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ABSTRACT The main aim of the paper is to measure the relative efficiency of the R&D sector in the EU-27 at the regional level. For this purpose, the paper applies a non-parametric approach, i.e. data envelopment analysis (DEA), to assess the relative technical efficiency of R&D activities across selected EU (NUTS-2) regions. The empirical analysis integrates available inputs (R&D expenditures, researchers and employment in high-tech sectors) and outputs (patent and high-tech patent applications) over the 2005–2010 period. The empirical results show that among regions with a high intensity of R&D activities the most efficient performers are Noord-Brabant (Netherlands), Stuttgart (Germany) and Tirol (Austria). In contrast, a wide range of NUTS-2 regions from the Baltics, Eastern and Southern Europe is characterized by an extremely low rate of knowledge production and its efficiency, particularly in Poland (Mazowieckie), Lithuania (Lietuva), Latvia (Latvija), Romania (Bucuresti-Ilfov), Bulgaria (Yugozapaden), Slovakia (Západné Slovensko), Greece (Attiki), Spain (Canarias) and Italy (Sardegna).

Keywords:
Data Envelopment Analysis (DEA), Efficiency, EU, NUTS-2 regions, R&D

1 Introduction

In today's knowledge-based economy, technological progress plays an increasingly important role for sustaining and improving the economic welfare and growth of national economy. It is an important input for economic growth and a central factor in determining the competitiveness of firms in the marketplace, regionally, nationally and internationally. R&D activities are widely recognized to be one of the main impetuses of technological advance, and levels and rates of growth of R&D expenditures are viewed as reliable indicators of innovative capacity. Therefore, EU member states spend significant amounts on R&D activities. Indeed, one of the key objectives of the EU during the last decade has been to encourage increasing levels of investment, in order to provide a stimulus to the EU's competitiveness. The Lisbon strategy set the EU an objective of devoting 3 % of its GDP to R&D activities by 2010. However, annual public and private R&D investments within the EU have, on an average, accounted for between 1.8 and 2.0 percent of GDP during the last decade. As the set target was not reached the 3 % target was maintained and forms one of five key targets within the Europe 2020 strategy adopted in 2010.

R&D activities are funded and performed by many organizations, including firms, universities, and government laboratories within the EU. Although the roles of various institutions involved in the national R&D enterprise vary from country to country, the main funder and performer of R&D in EU economies is generally the private sector. Accordingly, more than one-half of all EU R&D expenditure is financed by companies, and they perform two-thirds of all R&D activities. An analysis of R&D expenditure by source of funds shows that more than half of the total expenditure in last decade within the EU-27 was funded by business enterprises, while just over one third was funded by government, and less than one tenth from abroad. Relatively important role played by the business enterprise sector as a source of R&D funding is particularly highlighted in some of the most developed EU countries, such as Luxembourg, Finland and Germany, where business-funded R&D accounted for about two thirds of total expenditures. In contrast, a majority of the expenditure on R&D made in the new member states (Cyprus, Bulgaria, Poland, Romania, Slovakia and Lithuania) have been funded by the government sector (Eurostat, 2012).

The paper joins the efforts of other scholars in investigating R&D efficiency at regional level by applying a non-parametric methodology. The importance of examining R&D efficiency is particularly pronounced for the EU regions where R&D activities as well as innovation are at the heart of many regional policies, including above-mentioned Europe 2020 strategy for smart growth. Therefore, the aim of the paper is to review some previous researches on the efficiency measurement of R&D sector as well as some conceptual and methodological issues of non-parametric approach. More importantly, Data Envelopment Analysis (DEA) technique is presented and then applied to the wide range of the EU (NUTS-2) regions to evaluate their relative efficiency within the sector. Consequently, the paper provides some new evidence on regional R&D efficiency in terms of various inputs and outputs. This regional-level study can lend implications for R&D management as well as innovation policy at regional level. More specifically, the paper also provides a more complete picture of the regional R&D performance by measuring R&D efficiency with available inputs and outputs.

Very few recent studies examined the efficiency of countries or regions in utilizing R&D expenditures or other resources. For instance, Lee and Park (2005) and Wang and Huang (2007) both evaluated R&D efficiency across nations by considering three outputs (patents, technology balance of receipts, and journal articles) and two outputs (patents and SCI and EI articles), respectively. Lee et al. (2009) used the Data envelopment analysis (DEA) approach to measure and compare the performance of national R&D programs in South Korea. Sharma & Thomas (2008) took into account the time lags in the R&D process and investigating the R&D efficiency of developing countries in relation to the developed countries. Some other studies that focus on subject areas, institutions, firms, policy programs or regions are Chen et al. (2011), Guan & Chen (2009), Guan & Ma (2004), Guan & Wang (2004), Guan & He (2005), Huang et al. (2006), Karkazis & Thanassoulis (1998), Liu (2010), Meng et al. (2006), Moed (2002), Sueyoshi & Goto (2013) and Zhong et al. (2011). Most of these studies assess a particular nation, and very few studies attempt cross country or cross regional comparisons for R&D efficiency (see also Aristovnik, 2012). However, very insightful, cross-regional analyses for R&D sector are rarely used for policy analysis. This gap in the literature is addressed in the next sections of this paper where DEA approach is applied to EU (NUTS-2) regions.

The paper is organized as follows. In the next section we present a theoretical background of non-parametric methodologies with special focus on Data Envelopment Analysis (DEA), the specifications of the model and information about data. Section 3 outlines the results of the non-parametric efficiency analysis. The final section provides concluding remarks and some policy implications.

2 Methodology and Data

We adopted the mathematical development of DEA by Charnes et al. [19] who built on the work of Farrell [20] and others. DEA is a linear programming-based methodology that has proven to be a successful tool for measuring efficiency. It computes the comparative ratio of outputs to inputs for each unit, with the score expressed as 0–100%. A DMU with a score of less than 100% is inefficient compared to other units. It is used to identify best practices and is increasingly becoming a popular and practical management tool. DEA was initially used to investigate the relative efficiency of non-profit organizations but now its use has spread to hospitals, schools, banks and network industries, among others (Avkiran [21]). DEA empirically identifies the best producers by forming the efficient frontier based on observed indicators from all producers. We refer to the producers as decision-making units (DMUs). Consequently, DEA bases the resulting efficiency scores and potential efficiency improvements entirely on the actual performance of other DMUs, free of any questionable assumptions regarding the mathematical form of the underlying production function. We use the DEA methodology to evaluate the relative efficiency of each region as it converts, for instance, R&D expenditures into patent applications. We identify the regions (NUTS-2) as the DMUs. Let n (=271) be the number of (EU NUTS-2) regions in the data set. Let X_{ij} be the amount of input i consumed by Region j, for i = 1 and j = 1, 2, …, 271. Let Y_{j} be the number of patent applications by Region j, for j = 1, 2, …, 271. We are now ready to present the output-oriented DEA model for Region k, k = 1, 2, …, 271. We must solve one such linear programming model for each region. Mathematically, the technical efficiency of each DMU is computed as:

$$Max \ \ \phi_k \tag{1}$$

subject to

$$\sum_{j=1}^{271} \lambda_j X_{ij} \le X_{ik} \quad for \quad i = 1,2,3 \tag{2}$$

$$\sum_{j=1}^{271} \lambda_j Y_j \ge \phi_k Y_k \tag{3}$$

$$\sum_{j=1}^{271} \lambda_j = 1 \tag{4}$$

$$\lambda_j \ge 0 \quad for \quad j = 1,2,...,271 \tag{5}$$

$$\phi_k \ge 0 \tag{6}$$

We observe that setting $\lambda_k=1$, $\lambda_j=0$ for $j\neq k$ and $Ø_k=1$ is a feasible but not necessarily optimal solution to the linear program for Region *k*. This implies that $Ø_k*$, the optimal value of $Ø_k$, must be greater than or equal to 1. The optimal value, $Ø_k*$, is the *overall inverse efficiency* of DMU *k*, which represents one plus the proportion by which Region *k* can increase its patent applications. For instance, if $Ø_k*=1.10$, then Region *k* can increase its output by 10% without increasing any of its inputs. We refer to $E_k*=1/Ø_k*$ as the *overall efficiency* of region *k*. Thus, if $Ø_k*=1.10$ then $E_k*=0.91$ and we can say that Region *k* is 91% efficient overall. The left-hand side of Equations (2) and (3) are weighted averages because of Equations (4) and (5), of the inputs and output, respectively, of the 271 regions. At optimality, that is with the λ_j replaced by λ_j*, we call the left-hand side of Equations (2) and (3) the *target inputs* and *target output*, respectively, for Region *k*.

Equation (2) suggests that each target input will be less than or equal to the actual level of that input in Region *k*. Similarly, Equation (3) shows that the target output will be greater than or equal to the actual output level in Region *k*. Equation (4) ensures that the weights add up to one and allows us to interpret the target inputs and target output as weighted averages of the corresponding quantities in Region *k'*s reference regions, that is, those states for which $\lambda_j>0$. Accordingly, this constraint indicates that the production process is a variable return to scale (VRS), meaning that the productivity effect of an additional unit of an input may differ with the size of the region. Thus, the optimal solution to the linear program for Region *k* identifies a hypothetical target state *k** that, relative to Region *k:* (a) consumes the same or less of every input; and (b) produces the same or more of the output. Moreover, the objective function expressed in Equation (1) ensures that the target Region *k** produces outputs that are increased as much as possible.

In the majority of studies using DEA the data are analysed cross-sectionally, with each decision-making unit (DMU) – in our case a region – being observed only once. Nevertheless, data on DMUs are often available over multiple time periods. In such cases, it is possible to perform DEA over time where each DMU in each time period is treated as if it were a distinct DMU. However, in our case the data set for all the tests in the study includes average (available) data for the 2005–2010 period in order to evaluate long-term efficiency measures as the effects of R&D are characterized by time lags in selected EU (NUTS-2) regions. The inputs utilized are researchers (as % of total employment), total research expenditure (in % of GDP) and employment in high-tech sectors (high-tech manufacturing and high-tech knowledge-intensive services) (as % of total employment) in each selected region. The output can be in the form of publications or patents (see Sharma and Thomas, 2008) and therefore the raw data for output employed in this study comprise patent applications to the EPO by priority year (number of applications per million inhabitants) and high-tech patent applications to the EPO by priority year (number of applications per million inhabitants). The data come from the Eurostat database (for Summary statistics, see Table 1). The program used for calculating the relative efficiency scores is the Frontier Analyst 4.0 software.

Table 1 Summary Statistics

	Average	St. Dev.	Min.	Max.
Inputs				
Total research expenditure (in % of GDP)	1.46	1.25	0.10 (Severen tsentralen– BG)	7.23 (Prov. Brabant Wallon – BE)
Researchers (as % of total employment)	0.60	0.47	0.07 (Sud-Est– RO)	2.81 (NE Scotland – UK)
Employment in high-tech sectors (as % of total employment)	4.11	1.72	0.99 (Thessalia – GR)	10.99 (Berkshire, Buckinghamshire and Oxfordshire – UK)
Human resources in science and technology (% of economically active population)	35.83	8.34	14.63 (Região Autónoma dos Açores – PT)	61.10 (Inner London – UK)
Outputs				
Patent applications to the EPO by priority year (number of applications per million inhabitants)	84.70	102.79	0.26 (Sud – Muntenia – RO)	550.19 (Stuttgart - GER)
High-tech patent applications to the EPO by priority year (number of applications per million inhabitants)	14.46	22.14	0.15 Sud – Muntenia – RO)	163.03 (Noord-Brabant – NL)

Sources: Eurostat, 2013; own calculations

The degree of correlation between inputs and outputs is an important issue that has a great impact on the robustness of the DEA model. Thus, a correlation analysis is crucial to establish appropriate inputs and outputs. On one hand, if very high correlations (higher than 0.95) are found between an input variable and any other input variable (or between an output variable and any of the other output variables), this input or output variable may be thought of as a proxy of the other variables. On the other hand, if an input variable has a very low correlation with all the output variables (or an output variable has a very low correlation with all the input variables) this may indicate that this variable does not fit the model. In our correlation analysis we could not find any evidence of a very high (or low) correlation between the input variables (nor between the output variables) (see Table 2). Accordingly, this is a reasonable validation of the presented DEA model.

Table 2 Correlations among the inputs and outputs

	Total research expenditure (in % of GDP)	Researchers (as % of total employment)	Employment in high-tech sectors (as % of total employment)	Human resources in science and technology (% of economically active population)	Patent applications to the EPO by priority year (number of applications per million inhabitants)	High-tech patent applications to the EPO by priority year (number of applications per million inhabitants)
Inputs						
Total research expenditure (in % of GDP)	1.00					
Researchers (as % of total employment)	0.79	1.00				
Employment in high-tech sectors (as % of total employment)	0.62	0.65	1.00			
Human resources in science and technology (% of economically active population)	0.60	0.67	0.70	1.00		
Outputs						
Patent applications to the EPO by priority year (number of applications per million inhabitants)	0.66	0.44	0.53	0.52	1.00	
High-tech patent applications to the EPO by priority year (number of applications per million inhabitants)	0.67	0.56	0.59	0.53	0.78	1.00

Note: All correlations are significant at the 0.01 level (2-tailed)
Sources: Eurostat, 2013; calculations by the author

3 Empirical Results

In order to ensure relative homogeneity of the sample, the first part of the empirical research divides EU regions into two main groups, the “Top Half” and the “Bottom Half”. The “Top Half” group comprises NUTS-2 regions with R&D expenditures (in % of GDP) higher than the calculated median of 265 regions (i.e. 1.12%). On the other side, the “Bottom Half” includes regions with lower R&D expenditures. The results for the “Top Half” group based on an output-oriented VRS formulation of the DEA analysis suggest that the most efficient regions are in Austria (Tirol), Germany (Stuttgart) and the Netherlands (Noord-Brabant) (see Table 3). These regions, in particular Stuttgart, could serve as a good benchmark for the other regions as they featured among the highest in R&D expenditure. Some other regions also seem to be efficient (for instance, Salzburg, Niederösterreich, Lorraine and Campania), yet they show relatively low R&D intensity compared to the “Top Half” regions. Ultimately, almost 11% of the observed regions are efficient and could be a good example to less efficient regions. The least efficient regions in this group are from Poland, Czech Republic, the UK, Romania, France, Italy and Slovenia. These regions should significantly increase the number of their patent applications and high-tech applications to the EPO.

Table 3 Relative Efficiency of the Selected "Top Half" NUTS-2 Regions

Top Half – 131 regions			
The most efficient regions		The most inefficient regions	
Niederösterreich (AT)	100.0	Mazowieckie (PL)	3.5
Salzburg (AT)	100.0	Strední Cechy (CZ)	4.4
Tirol (AT)	**100.0**	NE Scotland (UK)	5.1
Vorarlberg (AT)	100.0	Praha (CZ)	5.3
Prov. Hainaut (BE)	100.0	Jihovýchod (CZ)	5.7
Oberfranken (DE)	100.0	SW Scotland (UK)	6.9
Sachsen-Anhalt (DE)	100.0	Bucuresti – Ilfov (RO)	7.4
Stuttgart (DE)	**100.0**	Lancashire (UK)	8.8
Com. Foral de Navarra (ES)	100.0	Languedoc-Roussillon (FR)	9.4
Basse-Normandie (FR)	100.0	Lisboa (PT)	11.0
Lorraine (FR)	100.0	Merseyside (UK)	11.1
Campania (IT)	100.0	Kent (UK)	11.1
Noord-Brabant (NL)	**100.0**	Lazio (IT)	11.3
South Yorkshire (UK)	100.0	Zahodna Slovenija (SI)	11.5
Average Efficiency Score	44.5		
Standard Deviation	29.4		
No. (%) of Efficient Regions	14 (10.7%)		

Note: The regions in bold employ above-average R&D inputs
Sources: Eurostat, 2013; calculations by the author

In the group of the "Bottom Half" regions, there are 15 efficient regions (or 13.4% of all observed regions) from both old and new EU member states. However, regions from the new EU member states are predominantly efficient due to the relatively low level of their R&D inputs. But the relevant benchmark regions, i.e. those with above-average inputs in the "Bottom Half" group, are from old members, i.e. Germany (Brandenburg-Nordost, Lüneburg and Schwaben), the Netherlands (Drenthe), Portugal (Centro) and the UK (Eastern Scotland and Highlands and Islands) (see Table 4). Some regions from Bulgaria, Poland, Romania and Greece seem to be efficient particularly due to their extremely low R&D inputs and it would therefore be crucial for them to increase their R&D resources and employ them in an efficient manner. On the other hand, the least efficient regions mainly come from the new EU member states (particularly from the Visegard and Baltic countries). In order to become an efficient region, these regional units should significantly increase their R&D outputs and should follow their peers in the old EU member states.

In the second part of the empirical research, the top 5% of regions with the highest output (patent applications to the EPO) and bottom 5% with the lowest input (R&D expenditures and researchers) were excluded in order to eliminate the outliers. The empirical results suggest that 30 regions or almost 15% of all regions (a total of 207) included in the analysis have been efficient. Similarly to the first part of the analysis, there are developed efficient regions in old member states such as Austria, Belgium, France, Germany and Spain (see Table 5). Some poor regions in Romania and Bulgaria are also efficient due to their extremely low R&D intensity. By contrast, the most inefficient regions are predominantly from a great majority of the new EU member states, particularly Poland, Bulgaria, Romania, Czech Republic, Slovakia and the Baltic states. In all of these regions, the key task should be to significantly increase R&D outputs via additional investment in the R&D sector (higher R&D expenditures). Hence, improving the R&D sector's efficiency, which could significantly contribute to the development and growth of the region, should therefore be a top priority for practically all of these regions in the near future.

Table 4 Relative Efficiency of Selected "Bottom Half" NUTS-2 Regions

Bottom Half – 112 regions			
The most efficient regions		The most inefficient regions	
Prov. Luxembourg (BE)	100.0	Malopolskie (PL)	3.7
Severen tsentralen (BG)	100.0	Lubelskie (PL)	4.9
Severozapaden (BG)	100.0	Moravskoslezsko (CZ)	5.0
Brandenburg – Nordost (DE)	**100.0**	Slaskie (PL)	5.1
Lüneburg (DE)	**100.0**	Západné Slovensko (SK)	5.4
Schwaben (DE)	**100.0**	Lietuva (LT)	5.5
Thessalia (GR)	100.0	Warminsko-Mazurskie (PL)	5.5
Drenthe (NL)	**100.0**	Jihozápad (CZ)	5.8
Lubuskie(PL)	100.0	Yugozapaden (BG)	6.2
Centro (PT)	**100.0**	Severovýchod (CZ)	6.7
Nord-Est (RO)	100.0	Kujawsko-Pomorskie (PL)	7.3
Sud-Est (RO)	100.0	Latvija (LV)	7.6
Sud-Vest Oltenia (RO)	100.0	Sardegna (IT)	8.4
Eastern Scotland (UK)	**100.0**	Észak-Alföld (HU)	8.8
Highlands and Islands (UK)	**100.0**	Nyugat-Dunántúl (HU)	8.9
Average Efficiency Score	36.8		
Standard Deviation	31.9		
No. (%) of Efficient Regions	15 (13.4%)		

Note: The regions in bold employ above-average R&D inputs
Sources: Eurostat, 2013; calculations by the author

Contrary to all expectations, some of the least efficient regions are also from highly developed member states, such as the UK. For instance, North East Scotland which spends an average of 3.2% of its GDP on R&D shows a dismal performance on the technical efficiency front as revealed by its efficiency score of 10.6 that emerges as one of the lowest among the regions in the old EU member states. A more detailed analysis shows that Prov. Brabant Wallon, which is one of the peers of NE Scotland, has 1.8 researchers per hundred employees and is able to file 262.9 patent applications to the EPO per million inhabitants as compared to 24.3 patent applications for NE Scotland (with more than 2.8 researchers per hundred employees). This example highlights the importance of the efficient use of relatively high R&D expenditure (or any other R&D inputs) in many regions. Indeed, we should be aware of the fact that R&D efficiency can significantly contribute to the development and growth of those regions that lag behind by tapping into their underlying potential.

Table 5 Relative Efficiency of Selected NUTS-2 Regions (without outliers)

Without outliers – 207 regions			
The most efficient regions		The most inefficient regions	
Burgenland (AT)	100.0	Mazowieckie (PL)	2.8
Oberösterreich (AT)	**100.0**	Lietuva (LT)	3.9
Salzburg (AT)	100.0	Moravskoslezsko (CZ)	4.5
Tirol (AT)	**100.0**	Malopolskie (PL)	4.9
Prov. Antwerpen (BE)	**100.0**	Yugozapaden (BG)	5.5
Prov. Brabant Wallon (BE)	**100.0**	Észak-Alföld (HU)	5.6
Prov. Vlaams-Brabant (BE)	**100.0**	Lubelskie (PL)	5.9

Yuzhen tsentralen (BG)	100.0	Bucuresti – Ilfov (RO)	5.9
Severoiztochen (BG)	100.0	Jihozápad (CZ)	6.2
Brandenburg – Nordost (DE)	100.0	Slaskie (PL)	6.3
Detmold (DE)	**100.0**	Canarias (ES)	7.1
Düsseldorf (DE)	**100.0**	Západné Slovensko (SK)	7.2
Koblenz (DE)	100.0	Jihovýchod (CZ)	7.5
Lüneburg (DE)	100.0	Strední Cechy (CZ)	7.6
Oberfranken (DE)	100.0	Latvija (LV)	7.6
Weser-Ems (DE)	100.0	Andalucía (ES)	7.9
Com. Foral de Navarra (ES)	**100.0**	Strední Morava (CZ)	8.0
Prov.-Alpes-Côte d'Azur (FR)	100.0	Severovýchod (CZ)	8.7
Rhône-Alpes (FR)	**100.0**	Nyugat-Dunántúl (HU)	9.0
Île de France (FR)	**100.0**	Attiki (GR)	9.7
Peloponnisos (GR)	100.0	Dolnoslaskie (PL)	10.3
Thessalia (GR)	100.0	NE Scotland (UK)	10.6
Prov. Autonoma Bolzano (IT)	100.0	Praha (CZ)	10.8
Zachodniopomorskie (PL)	100.0	Wielkopolskie (PL)	11.1
Centro (PT)	100.0	Lódzkie (PL)	11.3
Sud – Muntenia (RO)	100.0	Sardegna (IT)	11.8
Vest (RO)	100.0	Kujawsko-Pomorskie (PL)	11.9
Eastern Scotland (UK)	100.0	Basilicata (IT)	12.1
Hamp. and Isle of Wight (UK)	100.0	Észak-Magyarország (HU)	12.3
Surrey, E&W Sussex (UK)	100.0	Castilla y León (ES)	12.3
Average Efficiency Score	47.2		
Standard Deviation	32.5		
No. (%) of Efficient Regions	30 (14.5%)		

Note: The regions in bold employ above-average R&D inputs
Sources: Eurostat, 2013; calculations by the author

4 Conclusions

The paper joins the efforts of other scholars in investigating R&D efficiency by applying a non-parametric methodology at the regional level. In this respect, the Data Envelopment Analysis (DEA) technique was presented and then applied to a wide range of EU-27 (NUTS-2) regions to evaluate technical efficiency within the selected sector. The research findings suggest that Drenthe, Noord-Brabant (Netherlands), Prov. Antwerpen, Prov. Brabant Wallon, Prov. Vlaams-Brabant (Belgium), Tirol, Oberösterreich (Austria), Stuttgart, Detmold, Dusseldorf and Luneburg (Germany), Com. Foral de Navarra (Spain), Rhône-Alpes and Île de France (France) belong to the best-performing NUTS-2 regions located on the regional technology frontier. These EU regions could also serve as peers to improve the efficiency of the less efficient ones. The innovative capacity of advanced regions is their most important source of prosperity and growth. These results confirm the idea that regions with a mature economic system enjoy higher R&D efficiency compared to regions still developing their technology pattern. On the other hand, a wide range of NUTS-2 regions from the Baltics, Eastern and Southern Europe is characterized by an extremely low rate of knowledge production and its efficiency, particularly in Poland (e.g. Mazowieckie, Malopolskie, Lubelskie, Slaskie), Lithuania (Lietuva), Latvia (Latvija), Romania (Bucuresti-Ilfov), Bulgaria (Yugozapaden), Slovakia (e.g. Západné Slovensko), Greece (e.g. Attiki), Spain (e.g. Canarias, Andalucia), and Italy (e.g. Sardegna), suggesting that they are still in the phase of imitating and replicating existing technologies, while only little effort is made to innovate at the EU regions' technology frontier. Consequently, regional and other horizontal (R&D) policies (together with EU regional policy) should be especially aimed at ensuring a sufficient level of R&D spending in the abovementioned countries.

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