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R&D investment: A dynamic efficiency approach in the EU countries

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ABSTRACT

This paper aims to analyze the role of research and development (R&D) in the production efficiency of European Union Member States. Utilizing Bayesian methods within a dynamic framework, the study jointly estimates production functions and efficiency for a sample of 27 countries over the 2000–2021 period. The findings reveal that human capital investment exhibits a higher output elasticity compared to physical capital investment. Additionally, the results indicate that inefficiencies persist due to escalating costs—both monetary and temporal—as inputs expand. Across the studied countries, an upward trend in R&D expenditure is associated with increasing technical efficiency levels, establishing a positive relationship between R&D spending and technical efficiency scores. Geographically, eastern and southern European regions exhibit lower average efficiency levels. These insights are crucial for policymakers seeking to foster innovation-driven policies, highlighting the importance of maintaining or increasing R&D spending to achieve the economic and social objectives of the European Union. Through appropriate R&D policies, policymakers can enhance technical efficiency, ensure the EU's global competitiveness, and promote more equitable development across the Union.

Contribution/Originality: This study is original in its application of a dynamic stochastic frontier model with Bayesian methods to estimate the influence of EU membership and R&D expenditure on technical efficiency across 27 European Union Member States from 2000-2021, uniquely highlighting inefficiency persistence and regional disparities.

1. INTRODUCTION

The main objective of the European Community (EC) is to guide Member States towards sustainable growth. To achieve this goal, the EC has introduced a series of regulatory declarations and programmes designed to address specific issues, considering social and economic disparities among regions.

Over the past two decades, European funding earmarked for innovation has shown a consistent upward trend, underscoring its increasing recognition. Notably, between 2007 and 2013, Cohesion Policy programmes allocated nearly a quarter of total funds to innovation initiatives (European Commission, 2014). This commitment to innovation continued into the subsequent 2014-2020 programme, with a target of dedicating 30% of funds to innovation and research and development (R&D) activities (European Commission, 2014). Building on this momentum, the current Horizon Europe programme aims to foster an "Innovative Europe" by boosting innovation capacity, promoting the uptake of cutting-edge technologies, and ensuring sufficient funding for research and innovation projects. Consequently, the proportion of funds allocated to innovation-related initiatives has increased to 35%.

Innovation policies, recognized as vital drivers of sustainable economic growth (Grossman & Helpman, 1991; Li, Lee, & Ko, 2017; Pradhan, Arvin, Bahmani, & Bennett, 2017) grant individuals, companies, and public institutions the right to patent their innovative products for a specified period. By incentivizing potential profits, this right stimulates research and development activities across technologies, materials, and products.

Each European Community (EC) state possesses unique assets, capabilities, and social identities that set them apart from one another. Despite these differences, we can leverage these characteristics to differentiate products and services, thereby enhancing efficiency and competitiveness in the global market. State-specific assets and policies delineate sustainable growth paths and countries' performance (Sleuwaegen & Boiardi, 2014).

Research and development (R&D) has made significant strides, but evaluating its impact on the efficiency and growth of territories requires careful scrutiny. Therefore, this paper aims to contribute to the economic literature in two key areas: firstly, by estimating the effect of innovation activities on economic growth; and secondly, by assessing the relationship between innovation and efficiency. Understanding this relationship is critical, given the profound societal and economic implications of progress in R&D.

In an increasingly competitive landscape, it is essential to evaluate the impact of innovative activities on efficiency levels within the European Union (EU). This article seeks to assess productivity efficiency among EU Member States in the context of innovation. To achieve this objective, a theoretical model will be developed to analyse how innovation activities influence efficiency across European states. Additionally, the research will propose recommendations for economic and social policy.

We organize the remainder of the paper as follows: The first section reviews the existing literature on innovation and economic growth. The second section proposes the theoretical model and presents the methodology used to obtain the empirical results. The third part proposes the theoretical model and presents the methodology that yielded the empirical results. In the third part, the theoretical model is proposed, and the methodology used to obtain the empirical results is presented. The fourth section estimates the proposed model and discusses its main results. Finally, the last section presents the main conclusions and policy suggestions of this research.

2. LITERATURE REVIEW

2.1. Innovation and Economic Growth

Unravelling the drivers of economic growth has long captivated scholars (Dragoescu, 2015; Radua, 2015; Vedia-Jerez & Chasco, 2016). Since the early 1930s, researchers have placed particular emphasis on innovation (Hasan & Tucci, 2010) and its connections to entrepreneurial, regional, or national dynamics.

There is a consensus in scholarly discourse that innovation forms the cornerstone upon which nations build their competitive advantage (Drucker, 1993; Fare et al., 1994; Porter, 1990). Moreover, empirical evidence, both at regional and national levels, underscores its role as a catalyst for fostering progress and nurturing sustainable economic growth (Grossman & Helpman, 1991; Li et al., 2017; Pradhan et al., 2017; Thompson, 2018). Therefore, authors such as Galindo and Méndez (2014) and Pece, Simona, and Salisteanu (2015) argue that the trio of innovation, technology, and knowledge diffusion emerges as essential prerequisites for enhancing competitiveness, facilitating progress, and sustaining economic growth trajectories. However, achieving these ambitious goals requires concerted efforts to achieve a harmonious balance among physical capital, human capital, labour dynamics, and investment strategies (Schmitz Jr, 1989; Vedia-Jerez & Chasco, 2016).

The growth-accounting methodology (Solow, 1956) has been instrumental in studying the impact of innovation on economic growth. Over time, evidence has consistently supported a positive relationship between innovation and economic growth. Initially challenged by Solow (1987) paradox, studies in the 1990s found a weak link between economic growth, productivity, and new technologies (Brynjolfsson, 1993; Brynjolfsson & Hitt, 1996). However, it wasn't long before the first signs of a positive relationship between new technologies and growth emerged (Dedrick, Gurbaxani, & Kraemer, 2003; Griffith, Redding, & Reenen, 2004; Liman & Miller, 2004). This positive correlation gained stronger affirmation in subsequent years (Afonso & St. Aubyn, 2013; Coto-Millán, Fernández, Pesquera, & Agüeros, 2016; Drucker, 1993; Kneller & Stevens, 2006; Lu, 2021; Pires & Garcia, 2012; Wong, Ho, & Autio, 2005). However, recent studies indicate that productivity gains resulting from innovation are diminishing over time (Zabala-Iturriagagoitia, Aparicio, Ortiz, Carayannis, & Grigoroudis, 2021).

In addition to exploring the fundamental nexus between innovation and economic growth, researchers have delved into various aspects of this relationship, shedding light on its multifaceted nature. Studies have scrutinised the interplay between innovation, growth, and productivity alongside foreign direct investment (Gharneh, Nabavieh, Gholamiangonabadi, & Alimoradi, 2014; Ghosh & Mastromarco, 2013; Liu, 2016), as well as the influence of public and private capital in research and development endeavours (Liu, 2016). Furthermore, scholars have examined how foreign technological progress impacts domestic innovation dynamics (Brynjolfsson & McAfee, 2014) and analysed the role of institutional frameworks in shaping innovation outcomes (Bengoa, Martínez-San Román, & Pérez, 2017; Chen, Wang, & Singh, 2018; Gargallo-Castel & Galve-Górriz, 2012). There has also been a concerted effort to identify the determinants of misallocation in innovation, with studies aimed at unraveling the factors contributing to inefficiencies in resource allocation within innovation ecosystems (Li et al., 2017).

2.2. Efficiency and Innovation

The application of efficiency analysis to the innovation process has primarily focused on the concept of a knowledge production function (KPF) (Griliches, 1979). This concept assumes that the output of the innovation process is R&D capital or investment. Regional KPFs (RKPFs) extensively analyze innovation at the regional level to assess the contribution of regional inputs to the generation of new local knowledge (Charlot, Crescenzi, & Musolesi, 2015). Antonelli and Colombelli (2015) and Fernandes et al. (2021) provide a review of the KPF methodology and its applications.

The growth-accounting methodology (Solow, 1956) has also been employed to study the effect of innovation as a source of efficiency. In this context, states can be considered to be operating either on or within the Frontier, with the distance from the Frontier indicating inefficiency. Additionally, Koop, Osiewalski, and Steel (2000) proposed that output growth comprises three components: input change, technical change, and efficiency change, with the latter two components contributing to *productivity change.*

In recent years, several studies using the growth-accounting methodology have identified a positive impact of public and (higher) private capital stocks on regional efficiency (Cappelen, Castellacci, Fagerberg, & Verspagen, 2003; Delgado Rodriguez & Álvarez, 2004; Deliktas & Balcilar, 2005; Enflo & Hjertstrand, 2009). Additionally, investments in education (Delgado & Alvarez, 2003) logistics developments, and innovation (Coto-Millán et al., 2016) have also been found to be positive drivers of regional performance, among others.

This article aims to contribute uniquely to the literature by employing a dynamic stochastic frontier model to examine the contribution of innovation to the growth of European Total Factor Productivity.

3. THEORETICAL MODEL AND SPECIFICATION

According to Solow (1956) the growth rate of output can be decomposed into two main components the contribution of production factors (capital and labour) and the residual, usually called Total Factor Productivity (TFP). It can be shown that it is possible to express the level of TFP of state i at time t concerning the efficiency of a "base" state in a "base" year.

This study starts by considering the growth model described by Mankiw, Romer, and Weil (1992). The product of state *i* at time *t*, Y_{it}, is determined by the levels of K_{it} , L_{it} and HC_{it} (defining *K* as the capital stock, *L* as the effective amount of labour force, and *HC* as the stock of human capital used in the production process):

$$Y_{it} = f(A_{it}, K_{it}, L_{it}, HC_{it}) \quad (1)$$

The parameter *A* describes the Hicks-neutral productivity and can be decomposed (Coelli, Rao, O'Donnell, & Battese, 2015) into the level of technology, *B*, an inefficiency measure, *U*, and a measurement error, *V*, to capture the stochastic nature of the frontier. The inefficiency effects depend on environmental covariates (*Z*). Taking into account these concerns, expression (1) is transformed into (2) and (3):

$$y_{it} = B \cdot f(k_{it}, hc_{it}) \cdot g(V_{it} - U_{it}) \quad (2)$$

$$U_{it} = h(Z_{it}) + W_{it} \quad (3)$$

The level of total factor productivity in Equation 2, $TFP_{it} = g(V_{it} - U_{it})$ depends on both embodied and disembodied technological progress, A_{it}, as well as external covariates such as a set of growth determinants, Z_{it}.

The lowercase letters denoted in the previously defined variables are measured per unit of labour. Equation 3 requires an appropriate functional form, denoted as *f(·)*, that ideally offers flexibility, ease of calculation, and allows for homogeneity imposition. One commonly utilized functional form in production is the translog form, which meets these criteria effectively. An important consideration in analysing the translation of innovation efforts into production outcomes is the presence of time lags (Moralles & do Nascimento Rebelatto, 2016). There is a delay before inputs translate into outputs, necessitating that efficiency analysis account for these time lags.

By rewriting (2) into translog form (and considering individual effects) and (3) in additive formulation, considering efficiency time lags, one can get expressions (4) and (5), the production function and the effects model, respectively. Expression (6) is the specification of the effects model for the first observation of each DMU (Decision Making Unit):

$$\log p_{it} = \alpha_i + \beta_k \log pc_{it} + \beta_h \log hc_{it} + {}^1/_2\, \beta_{kk}(\log pc_{it})^2 + {}^1/_2\, \beta_{hh}(\log hc_{it})^2 + {}^1/_2\, \beta_{kh}(\log k_{it} \log hc_{it}) + V_{it} - U_{it} \quad (4)$$

$$\log U_{it} = \delta_0 + \textstyle\sum_j \delta_j Z_{jit} + \rho \log U_{it-1} + W_{it} \quad (5)$$

$$\log U_{i1} = \frac{\delta_0 + \sum_j \delta_j Z_{ji1}}{1-\rho} + W_{i1} \quad (6)$$

α, β, δ and ρ (the dynamic coefficient) are unknown parameters to estimate; U_{it} represents technical inefficiency, and it is assumed to follow a truncated normal $N^+(\mu,\sigma_u^2)$ and to depend on a set of environmental variables, *Z* (Battese & Coelli, 1995) V_{it} (stochastic effect) is a random variable assumed to be iid following $N(0,\sigma_v^2)$ independently distributed from U_{it}; and W_{it} is a random variable assumed to be $N(0,\sigma_w^2)$ for t=2,…, T, and $N(0,\sigma_w^2/(1-\rho^2)$ for t=1, but not necessarily identically distributed.

The calculation of the technical efficiency scores (TE) of European Member States is defined in expression (7):

$$TE_{it} = \exp\,(-U_{it}) \quad (7)$$

Fully efficient states, achieving technical efficiency (TE) scores of unity, operate precisely on the production-possibility frontier. In contrast, inefficient states, with TE scores below one, operate below this frontier, indicating they utilize production factors excessively relative to their output levels.

Building on the methodologies of Tsionas (2006) and Emvalomatis (2012) Bayesian methods were employed to assess the impact of EU membership and research and development (R&D) expenditure on technical efficiency within a dynamic framework. This analysis utilized the MCMC (Markov Chain Monte Carlo) technique, specifically employing the Gibbs sampler with data augmentation.

4. DATA

This paper empirically tests the proposed model using data sourced from Eurostat, the European Commission's database. The final sample comprises unbalanced panel data from 27 European states, totalling 563 observations spanning the period from 2000 to 2021.

Table 1. Variables definitions and sources.

Variable Production function	Definition	Source
Production (p)	Gross domestic product (GDP) per employee, per million purchasing power standards	EUROSTAT
Physical capital (PC)	Gross fixed capital formation (GFCF) per employee, per million purchasing power standards	EUROSTAT
Human capital (HC)	A proportion of employees with tertiary education	EUROSTAT
Efficiency effects model		
EU membership	Dummy variable - state membership in the European union	European union
COVID	Dummy variable – year 2020	WHO
R&D expenditure (RDExp)	Research and development (R&D) expenditure as a percentage of GDP	EUROSTAT

Table 1 provides a detailed description of the variables included in the model estimation specified in Section 3. The GDP per employee approximates the output of the production function (p). The independent variables used in the production function (the inputs) were the capital stock per employee (*pc*) and the human capital (*hc*), which measures the percentage of the labour force with tertiary education.

Table 2 shows the main statistics of the variables used in the analysis. The analysis displays both production and physical capital as millions of purchasing power standards in euros. We measure the variables of labor and human capital in individuals.

Table 2. Descriptive statistics.

Desc. stat.	Production	Physical capital	Human capital	Labour	R&D expenditure
Minimum	6,361	792.3	18.9	146	0.230
1st Quartil	52,770	8,514.6	364.4	1,423	0.735
Median	181,649	36,667.8	901.6	3,740	1.240
Mean	412,735	88,652.7	1,973.5	7,023	1.472
3rd Quartil	351,876	85,672.4	1,865.2	8,169	2.120
Maximum	3,146,724	742,361.0	12,992.6	42,221	3.870
Std. dev.	617,507	139,980.7	2,759.8	9,241	0.888

Source: Eurostat (2023).

To evaluate the effect of innovation on the TE of European countries' production, we included the variable expenditure in R&D as a percentage of GDP. The existing literature bases the selection of this variable as an economic indicator of innovation, given its proven impact on innovative activity (Acs & Audretsch, 1998; Cohen & Levinthal, 1989). We have introduced the variables COVID and EU membership into the model to assess and control their impact on technical efficiency. COVID is a binary variable that takes one in the observations of the year 2020 and zero in other cases. The model incorporates this dummy variable to regulate the impact of the COVID-19 pandemic on production activities. The variable EU Membership assumes a value of one when the state under consideration has been a Euro member since its accession and a value of zero in all other cases.

5. RESULTS

5.1. Production Frontier and Effects Model

Following Tsionas (2006) and Emvalomatis (2012) this paper evaluates the efficiency of European Member States and the contribution of innovation in a dynamic framework[1], where countries´ efficiency is considered to

[1] The Bayesian estimation of the efficiency in the European regions has been carried out with R-Statistics software.

depend on their behaviour during the previous years due to the difficulty (or the high costs) in increasing the quantities of capital (quasi-fixed) and time lags (Moralles & do Nascimento Rebelatto, 2016). One key advantage of the Bayesian approach is its capacity to incorporate external factors into the modelling process. By using Markov Chain Monte Carlo (MCMC) methods, Bayesian analysis can come up with conclusions that are based on the data itself rather than relying on the estimator's asymptotic properties. This approach ensures that computations remain manageable for all parameters, allowing for small-sample inference similar to that of large samples. Consequently, we can feasibly obtain comprehensive information regarding parameter distributions in a single computational step.

Following expressions (4), (5), and (6), the model is specified in (8), (9), and (10):

$$\log p_{it} = \alpha_i + \beta_1 \log pc_{it} + \beta_2 \log hc_{it} + {}^1\!/_2\, \beta_{11} (\log pc_{it})^2 + {}^1\!/_2\, \beta_{22} (\log hc_{it})^2 + {}^1\!/_2\, \beta_{12} (\log pc_{it} \log hc_{it}) + V_{it} - U_{it} \quad (8)$$

$$\log U_{it} = \delta_0 + \delta_1 UE_{it} + \delta_2 COVID_t + \delta_3 RDExp_{it} + \rho \log U_{it-1} + W_{it} \quad (9)$$

$$\log U_{i1} = \frac{\delta_0 + \delta_1 UE_{i1} + \delta_2 COVID_1 + \delta_3 RDExp_{i1}}{1-\rho} + W_{i1} \quad (10)$$

Table 3 shows the estimation, using Bayesian methods, of the stochastic production frontier of 27 European countries over the 2000–2021 period. We tested the suitability of the estimated model by varying the prior assumptions of the parameters and variances and found that the results did not significantly differ from Table 3.

Table 3. Estimation results.

Variable	Parameter	Coefficient	Std. dev.
Production function			
Physical capital	β_1	0.312	0.013
Human capital	β_2	0.427	0.020
Physical capital^2	β_{11}	0.005	0.027
Human capital^2	β_{22}	0.320	0.070
Physical * human capital	β_{12}	-0.141	0.057
Effects model			
Constant	δ_0	-0.286	0.073
EU membership	δ_1	-0.097	0.032
COVID	δ_2	0.173	0.069
R&D expenditure	δ_3	-0.047	0.015
Dynamic effect	ρ	0.796	0.032

Table 3's first-order coefficients represent output elasticities, measured as deviations from the geometric mean. Notably, these coefficients for the variables in the production function show the expected positive signs. Specifically, the coefficient associated with human capital indicates that a 1% increase in its level boosts output by 0.4%, whereas a similar increase in physical capital increases output by 0.3%. These results indicate that investing in human capital, especially tertiary education, yields higher returns compared to investing in increased physical capital stocks. Furthermore, the square and cross-product coefficients highlight the stronger impact of human capital relative to physical capital on production, as well as potential substitution possibilities within the available technological framework. Table 3's lower section presents the results of the effects model. In equation (4), inefficiency is defined as the distance from the production-possibility frontier. Therefore, a positive coefficient suggests that increasing levels of the examined variable result in a decrease in technical efficiency.

The ρ-parameter value, which is positive and less than one (a constraint indicating a stationary process), supports the earlier hypothesis of persistent inefficiency. The costs associated with increasing input availability, whether in monetary or time terms, are responsible for this persistence. Previous studies have also identified empirical evidence of dynamic effects on technical efficiency.

The coefficient for EU Membership is negative, indicating that the economic and social policies of the EC are associated with higher levels of technical efficiency. This aligns with the findings of Halkos and Tzeremes (2009), who suggest that these policies have had a greater impact on the efficiency of newer EU members compared to older ones (EU15) during the period from 1995 to 2005.

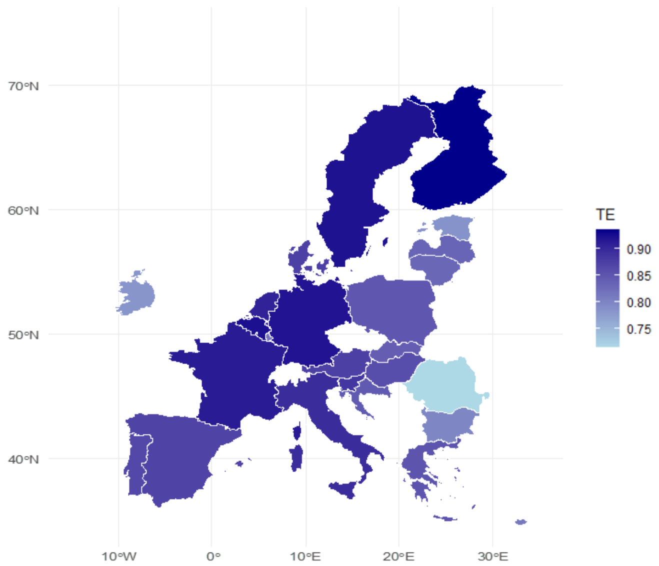

Figure 1. Period average technical efficiency (2000-2021).

Membership in the EU not only affects efficiency but also influences growth (Crespo Cuaresma, Ritzberger-Grünwald, & Silgoner, 2008), innovation (Crescenzi & Rodríguez-Pose, 2011) and competitiveness (Marčeta & Bojnec, 2021). The parameter associated with R&D expenditure, measured as a percentage of GDP, shows a negative sign. This suggests that while innovation activities have historically increased efficiency scores, according to previous studies by Coto-Millán et al. (2016), the impact on technical efficiency in this context appears to be negative. This result indicates that innovation is reshaping economic activities by enabling European countries to reduce input inefficiencies, allowing for redirection of resources towards other public or private interests. However, we observe a decline in productivity gains from innovation over time.

Figure 1 illustrates that, on average, during the study period, Eastern and Southern European countries attained lower levels of technical efficiency. Countries such as Finland, Belgium, Sweden, and Germany achieved higher scores, whereas Romania and Malta ranked lower. These results are consistent with those of Aytekin, Ecer, Korucuk, and Karamaşa (2022) who assessed global innovation efficiency among EU member and candidate countries. The disparities between countries may stem from their inherent heterogeneity and challenges in achieving convergence (Marelli, 2004). Detailed figures on average technical efficiency per country for each period can be found in the Appendix. Overall, despite a few exceptions, the trend over the study period has been towards increasing average technical efficiency. Beginning in 2000 with an observed technical efficiency of 0.76, by 2021, the average technical efficiency had risen to 0.83. In conclusion, this research suggests that innovation policies have played a pivotal role in enhancing efficiency. Moreover, reinforcing efforts in innovation could potentially advance the EU's primary objective of reducing social and economic disparities across its member states.

6. CONCLUSIONS

The primary aim of this study was to assess the efficiency of European regions and evaluate the impact of research and development activities. To achieve this, we employed the growth model outlined by Mankiw et al. (1992) in translog form. Drawing on Bayesian methods as advocated by Tsionas (2006) and Emvalomatis (2012) we applied these techniques across 27 European countries, spanning the years 2000 to 2021.

Our analysis revealed compelling empirical evidence highlighting the significant influence of human capital over physical capital in production. Moreover, inefficiencies persist due to escalating costs, whether in monetary or temporal terms, as inputs expand. These findings underscore the potential benefits of prioritizing investment in tertiary education, given its superior efficiency compared to greater physical capital accumulation. Furthermore, our study demonstrated that innovation efforts, gauged through R&D expenditures as a percentage of GDP, positively impacted efficiency gains. Regions in Eastern and Southern Europe exhibited lower levels of technical efficiency. On average, the countries examined in our empirical analysis experienced an upward trajectory in technical efficiency over the study period, mirroring trends in R&D expenditure. These collective findings not only enhance our comprehension of the intricate relationship between innovation and economic dynamics but also furnish critical insights for policymakers and stakeholders aiming to cultivate environments conducive to innovation-led growth.

Lastly, from a policy standpoint, our results advocate for sustaining or augmenting expenditures on research and development, recognizing innovation as a pivotal driver of efficiency. This approach is crucial for achieving the economic and social objectives of the European Union.

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APPENDIX

Table A.1. Average efficiency scores per country.

Country	TE
Austria	0.874
Belgium	0.924
Bulgaria	0.798
Croatia	0.846
Cyprus	0.813
Czechia	0.888
Denmark	0.874
Estonia	0.785
Finland	0.936
France	0.914
Germany	0.921
Greece	0.852
Hungary	0.860
Ireland	0.782
Italy	0.896
Latvia	0.834
Lithuania	0.832
Luxembourg	0.818
Malta	0.759
Netherlands	0.907
Poland	0.850
Portugal	0.866
Romania	0.714
Slovakia	0.842
Slovenia	0.886
Spain	0.871
Sweden	0.922