INNOVATION EFFICIENCY IN HETEROGENEITY CONTEXT: A MATTER OF INPUTS AND OUTPUTS OR OF INNOVATION CAPABILITIES? THE CASE OF CATCHING-UP COUNTRIES

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OUTLINE

MOTIVATION AND OBJECTIVE

- The existing literature in efficiency and productivity analysis presumes that the firms under consideration operate under similar conditions (Kumbhakar et al., 2015), have access to a similar range of resources (Dyson et al., 2001), and utilise similar inputs and technologies to produce the same outputs (Haas & Murphy, 2003; Huang, 2004).

- This is commonly known as the homogeneity assumption. However, heterogeneity is present in most cases due to a plethora of factors.

- Imposing full homogeneity in innovation efficiency analysis, results to what has named technological isolation, since important inter-linkages between firms, industries, regions, and countries are neglected and the estimation of innovation efficiency becomes inaccurate and shady. (Dyson et al., 2001; Tsekouras et al., 2016)

MOTIVATION AND OBJECTIVE

- Many researchers in Europe use CIS data. Indicatively: Brouwer et al (1999);Catozzella et al (2008);Conte et al (2005);Damijan et al (2017)
- In order to measure innovation efficiency, we use a multi-input multi output framework. In this case crucial information, such as patents, other forms of Intellectual Property Rights and the introduction of several types of innovation is of binary type.
- In this way we deviate from the input/output approach and introduce innovative capabilities in the efficiency analysis.
- The most prominent approach to estimate innovation efficiency is grounded on frontiers methodology.
- DEA is the most popular branch of frontier methodology in innovation efficiency estimation due to its nonparametric characteristics which not only allow for multiple inputs and outputs to be used regardless of measurement units, but also does not require assumptions regarding functional form and weight.
- On the contrary the main advantage of a parametric approach (SFA) is that it considers the existence of statistical noise in the data. Its main disadvantage, on the other hand, is the use of a specific functional form that presumably approximates the underlying technology; this however may impose unnecessary structure in the data. (Tsekouras et al 2004)
- However, using non continuous input output variables in DEA and especially in the case of innovation efficiency is not feasible.

MOTIVATION AND OBJECTIVE

- This work aims firstly to introduce an approach on how to handle the non-continuous, especially binary, variables in CIS data by implementation of Data Envelopment Analysis (DEA) model by Banker and Morey (1986).

- The methodological innovation introduced is closely related to conceptual dimension of the firms/country heterogeneity of innovation process

- In this vein, we introduce an approach of the innovation process with the use of non-continuous data, and provide solid theoretical arguments on which we develop estimation techniques of innovation efficiency

- The implementation of modified DEA models is illustrated by the innovation efficiency evaluation of the 5 Catching Up countries (Hollanders et al, 2007), namely Greece, Portugal, Hungary, Lithuania and Croatia from 2012-2014 wave of CIS microdata.

MAIN CONTRIBUTIONS

- The introduction of innovation capabilities in the innovation efficiency heterogeneity context.
- We exploit the information embedded in binary variables and feed the benchmarking process with additional information related to the ranking/hierarchy of innovative firms with respect to the proliferation of innovation outputs.
- We reveal latten heterogenous groups within the efficient frontier using a data driven heuristic algorithm instead of clustering the data into groups prior the efficiency estimation.

THEORETICAL ARGUMENTS

- Mediating role of Innovation Property Rights (IPRs) in the process of estimation of innovation efficiency.
- IPRs are handled as a mediation factor, acting both as an input and output variable. Therefore, "hard" innovation inputs exhibit direct and indirect effects.
- We reveal latent hierarchical heterogenous innovation efficiency groups. (Gkypali et al, 2019). For this purpose, we develop a heuristic algorithm that detects and determines ordinal efficiency cluster groups of the metafrontier.
- Finally, we identify the characteristics that influence the probability of firms belonging to each ordinal group using ordinal regression.

INNOVATION EFFICIENCY AND HETEROGENEITY

- When homogeneity is assumed without accounting for firm heterogeneity, the efficiency scores may lead to errors in the efficiency ranking of firms and erroneous conclusions about improvement potentials at individual and industry levels.

- Using a common frontier will most likely overestimate the inefficiency (Hockmann et al., 2007) and may pronounce firms as inefficient, although they may fully use their available technology (Almanidis, 2013).

- When technology heterogeneity is neglected, the efficiency scores may not reflect the inefficiencies but rather the differences in environments (Haas & Murphy, 2003).

- The existence of heterogeneous production structures in literature is attributed to technological opportunities and appropriability conditions (Dindaroğlu, 2017), different demand conditions (Pieri et al., 2018), accumulated knowledge (Malerba, 2002; Malerba and Orsenigo, 1996), absorptive capacity (Cohen & Levinthal, 1989, 1990) and the heterogeneous production environment (Dosi et al., 2010; Tsekouras et al., 2016; Tsekouras et al., 2017).

INNOVATION AND EFFICIENCY

- Overall, innovation should not be regarded as a single event, but rather as a continuous and cumulative process. Innovation is not a linear process in which inputs automatically are transformed into outputs, innovation performance should be measured and with efficiency dimension, including its input and output altogether.

- In general efficiency is defined as the ratio of outputs over inputs. In case of innovation efficiency is the ability to transform innovation inputs into innovation outputs.

- Innovation efficiency is improved when with the same amount of innovation inputs more innovation outputs are generated (output-orientation) or when less innovation inputs are needed for generating the same amount of innovation outputs (input-orientation).

- R&D plays a significant role in increasing the probability of product innovation, while technological acquisition (TA) increases the likelihood of process innovation. Catozzella et al (2008). Process innovation is much more related to TA , both through the "embodied technical change" acquired by investment in new machinery and equipment and through the purchasing of external technology incorporated in licences, consultancies and know-how. Salter, (1960);Freeman, (1982)

INNOVATION AND EFFICIENCY

- In order to generate new ideas literature suggests that prior knowledge stock available to the firm is used in the innovation process. Accumulated patents are regarded as the appropriate input for considering the path dependency effect.

- Relevant literature on the role of IPRs in innovation and economic growth tends to focus on the strength of IPR protection, given the trade-offs between innovation and diffusion.

- From development perspectives, recent literature has shifted attention to diverse forms of IPRs in promoting innovation and growth, considering not only regular invention patents, but also utility models and trademarks. (Kim et al, 2012)

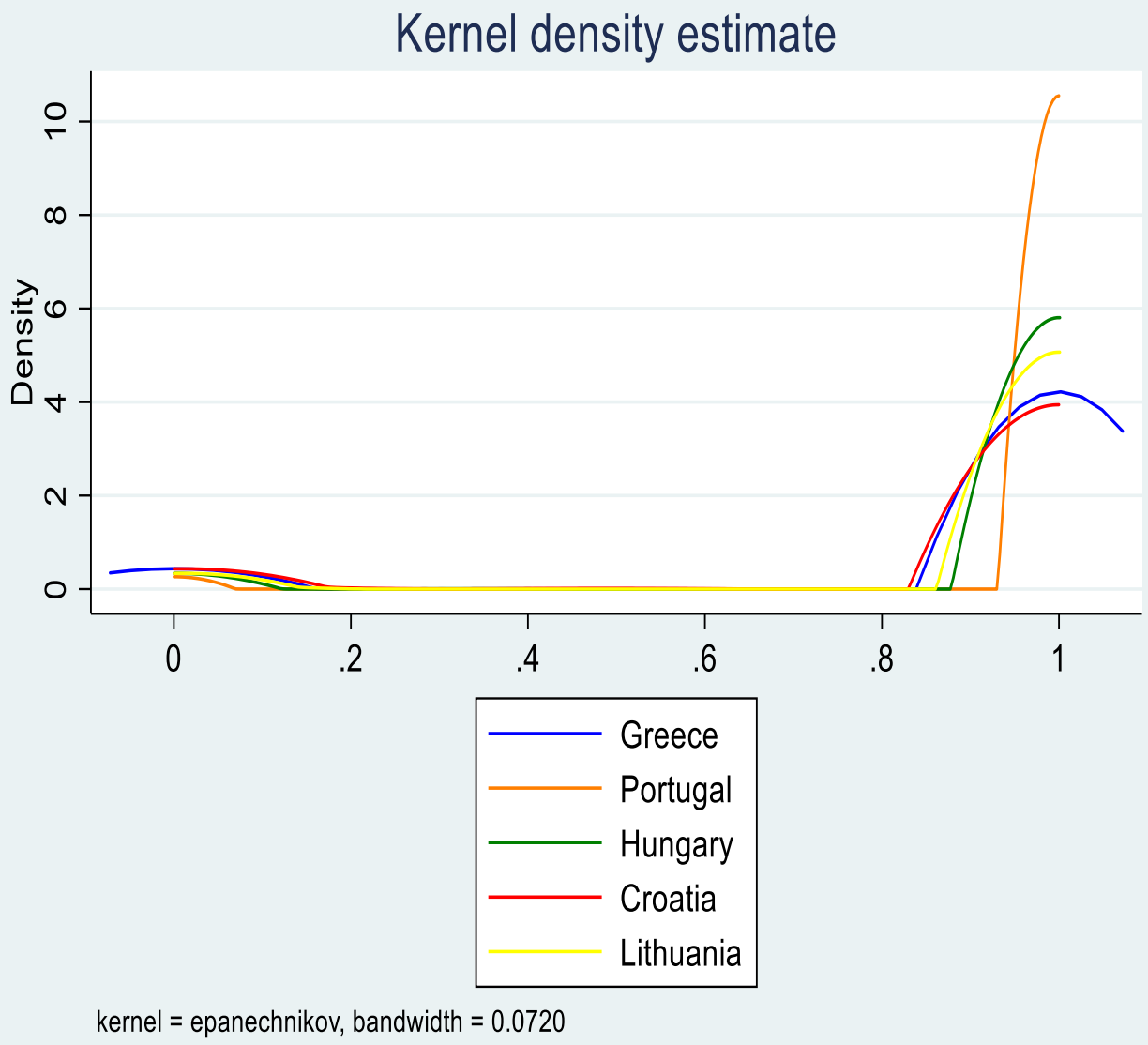
SIMPLE DEA RESULTS (WITH CONTINOUS INPUT-OUTPUT VARIABLES ONLY)

INPUTS

- Expenditures in intramural R&D
- Expenditures in acquisition of machinery
- Expenditures in extramural R&D
- Expenditures in acquisition of external knowledge

OUTPUT

- Innovative sales (cont.)



CIS DATA BINARY VARIABLES

- Using Community Innovation Survey (CIS) microdata, crucial information, such as patents, other forms of Intellectual Property Rights and the introduction of several types of innovation is of binary type and therefore does not allow for the estimation of knowledge generation and innovation efficiency.
- 87 % of variables in CIS microdata are binary.

TREATING BINARY INPUTS

BANKER AND MOREY(1986)

We define δ new variables $d_{m,j}^{(\delta)}$, where $\delta + 1$ is the number of values the categorical variable can take on

- 4 distinct levels

1. "none"
2. "low"
3. "average"
4. "high"

- Descriptor binary variables

1. $d_{m,j}^{(1)}$
2. $d_{m,j}^{(2)}$
3. $d_{m,j}^{(3)}$

for each of the DMU's

"none" level -> $d_{m,j}^{(1)} = d_{m,j}^{(2)} = d_{m,j}^{(3)} = 0$

"low" level -> $d_{m,j}^{(1)}=1, d_{m,j}^{(2)} = d_{m,j}^{(3)} = 0$

"average" level -> $d_{m,j}^{(1)} = d_{m,j}^{(2)} = 1 , d_{m,j}^{(3)} = 0$

"high" level -> $d_{m,j}^{(1)} = d_{m,j}^{(2)} = d_{m,j}^{(3)} = 1$

Example

Class	d1	d2	d3
"none"	0	0	0
"low"	1	0	0
"medium"	1	1	0
"high"	1	1	1

DATA ENVELOPMENT ANALYSIS

Simple DEA model , input oriented

Efficiency = Min θ

s.t.

$$\sum_{1}^{n} \lambda_j \cdot x_j \leq \theta \cdot x_{r_0}$$

$$\sum_{1}^{n} \lambda_j \cdot y_{r_j} \geq y_{r_0}$$

$$\sum_{1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \; \forall \; j = 1, \dots, r_0, \dots N$$

Modified DEA model , input oriented , with categorical input variables

Efficiency = Min θ

s.t.

$$\sum_{1}^{n} \lambda_j \cdot x_j \leq \theta \cdot x_{r_0}$$

$$\boldsymbol{\sum_{1}^{n} \lambda_j d_{m_j}^{(\delta)} \leq d_{mr_0}^{(\delta)}}$$

$$\sum_{1}^{n} \lambda_j \cdot y_{r_j} \geq y_{r_0}$$

$$\sum_{1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \; \forall \; j = 1, \dots, r_0, \dots N$$

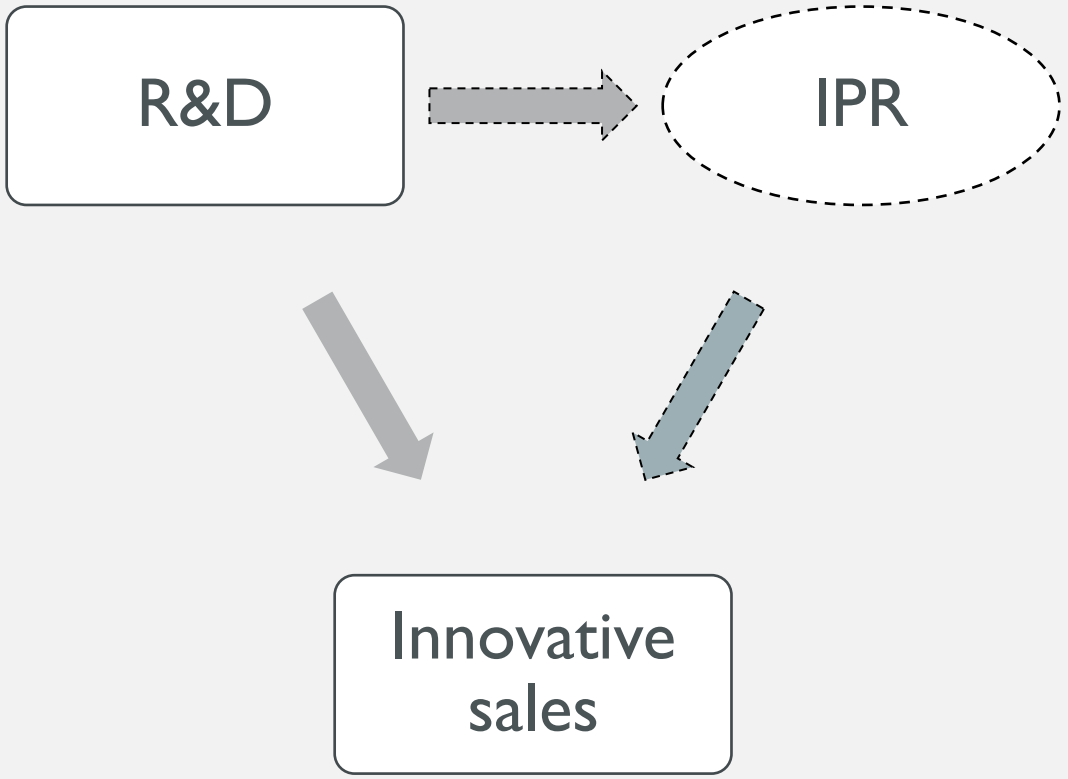
Restriction : There must be at least one continuous input and output in the model

THEORETICAL ARGUMENTS

IPR AS A LATENT MEDIATOR (ILM)

R&D expenditures along with a laten production process produce IPR which are then used as input to produce innovative sales

- IPR are considered as a mediator of the relationship between RD and innovative sales.
- Application for a patent, application for a European utility model, Registered an industrial design right, registered a trademark, licensed out or sell a patent, industrial design right, copyright or trademark to another enterprise, university or research institute are used as IPR-binary variables.
- DMU's which apply for more categories of IPR are considered to be higher on a intellectual property scale.



INPUT / OUTPUT VARIABLES STRUCTURE (BINARY VARIABLES INCLUDED)

Continuous Inputs

1) Product innovation (Expenditures in intramural R&D + Expenditures in extramural R&D)
2) Process innovation (Expenditures in acquisition of machinery + Expenditures in acquisition of external knowledge)

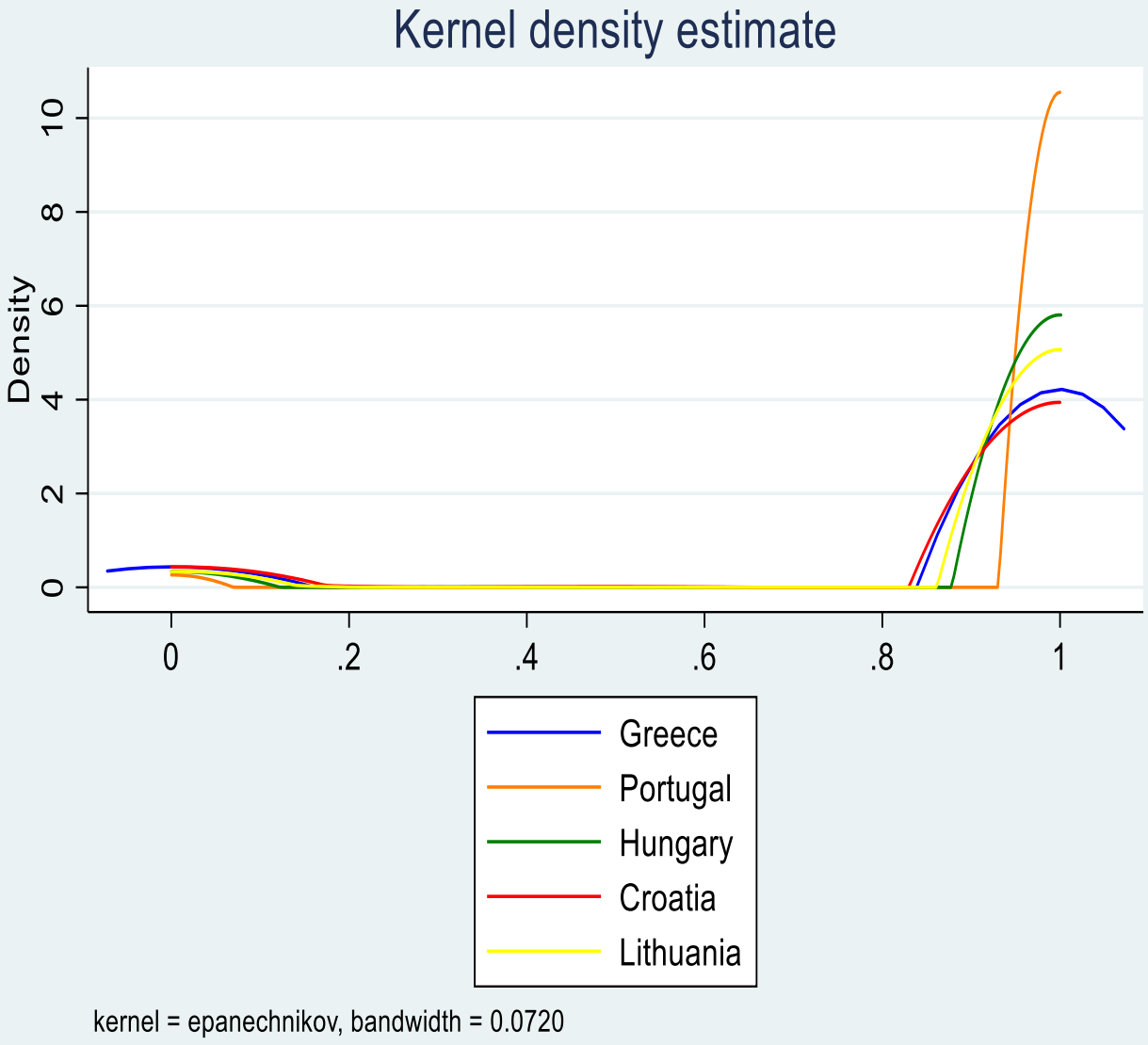
Categorical Inputs / Intermediate outputs

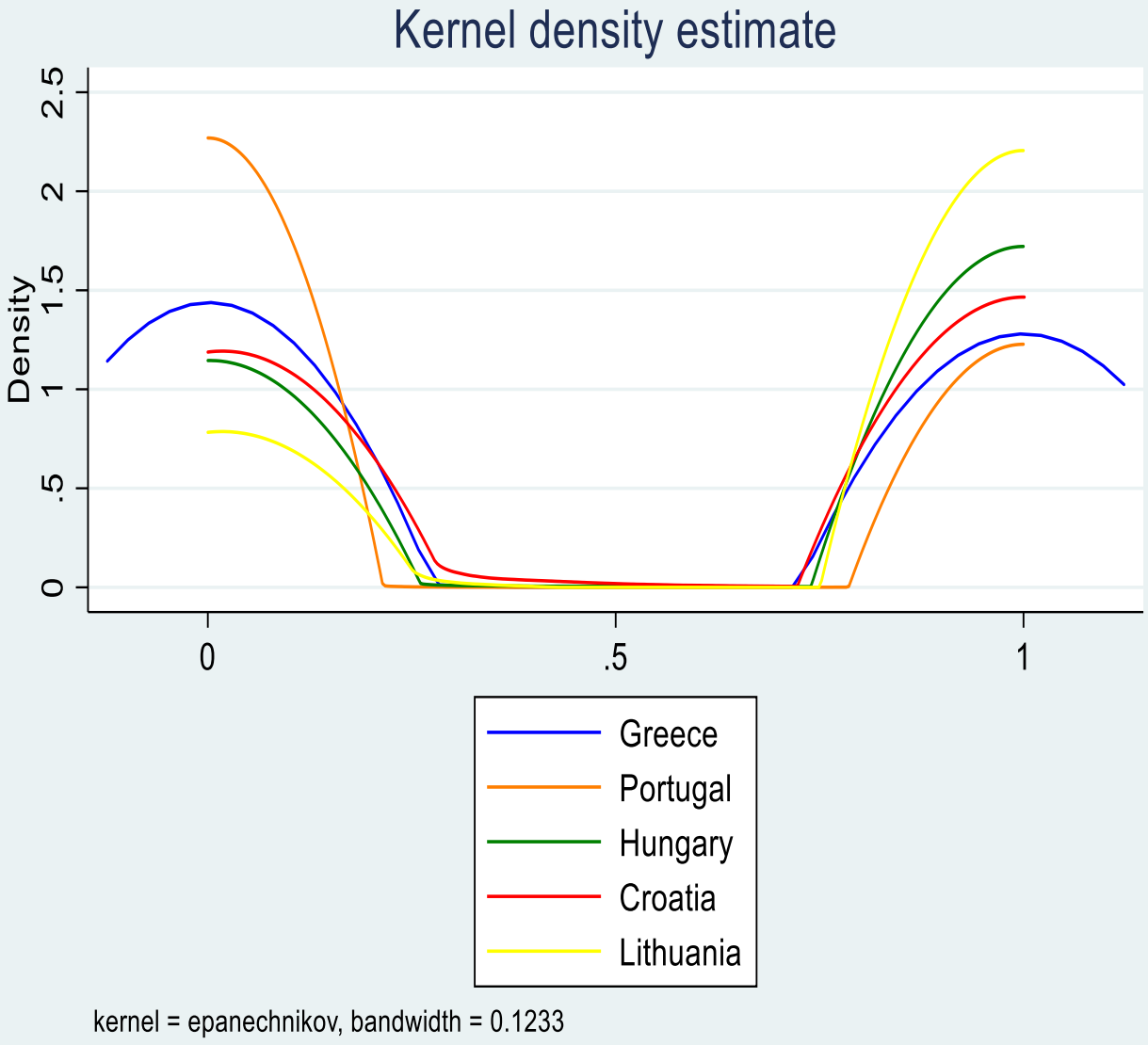
1) Applied for a patent
2) Applied for a European utility model
3) Registered an industrial design right
4) Registered a trademark
5) Licensed out or sell a patent, industrial design right, copyright or trademark to another enterprise, university or research institute

Continuous Outputs

Innovative sales

THE CATCHING UP COUNTRIES CASE



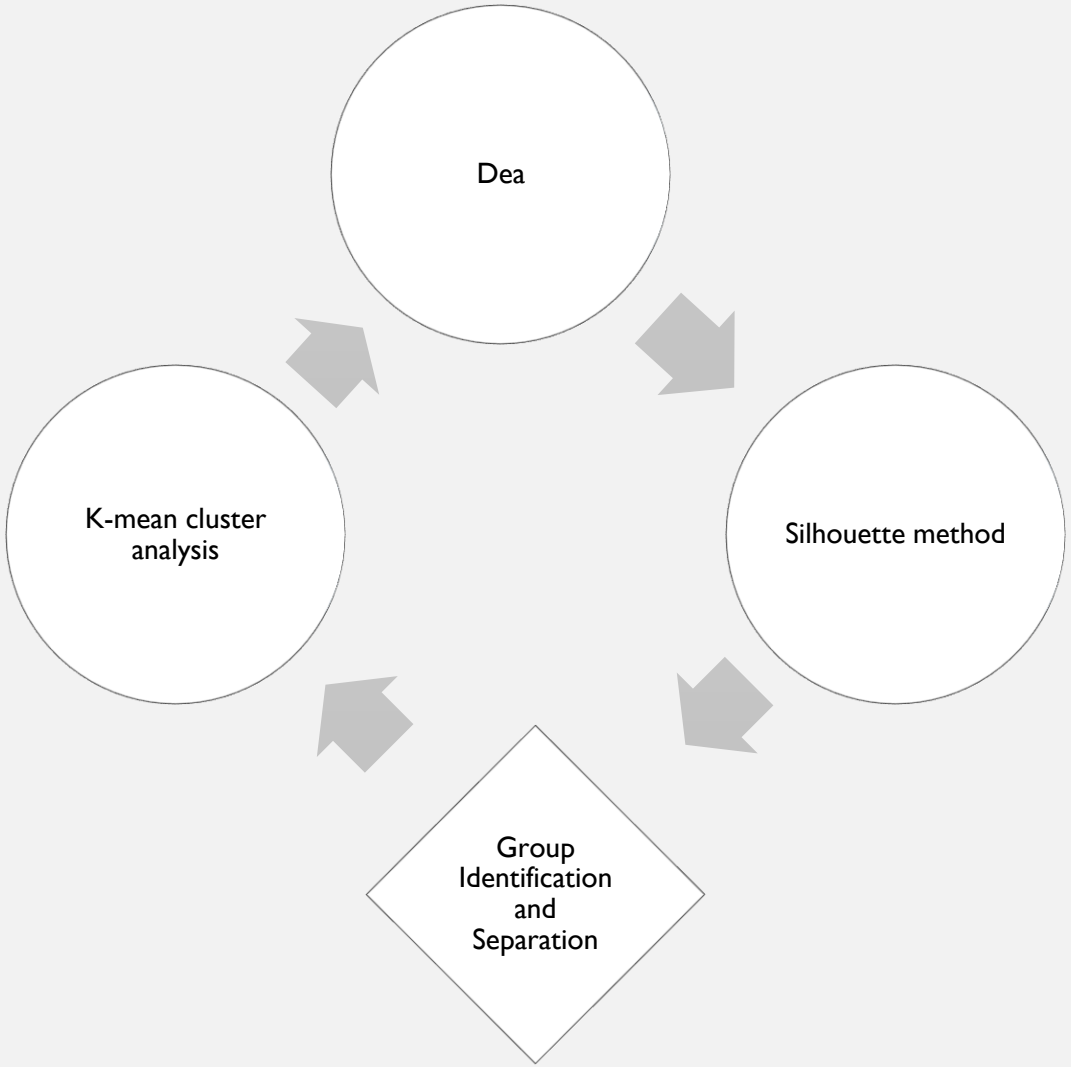


THE CATCHING UP COUNTRIES CASE

- Simple DEA gathers all efficiency scores close to one.
- Modified DEA along ILM approach, creates two efficiency groups, one low efficiency group and one high efficiency group.
- ILM approach shows similar efficiency scores in the case of Greece and Croatia.
- ILM approach inflates low efficiency scores and underestimates high efficiency scores in the case of Portugal.
- ILM approach underestimates low efficiency scores and inflates high efficiency scores in the case of Hungary and Lithuania.

HANDLING HETEROGENEITY: A HEURISTIC ALGORITHM

1. The two efficiency groups (Low efficiency group and High efficiency group) were split and analysed separately.
2. Conduct Modified DEA to each group separately
3. Observe for groups within the frontiers
4. Split the groups again and conduct Modified DEA
5. Terminate the process when no more distinct groups appear
6. Using ordered probit model, firm characteristics which influence the likelihood of a firm belonging to each one of the cluster groups, where obtained.

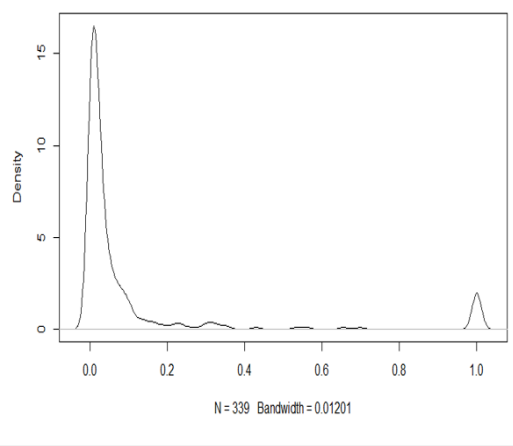


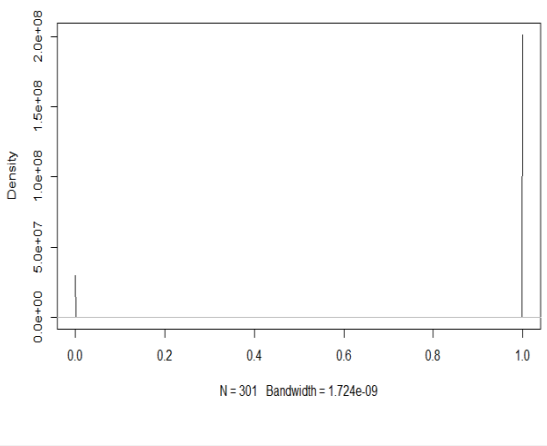
GREECE, A FEW PARTIONS

Low

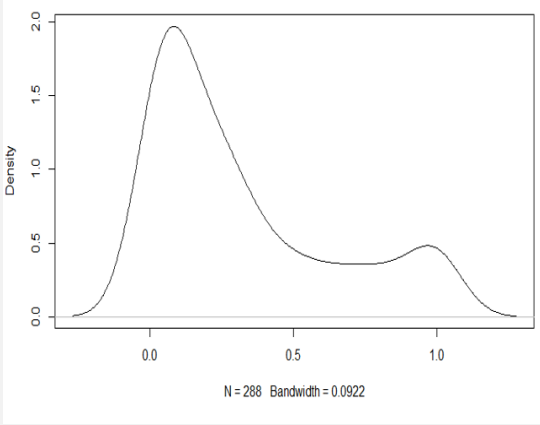
High

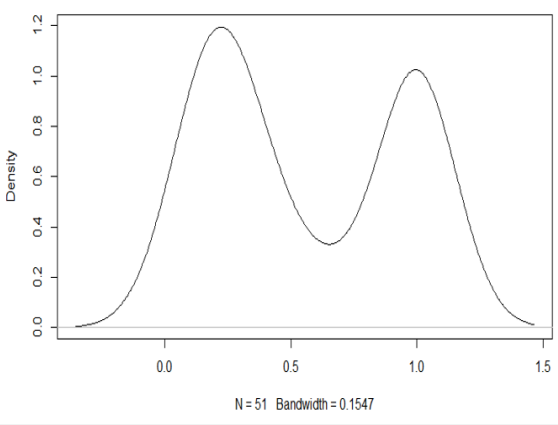
First Partition





Second Partition

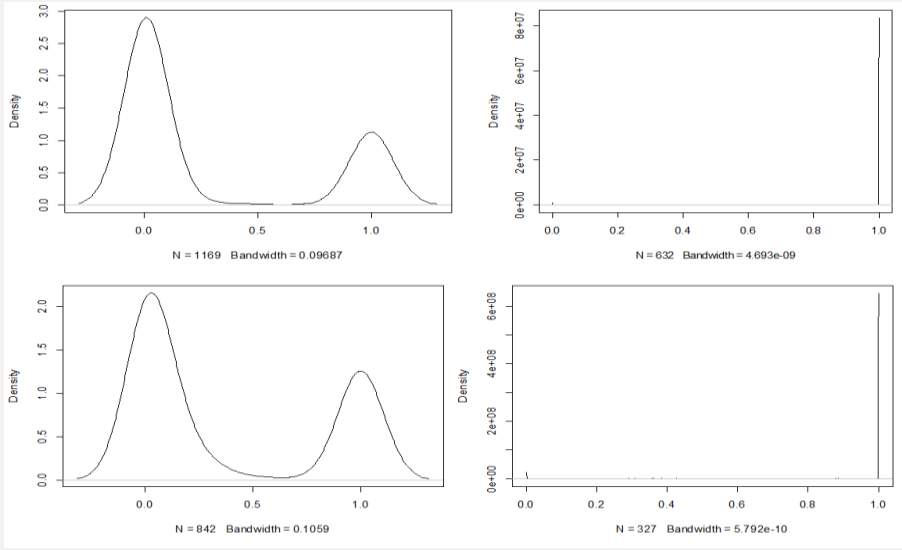




PORTUGAL, MORE PARTITIONS (MORE HETEROGENEITY/COMPLEXITY)

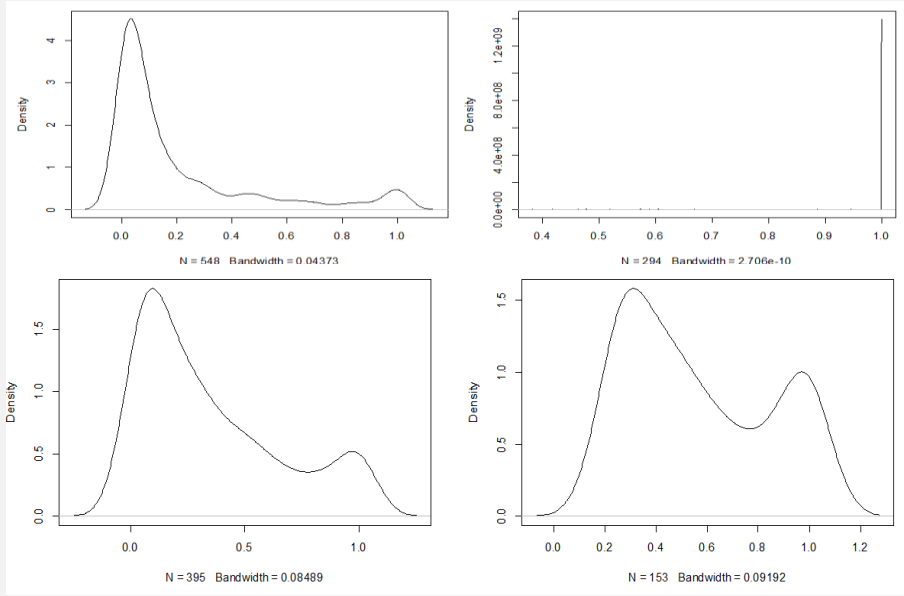
Low | High

First Partition



Second Partition

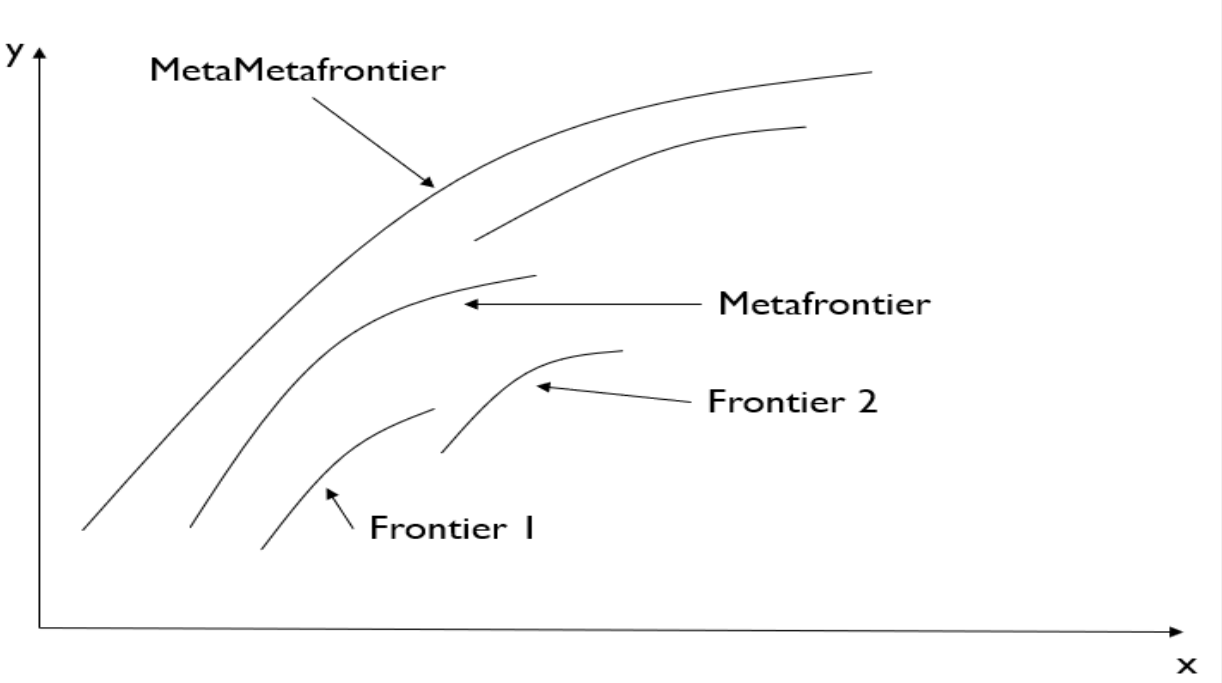
Third Partition



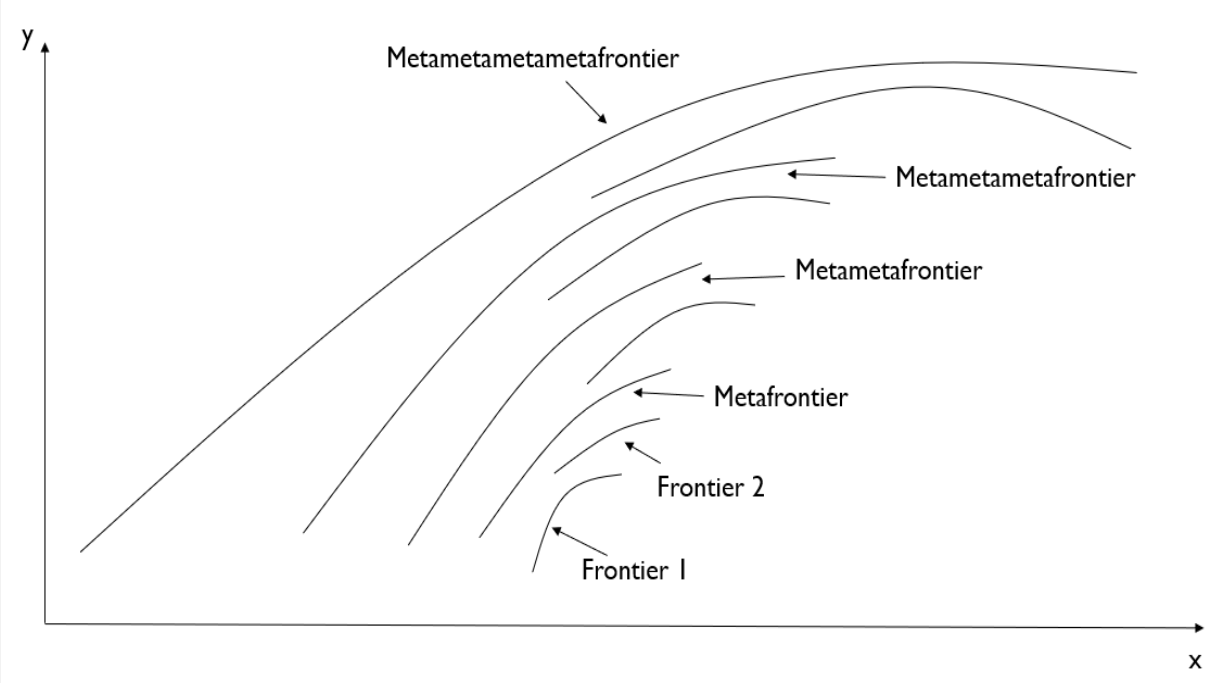
Four Partition

FRONTIER COMPARISON

GREECE



PORTUGAL



NUMBER OF GROUPS / COUNTRY

	Number of Firms	No of groups
Portugal	1801	5
Hungary	766	4
Greece	640	4
Croatia	559	4
Lithuania	533	3

VARIABLES INFLUENCING HETEROGENEITY

	Greece	Portugal	Hungary	Croatia	Lithuania
Part of an enterprise group		+	+		
Introduced onto the market a new or significantly improved good			—		
Did the enterprise introduce a product new to the firm	—		+		
Introduced a new or significantly improved method of production		—	—	—	
Public funding from the EU			—		—
Cooperation arrangements on innovation activities	—	—	—	—	
Percentage of employees with university degree	—	—	—		
Did the enterprise introduce a product new to the market				—	—
Public funding from the central government	—	—		—	
New business practices for organising procedures	—			—	—
New methods of pricing goods or services		+		—	
Percent of the total turnover from sales to clients outside the country in 2014				+	
New methods of organising external relations					—
Significant changes to the aesthetic design or packaging					—
New media or techniques for product promotion					+
Introduced onto the market a new or significant supporting activities		—			
New methods for product placement or sales channels		—			
Size		—			

CONCLUSION AND FURTHER RESEARCH

- We dig into innovation efficiency distribution and reveal "hidden" heterogeneity.
- Firm characteristics which influence the likelihood of a firm belonging to each efficiency cluster group where obtained.
- Public funding and cooperation negatively influence the likelihood of a firm being labelled as efficient.
- Multiple Heterogeneity revealed but not without cost: increased complexity.
- In the case of catching up innovators, we need to incorporate binary innovation outcome in the analysis.

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