2767 , 1.4370]	[0.8114 , 1.3220]
F-statistic	28.04**	27.10**	75.07***
Bootstrap P-value	0.0580	0.0300	0.0000
Test for double threshold *Statistical Hypotheses:* *H_0 : One threshold (K=1)* *H_1 : At most two thresholds (K=2)*	**Threshold variable ln(TRI)**	**Threshold variable ln(STRUCT)**	**Threshold variable ln(ENTRY)**
Threshold estimate $\hat{\gamma}_2$	**1.7441** **(5.720)**	**1.6330** **(5.119)**	**1.6584** **(5.250)**
95% confidence interval	[1.7140 , 1.7494]	[1.6314 , 1.6372]	[1.0636 , 1.1097]
F-statistic	10.41	4.10	6.15
Bootstrap P-value	0.3470	0.8980	0.2600

Notes: The trimming percentage is set to 0.02. 1000 bootstrap replications were used to obtain the p-values to test for the number of thresholds. The numbers in parentheses denote the absolute threshold value estimates. Significant at ***1%, **5% and *10% respectively.

On the contrary, the test for the second threshold is not statistically significant in any of the three models. As a consequence, we infer that there is only one threshold in all of the regression relationships. The sharp threshold point estimates ($\hat{\gamma}_1$) for the three models along with their 95% confidence intervals (CI) are also reported in the relevant table. More specifically, the threshold estimates range from 0.97 (Column 1) to 1.39 (Column 2). The interpretation of the overall regulatory index (TRI) threshold estimate ($\hat{\gamma}_1$) comes as follows:

a) The reported threshold (logged) value $\hat{\gamma}_1 = 0.9764$ for the single threshold splits the sample into two regimes.

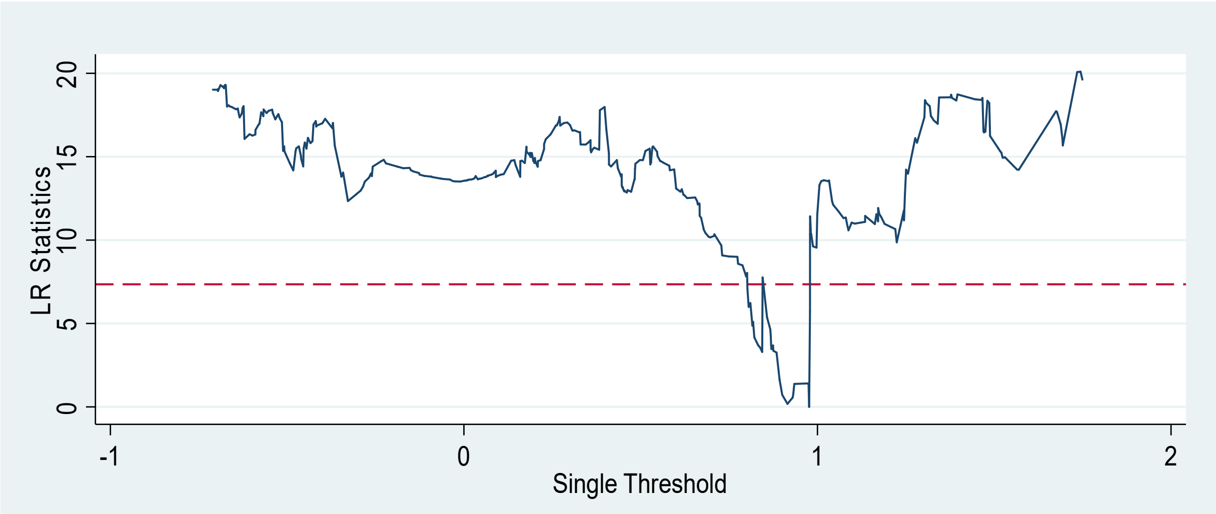
b) The first regime below the threshold ($\hat{\gamma}_1 \leq 0.9764$) captures the high levels of deregulation since it includes the sample countries where the TRI falls below the value of 2.65.[11]

c) The second regime above the threshold ($0.9764 < \hat{\gamma}_1$ or $2.65 < \hat{\gamma}_1$ in absolute levels) includes those OECD countries that are characterized by moderate and high levels of regulatory stringency.

More information about the threshold estimates can be obtained from plots of the confidence interval using likelihood ratio (LR) statistics (see Figure 3). Specifically, the point estimates are the value of γ at which the LR equals zero (see Hansen, 1999). From the inspection of the relevant figure, we observe that the (first-step) threshold estimate is the point where the $LR_1(\gamma)$ equals zero, which occurs at $\hat{\gamma}_1$ = 0.9764. Since there is not a statistically significant second major dip in the LR function around the second-step estimate of $\hat{\gamma}_2$ = 1.7441, we argue that the single threshold likelihood conveys information revealing that there is only one threshold in the regression.

Figure 3: Confidence interval construction in (single) threshold model

[11] Since we express the threshold variable in natural logarithm (lnTRI), the antilogarithmic or absolute value of threshold parameter can be simply estimated as: $2.718^{0.9764} = 2.65$



Notes: The figure portrays the LR confidence interval in the single threshold model. The dotted red line denotes the critical value (7.35) at the 95% confidence level.

It must be noted though, that testing a non-monotonic inverted-U shape relationship between innovation and regulation using country-level data raises important empirical difficulties (Aghion et al, 2019).

First, one significant issue is the sharp estimation of the turning point of this relationship. One simpler but not accurate way is to resort either to non-linear terms (i.e. quadratic terms of the regulation index) or to a non/semi-parametric specification using local smoothers or splines. However, as suggested by Polemis and Stengos, (2019) "*such methods involve bandwidth choices, and they do not lend themselves to estimating sharp turning points/thresholds as it is the case in the threshold model"*. To solve this difficulty, we rely on the estimation of a static panel threshold model with FE firstly introduced by Hansen (1999) and later developed by Hansen, (2000), Bick, (2010) and Kourtellos et al., (2016). The adopted threshold model avoids the ad hoc, subjective pre-selection of threshold values, since it uses LM tests for the presence of such a threshold and then estimates it (see Christie, 2014; Hansen, 2000; Kourtellos et al., 2016).

Second, we need to deal with the endogeneity of the regulatory stringency in our empirical setting. As mentioned before endogeneity may arise from omitted variable bias or reverse causality, and prevents us from arguing in favour of a causal effect (Aghion et al, 2019). Similarly to other studies (see Polemis and Stengos, 2017; Polemis and Stengos, 2019), we attempted to address the presence of a possible endogeneity of the regulatory variable (lnTRI) by using the lagged ln(TRI) as the regime-dependent (threshold) variable. It is noteworthy that our empirical results remained relatively robust. As a consequence, we argue that the issue of endogeneity is not as severe in our case.[12]

Having properly addressed the above estimation problems, and after defining the appropriate number of thresholds, we proceed with the discussion of results generated by the single threshold model that will be contrasted with the baseline parametric estimates. Table 7 presents the results for the empirical relationship between the (logged) regulatory stringency and its main drivers under the two classes (deregulated and regulated regime). The empirical estimates are presented for both specifications, i.e. without (column 1) and with (column 2) time dummies (year FE).[13]

The main variable of interest is the level of regulatory stringency measured by the logged values of the overall OECD regulatory index (lnTRI). As it is evident, the most striking point is that in absence of time FE (see Column 1), regulatory stringency above the threshold of 2.65 incurs a significant negative effect (-1.155) on innovation on the 5% significance level, while the positive impact (0.136) below the threshold of 2.65 (deregulated countries) is not statistically significant at all.

[12] The results are available upon request.

[13] The results remain fairly robust after the inclusion of country*year FE. To conserve space this set of results is available upon request.

It is evident that the TRI index is more important in the sample above the threshold (regulated regime) than below it. This means that a 10% increase in the level of regulatory stringency leads to slightly higher decrease (11.5%) in the patent activity of the telecommunications sector. This finding concurs that for highly regulated OECD countries the level of regulatory stringency does affect negatively the innovation output of the sector. In contrast, allowing for time FE reduces the magnitude of the estimates (0.0730, −0.911) and establishes significance on the 1% level of the marginal impacts of regulation on patents in both regimes. Surprisingly, the regime-independent regressors although in general plausibly signed (GDP, EXP and IMP) are not statistically significant in both specifications (with and without year FE) even at 10%.

Table 8: Threshold regression estimates

Coefficient estimates: $\ln PAT_{it} = \mu_i + \beta_1' x_{it} I(\ln TRI_{it} \leq \gamma) + \beta_2' x_{it} I(\ln TRI_{it} > \gamma) + \varepsilon_{it}$	**(1) Without year FE**	**(2) With year FE**
Regime-dependent regressor		
$\hat{\beta}_1$	***0.136*** ***(0.365)***	***0.0730****** ***(0.0048)***
$\hat{\beta}_2$	***-1.155***** ***(0.445)***	***-0.911****** ***(0.0559)***
Regime-independent regressors		
GDP	-0.000874 (0.0283)	0.0159 (0.0406)
EXP	-0.0342 (0.0448)	-0.0539 (0.0544)
IMP	0.00267 (0.0353)	0.0205 (0.0417)
Constant	4.432*** (1.128)	3.460** (1.489)
Country FE	Yes	Yes
Observations	576	576
Countries	32	32
R^2-within	0.112	0.151
F-statistic	3.63** [0.0106]	2.39** [0.0129]

Shape of the curve	***Nonlinear / Inverted V***	***Nonlinear / Inverted V***
Threshold estimate $\hat{\gamma}$ (turning point)	***0.9764 (Logged value)*** ***2.65 (Absolute value)***	***0.9764 (Logged value)*** ***2.65 (Absolute value)***

Notes: Standard errors are given in parentheses. The regime-dependent variable is the threshold variable (lnTRI). The numbers in square brackets denote the p-values. Similarly to Hansen (1999), each regime has to contain at least 5% of all observations. The trimming percentage is set to 0.02 and the Bootstrap replications are set to 1000. By construction, the confidence intervals for the threshold estimates can be highly asymmetric. Significant at ***1%, **5% and *10% respectively.

These results are in alignment with the study of Marino et al, (2019) who also argue that an inverted U shaped relationship between regulation intensity and innovation exists in the OECD electricity sector. However, our study departs significantly from the empirical findings of Prieger (2002) and Cette et al, (2017) who argue that there is a negative monotonic relationship between upstream product market regulation and innovation/productivity growth for most of the OECD countries. Their findings indicate that increased (decreased) regulatory stringency in a sector tends to decrease (increase) the innovation (productivity) growth, revealing that the less competitive is a sector the less profound is its innovation intensity. Our findings of an inverted-V relationship between regulation and innovation can be compared with the influential study of Aghion et al, (2005) in which it is a argued that a non-linear (concave) pattern between competition and innovation prevails.

Lastly, from the careful inspection of Table 4, some interesting remarks emerge. First, keeping regulation below the threshold has a marginally but statistically significant effect (see Column 2). Second, the impact for regulatory stringency above the threshold turns highly significant at 1% level of significance but decreased in absolute level (-0.911 compared to -1.155). Third, the absolute threshold estimated value is very close to the real average value of regulatory stringency over the turning point (1999) of the curve as illustrated in Figure 2 (2.65 compared to 2.87). This finding further justifies the inverted-V shaped relationship between innovation activity and regulatory intensity.

5.3 Robustness checks

In this section we perform several checks to sharpen the robustness of our empirical findings. Firstly, we re-estimate our benchmark model which is accordingly adjusted for the presence of two different components of the TRI index accounting for market structure (STRUCT) and entry conditions (ENTRY) respectively. Similarly to other empirical studies (see for example Marino et al, 2019; Polemis and Stengos, 2017), we run the model specification described by Eq. 12 replacing the TRI variable with its two components (STRUCT and ENTRY). We mention though that market structure regulation reveal the concentration conditions of the telecommunications sector and henceforth is an indirect measure of its competitiveness while entry regulation component refers to market contestability (Marino et al, 2019). Secondly, we use the two regulatory components as threshold variables instead of the overall regulatory index (TRI) to test the stability of the TR model and investigate possible discrepancies.

Table 9 reports the estimates by regulatory component. As it is evident, the empirical findings when market structure regulation (STRUCT) is taken into account do not reveal significant differences compared to the TRI regulatory index (see Columns 1-4). Specifically, the parametric results exhibit an inverted U shaped curve between upstream regulation and patent intensity since the relevant estimates alternate their signs from positive to negative (see Columns 2 and 4). The magnitude of the estimates are much larger in this case, implying that market concentration seems to be the main driver resulting to a change in the firms' incentive to innovate after a significant regulatory reform (Marino et al, 2019). Moreover, nearly all of the interaction terms remain statistically significant as in the previous benchmark model suggesting a non-linear relationship among the main variables of interest. Therefore, we argue that when a different regulatory index (STRUCT) enters the benchmark model the empirical findings do not reveal significant discrepancies implying that the results are robust.

However, when we account for the other regulatory index (ENTRY) a different picture emerges. As it is evident from the quadratic specifications (see Columns 6-8), the relationship between regulation and innovation remains non-linear although not of an inverted U shaped form (e.g. negative polynomial coefficients).

Table 9: Alternative parametric regression estimates

Dependent variable: ln(PAT)	**(1)** **OLS-FE**	**(2)** **OLS-FE**	**(3)** **IV-FE**	**(4)** **IV-FE**	**(5)** **OLS-FE**	**(6)** **OLS-FE**	**(7)** **IV-FE**	**(8)** **IV-FE**
ln(STRUCT)	0.569 (0.651)	3.553*** (1.176)	-0.509 (0.497)	3.321*** (0.970)	-	-	-	-
ln(STRUCT)^2	-	-1.573*** (0.518)	-	-2.095*** (0.459)	-	-	-	-
ln(ENTRY)	-	-	-	-	-0.00305 (0.0611)	-0.882*** (0.251)	-0.0805 (0.0536)	-1.274*** (0.200)
ln(ENTRY)^2	-	-	-	-	-	-0.144*** (0.0398)	-	-0.209*** (0.0338)
GDP	0.0276 (0.0650)	-0.0255 (0.0669)	0.0281 (0.0503)	-0.0481 (0.0522)	0.0491 (0.0430)	0.0371 (0.0425)	0.0130 (0.0399)	0.0252 (0.0386)
EXP	-0.133*** (0.0367)	-0.126*** (0.0365)	-0.128*** (0.0364)	-0.127*** (0.0357)	0.0896*** (0.0282)	0.0657** (0.0286)	0.0707** (0.0298)	0.0271 (0.0296)
IMP	0.148*** (0.0463)	0.130*** (0.0464)	0.129*** (0.0446)	0.125*** (0.0438)	-0.133*** (0.0324)	-0.114*** (0.0325)	-0.0801** (0.0330)	-0.0700** (0.0320)
ln(STRUCT) × GDP	0.0216 (0.0636)	0.0656 (0.0648)	0.000128 (0.0585)	0.0639 (0.0591)	-	-	-	-
ln(STRUCT) × EXP	0.180*** (0.0310)	0.166*** (0.0311)	0.155*** (0.0305)	0.149*** (0.0300)	-	-	-	-
ln(STRUCT) × IMP	-0.222*** (0.0372)	-0.200*** (0.0376)	-0.184*** (0.0365)	-0.169*** (0.0360)	-	-	-	-
ln(ENTRY) × GDP	-	-	-	-	0.00862 (0.00739)	0.00856 (0.00729)	0.00520 (0.00680)	0.00755 (0.00658)
ln(ENTRY) × EXP	-	-	-	-	0.0138*** (0.00328)	0.0108*** (0.00335)	0.0142*** (0.00326)	0.00984*** (0.00323)
ln(ENTRY) × IMP	-	-	-	-	-0.0164*** (0.00398)	-0.0131*** (0.00404)	-0.0156*** (0.00392)	-0.0120*** (0.00383)

Constant	1.626* (0.974)	0.756 (1.008)	-	-	2.383*** (0.733)	4.219*** (0.896)	-	-
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No	Yes	Yes	No	No
Observations	576	576	576	576	576	576	576	576
Countries	32	32	32	32	32	32	32	32
R^2-within	0.187	0.202	0.124	0.156		0.174	0.074	0.135
F-statistic/Wald chi2	5.00*** [0.000]	5.25*** [0.000]	10.82*** [0.000]	12.38*** [0.000]	99.57*** [0.000]	114.89*** [0.000]	6.16*** [0.000]	10.48*** [0.000]

Notes: OLS-FE stands for the OLS with fixed effects regressions. IV-FE is for the instrumental variable regression models. The numbers in parentheses and square brackets denote the standard errors and the p-values respectively. Instruments for the IV models (column 2 and 4) include the lagged set of the covariates. F-statistics are reported for OLS- FE and IV-FE regressions. Wald Chi-2 are reported for OLS-FE regressions. Significant at ***1%, **5% and *10% respectively.

The analysis now turns to the TR estimates generated by the inclusion of the two alternative regulatory measures. As it becomes clear, when market structure regulation (see Column 1) serves as the threshold variable, we notice that the relevant estimate (along with its CI) is larger in its magnitude than before (4.04 compared to 2.65). We notice though that this estimate is even larger than the average scale value (3 out of 6) revealing a right tail distribution. In other words, the TR model splits the sample into two regimes accounting for the heavily regulated countries (above the threshold) and the rest (below the threshold). The former includes those OECD countries with significant market concentration that are characterised by low levels of competitiveness in the telecommunications sector. It is also evident that the inverted-V shaped curve is also evident here, since the coefficient below the threshold $\hat{\beta}_1$ is positive (0.963), while the estimate above the threshold $\hat{\beta}_2$ is of the opposite sign (-0.299).

Moreover, when the market structure index of the average OECD country falls below the threshold, a 10% increase in regulatory intensity, will enhance innovation activity by a slightly lower rate of 9.6%. However, if the average country is above the threshold then a 10% increase in regulatory stringency will decrease innovation only by 3% approximately. Hence, the impact of regulatory intensity expressed by the market structure index (STRUCT) on innovation is larger quantitatively when it is below than above the estimated threshold. This finding is also evident in other threshold studies (see for example Asimakopoulos and Karavias, 2016; and Polemis and Stengos, 2019).

Table 10: Alternative threshold regression estimates

Coefficient estimates	**(1) Threshold variable ln(STRUCT)**	**(2) Threshold variable ln(ENTRY)**
Regime-dependent regressor		
$\hat{\beta}_1$	***0.963****** ***(0.256)***	***0.0123****** ***(0.0032)***
$\hat{\beta}_2$	***-0.299****** ***(0.094)***	***-1.283****** ***(0.413)***
Regime-independent regressors		
GDP	0.0226 (0.0383)	0.0154 (0.0355)
EXP	-0.0639 (0.0540)	-0.0631 (0.0552)
IMP	0.0225 (0.0451)	0.0133 (0.0445)
Constant	2.551 (2.055)	4.310*** (1.410)
Country FE	*Yes*	*Yes*
Year FE	*Yes*	*Yes*
Observations	576	576
Countries	32	32
R^2-within	0.165	0.190
F-statistic	12.50***	14.96***

	[0.000]	[0.000]
Shape of the curve	***Non linear / Inverted V***	***Non linear / Inverted V***
Threshold estimate $\hat{\gamma}$ (turning point)	***1.3965 (Logged value)*** ***4.04 (Absolute value)***	***1.0989 (Logged value)*** ***3.0 (Absolute value)***

Notes: Standard errors are given in parentheses. The numbers in square brackets denote the p-values. The trimming percentage is set to 0.02 and the Bootstrap replications are set to 1000. The regime dependent variable and the threshold variable is the natural logarithm of the regulatory index for telecoms (TRI) Significant at ***1%, **5% and *10% respectively.

Similar findings hold in the case of entry regulation (see Column 2). From the inspection of Table 10, we argue that an inverted-V shaped curve between regulation and innovation is also evident here since the coefficient estimates of the regime-dependent regressor (threshold variable) alternative their signs starting from positive (0.0123) to negative (-1.283), while they are both statistically significant at 1% level of significance.

However, in contrast with the previous regulatory component (STRUCT), we notice that the effect of regulatory stringency on patents is larger in its magnitude when it is above than below the estimated absolute threshold (3.0). Specifically, if the average country is above the threshold then a 10% increase in regulatory stringency will decrease innovation by a higher percentage equal to 12.8%. On the contrary, when the entry regulatory index of the average country is below the threshold, a 10% increase in regulatory intensity, will increase innovation by a negligible effect equal to 0.12%. The other coefficient estimates (regime-independent regressors), although properly signed are not statistically significant even at 10% significance level.

Lastly, our threshold estimated values are very close with the ones reported in the most related contribution with our work (see Papaioannou, 2017). In this study, it is argued that the relationship between PMR and ICT diffusion has a U-shaped form. However, the “*turning*” points of the overall weighted regulatory index (TRI) and the weighted entry regulation (ENTRY) are approximately 2.5 and 3.1 compared with the ones reported in our study (2.65 and 3.0 respectively).

6. Conclusions and policy implications

Effective regulation of telecommunications sector plays a crucial role in the political and economic agenda for both developed and developing OECD countries. A carefully designed regulatory scheme is also expected, to be a cornerstone of a successful and innovative telecommunications performance.

We attempt to shed light on this relationship by theoretically modeling the telecommunications sector, in which access regulation impacts the non-separable activity in process and product innovation. We then empirically test our model by deploying an efficient panel threshold technique along the lines of Hansen (1999). Our balanced panel dataset comprises of 32 OECD countries over the period 1995-2012.

We find strong theoretical and empirical evidence of the existence of an inverted "V-shaped" relationship between regulatory stringency and innovation in the telecommunications sector. We are the first to unravel a statistically significant relationship between regulatory stringency and innovation for both above and below the optimal level of regulatory intensity.

We argue that a further increase in regulatory intensity, stimulates an asymmetric effect on sector’s innovation across the two regimes (high and low levels of deregulation) leaving no doubt that regulatory environment shapes the nexus between deregulation and innovation. Specifically, this effect is positive in OECD countries that, on average, have experienced a drastic regulatory reform (below the threshold) and negative in those countries who have experienced a relatively weak liberalization process (above the threshold).

Our findings survive robustness checks after the inclusion of two alternative threshold variables (market structure and entry regulation) incurring significant implications for the policy makers and government officials.

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