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The dynamics of international patents production: A panel smooth transition regression approach

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Abstract

The main aim of this paper is to evaluate the major determinants of country-level production of international patents. We investigate a nonlinear relationship between ICTs' components and patents, using a PSTAR model based on the national innovative capacity framework. More particularly, we incorporate a wide set of policy and economic factors explaining cross-countries difference in the intensity of innovation. Our empirical results confirm the finding of R. Inglesi-Lotz and al (2018) whereby the Organization for Economic Co-operation and Development (OECD) and BRICS countries should not exceed the optimal levels of 1.688 and 0.975 (in % of GDP), respectively to engage in patenting and to get involved in the innovation system. The major explanations of our finding are the particular devoting of R&D budget to various sectors and the re-allocation of R&D resources in other productive sectors.

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Special issue “In memory of Professor Michel Terraza”

1. Introduction

J. Fagerberg (1994), Inglesi-Lotz and al (2014) argued that capital accumulation and labor force constitute the main factors explaining technology and international differences in growth rates. Based on growth theories, J. Fagerberg (1994) has conceived three perspectives of technology. Technological progress is considered either as "god-gifted", as an economic externality, or as a product of R&D investment in private firms. In this context, economists, even neoclassicals, have acknowledged the importance of integrating the third perspective of technological progress in economic growth models. The author has distinguished between formal and appreciative theories regarding technology differences in growth rates. Despite the convergence in assumptions between these two theorizing aspects, many conceptual differences remain. Based on neoclassical economies, formal theories perceive firms as profit maximizers in an ideal theoretical framework (perfect information). In contrast, appreciative theories describe firms as entities that produce and compete under an uncertain economic environment. These entities have different characteristics (innovation intensity, capital stock, strategies).

Formal theories consider technologies as commercial products. However, appreciative theorizing portrays technology as firmed up within organizations. It is a cumulative capability and is affected by inter-firm interactions with their environments (The concept of national innovation capacity). Differences in growth rates may result from government intervention in technology. According to appreciative theories, imperfect financial markets constrain the growth of national innovation capacity. In formal theorizing, this particular cause of technology differences does not arise since it adopts perfect financial markets' assumption nationally and internationally.

Countries devoting their resources to intensively investing in technological progress, R&D, and education have a higher potential to catch up with the international level of innovation capabilities. Pillar contributors to technological progress (i.e., R&D investment, number of researchers per field, human capital accumulation, …) must be perceived as complements rather than substitutes (J. Fagerberg, 1994).

The empirical literature has focused on the linearity of the "Innovation – Economic growth" linkage. However, few recent studies have examined the non-linear relationship between technological innovations and economic growth. Aristizabal-Ramirez and Canavire-Bacarreza (2015) explained the non-linearity of the innovation–growth relationship as follows: The impact of innovation on economic growth is not crucial at the very first levels of the innovation process. We may register a higher effect from a particular point. This long-run effect refers to human capital stock which emanates (resulting) from the innovation process. The concept of threshold was initially; identified by Azariadis and Drazen (1990). According to them, there is a threshold point of cumulative knowledge stock; from which countries may be characterized either by rapid economic growth (above threshold point) or slow economic growth (below a threshold point). J.L. Furman et al. (2002) have studied the relationship between the national innovative capacity and the production of international patents by exploring cross-country differences in terms of the innovation process determinants. The framework of national innovative capacity was established by referring to three prior research areas: National industrial clusters (Porter, 1990), National innovation systems (Nelson, 1993) and, Endogenous growth theory (Romer, 1990).

The endogenous growth theory identifies aggregate factors of the innovation process, such as the knowledge stock, while the other two formulations operate at a microeconomic level. The perspective of national innovation systems identifies political, institutional, and educational determinants of the innovation flow. The cluster-based theory focuses on the interaction between industrial clusters and the innovation infrastructure.

According to Porter (1990), the competitiveness in terms of innovation relies on (depends on) the economic environment in which firms invest and compete (J.L. Furman et al. (2002)). A robust innovation infrastructure is also a pillar factor to broaden the national patent scope and thus innovation output. The relationship between industrial clusters and the common innovation infrastructure plays a crucial role in the definition (defining) of national innovativeness. Furthermore, GDP by ICT industry and ICT patents are positively correlated. Industrialized countries, characterized by high GDP levels, expand their patenting activity in high-tech sectors to stimulate their economies. The empirical results of J.L. Furman et al. (2002) showed that the production of international patents depends on the strength of intellectual property protection, the extent of openness to other economies, expenditures on R&D, cluster specialization, and human capital stock (J.L. Furman et al. (2002)).

In our empirical analysis, we will assess the impact of country-specific determinants of innovation intensity on patents. To do so, we explore the relationship between national innovation capacity and international patenting. We will adopt patents in force to measure innovation intensity where patents are considered as a pillar contributor to economic growth. M. MacGarvie (2005) used patent citations as an indicator of international knowledge diffusion. He found that technology diffusion may be reinforced if countries share the same geographic boundary (or at least, geographically close); and the same language. Openness to international trade is a key determinant of international knowledge diffusion. The latter can be extended in case that countries share similar patents' distributions in each form of technology (M. MacGarvie. 2005).

This paper is structured as follows. In section 1, we present a brief literature review and our theoretical framework. In section 2, we develop the PSTR model. Section 3 depicts data and defines variables. In section 4, we estimate our model and discuss empirical results. Section 5 concludes and addresses policy implications.

2. Literature review

R.U. Ayres and E. Williams (2004) have likened Information and communication technologies (ICTs[1]) to *"a vehicle for economic growth".* Researchers are always questioning about the prospects for ICTs in the future especially with the incremental technological advancement. Pohjola (2002) has explained the reason for which ICTs affect economic growth. He clarified that ICTs' impact on growth is derived from the fact that technology-intensive industries exploit jointly ICT as input and output.

According to Roller and Waverman (2001), ICT ensures economic growth through its capability to enhance productivity. ICT plays a substantial role in stimulating economic growth by increasing "the demand for inputs which are used in its production" (G.G. Haftu, 2018).
The effect of innovative productivity on the economic development refers to the technological progress and the innovation intensity of ICTs. According to Hasan and Tucci (2010), the most

[1]ICT, Information and Communication Technologies.

flourishing economies are those which invest intensively and regularly in innovation. However, countries with lower innovative capacity register low economic growth levels.

The framework of J.L. Furman et al. (2002) is based on the concept of *national innovative capacity*[2]. They have explored the determinants of cross-country disparities in terms of innovative capacity. In developed countries, the economic incentives to innovation investment enhance related policy commitments and intensify innovative capacities. These countries have increased their R&D expenditures along with patents and copyrights. Generating new-to-the-world innovations promote the rate of per capita patenting.

J.L. Furman et al. (2002) have proven that classifying countries on the basis of innovative capacity depends not only on R&D expenditure but also on R&D productivity. The national innovative productivity depends broadly on the country's stock of knowledge and its mobility degree across borders. It also depends on policy commitment, innovation investments in R&D and patenting. All these R&D productivity factors allow us to measure the innovative output and thus, the economic growth of the country in question.

Following J.L. Furman et al. (2002), the national innovative capacity constitutes (NIC) the main sources of differences among countries in the production innovative output. It is defined as the ability of a country, political or economic entity to create and commercialize a flow of new-to-the world technologies over the long term. Regarding to the sources of innovation, The NIC framework draws on three perspectives: ideas-driven endogenous growth theory (Romer, 1990), the cluster-based theory of national industrial competitive advantage (Porter, 1990), and research on national innovation systems (Nelson, 1993). Innovation infrastructure, industrial clusters and the quality of their interaction are the main determinants of a country's innovative capacity and performance (Furman et al. 2004). The competitiveness of industrial clusters in terms of technological progress is fully incorporated in growth models (Nelson, 1993).

Prior empirical studies have thoroughly investigated the long-run relationship between innovation and economic growth, identifying its "transitional dynamics" (Fagerberg, 1994). These studies show multi-facets results. Bielig (2015), Lee and Lee (2019) have proven the existence of a positive relationship between innovation and economic growth. Other empirical investigations have emphasized a negative relationship (Aghion et al. 2015) or no linkage at all (Sweet and Eterovic, 2019).

The first version of Solow's economic growth theory was not based on real world assumptions. In fact, the absence of economic interventionism, the stasis of technological development and the stagnation of population growth are not realistic. Solow has developed his model by relaxing these assumptions: the effectiveness of capital and labor factors is ensured at an exogenous level of technological progress.

In contrast to Solow's exogenous model, Arrow (1962) endogenized the technological progress. Romer (1990) highlighted that boosting innovation and ensuring its mobility across countries are the key mechanisms of economic stimulation. He clarified that economic wealth may differ from one country to another since innovation advancement alters across economies. Otherwise, neoclassical growth theories argued that technology and knowledge are transferable factors leading to inevitable convergence in economic wealth between countries.

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[2] J.L Furman et al. (2002) have defined this concept as follows:" National innovation capacity is the ability of a country to produce and commercialize a flow of innovative technology over the long term." J.L. Furman et al. / Research Policy 31 (2002).

To study innovation-growth relationship, Hasan and Tucci have conducted a panel regression analysis on 58 countries between 1980 and 2003. The results show that ventures with exceptional patents enhance significantly the economic growth of technology-intensive countries. The results also revealed that the more patenting, the more economic growth is positively affected. Patenting rate is a consistent determinant of a country's innovative output. This indicator is specifically used to measure commercially significant innovations (Furman et al, 2002).

Sweet and Eterovic (2019) have demonstrated that economic growth and patent rights are disassociated despite the irrelevance of patenting to productivity. They have purported that technological advancement is highly related to economic complexity and not to patent rights. Using a panel regression analysis on 42 countries over 14 years, Papageorgiadis, Alexiou and Nellis (2016) have proven that higher-quality patents and economic growth are positively linked. In this context, Bielig (2015) has appraised the effect of intellectual property on German economic growth. He found that intellectual property boosts significantly the economic growth. Several studies have substantiated that the positive relationship between innovation and growth emanates essentially from patent protection (Saito, 2017). Gould and Gruben (1996) have demonstrated that economic growth depends on the extent to which a country protects its patents. The authors have also noticed that openness to other economies may strengthen the relationship between economic growth and patent protection (R. Inglesi-Lotz et al. 2020).

In contrast to Gould and Gruben (2014) analysis, several studies have agreed that reinforcing patent protection may hamper physical and human capital accumulation. More precisely, R. Inglesi-Lotz et al (2020) have pointed that: *"Strengthening patent protection allows firms producing intermediate goods to charge higher prices and reduces the volume of production. This process reduces demand for capital and capital rents, and consequently, discourages capital accumulation, and then impedes economic growth."* Reinforcing patent protection may promote innovative productivity of the final goods sector. Saito (2017) has clarified that firms producing intermediate goods do not fully benefit from patent protection. Discussions regarding linear relationship between economic growth and innovation have dominated research in recent years. However, little research has been conducted to investigate a nonlinear innovation-growth relationship.

Aristizabal-Ramirez and Canavire-Bacarreza (2015) have demonstrated that the innovation-growth relationship is not linear and only sophisticated innovations stimulate economic growth. Using a PSTR[3] model, the authors have determined an optimal threshold for innovation level to study its impact above and below the threshold. R. Inglesi-Lotz et al. (2020) have also applied a PSTR model to examine a patent-growth relationship. Using a sample of 60 developing and developed countries over the period 2008-2017, they have proven a threshold impact of patents on economic growth. The results reveal that below the optimal threshold, patents have no significant effect on growth for both developed and developing countries. Above the threshold, patents affect positively and significantly the economic growth for developed countries and the whole sample. The impact on developing countries is not statistically significant. Concerning developing countries, the policy implications of this study are essentially, increasing R&D expenditure and importing higher-quality innovations to enhance economic growth.

[3] PSTR, Panel Smooth Transition Regression.

In this paper, we investigate a nonlinear relationship between ICTs' components and patents, using a PSTAR[4] model based on the national innovative capacity framework. More particularly, we incorporate a wide set of policy and economic factors explaining cross-countries difference in the intensity of innovation. To estimate the relationship between the production of international patents and observable contributors to national innovative capacity, we adopt the ideas production function of endogenous growth theory as a baseline.

3. National innovative capacity: An overview on PSTR modelling technique

In our study we consider a production function for new-to-the-world technologies given by:

$$\dot{A}_{j,t} = g(X_{j,t}, Y_{j,t}, Z_{j,t}) H_{j,t}{}^{\lambda} A_{j,t}{}^{\beta} \qquad (1)$$

Where $\dot{A}_{j,t}$ is the flow of new-to-the-world technologies from country j in year t, $H_{j,t}$ is the total level of capital and labor resources devoted to the ideas sector of the economy, and $A_{j,t}$ is the total stock of knowledge which could generate future ideas production. X and Y refer to the common innovation and the particular environments for innovation in a countries' industrial clusters. Z captures the strength of linkages between the common infrastructure and the nation's industrial clusters. letting L denote the natural logarithm, our main specification can be written as following:

$$L\dot{A}_{j,t} = \theta YEAR_t + \theta COUNTRY_j + \alpha LX_{j,t} + \delta LY_{j,t} + \gamma LZ_{j,t} + \lambda LH_{j,t} + \beta LA_{j,t} + \varepsilon_{j,t} \qquad (2)$$

Following equation (2), our analysis is organized around a log–log specification. Except, the qualitative variables which are expressed as a percentage, the estimates have a natural interpretation in terms of elasticities. In the regression model, we identify heterogeneity through individual or time effects by assuming that the estimated parameters are constant over time and/or across individuals. "This poolability assumption may be violated or at least may be viewed as questionable" (González, Teräsvirta, Dijk and Yang, 2017).

In this context, Hansen (1999) has elaborated a panel threshold regression model (PTR). He assumed that explanatory variables' coefficients may slightly vary, depending on another exogenous variable. In other words, data can be divided into a determined number of homogenous panels, known as "regimes" where coefficients vary from one regime to another. The panel smooth transition regression (PSTR)[5] is a generalization of the PTR model. Using this nonlinear model, "smooth" variations of coefficients are allowed when transitioning from one regime to another. Once the transition variable and the threshold are determined, the PSTR model divides observations into groups.

The PSTR model was initially developed and applied by González et al. (2005) to assess the effect of capital market imperfections on firms' investment decisions. According to the authors,

[4] PSTAR, Panel Smooth Transition Autoregressive.

[5] R. Inglesi-Lotz et al. (2020) have stated:" This model allows to define the optimal threshold and to examine the effect of the transition variable below and above the threshold." https://doi.org/10.1080/00036846.2020.1713295

PSTR modelling technique may identify either a linear heterogeneous panel or a non-linear homogenous panel model.
The two-regime PSTR model is defined as follows:

$$Y_{it} = \mu_i + \beta_0 X_{it} + \beta_1{}' X_{it} g(q_{it}, \gamma, c) + \varepsilon_{it} \qquad (3)$$
$$i = 1,2, \dots, N \text{ and } t = 1,2, \dots, T.$$

Where N and T denote the cross-section and time dimensions respectively. Y_{it} is the dependent variable, X_{it} is the vector of explanatory variables, μ_i represents the fixed individual effects and ε_{it} is the error term. $g(q_{it}, \gamma, c)$ is the transition function. It is a continuous function that depends on the transition variable q_{it}, the slope parameter γ and the location parameter c.

The transition function is specified by a logistic regression as follows:

$$g(q_{it}, \gamma, c) = (1 + \exp(-\gamma \prod_{j=1}^{m} (q_{it} - c_j))^{-1} \quad , \gamma > 0 \; and \; c_1 \le c_2 \le \dots \le c_m \quad (4)$$

Where $j = 1,2, \dots, m$ and m refers to the number of extreme regimes. Note that the slope parameter determines to which extent the transition is smooth.

If the slope parameter γ is extremely small $(\gamma \to 0)$, then the transition function approximates to a constant and the PSTR model becomes homogenous. On the contrary, if $\gamma \to \infty$, the transition function approaches an index function that takes 1 if the transition variable surpasses the threshold. According to Khan and Senhadji (2001), if γ is sufficiently high, the PSTR model turns into a two-regime threshold model.

Several studies have applied the PSTR model and have proven that the advantage of this method emanates from its capability to detect heterogeneity in panel data. The PSTR modelling constitutes of three procedures: specification, estimation and evaluation.
Before model specification, we should check the linearity test against the PSTR model. The aim of this pre-test is to verify the non-linearity of a relationship between variables. The null-hypothesis of the linearity test can be given by reducing the PSTR model to a linear model. To do so, we impose either $\gamma = 0$ or $\beta_1{}' = 0$. Thus, the null-hypothesis can be written as:

$$H_0 : \gamma = 0 \; or \; H_0 : \beta_1{}' = 0$$

Notice that under either null-hypotheses, the test is non-standard because of unidentified nuisance parameters in the PSTR model. To circumvent this problem, we replace the transition function by its first-order Taylor expansion as suggested by Lukkonnen et al. (1988). Therefore, the reparametrized auxiliary equation is as follows:

$$Y_{it} = \mu_i + \beta_0{}^* Z_{it} + \beta_1{}^* Z_{it} q_{it} + \beta_2{}^* Z_{it} q_{it}{}^2 + \dots + \beta_m{}^* Z_{it} q_{it}{}^m + \varepsilon_{it}{}^* \quad (5)$$

In this new equation, the vector $(\beta_0{}^*, \dots, \beta_m{}^*)$ is multiplied by the slope parameter γ. As a result, testing $(H_0 : \gamma = 0)$ in model (1) is equivalent to testing the null-hypothesis$(H_0{}' : \beta_0{}^* = \beta_1{}^* = \dots = \beta_m{}^* = 0)$ in equation (4). Lagrange Multiplier (LM) of Wald and Fischer tests is served to decide whether our model is linear or not. If the null-hypothesis of linearity is rejected then, a non-linear relationship is confirmed and it is captured by a PSTR model with at least two regimes.

The next step consists of determining the number of transition functions in the model. In order to select the appropriate number of regimes, we should check for no remaining non-linearity in the PSTR model. The purpose is to test a two-regime PSTR model against a PSTR model with at least three regimes.

Under the alternative hypothesis, the PSTR model with three extreme regimes is given by:

$$Y_{it} = \mu_i + \beta_0 Z_{it} + \beta_1 Z_{it} g_1(q_{it}, \gamma_1, c_1) + \beta_2 Z_{it} g_2(q_{it}, \gamma_2, c_2) + \varepsilon_{it} \quad (6)$$

The null-hypothesis of no remaining non-linearity test is $(H_0: \gamma_2 = 0)$. Once again, we face the identification problem. We overcome this issue by using a first-order Taylor expansion of $g_2(q_{it}, \gamma_2, c_2)$. After reparametrization, this leads to the following equation and test:

$$\begin{aligned} Y_{it} = {} & \mu_i + \beta_0{}^* Z_{it} + \beta_1{}^* Z_{it} g_1(q_{it}, \gamma_1, c_1) \\ & + \beta_{21}{}^* Z_{it} q_{it}{}^2 + \cdots + \beta_{2m}{}^* Z_{it} q_{it}{}^m + \varepsilon_{it}{}^* \quad (7) \end{aligned}$$

and,

$$H_0: \beta_{21}{}^* = \beta_{22}{}^* = \cdots = \beta_{2m}{}^* = 0$$

The procedure of this test consists of testing the following null-hypotheses in order for an auxiliary regression with $(m = 3)$:

$$(1). H_{00}{}': \beta_{21}{}^* = \beta_{22}{}^* = \beta_{23}{}^* = 0$$
$$(2). H_{03}{}': \beta_{23}{}^* = 0$$
$$(3). H_{02}{}': \beta_{22}{}^* = 0 | \beta_{23}{}^* = 0$$
$$(4). H_{01}{}': \beta_{21}{}^* = 0 | \beta_{22}{}^* = \beta_{23}{}^* = 0$$

Suppose that (1) is already rejected, confirming a non-linear relationship between variables. In the case of acceptance of $H_{03}{}'$, we stop the testing procedure and we conclude that our PSTR has one transition function (two extreme regimes). If it is rejected, we proceed and test $H_{02}{}'$. If the rejection of $H_{02}{}'$ is the strongest in comparison to $H_{03}{}'$ and $H_{01}{}'$ then, the PSTR is a three-regime model and therefore, has two thresholds $(m = 2)$.

We continue the sequential testing until the first acceptance of the null-hypothesis of the no remaining non-linearity test. After selecting the number of regimes, we estimate coefficients of PSTR model with non-linear least squares method (NLS). The test of no remaining heterogeneity serves as a misspecification evaluation but also permits to determine the number of transitions in a PSTR model.

At model evaluation stage, we conduct misspecification tests[6]: a test of parameter constancy[7] and the test of no remaining heterogeneity (González, Teräsvirta and Dijk, 2005). Little research has been conducted to test the constancy of coefficients in panel data regressions. Due to the fact that time dimension was not large enough in a wide variety of empirical investigations, researchers become less interested in testing parameter constancy. The incremental increase of panel data with large time dimension allows us to test parameter constancy.

Two major limitations of the PSTR model should be treated with caution. First, the use of Taylor expansions may diminish significantly the degrees of freedom if the model contains

[6] For more details about misspecification tests, see Özgür Ömer Ersin (2016) and González et al. (2017)

[7] For more details, see Appendix 1.

variables with higher orders. Second, studying nonlinear relationships may be biased since annual observations do not cover seasonal transitions by smoothing some nonlinearities that can be frequently incorporated in quarterly or monthly data for example. To ascertain the robustness of PSTR model, it is recommended to use seasonally data in PSTR models (R. Inglesi-Lotz et al. 2020).

4. Empirical analysis

4.1.Data and variables definition

We attempt to illustrate a non-linear relationship between ICT patents and indicators of the quality of innovation infrastructure (ICT R&D expenditure and full-time researchers in ICT industry) for a sample of annual panel data of 30 countries from 2000 to 2015. We focused on countries that highly invest in ICT sector. In Table 1, we describe our data in more details.

Table .1 – Variables and definitions. This tables includes all variables used in our empirical investigation.

Variable	*Full variable name*	*Definition*	*Source*
		Digital innovation output	
ICT patents $_{it}$	International patents	Number of ICT patents granted to inventors from a particular country other than US country in a given year. For US, ICT patents is equal to the number of patents granted to corporate or government establishments (excluding individual inventors). To ensure that this symmetry between US and non-US patents does not affect results, we included a US dummy variable in our regressions.	OECD dataset (patents by technology)
		Quality of the common innovation infrastructure	
GDP $_{it}$ ***(value added) in ICT sector***	(GDP)-by-industry	GDP (value added) by ICT industry (Millions of current euros)	European commission (2017 PREDICT Dataset)
ICT Researchers $_{it}$	Aggregate researchers employed in R&D of ICT sector	Full time equivalent R&D researchers in ICT sector	European commission (2017 PREDICT Dataset), GII2017
ICT R&D expenditure $_{it}$	Aggregate expenditure on R&D in ICT sector	Business R&D expenditure in ICT sector (Millions of current euros)	World Bank,
ICT OPENNESS $_{it}$	Openness to international trade and investment	ICT exports and imports (US Dollar, Millions)	OECD Science and Technology Indicators

Descriptive statistics are depicted in Table 2 to present the basic features of our data. For each variable, we determine the average value, the median and minimum and maximum values. Note that results reported in Table 2 are calculated before applying the logarithm on the variables. The average value of ICT patents is 2583 with a minimum value of 0 and a maximum value of 50850. The ICT R&D expenditure showed an average value of 4471.56 (million euros) with a minimum value of 18 (thousand euros = 0.18 million euros) and a maximum value of 89836 (million euros). With regard to the number of full-time researchers in ICT industry, the average value is 26705 (researchers), with a minimum value of one researcher and a maximum value of 392700 (researchers). The average value of GDP in ICT sector is 49073.5 (million euros) with a minimum value of 258.3 (million euros) and a maximum value of 7160669 (million euros). The ICT openness variable describes the openness of a country to international trade and investment. It indicates ICT imports and exports measured in US million dollars. It showed an average value of 61651.1 with a minimum value of 287.9 and a maximum value of 571507.1 (million dollars).

Table .2 - Descriptive statistics. Table 2 displays variables' descriptive statistics.

Variable	$\boldsymbol{ICT\ Patents_{it}}$	$\boldsymbol{ICT\ R\&D\ expenditure_{it}}$	$\boldsymbol{ICT\ Researchers_{it}}$	$\boldsymbol{GDP_{it}}$	$\boldsymbol{ICT\ Openness_{it}}$
Max	50850	89836	392700	7160669	571507.1
Median	161.40	689	4550	11292.7	26563.9
Mean	2583	4471.56	26705	49073.5	61651.1
Min	0	0.18	1	258.3	287.9
Observations	480	480	480	480	480

Source: Authors' calculations.

4.2.Empirical results: Estimations and interpretation

Our PSTR models (equations 6 and 7) were specified based on the production function of new-to-the-world technologies (equation 2). We only focused on studying the impact of the quality of innovative infrastructure on the production of ICT patents. We derive our models from the following specific version of equation (2):

$$L\dot{A}_{j,t} = \theta YEAR_t + \theta COUNTRY_j + \alpha LX_{j,t} + \varepsilon_{j,t}$$

Where, X captures the common innovation infrastructure in a specific country as previously mentioned.

In this study, we aim to examine the association between digital innovation output and indicators of innovation infrastructure quality. We assume a non-linear threshold effect of ICT R&D expenditure and the number of ICT researchers as indicators of innovation infrastructure quality on ICT patents. To prove the non-linearity of the relationship between the transition variables and the dependent variable, we apply a panel smooth transition regression (PSTR) technique. In our model, $ICT\ Patents_{it}$ is the dependent variable, $ICT\ R\&D\ expenditure_{it}$ is the first transition variable, $ICT\ Researchers_{it}$ is the second transition variable. GDP_{it} and $ICT\ Openness_{it}$ are explanatory variables. Hence, the PSTR model can be written as follows:

$$\begin{aligned} Ln\,ICT\,Patents_{it} &= \beta_0{}^1 Ln\,GDP_{it} + \beta_0{}^2 Ln\,ICT\,R\&D\,expenditure_{it} \\ &+ \beta_0{}^3 Ln\,ICT\,Researchers_{it} + \beta_0{}^4 Ln\,ICT\,Openness_{it} \\ &+ \left[\beta_1{}^1 Ln\,GDP_{it} + \beta_1{}^2 Ln\,ICT\,R\&D\,expenditure_{it}\right. \\ &+ \beta_1{}^3 Ln\,ICT\,Researchers_{it} \\ &\left.+ \beta_1{}^4 Ln\,ICT\,Openness_{it}\right] g(Ln\,ICT\,R\&D\,expenditure_{it}\,, \gamma, c) + \varepsilon_{it} \quad (6) \end{aligned}$$

$$\begin{aligned} Ln\,ICT\,Patents_{it} &= \beta_0{}^1 Ln\,GDP_{it} + \beta_0{}^2 Ln\,ICT\,R\&D\,expenditure_{it} \\ &+ \beta_0{}^3 Ln\,ICT\,Researchers_{it} + \beta_0{}^4 Ln\,ICT\,Openness_{it} \\ &+ \left[\beta_1{}^1 Ln\,GDP_{it} + \beta_1{}^2 Ln\,ICT\,R\&D\,expenditure_{it}\right. \\ &+ \beta_1{}^3 Ln\,ICT\,Researchers_{it} \\ &\left.+ \beta_1{}^4 Ln\,ICT\,Openness_{it}\right] g(Ln\,ICT\,Researchers_{it}\,, \gamma, c) + \varepsilon_{it} \quad (7) \end{aligned}$$

In equation (6), the transition variable is $Ln\,ICT\,R\&D\,expenditure_{it}$ while, in equation (7), it is $Ln\,ICT\,Researchers_{it}$.We have chosen $ICT\,researchers_{it}$ and $ICT\,R\&D\,expenditure_{it}$ as transition variables since they best describe the quality of domestic innovative infrastructure in a particular country. Most previous studies attempted to analyze the innovation-growth relationship using GDP_{it} as a variable of interest that is why, we preferred to keep it as an explanatory variable in our model. Moreover, choosing $ICT\,openness_{it}$ as a transition variable will deviate our analysis from its initial aim. Note that the purpose of our study is to analyze whether there is a threshold effect of a country's domestic innovation system on the production of international patents. $ICT\,openness_{it}$ represents the imports and exports of ICT technologies between countries. It denotes an international dimension of the innovation process rather than a domestic innovation environment.

Table .3 – Linearity (homogeneity) test. Results of the homogeneity test are depicted in table 3.

Tests	$\boldsymbol{Ln\,ICT\,R\&D\,expenditure_{it}}$ $\boldsymbol{Ln\,ICT\,Patents_{it}}$	$\boldsymbol{Ln\,ICT\,Researchers_{it}}$ $\boldsymbol{Ln\,ICT\,Patents_{it}}$
Lagrange Multiplier Wald test (LM_W)	43.57 (7.885e-09) ***	36.04 (2.846e-07) ***
Lagrange Multiplier F-test (LM_F)	10.03 (8.887e-08) ***	8.296 (1.853e-06) ***

Values in parentheses are p-values and "***" stands for 1% significance level.

The first step of PSTR modelling is to check the assumptions required for the use of this approach. We test for linearity (homogeneity) and then, for the number of regimes.
The linearity test consists of testing the null-hypothesis (H_0: $linear\ model$) against the alternative (H_1: $PSTR\ model\ with\ at\ least\ one\ threshold\ variable, r = 1$). Through this test, we aim to verify the nonlinearity between ICT patents and R&D expenditure in ICT sector on one hand, and between full-time R&D researchers in ICT industry and ICT patents on the other hand.

We use statistics of Wald and F tests to confirm the nonlinearity between variables. Note that PSTR model may contain unidentified nuisance parameters under the null-hypothesis. To remedy this issue, we implement the first-order Taylor expansion on the transition function. After transformation, the linearity test can be written as follows:

$$\begin{cases} H_0 : Linear\ model\ with\ individual\ effects \\ \quad\quad\quad\quad\quad\quad Vs. \\ H_1 : PSTR\ model\ with\ (m)\ regimes. \end{cases}$$

We test the null-hypothesis with Wald, F or Likelihood-ratio (LR) tests.

Results in Table.3 show that estimated Lagrange Multiplier (LM) of both Wald and F-tests is statistically significant at level of 1%. In this case, we reject the null-hypothesis of linearity. We conclude that the nexus between aggregate expenditure on R&D in ICT sector and ICT patents is non-linear. The same conclusion is drawn for the ICT researchers - Patents relationship.

After confirming the nonlinear relationship between transition variables and the endogenous variable, we determine the number of transitions. To test the number of regimes, we should check the null-hypothesis (H_0: $PSTR\ model\ with\ one\ threshold, r = 1$) against the alternative hypothesis (H_1: $PSTR\ model\ with\ at\ least\ two\ thresholds, r = 2$).

To decide whether the PSTR model has one threshold or at least two thresholds, we estimate Lagrange Multiplier (LM) for Wald and F-tests. We reject the null-hypothesis if the regressors' p-value is inferior to the critical level of 5%. Thus, the PSTR model has at least two regimes. If LM_W and LM_F statistics are not statistically significant at the level of 5% then, we admit that PSTR model has only one transition function.

Results reported in Table.4 show that statistics of Wald test and F-test are not statistically significant at critical levels of 1% and 5%. Thus, we reject the hypotheses of no transitions ($r = 0$) and with at least two transitions ($r = 2$). We conclude that our PSTR model has ($r = 1$) one threshold of R&D expenditure and full-time R&D researchers in ICT industry. In other words, a two-regime PSTR model ($m = 2$) is confirmed.

Table .4 – Test of no remaining non-linearity (number of regimes). In table 4, we test the appropriate number of regimes that should be selected.

Hypotheses	*Tests*	*Statistics*	*P-value*
$\boldsymbol{Ln\ ICT\ R\&D\ expenditure_{it}}$ ***(Transition variable)***			
(1). $H_0 : r = 0$; $H_1 : r = 1$	$\boldsymbol{LM_{(W)}}$	37.610	1.346e-07***
	$\boldsymbol{LM_{(F)}}$	8.581	1.129e-06***
(2). $H_0 : r = 1$; $H_1 : r = 2$	$\boldsymbol{LM_{(W)}}$	9.755	0.2564
	$\boldsymbol{LM_{(F)}}$	2.205	0.3094
$\boldsymbol{Ln\ ICT\ Researchers_{it}}$ ***(Transition variable)***			
(1). $H_0 : r = 0$; $H_1 : r = 1$	$\boldsymbol{LM_{(W)}}$	54.75	3.669e-11***
	$\boldsymbol{LM_{(F)}}$	12.490	1.250e-09***

(2). $H_0: r = 1$; $H_1: r = 2$	$\boldsymbol{LM_{(W)}}$	18.21	0.4083
	$\boldsymbol{LM_{(F)}}$	4.116	0.4636

r indicates the number of thresholds (transitions) and "***" indicates the significance level at 1%.

After testing the nonlinearity and the number of regimes pre-tests, we determine the optimal threshold of the transition variables that allow countries to engage in ICT patenting. At this stage, we estimate the PSTR model. Estimates are depicted in Table.5. Thresholds of the transition variables are reported in Table.6.

Results show a positive correlation between GDP by ICT industry and ICT patents. The correspondent coefficient is statistically significant at the critical level of 1%. The effect of R&D researchers in ICT sector on patenting is positive in our PSTR models. Raising GDP levels increases the opportunity for a country to engage in invention and innovation processes and especially in patenting. Countries, characterized by high GDP levels, will boost their investment in R&D to improve the quality of education, the quality of scientific research and the innovative capacity. To increase the innovative output and enhance its quality, these countries must provide researchers and high-tech industries with a solid innovation infrastructure where all sorts of inputs are afforded (R. Inglesi-Lotz et al. 2018).

Table .5 – Estimation results of PSTR models. Table 5 displays the estimation of PSTR models. In the first specification, ICT expenditure is the transition variable. The latter is referred by the number of ICT researchers in the second model.

	$\boldsymbol{Ln\ ICT\ R\&D\ expenditure_{it}}$ $\boldsymbol{Ln\ ICT\ Patents_{it}}$		$\boldsymbol{Ln\ ICT\ Researchers_{it}}$ $\boldsymbol{Ln\ ICT\ Patents_{it}}$	
$\boldsymbol{Threshold: C^*}$ $\boldsymbol{Slope: \gamma}$	8.284 66.84		9.689 51.860	
Variable	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1}$
$\boldsymbol{Ln\ ICT\ R\&D\ expenditure_{it}}^*$	-0.007 (0.0481)	-0.5166** (0.3103)	0.0034 (0.048)	-0.74*** (0.3073)
$\boldsymbol{Ln\ GDP_{it}}$	0.8682*** (0.2373)	2.6060*** (0.7193)	0.8547*** (0.2513)	2.42*** (0.7953)
$\boldsymbol{Ln\ ICT\ Researchers_{it}}^*$	0.036 (0.063)	0.1382 (0.2689)	0.011 (0.063)	0.3106 (0.3391)
$\boldsymbol{Ln\ ICT\ Openness_{it}}$	0.2311 (0.1581)	-1.1620** (0.6023)	0.2303 (0.1623)	-0.9860 (0.6747)

Values in parentheses are standard errors corrected for heteroskedasticity.
β_0 and β_1 stand for regime 1 and regime 2, respectively.
"***" and "**" indicate respectively the significance levels at 1% and 5%.

The link between ICT patents and R&D expenditure is statistically significant at 5% and 1% level of significance in the first and the second PSTR models, respectively. Note that the significance of the impact of R&D spending on ICT patents is registered only in the second extreme regime of the transition functions. The surprising finding is the depressing effect of

R&D expenditure over ICT patenting. This negative impact may be illustrated by the following explanations:

- Due to their lower level of R&D investment in comparison to the US's, EU countries register inferior innovative capacity.

- Sakakibara and Branstetter (2001); Varsakelis (2001) pointed that future innovative output and its expected return may decrease and thus R&D expenditure becomes under-supplied if patent rights are not strengthened. Thus, weak patent rights explain to some point why excessive R&D investment may be sub-optimal, generating substandard technological progress and leading to a stagnation or even a downturn in the economic growth rate.

- The study of lags in the Patents-R&D nexus is a worthy investigation area. One may think that patenting is a long process since invention and innovation require time. Hall et al. (1986) assessed the lag between patents as innovative output and R&D efforts. They proved that lags in R&D investment, namely random walk pattern of R&D, affect significantly patents. The estimated lag is another (sort of) explanation of the negative relationship between patenting and R&D spending.

- Expanding patent breadth may engender a negative impact on R&D efforts and innovation in industries characterized by cumulative innovation such as ICT. In this context, Gallini (2002) pointed that extending patent scope in such type of industries may cause obstructions decelerating the innovative process. Bessen and Maskin (2002) stated that broadening high tech patents may raise invention costs like those related to the purchase of licenses. This increase in transaction costs and blockings generated by continuous and cumulative innovative process result in innovation downturn.

Our results are not in line with the findings of Bound et al (1984); Pakes and Grilishes (1984); Hall and all (1986) who assume that more R&D investment will result in more patenting. However, this evidence is questionable because it does not take into account the different types of innovation. In this case, Jaffe (2000) stresses the importance of distinguishing between various types of innovation[8] in the evaluation of the R&D investment – patenting relationship. Beyond the optimal threshold, R&D expenditure generates a negative impact on ICT patents. According to our results, if the amount of R&D spending reaches or exceeds **3960 million euros**, then investing in R&D may inhibit innovation and patenting in ICT Industry becomes sub-optimal. We conclude that 3960 (million euros) is not a threshold from which countries should engage in cumulative innovation but, it is a maximum level that should not be surpassed. As a country moves to an overinvestment in R&D efforts regime (above threshold), the association between ICT patents and R&D expenditure in ICT sector becomes negative and significant. 3960 (million euros) is a maximum threshold value of the R&D spending above which any overinvestment in R&D or any suboptimal resources' allocation to ICT sector may inhibit patenting in such industry. Hence, countries other than USA should appropriately and optimally assign financial resources to high tech sectors (such as ICT).

[8] According to Jaffe (2000), we have to distinguish between cumulative inventions such as ICTs, independent inventions and research tools.

Table .6 – Optimal thresholds of the transition variables. Table 6 shows the estimated threshold values of transition variables

	$Ln\ ICT\ R\&D\ expenditure_{it}$ $Ln\ ICT\ Patents_{it}$	$Ln\ ICT\ Researchers_{it}$ $Ln\ ICT\ Patents_{it}$
Tests		
γ	66.84	51.860
c	8.284	9.689
Equivalent number of ICT R&D expenditure	3960	—
Equivalent number of full-time researchers in ICT sector	—	16139
Estimated standard error of the residuals	0.006748	0.01383

We apply the exponential function on the parameter c in order to determine the exact value of the thresholds since our variables are in Napierian logarithm.

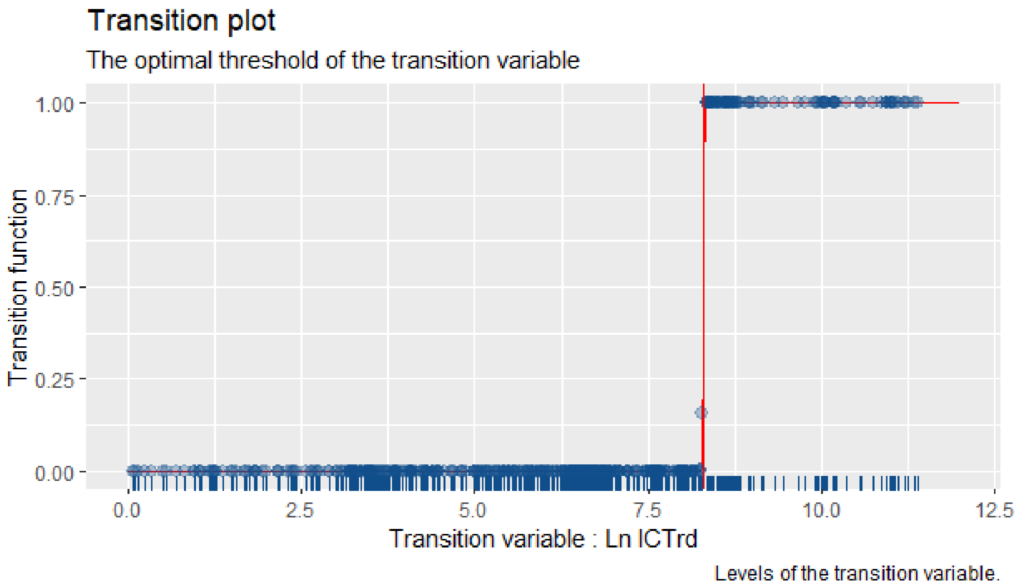
Our results confirm the finding of R. Inglesi-Lotz et al (2018). The authors found that OECD[9] and BRICS[10] countries should not exceed the optimal levels of 1.688 and 0.975 (in % of GDP), respectively to engage in patenting and to get involved in the innovation system. The major explanations of our finding are the particular devoting of R&D budget to various sectors and the re-allocation of R&D resources in other productive sectors.

The estimate of γ is such that the transition from the lower regime to the upper regime is abrupt and relatively rapid as the slope of the transition function is extremely high. In figure (1), the transition function $g(Ln\ ICT\ R\&D\ expenditure_{it}\ ,\gamma, c)$ is plotted against the R&D spending in ICT sector. The negative impact of R&D expenditure on ICT patents occurs when levels of our transition variable (R&D spending) are above the threshold. Notice that observations lie in either the lower extreme regime or the upper extreme regime. Only one observation is located in between as shown in figure (1).

[9] The Organisation for Economic Co-operation and Development.

[10] BRICS is the acronym for an association of five major emerging national economies that regroups: Brazil, Russia, India, China and South Africa.

Figure (1)- Estimated transition function. Graphical representation of the transition function and the optimal threshold of ICT R&D expenditure.



Source: authors' estimations

It should be noted that, for both PSTR models, the estimate of $Ln\ ICT\ R\&D\ expenditure_{it}$ ($\beta_0\ in\ the\ first\ regime$) is not significant. In the second extreme regime, the estimated coefficient β_1 is negative and statistically significant, at 5% significance level in the first PSTR model (equation 4) where R&D expenditure on ICT sector is the transition variable. This means that the relationship between R&D expenditure and patenting activities in ICT industry is not statistically significant when R&D spending is below the threshold but its effect becomes significant once it reaches the threshold. Note that coefficients curves, the standard errors and p-values of explanatory variables are plotted against the transition variables ($Ln\ ICT\ R\&D\ expenditure\ in\ model\ (6)\ and\ Ln\ ICT\ Researchers\ in\ model\ (7)$) in Appendix.2.

The second PSTR model (equation 7) permits to investigate the non-linear relationship that may exist between ICT patents and full-time researchers in ICT sector. Results reported in Table.6 show that the required number of researchers is **16139 researchers**. The estimated threshold of full-time researchers in ICT industry allows us to distinguish between countries that can engage in ICT patenting and countries that are unable to get involved in innovation processes.

Countries that are able to broaden their ICT scope with reference to the threshold of full-time researchers in high tech industry are: Canada, Estonia, France, Finland, Germany, Japan, Korea, Romania, Slovenia, Spain, Sweden, United Kingdom and United States[11]. Results reported in Appendix.3 indicate that, in these countries, the number of full-time researchers in ICT sector exceeds the threshold of 16139 (researchers). Czech Republic, Hungary and Slovakia are essentially former socialist countries. These countries are characterized by their self-sufficient economies. This autarky character enforces technological stagnation. Notice that during socialism, governments and political parties had dominated innovation processes (Prodan, I. 2005).

5. Conclusion

This paper investigates the relationship between national innovative capacity and international patenting. We proved the nonlinearity of this linkage using a PSTR model. We estimated and assessed the threshold effect of country-specific innovation intensity on the production of international patents. Taking into account R&D expenditure and full-time researchers in the ICT sector as indicators of innovative capacity, we determined the optimal threshold from which innovation will boost the patenting activity.

Empirical results show that R&D spending has a significant and negative impact on international patents by reaching a threshold of 3960 million euros. Surpassing this optimal value refers to an overinvestment in R&D which inhibits patenting. This finding may be explained by the weakness or the lack of intellectual property protection (patent rights) resulting in R&D expenditure under-supplying, thus decreasing the expected return of the innovation output. Another explanation of (for) this negative effect is the extension of the patent scope in industries that require sophisticated and costly inventions, such as the ICT sector. The impact of R&D spending on ICT patents before reaching the optimal threshold is not statistically significant. The "R&D Investment-Patenting" relationship requires further investigation since it does not consider the differences between innovation types as stressed by Jaffe (2000).

Concerning full-time researchers, the required number that allows countries to engage in patenting is, on average, 16139 researchers in the ICT sector. Above this threshold, the benefits of high-tech industries will be broadened with the extension of the patenting activity stimulating thus the economy. This threshold effect distinguishes between two groups of countries: countries unable to intensify their innovation flow (below threshold) and countries that can straightforwardly get involved in ICT patenting (above threshold).

Our findings provide important policy implications. Countries are invited to surpass the optimal value of 16139 researchers in the ICT sector and not exceed the number of 3960 million euros averagely; to get involved in the production of international patents. Nevertheless, these countries must be more vigilant regarding the negative impact of R&D spending on the production of ICT patents. Hence, countries should assign optimally financial resources to high-tech industries.

Countries should implement policies that increase knowledge stock (human capital accumulation), enlarge the openness extent to international trade, promote competitiveness in the innovation environment nationally and internationally to enhance their innovative capacity. OECD countries invest increasingly in innovation. That's why differences in terms of innovation intensity across these countries are decreasing. This convergence emanates from the wideness degree of international knowledge diffusion and its commercial exploitation across technology classes.

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Appendices

Appendix. 1 Parameter constancy test.

The parameter constancy test aims to verify if the estimates vary smoothly with time or not. Under the alternative hypothesis of time-varying PSTR model, the transition function $g_2({}^{t}/_{T}, \gamma_2, c_2)$ depends on time factor.

A three-regime PSTR model is mentioned below:

$$Y_{it} = \mu_i + \beta_0{}^T X_{it} + \beta_1{}^T X_{it} g(q_{it}, \gamma_1, c_1) + \beta_2{}^T X_{it} g\left({}^{t}/_{T}, \gamma_2, c_2\right) + \beta_3{}^T X_{it} g(q_{it}, \gamma_1, c_1) g\left({}^{t}/_{T}, \gamma_2, c_2\right) + \varepsilon_{it}$$

We apply a first-order Taylor expansion around $\gamma_2 = 0$. The auxiliary regression and the new null-hypothesis are mentioned below:

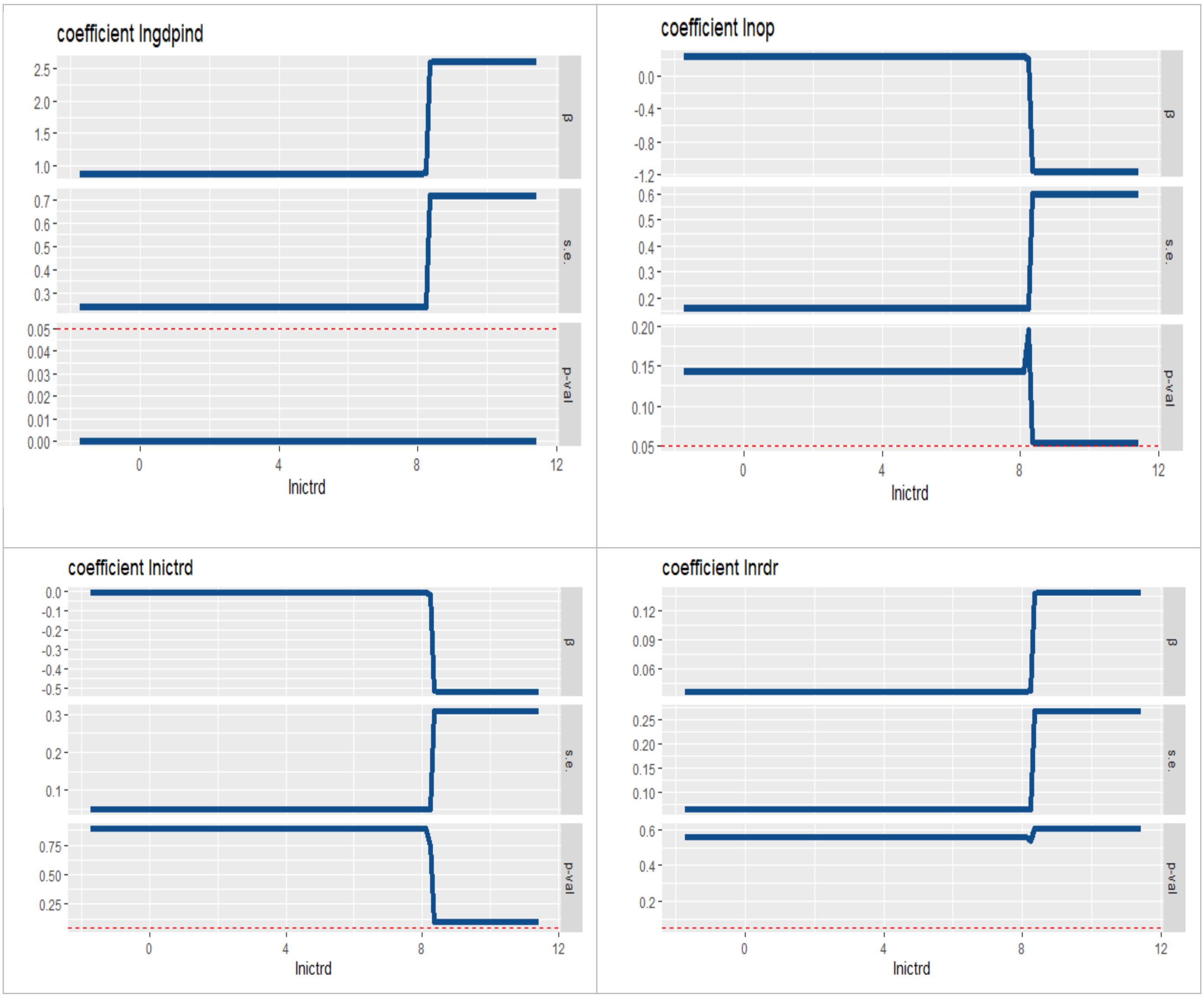
$$\begin{aligned} Y_{it} = \mu_i + \beta_0{}^T X_{it} + \beta_1{}^T X_{it} g(q_{it}, \gamma_1, c_1) + \beta_{21}{}^{*T} X_{it} \left(\frac{t}{T}\right) + \beta_{22}{}^{*T} X_{it} \left(\frac{t}{T}\right)^2 + \cdots \\ + \beta_{2m}{}^{*T} X_{it} \left(\frac{t}{T}\right)^m + \beta_{m+1}{}^{*T} X_{it} g(q_{it}, \gamma_1, c_1) \left(\frac{t}{T}\right) \\ + \beta_{m+2}{}^{*T} X_{it} g(q_{it}, \gamma_1, c_1) \left(\frac{t}{T}\right)^2 + \cdots + \beta_{2m}{}^{*T} X_{it} g(q_{it}, \gamma_1, c_1) \left(\frac{t}{T}\right)^m \end{aligned}$$

And,

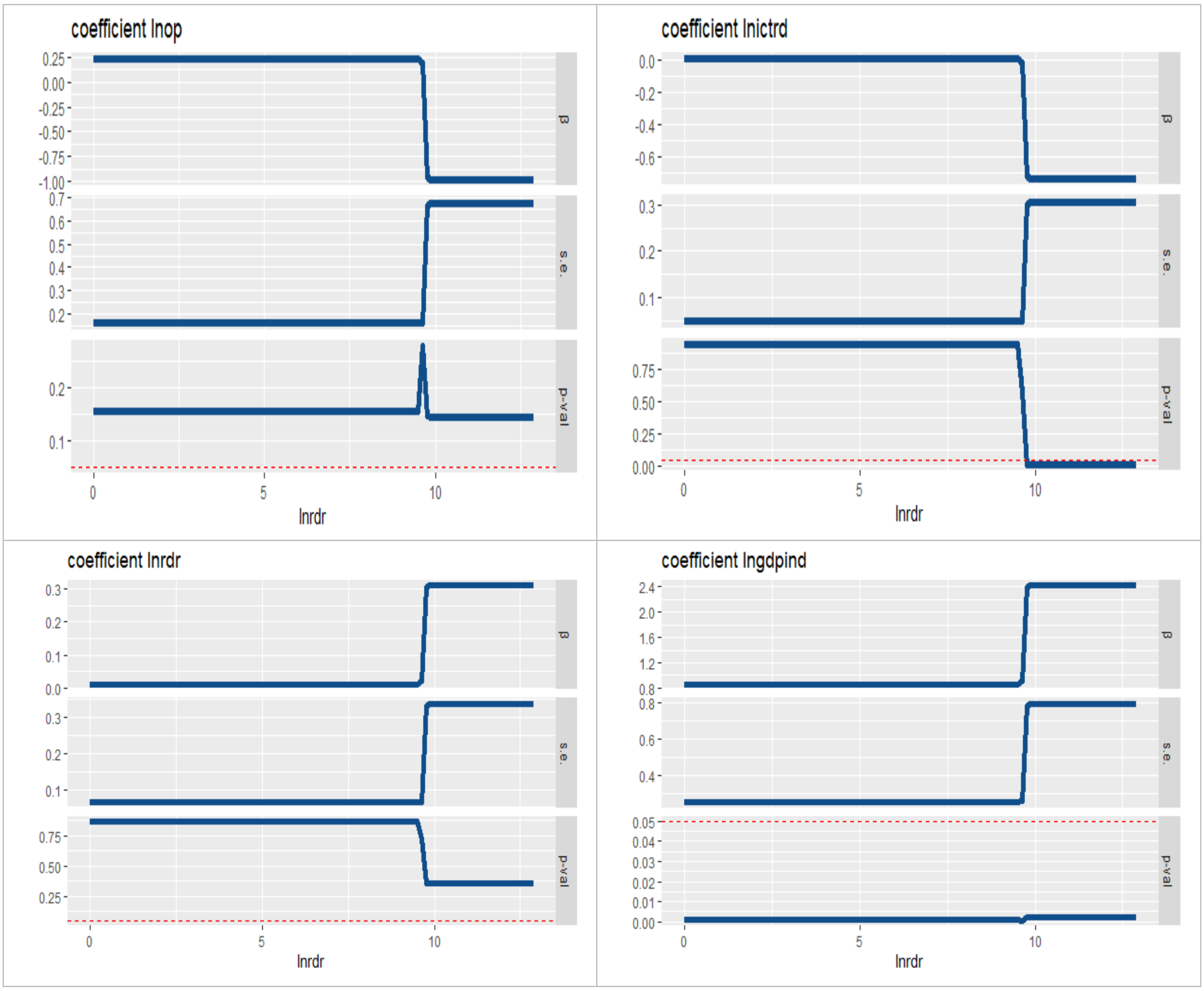
$$H_0: \beta_i{}^* = 0, i = 1, \ldots, 2m.$$

Appendix. 2 Transition plots.

Plots of coefficients curves, standard errors and p-values of explanatory variables against the transition variable $Ln\ ICT\ R\&D\ expenditure_{it}$ in model (6).



Plots of coefficients curves, standard errors and p-values of explanatory variables against the transition variable $Ln\ ICT\ Researchers_{it}$ in model (7).



Appendix. 3 Selected statistics of ICT researchers in the countries of our sample.

Countries	*Australia*	*Austria*	*Belgium*	*Canada*	*Czech Republic*
Max	9239	6086	5049	**35236**	4380
Min	4923	3614	155	**13**	52
Mean	6817	4617	4108	**28283**	2017
Countries	*Denmark*	*Estonia*	*Finland*	*France*	*Germany*
Max	13154	**32297**	**38373**	**43127**	**35323**
Min	2743	**115**	**8075**	**893**	**698**
Mean	5606	**4039**	**14406**	**31228**	**27193**
Countries	*Greece*	*Hungary*	*Ireland*	*Italy*	*Japan*
Max	3222	6136	5007	8624	**159744**
Min	1083	680	9	1	**20**
Mean	1900	2954	3103	6307	**131473**
Countries	*Korea*	*Latvia*	*Luxembourg*	*Netherlands*	*Norway*
Max	**137080**	4144	797	9298	4747
Min	**9**	14	10	130	123
Mean	**81650**	537	139	5162	3438
Countries	*Poland*	*Portugal*	*Romania*	*Russia*	*Slovakia*
Max	7269	5799	**22777**	7111	5694
Min	442	918	**121**	1501	25
Mean	3250	2732	**3242**	4182	861
Countries	*Slovenia*	*Spain*	*Sweden*	*United Kingdom*	*United States*
Max	**33772**	**145120**	**57065**	**27125**	**392700**
Min	**103**	**4424**	**3947**	**18939**	**300341**
Mean	**4436**	**23813**	**11162**	**21268**	**361217**

Bold highlight indicates countries that are capable to involve in ICT patenting with reference to the threshold of full-time R&D researchers in ICT industry.