Innovation, productive performance and undesirable outputs across European regions: Are there any missing links?

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17th Annual Seminar

Ermoupoli, July 8, 2022

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Conceptual Foundation-Motivation

- European Union (EU) is implementing the strategy which aims at becoming a **global leader in climate change** by 2050 (EC, 2020) achieving a climate neutral economy and **at the same time to enjoy high levels of growth**.
- Technological innovation has become a significant driver of **competitiveness** and **productivity growth** at firm, region and country level.
- Technological progress must be radical and massive to enable the **de-carbonization of European regions** and at the same time lead to **substantial increases of productive performance** (EC, 2010).
- The processes of **(i) knowledge generation, (ii) conventional production** and **(iii) emissions of pollutants** should be considered as nodes of the same system. This interdependency results in increased heterogeneity as different (heterogeneous) patterns are mixed.

Research Question

- Research Objective:
  - **Examine the links between knowledge generation efficiency and productive performance with undesirable outputs in a regional setting**
- More precisely, we explore:
  - The **multi-faceted efficiency of regions across Europe** employing a network type, chain-DDF, production frontier.
  - The **significance of innovation and bad outputs in regional performance**.
  - Dynamics, convergence/divergence, patterns of European regions to trace the **heterogeneity (divergence or club convergence) vs the existence of representative region (steady state convergence)**.

Theoretical background and Literature review: Developments

- **Technological progress** has presented a long-term relationship with **economic growth** (Solow, 1956). In this tradition **innovation is a residual** of the overall economic activities and not as an autonomous process.
- Since then, several studies have included **innovation**, among other factors, into models to explain economic growth and **productivity differentials** (indicatively, Grossman and Helpman, 1991; Freeman, 2002; Wong et al., 2005; Ortega-Argiles et al, 2014)
- On the grounds of the Schumpeterian ideas, **innovation** may be described in the context of a **production function/frontier** (Griliches, 1979; Romer, 1990; Chiesa and Fratini, 2009; Pellegrino and Piva, 2020).
- The examination of **innovation efficiency** through frontier analysis is becoming more and more popular (i.e Guan and Chen, 2010; Wang and Huang, 2007; Zabala-Iturriagagoitia et al., 2007; Kumbhakar et al, 2012; Gkypali and Tsekouras, 2015; Haschka, and Herwartz, 2020).
- Although **firm-level analysis is dominant**, numerous studies were conducted at **industrial** (i.e. Loof et al., 2004; Masso and Vahter, 2008; Hashimoto and Haneda, 2008; Uppenberg and Strauss, 2010; Schmidt-Ehmcke and Zloczysti, 2011) and **country** level (Nadiri and Kim, 1996; Aghion and Howitt, 1998; Griffith et al., 2006; Crespi and Zuniga, 2012; Broekel et al., 2013; Wang et al., 2016) employing the **nonparametric approach of Data Envelopment Analysis** (DEA)

Theoretical background and Literature review: The gap

- Two main drawbacks of the existing approaches:

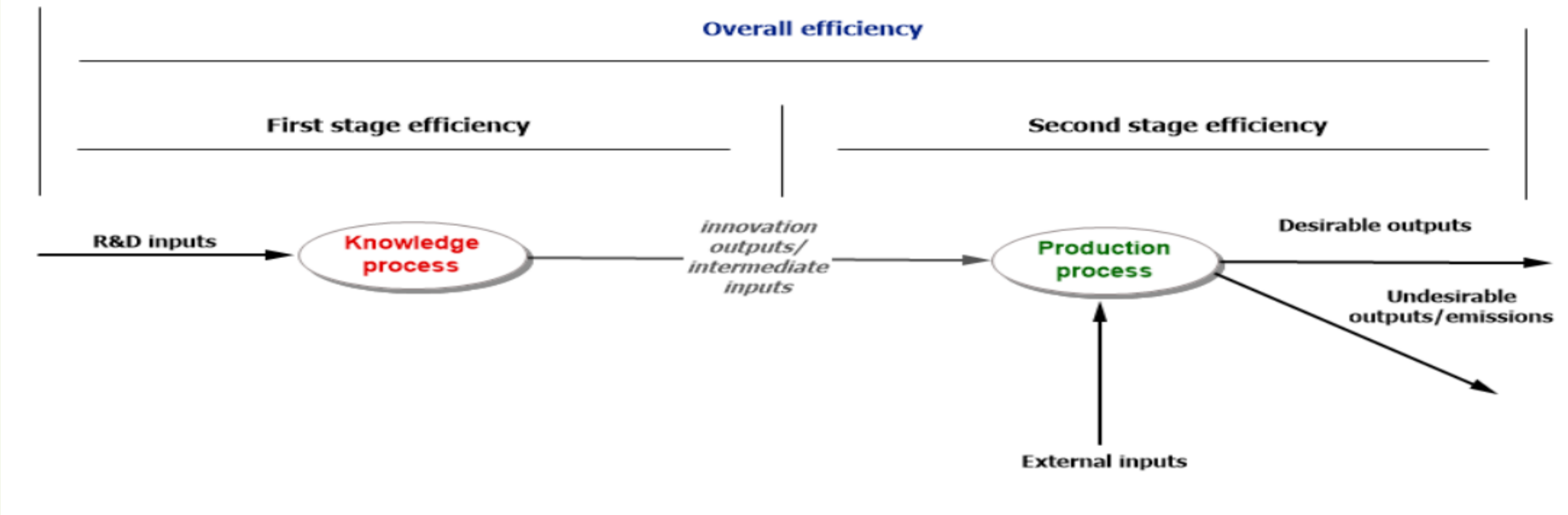
(i) They **neglect the multi-stage characteristics of the production process** and imply strong separability between the different stages. Therefore, **inefficiencies in different stages are not conveyed in the system**. The final estimation may be biased due to “measurement” errors (Wang et al. 2016)

(ii) They do not consider the **production of undesirable outputs** (Fare et al, 1997; Guan and Chen, 2012; Adetutu et al. 2015; Zhang and Vigne, 2019)

- Due to the growing consensus regarding climate change effects, **innovation** is considered as one of the most important instrument to **mitigate GHG emissions**, **reduce energy** inputs consumption and lead modern societies to a **sustainable future** (Fernandez et al. 2018; Fereira et al. 2020; Ahmad et al. 2021)
- In recent years, considerable research has revealed the **positive effect of innovation** activities on **carbon emissions** (Huaman and Tian, 2014; Lee and Min, 2015; Zhang et al. 2017; Du et al., 2019; Liu et al., 2020; Zhang et al., 2020)

Methodological Strategy – The Production Network

- The **efficiency** is measured in each one of the two **stages** and in the **overall** system
- The role od the **z intermediate inputs/outputs** is crucial. **Inefficiencies are conveyed** between between processes.
- **Inefficiencies of the first stage** are transmitted to the whole regional system
- An **increase of emissions** per unit of output **reduces regional productive performance**



$$D\left(x_l^t, z_q^t, z_l^{t-1}, x_e^t, y_s^t, b_m^t\right) = INE = \max\frac{1}{2}\left(INE^{KP} + INE^{PP}\right) = \max\frac{1}{2}\left(\frac{1}{Q} * \sum_{n=1}^{N} \beta^{KPz} + \frac{1}{2}\left(\frac{1}{S} * \sum_{n=1}^{N} \beta^{PPy} + \frac{1}{M} * \sum_{n=1}^{N} \beta^{PPb}\right)\right)$$

a) Knowledge generation process:

$$\sum_{n=1}^{N} \lambda_n^{KP} x_{ln}^t \le x_{ln'}^t, \qquad l = 1, \dots, L$$

$$\sum_{n=1}^{N} \lambda_n^{KP} z_{qn}^t - \beta^{KPz} g_{zq}^{KP} \ge z_{qn'}^t, \qquad q = 1, \dots, Q$$

$$\lambda_n^{KP} \ge 0, \qquad n = 1, \dots, N$$

b) Production process:

$$\sum_{n=1}^{N} \lambda_n^{PP} z_{qn}^{t-1} \le z_{qn'}^{t-1}, \qquad q = 1, \dots, Q$$

$$\sum_{n=1}^{N} \lambda_n^{PP} x_{en}^t \le x_{en'}^t, \qquad e = 1, \dots, E$$

$$\sum_{n=1}^{N} \lambda_n^{PP} b_{mn}^t + \beta^{PPb} g_{bm}^{PP} = b_{mn'}^t, \qquad m = 1, \dots, M$$

$$\sum_{n=1}^{N} \lambda_n^{PP} y_{sn}^t - \beta^{PPy} g_{ys}^{PP} \ge y_{sn'}^t, \qquad s = 1, \dots, S$$

$$\lambda_n^{PP} \ge 0, \quad n = 1, \dots, N$$

Empirical Strategy -Convergence analysis

- The Phillips and Sul (2007) approach covers a wide variety of possible transition paths towards convergence, including subgroup convergence. The heterogeneity of the individuals can be captured by utilizing the model: $EFF_{it}^{k} = \delta_{it}^{k}\mu_{t}^{k}$
- PS defined the relative transition parameter, h_{it} as: $h_{it}^{k} = \frac{EFF_{it}^{k}}{\frac{1}{N}\sum_{i=1}^{N} EFF_{it}^{k}} = \frac{\delta_{it}^{k}}{\frac{1}{N}\sum_{i=1}^{N} \delta_{it}^{k}}$

that measures the loading coefficient of *i-th* region in time *t* in relation to the panel average at time t.

  - The null hypothesis of full convergence is: $H_0 : \delta_i^k = \delta^k \; and \; \alpha(transition) \geq 0$
  - $H_1 : \delta_i^k \neq \delta^k \; for \; some \; i \; and/or \; \alpha < 0$

- The null hypothesis is tested using the following log t regression:

$$log\left(\frac{H_1^k}{H_t^k}\right) - 2logL(t) = \hat{c} + \hat{b}logt + u_t^k$$

- where L(t) = log(t + 1) and $H_t^k = N^{-1}\sum_{i=1}^{N}(h_{it}^k - 1)^2$. The coefficient of log t is $\hat{b} = 2\hat{a}$ where $\hat{a}$ is the estimate of α in H_0. When $b \geq 0$, a full panel convergence occurs while higher values indicate faster rates of convergence. However, **a rejection of the null hypothesis of full panel convergence, does not necessarily imply evidence against convergence at the level of subgroups within the panel**

Database

- **22 European Countries**: Austria, Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, Germany, Greece, Hungary, Italy, Latvia, Netherlands, Norway, Poland, Portugal, Romania, Slovak Republic, Spain, Sweden and United Kingdom
- **199 Regions**
- **19 Years**: 2000-2018; 3,781 observations, lag 3,582
- **Variables:**

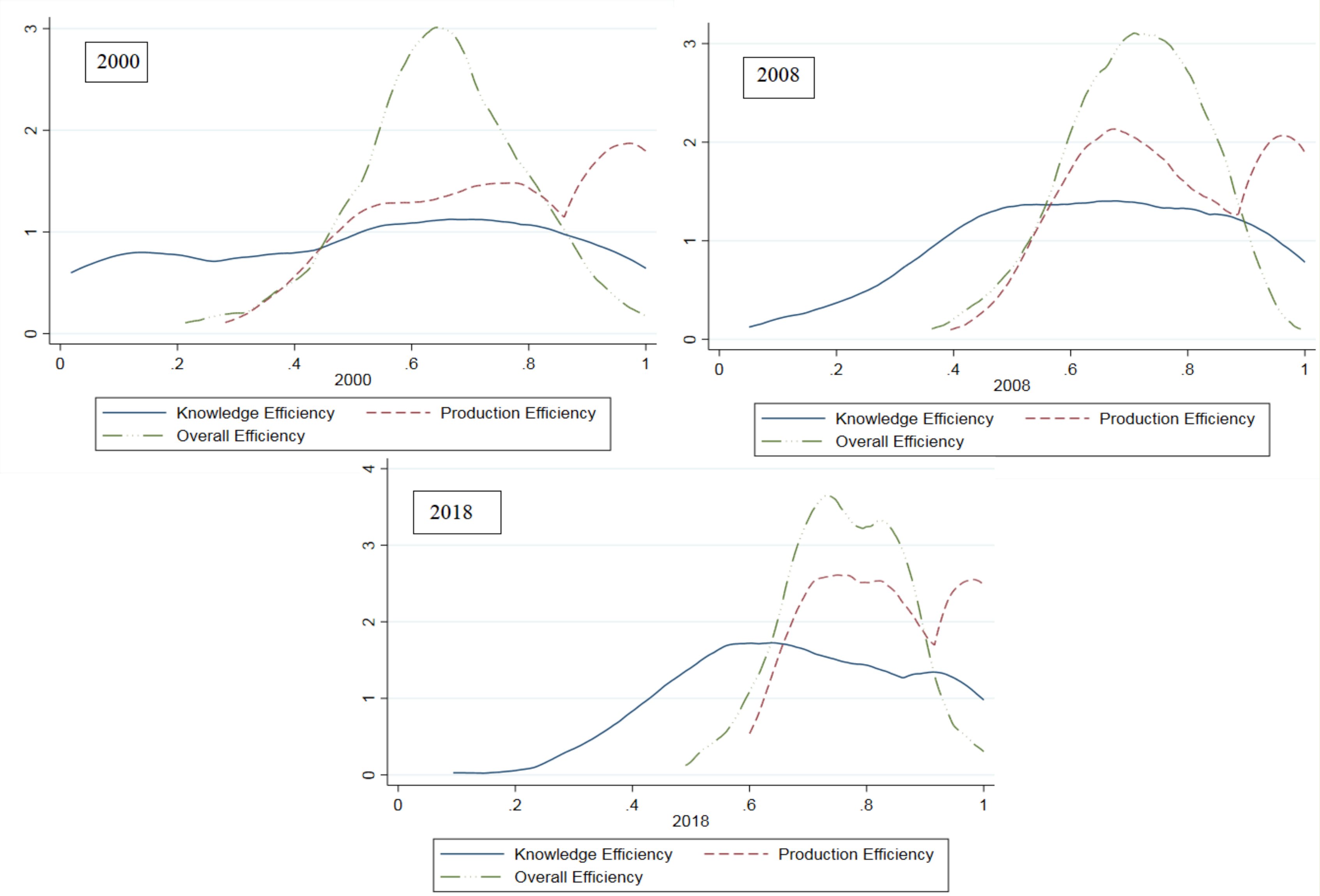
Knowledge Generation (KP)	**Innovation Outputs**	Patents (P) Community Designs (CD) Community Trademarks (CTM)
	Innovation Inputs	R&D personnel (RDPERS) Gross domestic expenditure on R&D (GERD) Human Resources in Science and Technology (RDPERS)
Conventional Production (PP)	**Conventional inputs**	Capital stock (K) Labor Input (L)
	Conventional output	Gross Domestic Product (GDP)
	Bad Output	CO_2 emissions (CO_2)

Empirical Analysis-Descriptive statistics

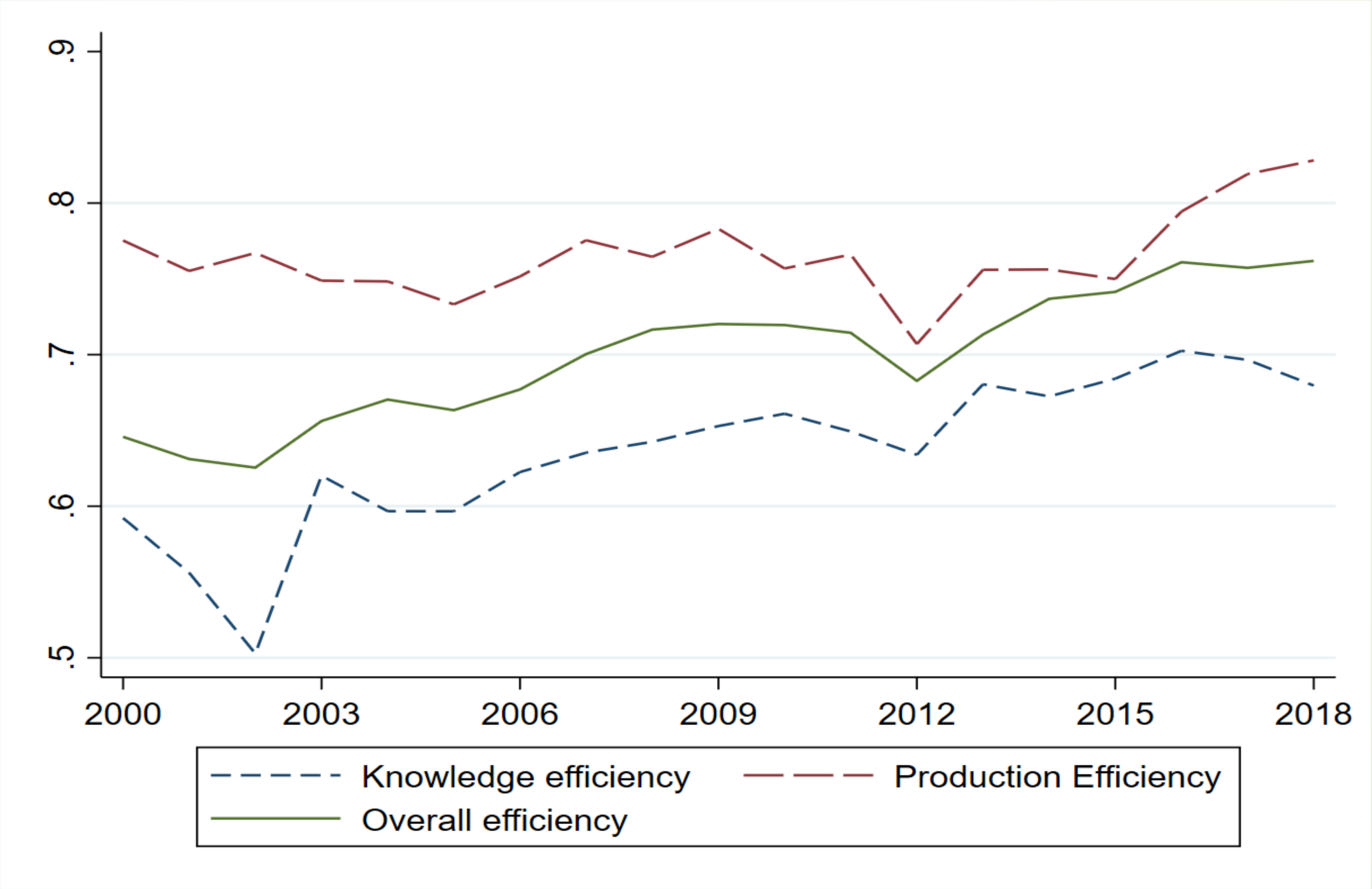
- Innovation and Economic Data are from Eurostat database.
- Capital input information is drawn from Cambridge Econometrics database
- Regional CO_2 emissions are from the E-PRTR database

Variables	Mean	SD	Min	Max
		Knowledge generation inputs		
GERD	873.742	1,338.296	1	15,918.810
RDPERS	13,105.440	14567.2	5	113,563
HRST	373.782	308.4608	9.300	2,174.100
		Knowledge generation outputs / Intermediate inputs		
P	206.420	361.818	0.500	2,733.400
CD	185.744	322.490	0.567	2,822
CTM	214.685	336.927	1	2762
		2nd stage (additional external) inputs		
K	58,846.930	62,418.030	379.287	567,589.200
L	815.741	630.510	59.800	4.798.300
		2nd stage outputs		
GDP	44,151.850	44,227.140	1,499.520	388,064.700
CO_2 (in millions)	7,290	10,400	12.800	99,400

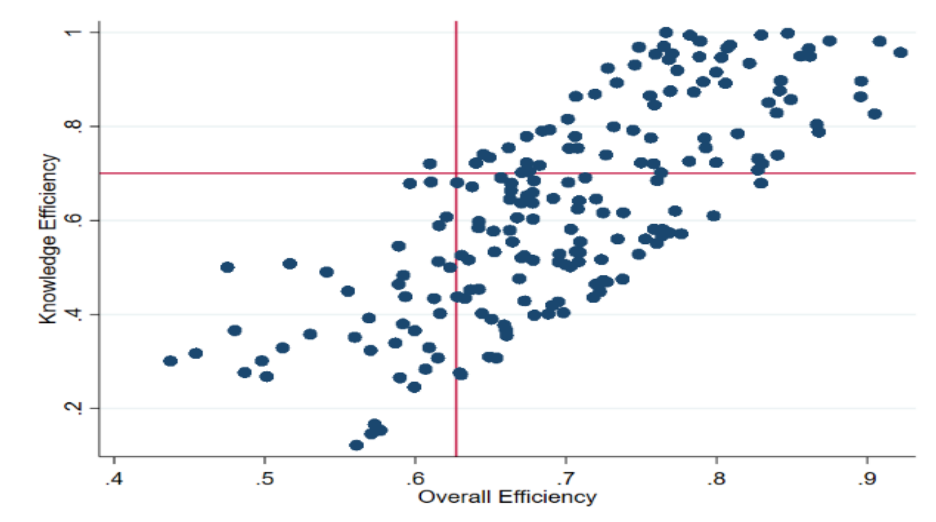
Kernel densities for knowledge, production and overall efficiency in 2000, 2008 and 2018

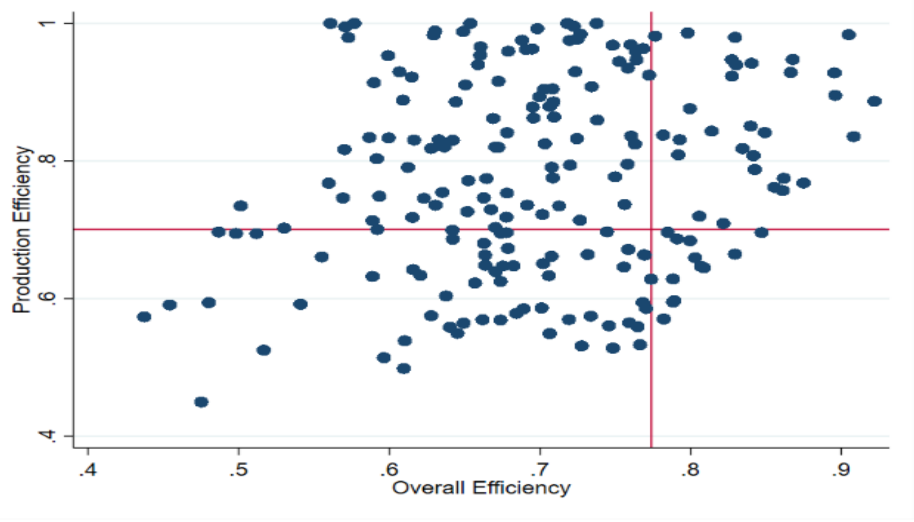


Regional average efficiency over the 2000-2018-time period

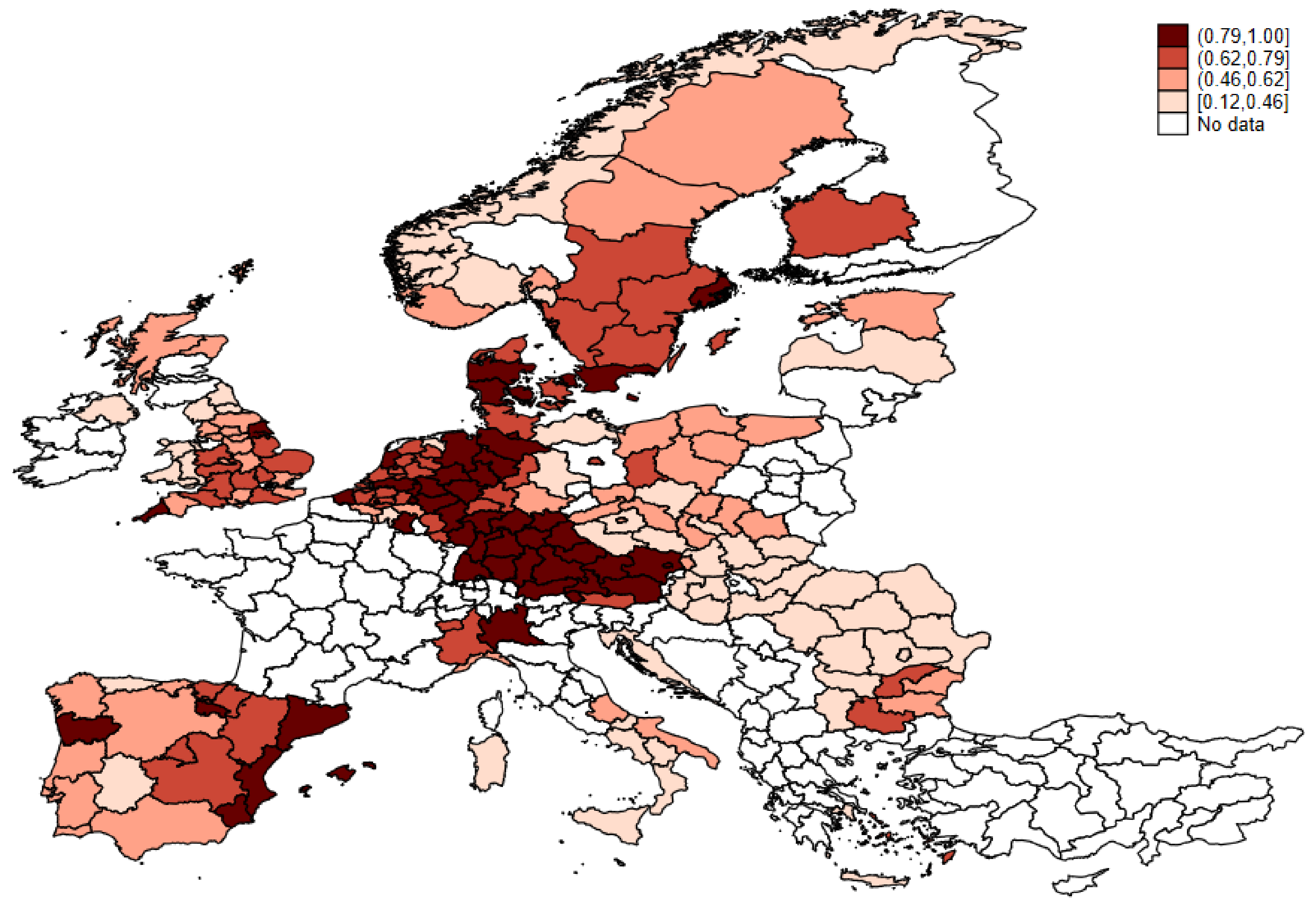


Scatter plot of knowledge generation, production and overall efficiency on European regions

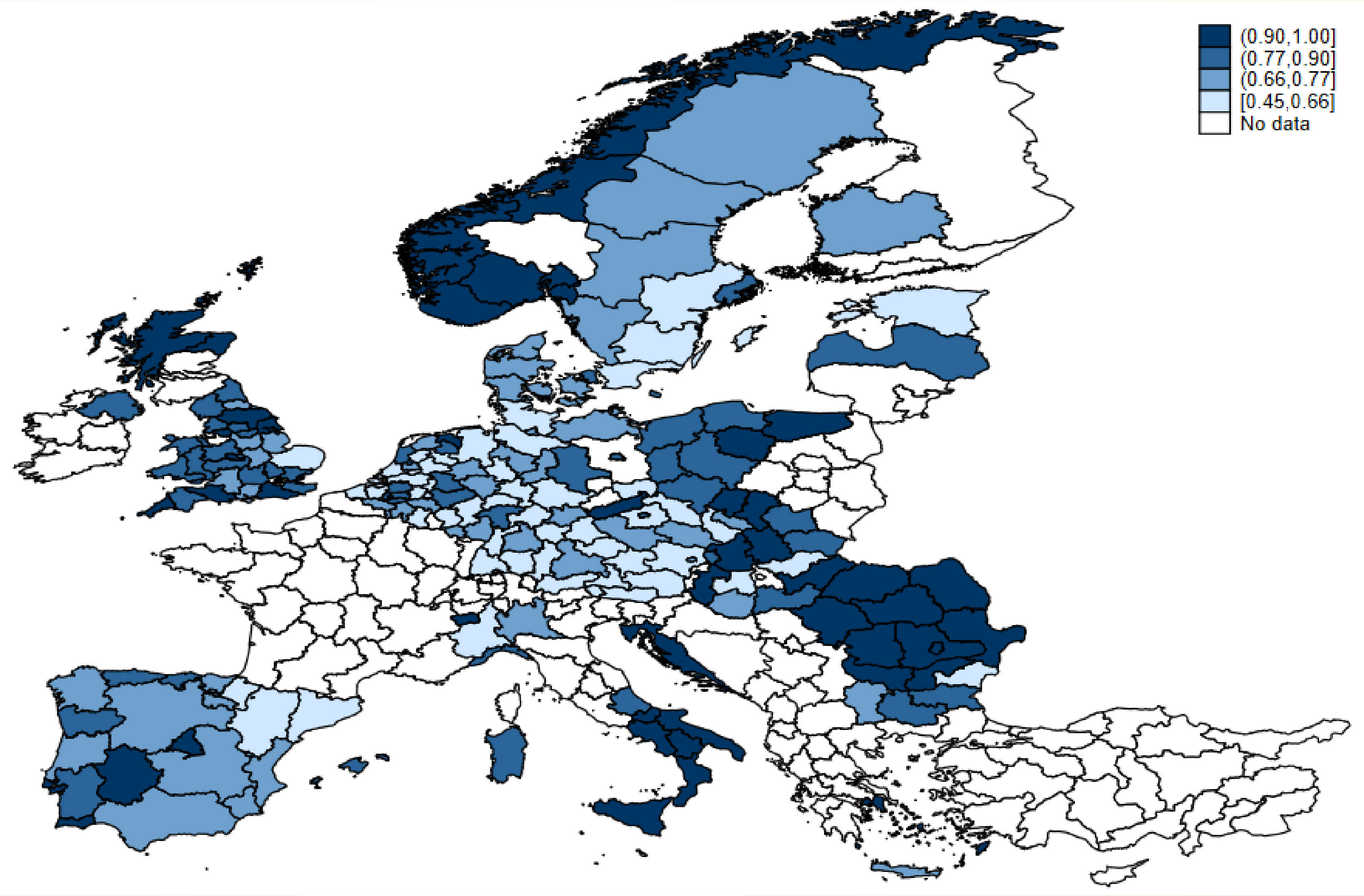




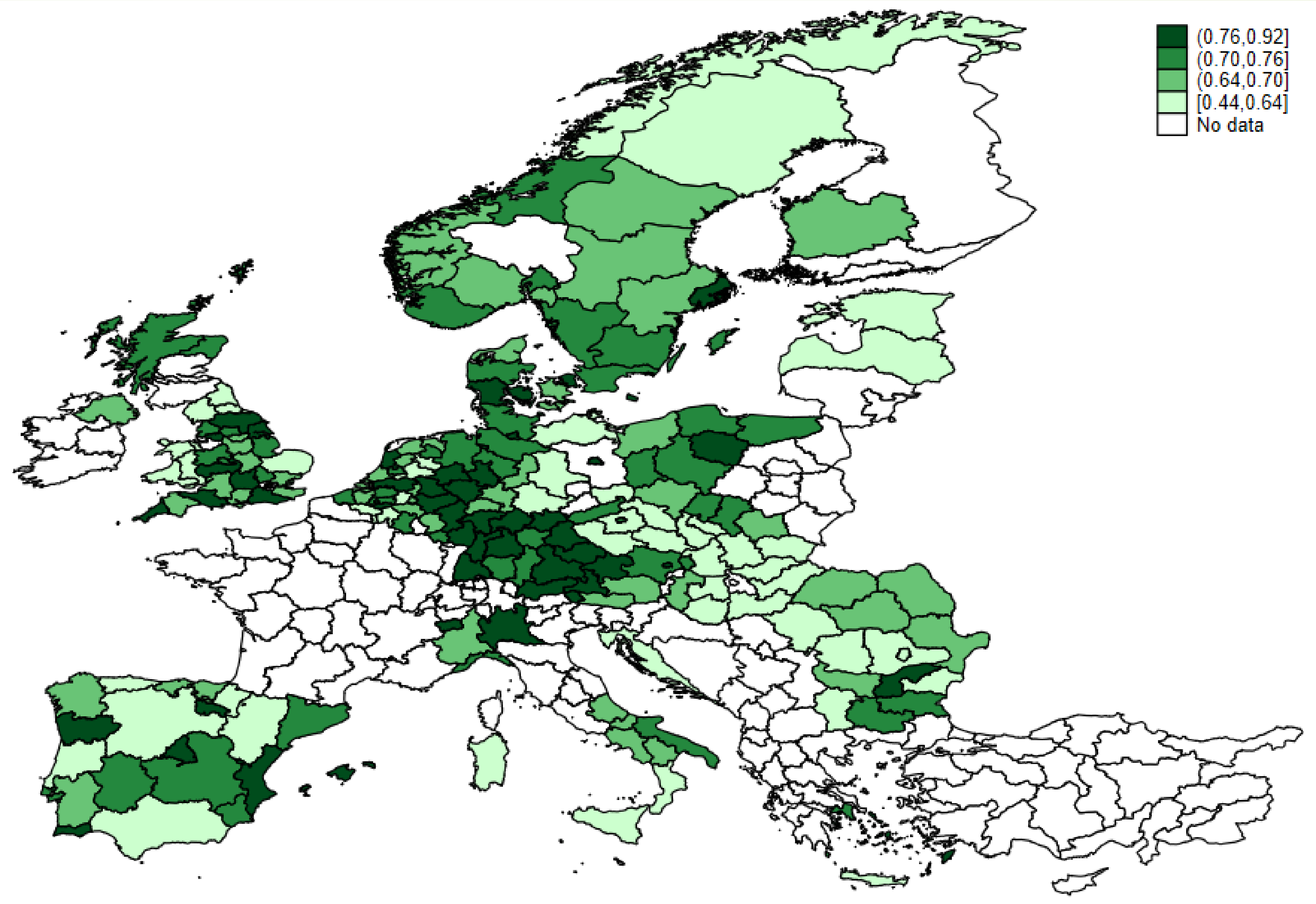
Knowledge generation efficiency scores of the European regions



Production efficiency scores of the European regions



Overall efficiency scores of the European regions



Dynamics of Efficiency: One or more regimes?

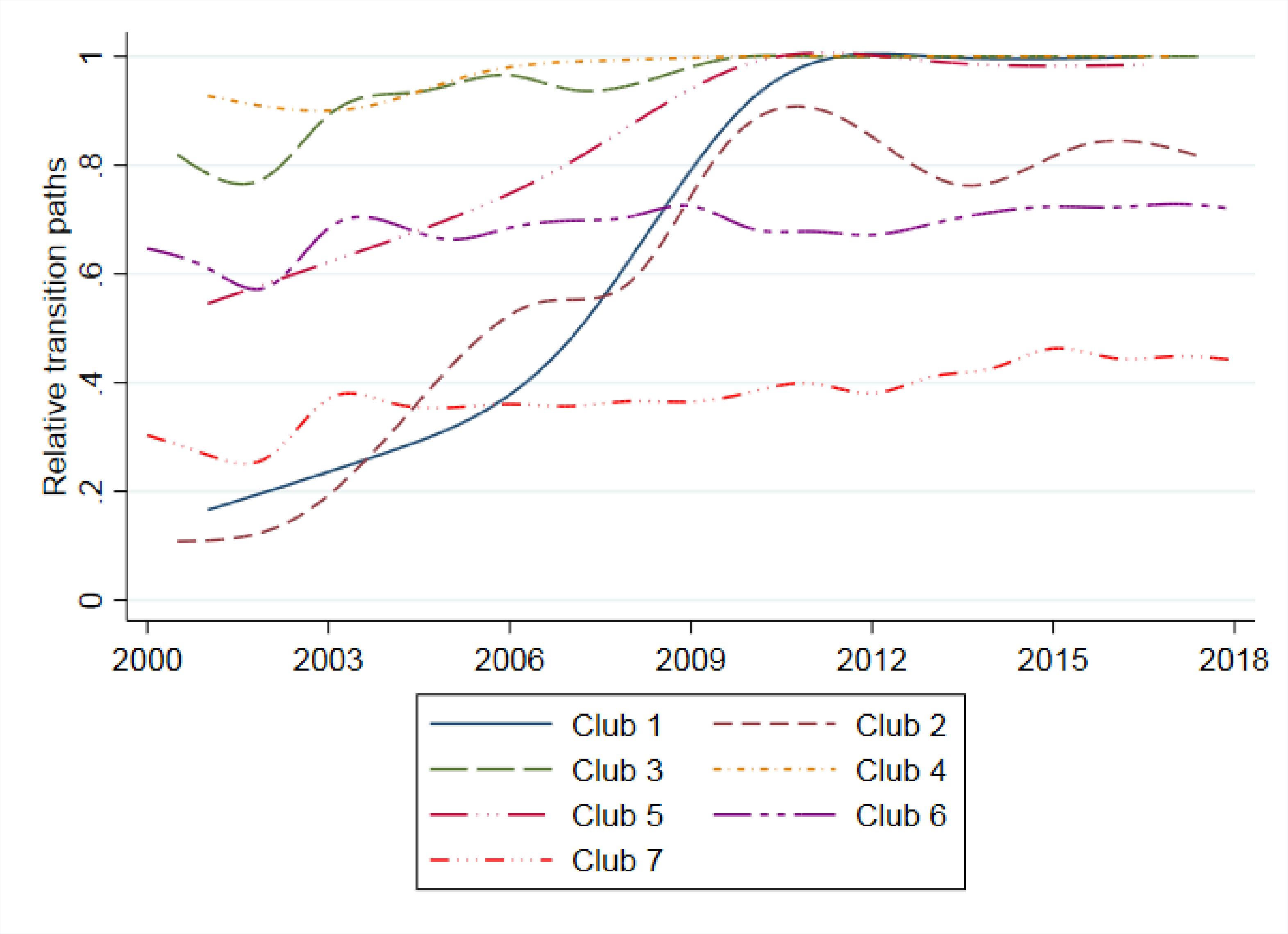
Four types of convergence/divergence regimes have been recorded in the literature (Giovanetti, 2013)

- **Persistent non-convergence (PNC)** regime, where nobody converges, and everybody remains at the initial level
- **Leapfrogging (LF)** regime where followers catchup with the leaders
- **Forging ahead (FA)**, regime where leaders remain leaders and increase the gap from the followers
- **Catching up (CU)** regime, where everybody converges at a steady state

Heterogeneity: Convergence club classification for knowledge efficiency

Initial classification $\hat{b}$ (SE of $\hat{b}$)		Tests of club converging $\hat{b}$ (SE of $\hat{b}$)		Final classification $\hat{b}$ (SE of $\hat{b}$)	
Club 1 [2]	-0.672	Club1+2	**-3.913***	Club 1 [2]	-0.672
	(1.988)		(1.119)		(1.988)
Club 2 [2]	-1.307	Club2+3	-1.280	Club 2 [5]	-1.280
	(1.509)		(1.163)		(1.163)
Club 3 [3]	-0.630	Club3+4	-0.966	Club 3 [10]	-1.061
	(1.590)		(0.946)		(0.686)
Club 4 [2]	0.688	Club4+5	-3.351	Club 4 [3]	1.000
	(1.960)		(2.229)		(1.915)
Club 5 [2]	0.011	Club5+6	-0.818	Club 5 [2]	-2.096
	(1.833)		(1.170)		(1.456)
Club 6 [3]	0.374	Club6+7	-1.792	Club 6 [138]	-0.100
	(2.527)		(1.232)		(0.065)
Club 7 [3]	0.256	Club7+8	-3.631	Club 7 [38]	1.188
	(2.015)		(3.545)		(.150)
Club 8 [3]	1.000	Club8+9	**-3.831***	Club 8 [2]	**-3.066***
	(1.915)		(1.413)		(0.082)
Club 9 [2]	-2.096	Club9+10	**-0.197***		
	(1.456)		(0.074)		
Club 10 [138]	-0.100	Club10+11	**-0.436***		
	(0.065)		(0.033)		
Club 11 [37]	1.188	Club11+12	**-0.427***		
	(0.150)		(0,063)		
Club 12 [2]	**-3.066***				
	(0.082)				

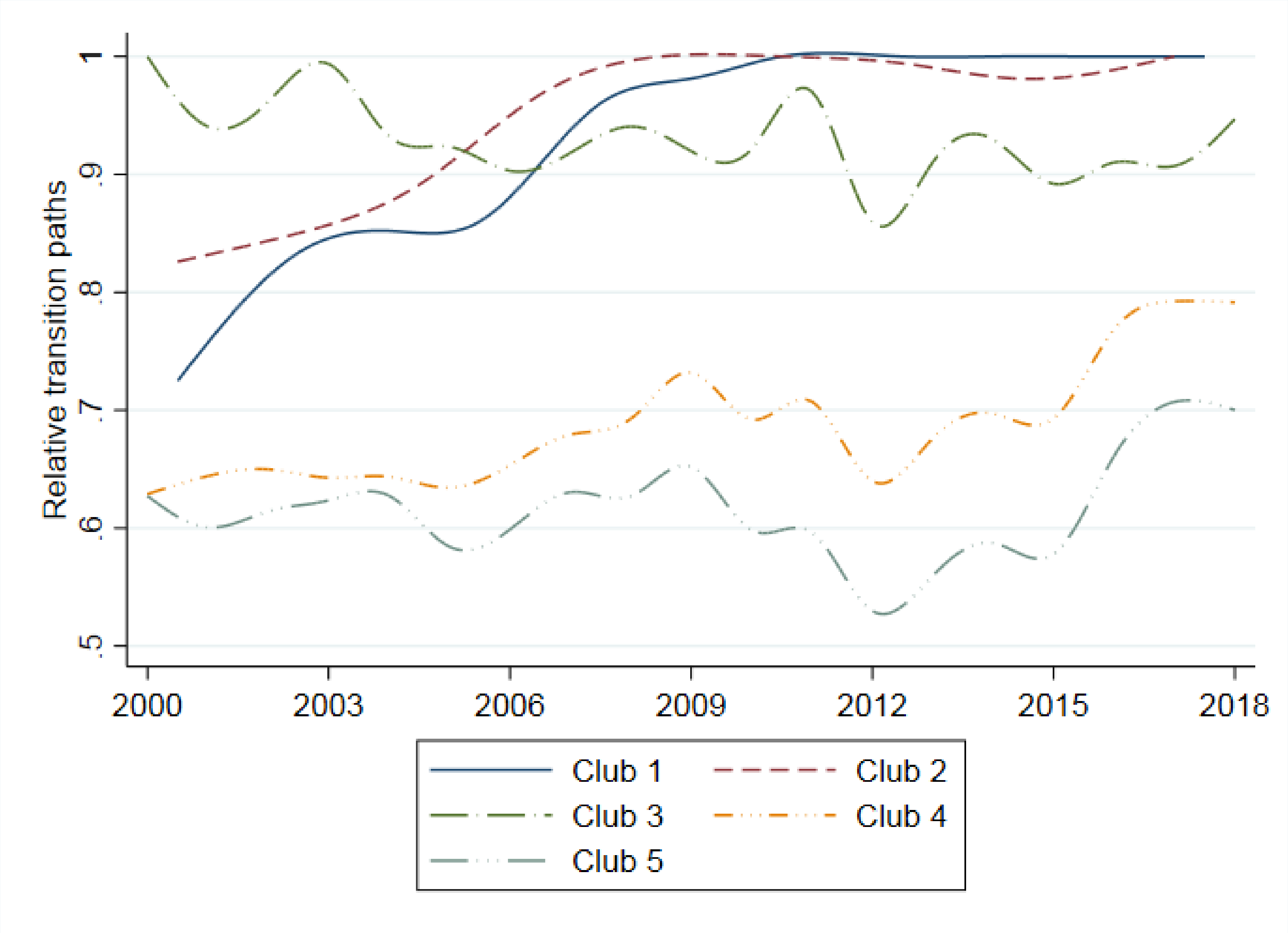
Relative transitory path for convergent clubs regarding knowledge generation efficiency



Heterogeneity: Convergence club classification for production efficiency

Initial classification $\hat{b}$ (SE of $\hat{b}$)		Tests of club converging $\hat{b}$ (SE of $\hat{b}$)							Final classification $\hat{b}$ (SE of $\hat{b}$)	
Club 1 [3]	0.010	Club1+2							Club 1 [6]	-2.119
	(2.500)	-2.119								(1.383)
Club 2 [3]	-1.947	(1.383)	Club 2+3						Club 2 [4]	-0.061
	(2.207)		**-2.647***							(1967)
Club 3 [4]	-0.061		(0.899)	Club 3+4					Club 3 [84]	-0.155
	(1.967)			**-1.448***						(0.138)
Club 4 [7]	**-0.820***			(0.459)	Club 4+5				Club 4 [51]	1.132
	(0.017)				0.186					(0.235)
Club 5 [46]	0.433				(0.125)	Club 5+6			Club 5 [54]	0.816
	(0.164)					-0.033				(0.117)
Club 6 [31]	1.968					(0.162)	Club 6+7			
	(0.351)						0.925			
Club 7 [51]	1.132						(1.700)	Club7+8		
	(0.235)							**-0.259***		
Club 8 [54]	0.816							(0.113)		
	(0.117)									

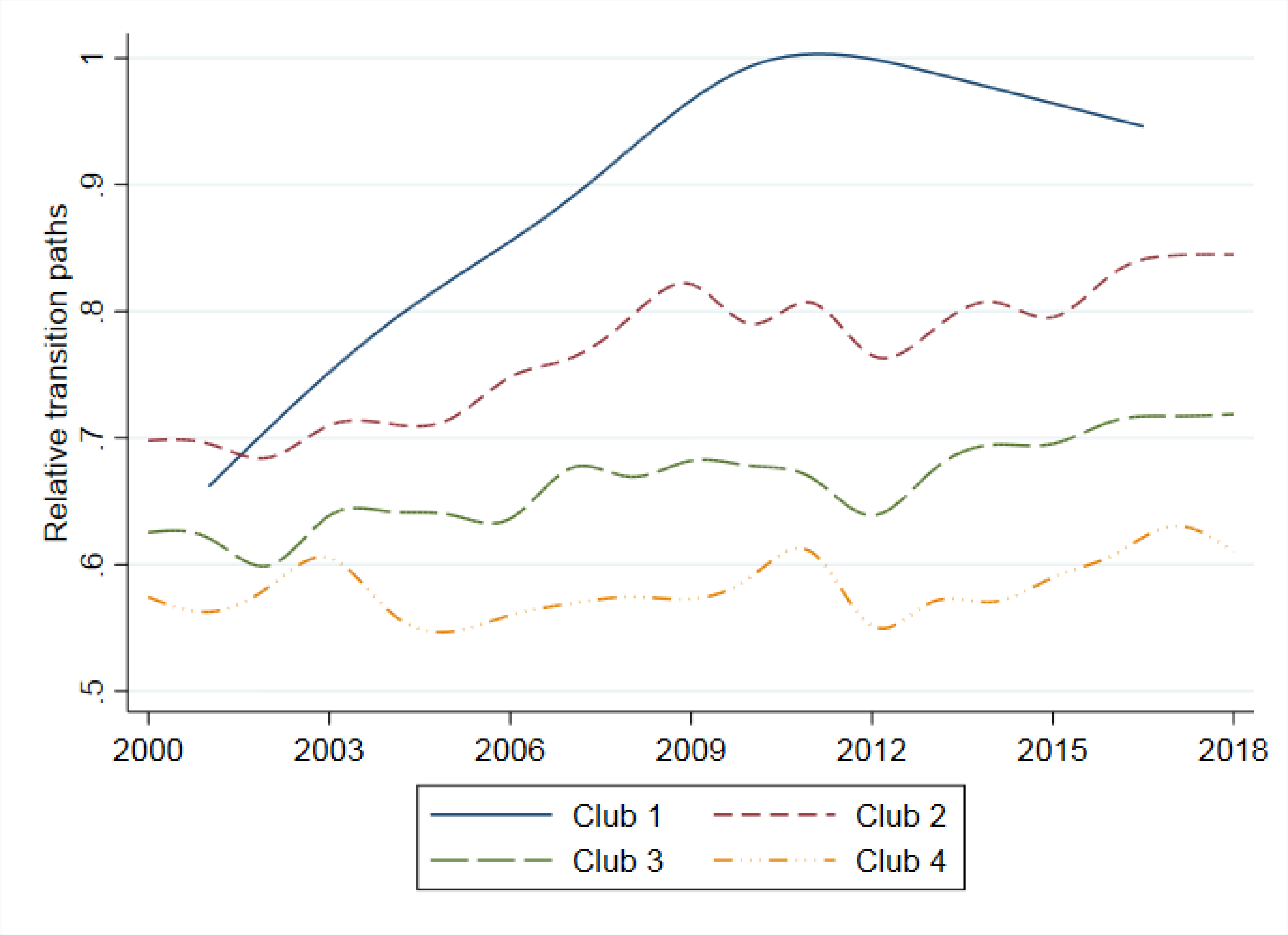
Relative transitory path for convergent clubs regarding production efficiency



Heterogeneity: Convergence club classification for overall efficiency

Initial classification $\hat{b}$ (SE of $\hat{b}$)		Tests of club converging $\hat{b}$ (SE of $\hat{b}$)			Final classification $\hat{b}$ (SE of $\hat{b}$)	
Club 1 [2]	-0.729	Club1+2			Club 1 [2]	-0.729
	(1.584)	-0.404*				(1.584)
Club 2 [90]	-0.204	(0.118)	Club2+3		Club 2 [90]	-0.204
	(0.126)		-0.934*			(0.126)
Club 3 [83]	0.346		(0.052)	Club3+4	Club 3 [83]	0.346
	(0.091)			-0.547*		(0.091)
Club 4 [24]	-0.051			(0.017)	Club 4 [24]	-0.051
	(0.035)					(0.035)

Relative transitory path for convergent clubs regarding overall efficiency



Some discussion and Conclusions (1/2)

- This study employs panel data to examine the multifaceted efficiency of 199 European regions from 2000 to 2018.
- The employed model is a two-stage network type approach that considers the knowledge inputs, the intermediate products, additional external inputs and the desirable/undesirable outputs to evaluate the integrated regional efficiency and all-phase efficiency scores.
- The results reveal an overall upward trend in efficiency levels across European regions between 2000 and 2018. However, the efficiency levels of each region exhibit significant differences in both knowledge generation and production activity.
- From a knowledge perspective, regions located in central Europe seems to be better placed to induce regional economies towards the promotion of more innovative activities.
- The highest production efficiency levels accounting for bad outputs are observed in regions located in the northern and eastern part of Europe.
- Overall, regions of the Central Europe are the most efficient in the system highlighting the balance of high performance in innovation, production and environmental protection activities

Some discussion and Conclusions (2/2)

- Panel convergence or steady state convergence is not confirmed. Representative region approach does not facilitate the development of effective policies. Differentiated Regional and industrial policies may be valuable
- The investigation of convergence dynamics reveals patterns of high complexity, both within each one of the three examined efficiency contexts as well as between them.
- Knowledge generation efficiency evolution pattern is the most complex case
- The transition paths of European Regions reveal the coexistence of multi-type convergence clubs
- Convergence is more likely to occur among regions within a country rather than regions located in different European countries.
- There is no confirmation that regions of the North or South Europe establish their own clubs grounded solely on this geographical division.
- Policymakers may benefit from detecting common features in the regions of each club to redirect their efforts in a more precise manner with higher levels of differentiation.
- The examination of the factors that influence the efficiency scores of each stage and the overall system, could be valuable in the sense that could provide regional policymakers with a more in-depth and far-reaching perspective on the overlap between innovation standards and broader sustainability goals.

Thank you for your attention!!!

The research was supported by the Hellenic Foundation for Research and Innovation (H.F.R.I.) under the "First Call for H.F.R.I. Research Projects to support Faculty members and Researchers and the procurement of high-cost research equipment grant"(Project Number:HFRI-FM17-0320)