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

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Abstract

Whether innovation is spurred by more stringent regulation or more extensive deregulation constitutes a long-lasting debate among the economists and policy makers. We attempt to exemplify and elaborate on this relationship by theoretically modeling the upstream telecommunications market where access regulation impacts the non-separable activity in process and product innovation. We find that although the impact of regulation intensity on innovation activity is *a priori* ambiguous, an "*inverted U-shaped*" relationship arises when correlating the evolution of the telecommunications sector with the ease of transforming non-separable activities into each type of innovation. We then empirically test the unveiled non-monotonic relationship by deploying an efficient panel threshold model. Our balanced panel dataset comprises of 32 OECD countries over the period 1995-2012. The empirical results unveil that beyond a certain threshold, further increasing the (de)regulatory intensity negatively affects sector innovation. This means that the empirical and theoretical findings well explain the descriptive evidence of an inverted U-shaped relationship between regulation and innovation activity in the OECD telecommunications sector. Our findings survive robustness checks after the inclusion of two alternative threshold variables (market structure and entry regulation) incurring significant policy implications.

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1. Introduction

In many network industries, such as electricity 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 obvious that regulation dictates the intensity of competition, which in turn determines the market performance in terms of static and dynamic efficiency. Although it is widely acknowledged that perfectly competitive markets achieve static efficiency, the impact of competition intensity on firms' incentives to innovate 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. Schumpeter (1942) argues that innovation activity is positively correlated with large firms and market power since competition stifles innovation profits. On the other hand, Arrow (1962) points out that market power induces firms to protect the status quo, thus discourages them from engaging in developing costly disruptive technologies. 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.[†]

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.

In this paper, we introduce the novel theory of non-separable activity in process innovation (which reflects a cost-reducing activity) and product innovation (which reflects a quality-upgrading activity) into a simple theoretical framework in order to explain the time-evolving relationship between regulation and innovation in the telecommunications sector. We find 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 interpretation of this finding based on the evolution of the telecommunications sector unveils an inverted V-shaped relationship between regulation and innovation.

Afterwards, 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. To the best of our knowledge, this is the first attempt to unravel a

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

statistically significant relationship between regulatory stringency and innovation for both above and below the optimal level of regulatory intensity in terms of innovation incentives.

For this reason, we rely on a suitable econometric methodology along the lines of Hansen (1999) to precisely estimate the threshold parameter, which is arbitrarily given in most studies (see, for instance, Marino et al., 2019; Papaioannou, 2017). The theoretical and empirical findings well explain the descriptive evidence of an inverted U-shaped relationship between regulation and innovation activity in the OECD telecommunications sector.

The rest of this paper proceeds as follows. Section 2 describes the deregulatory and innovation process in the OECD telecommunications sector. Section 3 builds the theoretical model, while Section 4 presents the data and the empirical methodology. Section 5 discusses the empirical findings and performs the necessary robustness checks. Finally, Section 6 concludes the paper and draws some policy implications.

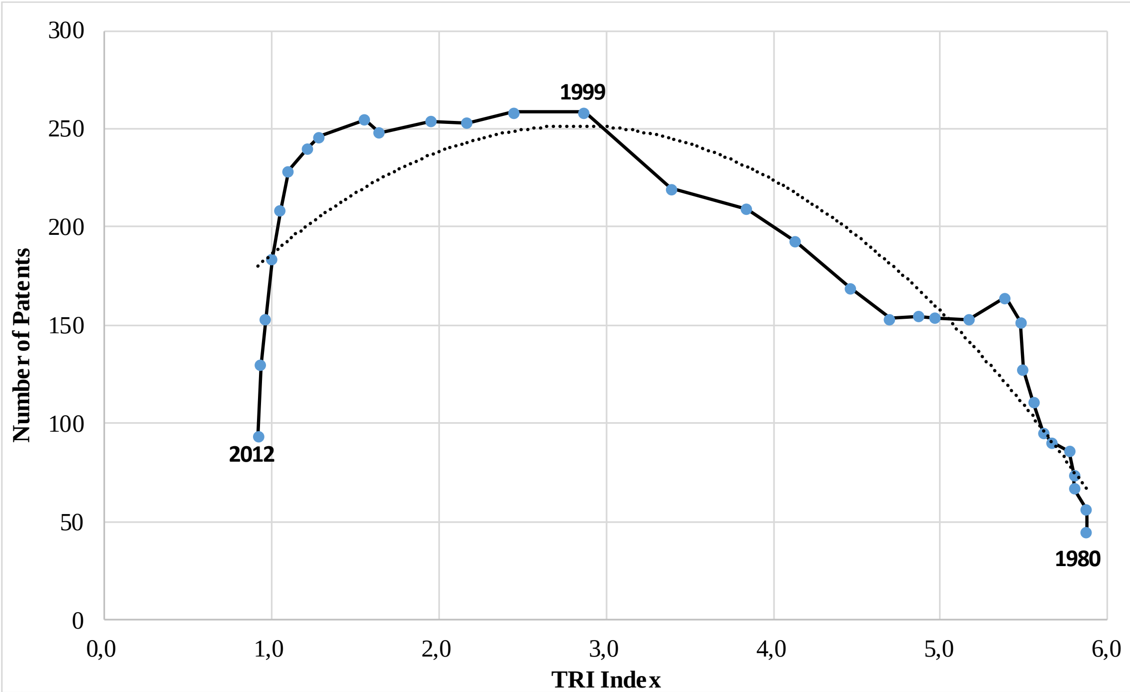
2. Regulation and innovation in the OECD telecommunications sector

The telecommunications sector in the OECD countries has undergone substantial regulatory and institutional reforms towards establishing effective competition in sectors previously monopolized by state-owned "*incumbent*" operators. However, the absence of competition and the imposition of rate-of-return regulation were deterring factors for undertaking costly innovation initiatives.

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 static efficiency (Peitz, 2003). Although there is an indisputable positive effect of less strict regulation on competition intensity, its impact on firms' innovation activity is quite ambiguous.

Figure 1 correlates the average level of the Telecommunications Regulation Index (TRI), scaled from least (0) to most stringent regulation (6), with the average number of telecommunications-related patent grants to the European Patent Office (EPO) in a yearly basis from 1980 to 2012. Despite some limitations such as secrecy, lead time, comparison deficiencies that are raised when patents are used as proxy for innovation activity, they are regarded by the existing literature as reliable and efficient measure of innovation (Marino et al., 2019; Drivas et al., 2017; Blind, 2012; Bercovitz and Feldman, 2007).

Figure 1: Patent grants and regulatory stringency in the OECD telecommunications sector (1980-2012).



Source: OECD TRI Data Regulation and OECD Patent Grants

From the inspection of Figure 1, we can deduce that the trend (dashed) line reveals an inverted-U relationship between regulation and innovation in the OECD telecommunications sector proxied by the patent activity. 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 analyze the evolution of the OECD telecommunications market during the examined period.

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 schemes, such as price-cap regulation. Ai and Sappington (2002) find that such changes lead to an increase in process innovation.

During the second wave of deregulation, governments authorized entry by alternative operators, the so-called "*new entrants*", and the provision of new services into 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 telecom firms to invest in product innovation.

The positive relationship between less strict regulation and innovation was prevailing until the late 1990s. Most OECD countries fully liberalized the telecommunications market in 1998 (third wave of deregulation), while continuing to withdraw regulatory restrictions with the goal of further increasing competition.[‡] The promotion of service-based competition was achieved by mandating incumbents to unbundle their local loops (LLU) from their overall core facilities and downstream operations in order to allow for commercial wholesale supply of this upstream input (De bijl and Peitz, 2004).

However, just one year after the full liberalization, firms started to decrease their innovation rate as a reaction to the increased competition level. As the regulated LLU prices were moving towards the cost of providing the access, with the goal of cancelling any advantage of the vertically integrated firms, the innovation incentives of both incumbents and entrants were decreasing.[§] Hence, 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 has therefore been 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; Amable et al., 2016).

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.

The estimation of the optimal degree of regulatory intensity in terms of innovation activity 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 well describes the evolving relationship between regulation and innovation in the telecommunications market.

[‡] Figure A.1 in the Appendix proves that all OECD countries (except US) have decreased the regulatory restrictions imposed to the telecommunications sector during the third wave of deregulation. However, the rate of deregulatory process varies significantly among countries due to the differences in the timing of entry liberalization in each of the three telecommunications market segments (see Table A.1 in the Appendix).

[§] Cambini and Jiang (2009) and Tselekounis et al. (2014) provide an extensive review of the literature on the relationship between regulation and innovation in the liberalized telecommunications sector.

3. Theoretical Framework

In this section, we present a theoretical modeling setup which captures the relationship between regulation and innovation in the telecommunications market. We then characterize the equilibrium of the game which is solved backwards. Last, we discuss the impact of regulation on innovation activity based on the main findings of our analysis.

3.1. 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 (Cabral, 2017).

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.[**] 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.

3.2. 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*: [††]

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

and

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

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 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

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

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

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

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 taking its first-order condition with respect to δ, gives the level of innovation activity that maximizes the profit of the incumbent:

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

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.

3.3. The impact of regulation

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 input price regulation on the overall innovation activity from a theoretical perspective.

Interestingly enough, the impact of input price 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 input price 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 input price regulation and innovation activity can be used to explain the evolution of the average number of telecommunications-related patent grants in the OECD countries. The deregulation process described in Section 2 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 can serve as a proxy of regulatory stringency.

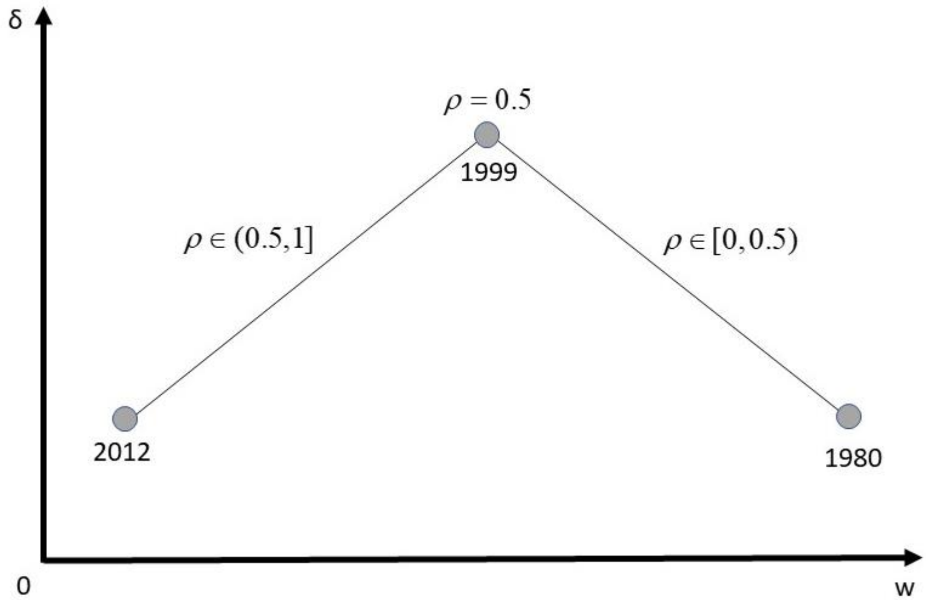
As we have discussed in the previous section, in the early stages of market deregulation most innovation activities undertaken by the incumbents could be more easily transformed into cost-reducing rather than quality-enhancing innovations due to their cost inefficiency. This liberalization period is 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, 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 or to enhance the quality of its upstream input, whereas the entrant prefers to free-ride on the incumbents' networks (Valletti, 2003) .

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 (see Figure 2). This non-monotonic 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.

Figure 2: The time-evolving impact of regulatory intensity (w) on innovation activity (δ)



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 we use, while providing and analyzing the descriptive statistics for the sample variables. Moreover, we discuss and analyze 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 sample variables

We use a yearly balanced panel data set for 32 OECD countries over the period 1995 to 2012 as appeared in Figure 1. The reason we restrict our sample to this time span is 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.

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.[‡‡] The data for this variable are publicly available from the OECD patent database.[§§]

To capture the effect of regulatory intensity on innovation, we used three measures of upstream product market regulation.[***] Firstly, we used the overall regulatory index of the sector (TRI) as our main regime-dependent variable (threshold variable). We also used two other measures, 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) respectively, in the specific sector.

All the above 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 is attributed to the fact that these indices "[…] *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; Amamble et al, 2016).

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; and 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.[†††]. Table 1 presents the descriptive statistics of the sample variables.

[‡‡] 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.

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

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

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

Table 1: Summary statistics

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 (Pesaran 2015).

Table 2: 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%.

For this reason, we use the cross-section dependence test (CD test) developed by Pesaran (2004). As it is evident from Table 2, 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: 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.

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. 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).

Having identified the order of integration in the model variables, we proceed with the panel cointegration testing. 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 results of the tests are presented in Table 4. 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 4: 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, which will be contrasted with the threshold model (TR) described below, takes the following form:

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

where logged patent intensity (lnPAT) of country *i* in time *t* is regressed on the logged value of upstream product market regulation expressed in levels (lnTRI) and its squared (non-linear) term $(\ln TRI)^2$. 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. 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[‡‡‡]

The TR model is expressed by the following equations:

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

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

These equations describe the relationship between the variables of interest in each of the two regimes (high and low deregulation), while q_t stands for the threshold variable with γ being the unknown sample split (threshold) value that needs to be estimated. The threshold variable could be an element of x_t^T, the k-dimensional vector of exogenous regressors (Hansen, 1999; 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 $d_t(\gamma) = I(q_t \le \gamma)$, 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: $\beta_1 = \beta_2$. Based on the above, our threshold model takes the following algebraic form:

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

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

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

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 estimates

Table 5 presents the results from the benchmark parametric (linear and quadratic) regressions. As it is observed, the estimates presented in the second column of Table 2 give a strong evidence for the existence of a hump-shaped relationship (inverted U-shaped curvature) between patents and regulatory stringency across countries: $\hat{a}_1 > 0$, $\hat{a}_2 < 0$, and $TRI^* = -\frac{\hat{a}_1}{2\hat{a}_2}$.[§§§] Both the linear influence of regulation on patent 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 finding 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).

[§§§] TRI^* denotes the optimal regulatory level. These are the sufficient conditions for strict concavity, implying that the first (linear) and second order (quadratic) coefficients alternate their signs from positive to negative. The relevant conditions ensure also that the optimal regulatory level (TRI^*) falls within the domain of regulatory stringency (TRI^{min}, TRI^{max}) observed in the panel sample (Ashraf and Michalopoulos, 2015).

Table 5: 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*
Optimal regulatory level	-	2,16*** (0.745)	2,55*** (0.647)	-	1,52*** (0.436)	3,96*** (0.987)
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*** [0.000]	4.79*** [0.000]	4.88*** [0.000]	9.11*** [0.000]	11.13*** [0.000]	40.32*** [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.

We notice that the first and second order coefficients on regulatory intensity are both statistically significant at least at the 10% level of significance and possess their expected signs (positive and negative). Specifically, the coefficients of interest imply that the optimal level of regulatory stringency for the innovation intensity ranges from 2.16 to

2.55 in absolute terms.[****] Similarly to Ashraf and Michalopoulos (2015), the overall metric effect of a Δ(TRI) change in regulatory stringency at the level $\overline{TRI}$ is given by $\Delta REG = \hat{a}_1 \Delta TRI + \hat{a}_2 (2\overline{TRI} + \Delta TRI)\Delta TRI$. In other words, evaluating this equation at the optimum regulatory level for a one metric change in regulatory index, that is, setting ΔTRI = 1 and $TRI = -\frac{\hat{a}_1}{2\hat{a}_2}$, we expect that patent activity will be affected by 1.56 and 3.24 units respectively.[††††]

We should 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 (for example, Papaioannou, 2017; Dai et al, 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. In this case, we notice that without the inclusion of the quadratic term the effect of product market regulation (PMR) appears statistically insignificant (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).

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. Similarly to the FE estimates (see Columns 2 and 3), we argue that the linear and the non-linear (quadratic) coefficients on regulatory stringency are both statistically significant alternating their signs ($\hat{a}_1$>0 and $\hat{a}_2$<0).

In particular, we notice that the optimal regulatory level in this case is characterised by a wider statistically significant confidence interval since it ranges from

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[****] Since the regulation variable is expressed in natural logarithm (lnTRI), the antilogarithmic or absolute value of the coefficients can be simply estimated as $2.718^{0.771} = 2.16$ and $2.718^{0.937} = 2.55$ respectively.

[††††] These values denote the antilogarithmic estimates of the logged metric effect which are calculated as follows: $2.718^{0.447} = 1.56$ and $2.718^{1.174} = 3.24$ respectively.

1.52 to 3.96 expressed in absolute terms. It is worth mentioning that the overall metric effect implied by these estimated coefficients denotes that a 10% percent increase in the level of regulatory index (TRI) is associated with a decrease of the innovation activity by approximately 24% and 53.5% respectively.

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; Correa and Ornaghi, 2014) that give sufficient ground on the validity of an inverted U-shaped relationship between product market competition and innovation. To summarize, the empirical results postulated in Table 6, we argue that the significant hump-shaped effect of upstream product market regulation on the patent adoption of the telecommunications sector does not constitute a spurious relationship but one that can be explained by the proposed theoretical model.

The decreasing part of the curve can be attributed to the fact that regulatory stringency increases post entry monopoly rents, thus 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 (Hashmi, 2013).

Moreover, our empirical findings differ significantly from the recent study of Papaioannou (2017) who argues 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, contrary to our study, Papaioannou (2017) uses a semiparametric regression approach where no assumption for the functional form between the sample variables is needed.

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

Before proceeding with the threshold estimates, we should first determine the number of thresholds (K) in each model since it is possible to obtain multiple sorting point estimates (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 6, Columns 1-3) since the bootstrap p-values are equal to zero.

Table 6: Threshold test results

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

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

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:

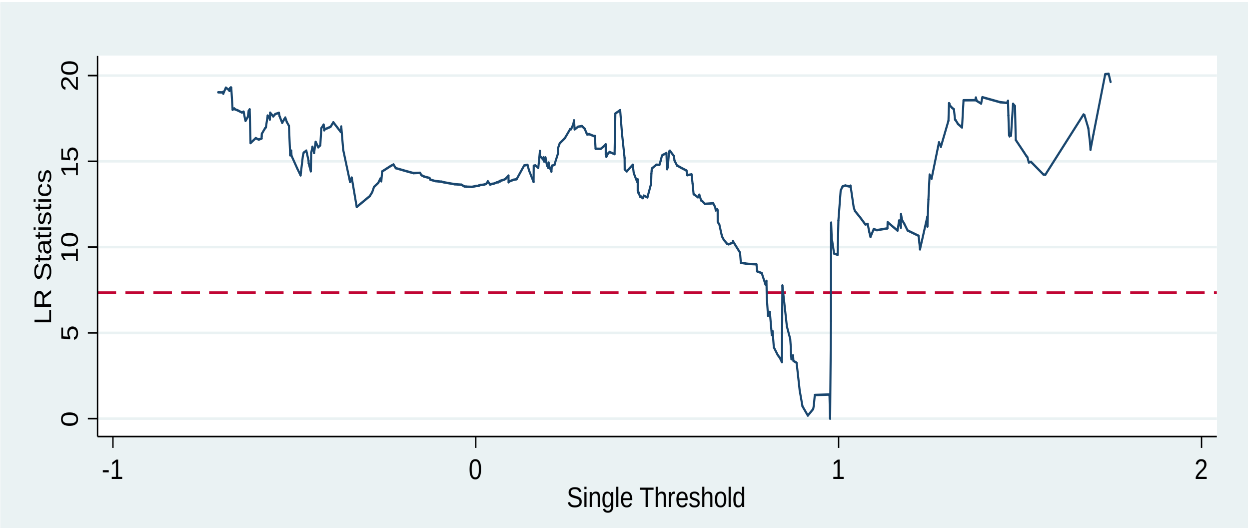
a) The reported threshold (logged) value $\hat{\gamma}_1$= 0.9764 for the single threshold splits the sample into two regimes.

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.[§§§§]

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 (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



[§§§§] As explained before, 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 should be noted though, that testing a non-monotonic inverted-U shape relationship between innovation and regulation using country-level data raises important empirical difficulties.

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 (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 (Polemis and Stengos, 2017), 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.[*****]

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).[†††††]

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.

[*****] The results are available upon request.

[†††††] 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 7: Threshold regression estimates

Coefficient estimates: $\ln PAT_{it} = \mu_i + \beta_1' x_{it} I(\ln TRI_{it} \le \gamma) + \beta_2' x_{it} I(\ln TRI_{it} > \gamma) + \varepsilon_{it}$	**(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 U***	***Nonlinear / Inverted U***
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 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-U 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 8, 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-U 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. In particular, 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.

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 Appendix-Table A.2). 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.

The analysis now turns to the TR estimates generated by the inclusion of the two alternative regulatory measures (see Table 8). 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-U 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.

Similar findings hold in the case of entry regulation (see Column 2). From the inspection of Table 9, we argue that an inverted-U 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.

Table 8: 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*** [0.000]	14.96*** [0.000]
Shape of the curve	***Non linear / Inverted U***	***Non linear / Inverted U***
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.

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 to the ones reported in the most related literature (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

This study lends support to the existence of an inverted "*U-shaped*" relationship between regulation 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 in terms of innovation incentives.

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, "*reguvation*" emerges in OECD countries that, on average, have experienced a drastic regulatory reform (below the threshold) and "*dennovation*" arises in those countries which have experienced a relatively weak liberalization process (above the threshold).

We argue that when regulators implement a deregulatory process, they should pay much more attention to the policies reducing the entry barriers than to the policies affecting the market concentration. The reason is that when a country has undergone a relatively weak liberalization process, the main driver for innovation is the reduction of entry barriers; and when a major reform has been implemented, a further reduction of entry barriers provides firms with less disincentives to innovate than further decreasing the market concentration. Therefore, the deregulatory process should be mainly implemented by gradually increasing the degree of market contestability.

Finally, we verify that the common trade-off between static and dynamic efficiency arises once the liberalization process has been sufficiently extensive. This means that the benefits of increasing competition come at the cost of lower innovation activity. In such cases, regulators should develop mechanisms that foster innovation without much affecting the intensity of market competition. For instance, providing greater regulatory certainty by clarifying the remedies that will be imposed during the economic lifetime of a successful innovation increases the incentives to innovate without much affecting the degree of competition. Indeed, when regulators can make *ex-ante* credible commitments, firms can assess their future revenues and thus make optimal innovation decisions based on a predictable cost-benefit analysis.

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APPENDIX

Figure A.1: Changes in the TRI (1999-horizontal axis and 2013- vertical axis).

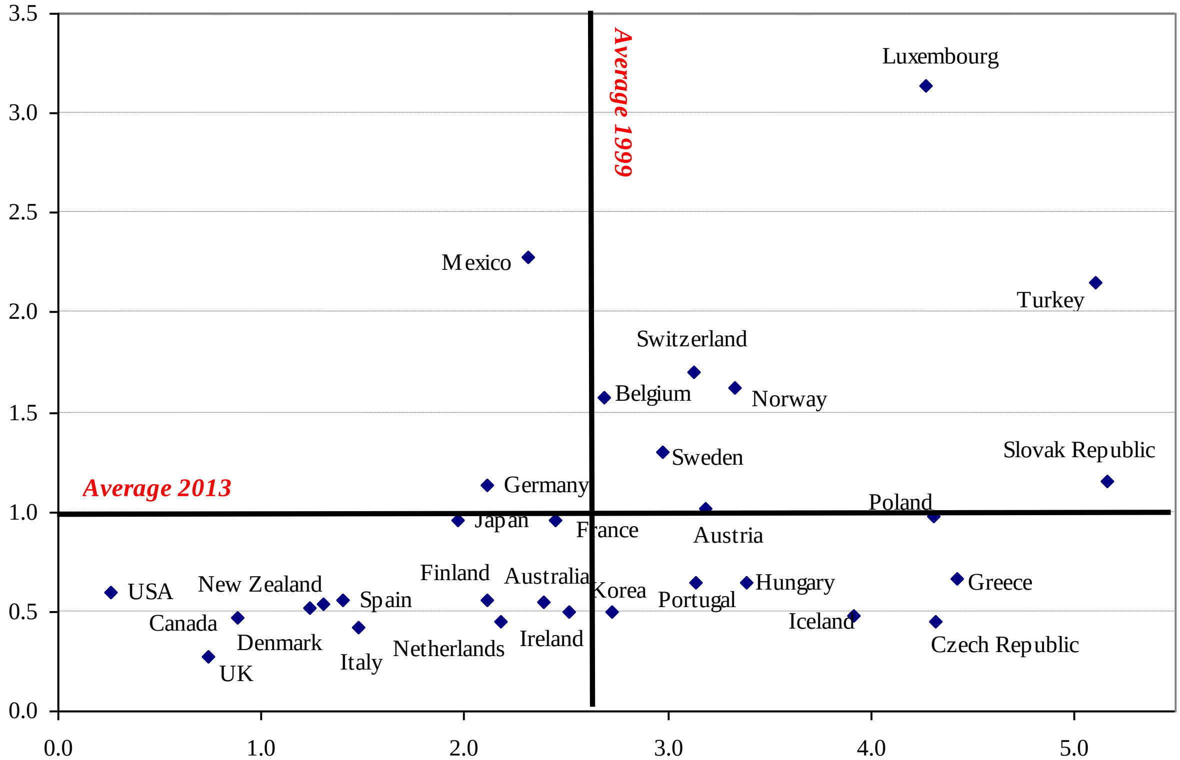

Table A.1: Regulation of entry

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).

Table A.2: 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^{***}	-0.0131^{***}	-0.0156^{***}	-0.0120^{***}

					(0.00398)	(0.00404)	(0.00392)	(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]

Significant at ***1%, **5% and *10% respectively.