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Human Resources in Europe. Estimation, Clusterization, Machine Learning and Prediction

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ABSTRACT: We estimate the relationships between innovation and Human Resources in Europe using the European Innovation Scoreboard of the European Commission for 36 countries for the period 2010-2019. We perform Panel Data with Fixed Effects, Random Effects, Pooled OLS, Dynamic Panel and WLS. We found that Human Resources is positively associated to *"Basic-school entrepreneurial education and training", "Employment MHT manufacturing KIS services", "Employment share Manufacturing (SD)", "Lifelong learning", "New doctorate graduates", "R&D expenditure business sector", "R&D expenditure public sector", "Tertiary education".* Our results also show that *"Human Resources"* is negatively associated to *"Government procurement of advanced technology products", "Medium and high-tech product exports", "SMEs innovating in-house", "Venture capital".* In adjunct we perform a clusterization with k-Means algorithm and we find the presence of three clusters. Clusterization shows the presence of Central and Northern European countries that have higher levels of Human Resources, while Southern and Eastern European countries have very low degree of Human Resources. Finally, we use seven machine learningalgorithms to predict the value of Human Resources in Europeancountries using data in the period 2014-2021 and we show that the linear regression algorithm performs at the highest level.
JEL CODE: O31, O32, O34, O36, O38.

Keywords:*Innovation and Invention: Processes and Incentives, Management of Technological Innovation and R&D, Technological Change: Choices and Consequences, Diffusion Processes Intellectual Property and Intellectual Capital, Open Innovation, Government Policy.*

I.   INTRODUCTION

In this article we analyze the determinants of Human Resources that are related to innovation. We use data from the European Innovation Scoreboard of the European Commission for the period 2010-2019 for 36 countries[3]. The level of Human Resources is positively associated to the level of economic growth even in the classical and endogenous theories[1], [2]. Also, in the theory of Schumpeter there is a positive role for the Human Resources in the sense of the ability of entrepreneurs to operate as Demiurge of the economic development [3]. The level of Human Resources is relevant to human capital and to promote innovation[4]. The degree of Human Resources in its ability to improve innovation has a positive effect on sales [5], firms' investments in new products and services [6]. The presence of innovators among European countries is associated to the ability to produce intangible assets that depends onHuman Resources [7]. European countries that sustain high level of Human Resources also to invest more in innovation and Research and Development-R&D [8]. Innovation has a positive effect on employment and specifically, in European countries that have a higher level of Human Resources also the impact of innovation on employment is higher[9]. European countries that have a more developed economic systems, based on more skilled and educated Human Resources, also have a greater level of the attractiveness of research systems[10]. At a corporate level the increase in employment in European big firms is positively associated to an increase in investment in Research and Development with a relevant impact on net sales [11]. There is also a positive relationship between Human Resources and the creation of an innovation friendly environment in European countries[12]. Universities have a strategic role in

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[3] Countries are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finlandia, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Latvia, Lithuania, Luxembourg, Malta, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Switzerland, Turkey, Ukraine.

promoting the development of Human Resources, and social capital [13]. Human Resources capabilities improve the competitiveness of tech firms [14]. To strengthen the relationship between Human Resources and innovation it is necessary to apply a quali-quantitative political economy oriented to promote a growth in R&D[15]and high skills professionals. Human Resources matter not only for innovation technology but also for social innovation[16]. Creative industries that practice soft innovation through co-creation require high skilled Human Resources [17]. Human Resources have a role in creating the condition by which corporations can adopt innovation technology at an enterprise level [18]. Firms that are interested in implementing innovation require to produce more flexible organizational structure through more qualified Human Resources [19]. Digital transformation can be realized only with the implementation of digital skills among Human Resources through investments in education and organizational innovation[20]. Human resources are also relevant to apply strategies of innovation management through the hiring of high skilled workers and experienced managers [21]. There is a positive relationship between Human Resources, technological innovation, and change management also in the handicraft sector[22]. The improvement of Human Resources in universities can increase the level of organizational commitment of staff [23]. The Human Resources management in innovative firms is relevant since the market for technology is characterized by organizationalchange with new professionals and new skills that enter in the context of the enterprise and require to be recognized in the firm's structure [24]. The ability of a firm to manage efficiently Human Resources driving them towards innovative activities, during a financial crisis, depends on the financial stability of banking partners i.e.: if a firm has a banking partner that suffer less during a financial crisis, then the firm show a deeper capability to orient the Human Resources in the sense of innovation [25]. Human resources are a driver to promote innovation, Gdp growth and competitiveness at a national level in Europe[26]. Human Resource Management-HRM and Research and Development-R&D have a positive role in promoting the ability of firm to innovate and both strongly depend on top management support [27].

The article continues as follows: the second paragraph presents the econometric model, the third paragraph contains the clusterization analysis with the k-Means algorithm optimized with the Silhouette coefficient, the third paragraph proposes a confrontation among seven different algorithms of machine learning and predictions, the fourth paragraph concludes.

II.   THE ECONOMETRIC MODEL

We have estimated the following econometric model:

$$HumanResources_{it}$$
$$= a_1 + b_1(BasicSchoolEntrepreneurialEducationAndTraining)_{it}$$
$$+ b_2(EmploymentMHTManufacturingKISServices)_{it}$$
$$+ b_3(EmploymentShareManufacturing)_{it}$$
$$+ b_4(GovernmentProcurementOfAdvancedTechnologyProducts)_{it}$$
$$+ b_5(LifelongLearning)_{it} + b_6(MediumAndHighTechProductExports)_{it}$$
$$+ b_7(NewDoctorateGraduates)_{it} + b_8(R\&DExpenditureBusinessSector)_{it}$$
$$+ b_9(R\&DExpenditurePublicSector)_{it} + b_{10}(SMEsInnovatingInHouse)_{it}$$
$$+ b_{11}(TertiaryEducation)_{it} + b_{12}(VentureCapital)_{it}$$

Where i is equal to 36 and t is the period 2010-2019.
We have used Dynamic Panel, Pooled OLS, Fixed Effects, Random Effects, WLS. We found that the level of Human Resources is positively associated to:

- *Basic-school entrepreneurial education and training:*is defined in the European Innovation scoreboard as an indicator that« *[…] measures the extent to which training in creating or managing SMEs is incorporated within the education and training system at primary and secondary school levels*». This means that if the managerial and entrepreneurial culture is promoted in schools there is a global positive impact on the ability of that country to have an improvement in human capital with positive effect in the sense of human resources.

- *Employment MHT manufacturing KIS services:*this variable is defined as the number« *[…] of employed persons in knowledge-intensive activities in business industries*». This means that if there are firms that operates in knowledge-intensive activities, they can have a positive impact on human capital either offering new products and services to customers either creating a demand for high level products and services for their suppliers. The combined effects on consumers and suppliers generate an improvement in the level of human resources at a country level.

- *Employment Share in Manufacturing:*is the percentage of employment in manufacturing industries. The presence of manufacturing industries with a relevant employment share as a percentage of total employment per countries has a positive impact of human resources. Manufacturing industries requires

specialized employee and high skilled Human Resources especially in the case of medium and high-tech firms.

- *Lifelong learning:* is a measure of the percentage of the population in the age 25-64 that participate in education and training. The learning activity considered in this variable is either formal either informal and is oriented to improve the level of knowledge, skills and know how in the population. Learning activities cannot be confused with cultural and sporting activities. The analysis shows that the increasing percentage of population that practice lifelong learning has a positive impact in improving the level of Human Resources.
- *New doctorate graduates:* is the number of doctorate graduates per thousand for the population in the age 25-34. The increasing number of doctorate graduates is positively associated to an improvement in Human Resources. But this indicator has a limitation since it is possible that there are doctorate graduates also in the population 34-65 due to the new Ph.D. programs that are designed for the working professionals and employees.
- *R&D expenditure business sector:* is a variable that consider all the expenditures in the business sector as a percentage of Gross Domestic Product-GDP. The variable can indicate the relevance of the process of knowledge creation in the private sector even if the large part of innovation and knowledge is generated in connection within the pharmaceutical and the chemical industries. This variable is positively associated to the improvement of Human Resources at a country level. The greater the expenditure of the business sector in Research and Development the greater the impact on human resources.
- *R&D expenditure public sector:* the variable considers all the expenditure in Research and Development either at a government level either in the educational sector. The degree of R&D expenditure can promote the economic growth in the long run, with a positive impact on the ability of firms and productive organizations to generate more innovative and knowledge intense products and services. Specifically, the increase in the level of R&D expenditure in the public sector is positively associated to an improve in the level of Human Resources.
- *Tertiary education:* percentage of the population in the age 25-34 that has completed a tertiary education. This indicator has two limitations: on the one side it does not consider the possibility of the people in the population 35-65 that can be enrolled in tertiary education program, and on the other side it comprehends either scientific and non-scientific skills acquired in the educational system at a national level. There is a positive relationship between the increasing in tertiary education and the improvement of human resources in European Countries.

	Variables	Label	Relations
y	Human Resources	A23	
x_1	Basic-school entrepreneurial education and training	A4	+
x_2	Employment MHT manufacturing KIS services	A11	+
x_3	Employment share Manufacturing	A12	+
x_4	Government procurement of advanced technology products	A22	-
x_5	Lifelong learning	A32	+
x_6	Medium and high-tech product exports	A35	-
x_7	New doctorate graduates	A37	+
x_8	R&D expenditure business sector	A46	+
x_9	R&D expenditure public sector	A47	+
x_{10}	SMEs innovating in-house	A52	-
x_{11}	Tertiary education	A53	+
x_{12}	Venture capital	A59	-

Figure1. Variables, Labels, and main relationships of the panel data econometric model estimated.

The level of Human Resources is negatively associated to:

- *Government procurement of advanced technology products:* considers the ability of a government to improve the level of technology at a country level through its procurement i.e. by the means of the public demand for medium and high tech products and services. Our analysis shows that there is a negative relationship between the public demand of high-tech products and services and its impact on Human Resources.
- *Medium and high-tech product exports:* it's a measure of the level of exports for high and medium products. There is a negative impact of medium and high-tech product exports and the level of Human Resources at a country level. The fact that the exports of medium and high-tech product is negatively associated with Human Resources can be explained considering that if a firm exports high tech products probably the internal demand for that product is low. And if the domestic demand for a high-tech product is low or insufficient then the level of human capital in that country can be low and insufficient, too.

- *SMEs innovating in-house:*is the percentage of Small and Medium-Sized Enterprises-SMEs that can introduce in-house innovation activities in respect to the total number of SMEs. SMEs activities of innovation is considered as "*in-house*" either in the case in which the firm creates innovation by itself either in co-operation with other enterprises and organisations.In-house innovation is considered either as product innovation either as process innovation. This variable is negatively associated to Human Resources. The reason for this negative relationship can be better understood considering that generally the level of Human Resources applied in SMEs is lower than the level of Human Resources applied in greater corporations.

- *Venture capital:*is a measure of the level of private equity that is invested in companies. The European Innovation Scoreboard considers as venture capital expenditure only three operations: the financing of startups, the expansion of capital and the replacement of capital. The variable venture capital expenditure is expressed as a share of the Gross Domestic Product. There is a negative relationship between venture capital expenditure and the level of Human resources in Europe.

	DYNAMIC PANEL			POOLED OLS			FIXED EFFECTS			RANDOM EFFECTS			WLS		
	Coefficient	P-value		Coefficient	P-value		Coefficient	P-value		Coefficient	P-value		Coefficient	P-value	
const	0,0362006	0,9289		1,66348	0,0302	**	0,174644	0,7588		0,258045	0,8219		0,164731	0,6702	
A4	0,212464	<0,0001	***	0,151388	<0,0001	***	0,131767	<0,0001	***	0,136655	<0,0001	***	0,18446	<0,0001	***
A11	0,176625	0,0002	***	0,235696	<0,0001	***	0,209329	<0,0001	***	0,215103	<0,0001	***	0,151996	<0,0001	***
A12	0,140276	0,0027	***	0,260197	<0,0001	***	0,142652	<0,0001	***	0,1595	<0,0001	***	0,157114	<0,0001	***
A22	-0,412619	<0,0001	***	-0,534613	<0,0001	***	-0,464164	<0,0001	***	-0,470201	<0,0001	***	-0,430288	<0,0001	***
A32	0,196726	<0,0001	***	0,206297	<0,0001	***	0,214497	<0,0001	***	0,211251	<0,0001	***	0,232997	<0,0001	***
A35	-0,0665088	0,0036	***	-0,0960481	<0,0001	***	-0,0755852	<0,0001	***	-0,0795062	<0,0001	***	-0,0631772	<0,0001	***
A37	0,321272	<0,0001	***	0,273373	<0,0001	***	0,306128	<0,0001	***	0,300994	<0,0001	***	0,30548	<0,0001	***
A46	0,118728	<0,0001	***	0,101147	<0,0001	***	0,0904869	<0,0001	***	0,0900508	<0,0001	***	0,0621947	<0,0001	***
A47	0,096362	0,0201	**	0,168065	<0,0001	***	0,116663	<0,0001	***	0,129266	<0,0001	***	0,119997	<0,0001	***
A52	-0,0672924	0,0045	***	-0,133505	<0,0001	***	-0,072698	<0,0001	***	-0,082215	<0,0001	***	-0,0822811	<0,0001	***
A53	0,292701	<0,0001	***	0,276928	<0,0001	***	0,26558	<0,0001	***	0,267027	<0,0001	***	0,299345	<0,0001	***
A59	-0,0159627	0,0827	*	-0,0308628	0,0002	***	-0,013922	0,0625	*	-0,0160321	0,0275	**	-0,0127805	0,0028	***
A23(-1)	-0,0094124	0,4655													

Figure2. Synthesis of the main results of the panel data regressions. Source of data: European Innovation Scoreboard.

But if we take the mean of the coefficient for the five panel data models proposed we can observe the presence of the following characteristics:

- The three main variables that have a positive impact on Human Resources are "*New Doctorate Graduates*" with a mean value of 0,3, "*Tertiary Education*" with 0,28 and "*Life Long Learning*" with 0,21;
- The presence of an industrial and manufacturing sector that promote knowledge intensive products and services has a moderate positive impact on the increasing of Human Resources with a level comprehended between 1,71 and 1,19;
- The promotion of an education on entrepreneurship in schools has a low positive impact on Human Resources with a level equal to 1,261;
- The public and private investment in Research and Development has a low positive effect on Human Resources with a degree between 0,092 and 0,12;
- Government procurement of advanced technology product, among the variables that have a negative impact on Human Resources is that that have the worst effect on the independent variable with a mean value of -0,45.

Rank	Variables	Mean	Impact
	Ranking of the variables based on the mean value of the coefficient computed with the 5 panel data techniques proposed in the model.		
1	*New doctorate graduates*	0,3014	**Positive**
2	*Tertiary education*	0,2803	
3	*Lifelong learning*	0,2124	
4	*Employment MHT manufacturing KIS services*	0,1977	
5	*Employment share Manufacturing*	0,1719	
6	*Basic-school entrepreneurial education and training*	0,1633	
7	*R&D expenditure public sector*	0,1261	
8	*R&D expenditure business sector*	0,0925	
9	*Venture capital*	-0,0179	**Negative**
10	*Medium and high-tech product exports*	-0,0765	
11	*SMEs innovating in-house*	-0,0876	
12	*Government procurement of advanced technology products*	-0,4584	

Figure3. Ranking of the variables based on the mean value of the coefficient computed with the 5 panel data techniques proposed in the model. Source: European Innovation Scoreboard.

III.   CLUSTERIZATION

Using the software Orange, we have performed a clusterization through the algorithm k-means and t-SNE. We choose the efficient number of clusters using the Silhouette coefficient for the year 2021. We found three different typologies of clusters:

- *Cluster 1*:Denmark, Finland, Norway, Sweden, Switzerland and United Kingdom;
- *Cluster 2*: Bosnia and Herzegovina, Bulgaria, Croatia, Czechia, Greece, Hungary, Italy, Latvia, Malta, Montenegro, North Macedonia, Poland, Portugal, Romania, Serbia, Slovakia, Turkey, Ukraine;
- *Cluster 3*: Austria, Belgium,Cyprus, Estonia, France, Germany, Iceland, Ireland, Israel, Lithuania, Luxembourg; Netherlands, Slovenia, Spain.

In terms of value cluster 1 is the more efficient in the sense of Human Resources with a mean value of 187 followed by the Cluster 3 with a mean of 136. Cluster 2 closes the ranking with a mean level of Human Resources equal to 56,00.

Rank	Clusters	Mean Value	Min	Max
Characteristics of the Clusters for Level of Human Resources in 2021 in European Countries. Source: European Innovation Scoreboard.				
1	*Cluster 1*	187,00	163,00	222,61
3	*Cluster 2*	56,00	8,95	100,26
2	*Cluster 3*	136,00	104,11	180,77

Figure4. Characteristics of the Clusters for the level of Human Resources in 2021 in European Countries. Source: European Innovation Scoreboard.

Our results show that the half ofcountries analyzed in the European Innovation Scoreboard have a low level of Human Resources that can be considered insufficient to sustain an effective process of production of innovation technology. The Cluster 2 has a level of mean value of Human Resources that is equal 70% lower than Cluster 1 and 59% lower that cluster 3. These differences cannot be solved in the short run and require long run investment in education, Research and Development, and entrepreneurship to promote a convergence of the values of countries in Cluster 2 towards the levels of countries in clusters 1 and 3.
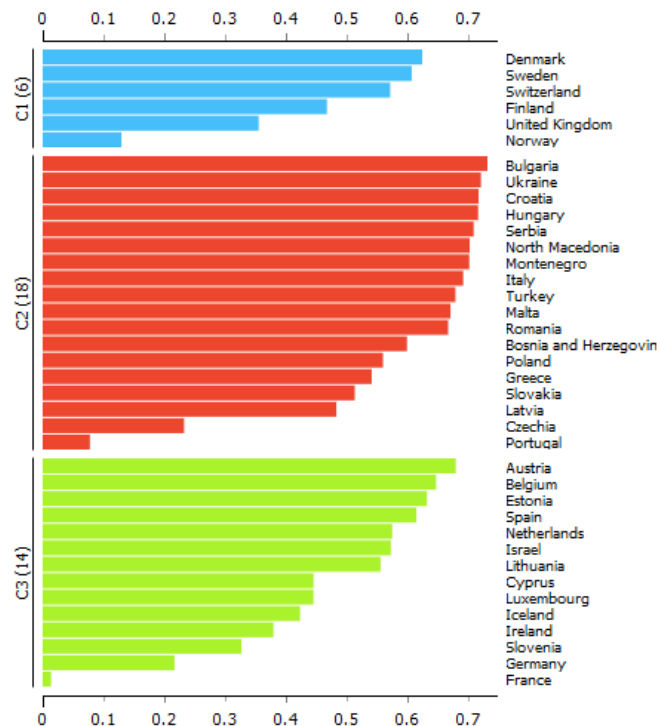

Figure 5. Clusterization of European Countries in 2021 based on the level of Human Resources. Source: European Innovation Scoreboard. Tool: Orange. Algorithm: k-Means. Optimization: Silhouette Coefficient.

We can also observe that countries in the Cluster 1 and in the Cluster 2 that have the higher levels of "*Human Resources*" also have higher levels of Gross Domestic Products. While countries in the Clusters 3, i.e., Italy, Portugal and Eastern Europe countries have lower levels of income per capita in respect of countries in Clusters 1 and 2. These considerations can reinforce the idea that Human Resources is a significant driver for economic growth measured in terms of GDP per capita. European policy makers that are interested in promoting a deeper

economic growth among European countries and in southern and eastern Europe should promote an improve in policies able to finance "*New Doctorate*", "*Lifelong Learning*" and "*Tertiary Education*".
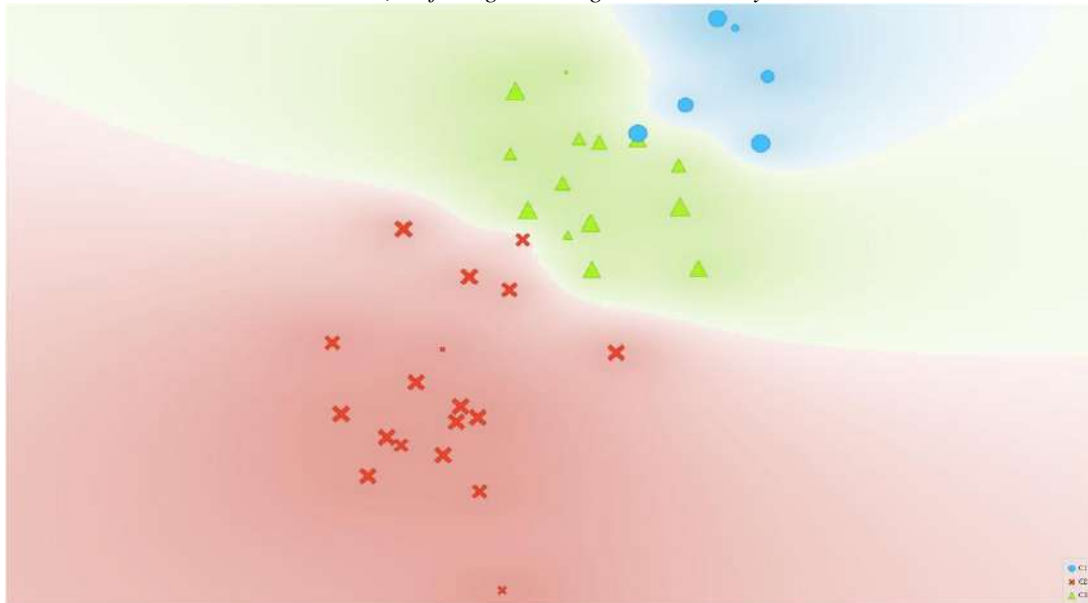

Figure 6. Representation of the clusterization with the algorithm t-SNE. Tool: Orange. Source: European Innovation Scoreboard. Year: 2021.

Finally, we can conclude that there is a great gap between countries in the Cluster 3 and countries in Clusters 1 and 2. The gap impedes to many countries in southern and eastern Europe to have access to the knowledge society, the knowledge economy and to develop firms and institutions able to sustain the growing servitization of the production processes at a corporate level. The economy based of intangibles, of intellectual property rights and of immaterial assets based on the valuation of human capital is not feasible for at least 18 European countries. This gap creates new inequalities and can have a long run effect on the perspective of economic growth for medium and low-income countries in Europe.

IV.   MACHINE LEARNING AND PREDICTIONS

We have also performed a form of machine learning and prediction with the sequent models:
- *Linear Regression;*
- *Tree Ensemble Regression;*
- *Polynomial Regression;*
- *Artificial Neural Network-ANN;*
- *Gradient Boosted Trees;*
- *Random Forest Regression;*
- *Probabilistic Neural Networks-PNN.*

Our goal is to estimate the value of Human Resources using the historical series of the European Innovation Scoreboard in the period 2014-2021 using KNIME to find the best predictor algorithm. We divide the data in two partitions using the KNIME node "*Partitioning*" with a 70% of training data and the remaining 30% of test data. To evaluate the best predictor algorithm, we have computed a maximization of R-squared and the minimization of the following errors:
- *Mean Absolute Error;*
- *Mean Squared Error;*
- *Root Mean Squared Error;*
- *Mean Signed Difference.*

Machine Learning and Prediction of Human Resources in Europe. Source: European Innovation Scoreboard.					
	R^2	Mean Absolute Error	Mean Squared Error	Root Mean Squared Error	Mean Signed Difference
ANN	0,9626	0,0370	0,0030	0,0552	0,0226
PNN	0,8853	0,0622	0,0046	0,0679	0,0114
GRADIENT BOOSTED TREES	0,9036	0,0492	0,0039	0,0623	0,0016
RANDOM FOREST REGRESSION	0,9380	0,0532	0,0039	0,0625	0,0093
TREE ENSEMBLE REGRESSION	0,9569	0,0364	0,0018	0,0420	0,0010
LINEAR REGRESSION	0,9787	0,0270	0,0011	0,0331	0,0078
POLYNOMIAL REGRESSION	0,9681	0,0396	0,0019	0,0441	0,0047

Figure 7. Results of the Machine Learning and Prediction Algorithms using KNIME.

Machine Learning and Prediction of Human Resources in
Europe. Source: European Innovation Scoreboard.

■ Mean Absolute Error   ■ Mean Squared Error   ■ Root Mean Squared Error   ■ Mean Signed Difference

POLYNOMIAL REGRESSION

LINEAR REGRESSION

TREE ENSEMBLE REGRESSION

RANDOM FOREST REGRESSION

GRADIENT BOOSTED TREES

PNN

ANN

0,0000   0,0200   0,0400   0,0600   0,0800   0,1000   0,1200   0,1400   0,1600
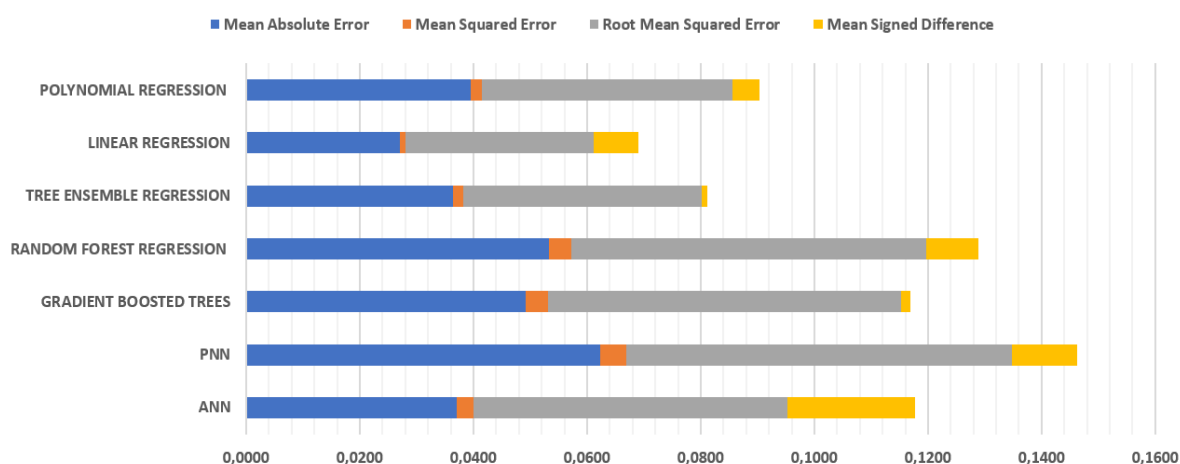
Figure 8. Results of Machine Learning and Prediction Algorithms using KNIME. Linear Regression, in the combination of learner and prediction, has the lower values of estimated errors.

We found that the best predictor algorithm is the linear regression followed in order by Tree Ensemble Regression, Polynomial Regression, Artificial Neural Network[4]-ANN, Gradient Boosted Trees, Random Forest Regression and Probabilistic Neural Network-PNN.

V.   CONCLUSIONS

In this article we have estimated the innovational determinants of Human Resources. We perform five different panel data model i.e., Panel Data with Fixed Effects, Panel Data with Random Effects, Dynamic Panel Data, Pooled OLS, WLS. Data are collected from the European Innovation Scoreboard for 36 European countries in the period 2010-2019. We found that the level of Human Resources is positively and primarily associated to variables associated to instruction such as: lifelong learning, new doctorates, and tertiary education. The clusterization analysis realized with the k-Means algorithm, optimized with the Silhouette coefficient, shows the presence of three different clusters in Europe. The first cluster represents the Northern European countries with higher levels of Human Resources, followed by Central European countries with lower levels of HumanResources in respect to cluster 1, while the third cluster contains Southern and Eastern European countries show very low levels of Human Resources either in respect to cluster 2 either to cluster 1. Finally, we use seven different machine learning algorithms to predict the level of Human Resources based ondata in the period 2014-2021. We show that the linear regression algorithm is the best predictor of the level of Human Resources in the sense of minimization of errors and maximization of R-squared. Finally, we can conclude that the level of Human Resources is an essential input of the innovation technology and of the Research and Development activities either at a national either at a corporate level. As the clusterization analysis has clearly showed there is an evident gap between Central-Northern European countries and Southern-Eastern European countries. As our econometric model shows, policy makers can improve the level of Human Resources, through the investment in lifelong learning, tertiary education, and new doctorates. In the end, machine learning algorithms can be used to efficiently predict the level of Human Resources as a target for political economies oriented to growth and development.

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1.   **Appendix**
1.1 **Regression Results with Gretl**

	Variables	Label	
y	Human Resources	A23	
x_1	Basic-school entrepreneurial education and training (SD)	A4	+
x_2	Employment MHT manufacturing KIS services	A11	+
x_3	Employment share Manufacturing (SD)	A12	+
x_4	Government procurement of advanced technology products (SD)	A22	-
x_5	Lifelong learning	A32	+
x_6	Medium and high-tech product exports	A35	-
x_7	New doctorate graduates	A37	+
x_8	R&D expenditure business sector	A46	+
x_9	R&D expenditure public sector	A47	+
x_{10}	SMEs innovating in-house	A52	-
x_{11}	Tertiary education	A53	+
x_{12}	Venture capital	A59	-

One-step dynamic panel, using 287 observations				
36 cross section units included				
Time series length: minimum 7, maximum 8				
Ox / DPD compliant H matrix				
Dependent variable: A23				
	Coefficient	*Std. Error*	*z*	*p-value*
A23(-1)	−0,00941240	0,0128960	−0,7299	0,4655
const	0,0362006	0,405848	0,08920	0,9289
A4	0,212464	0,0244906	8,675	<0,0001	***
A11	0,176625	0,0478896	3,688	0,0002	***
A12	0,140276	0,0468362	2,995	0,0027	***
A22	−0,412619	0,0463765	−8,897	<0,0001	***
A32	0,196726	0,0325598	6,042	<0,0001	***
A35	−0,0665088	0,0228194	−2,915	0,0036	***
A37	0,321272	0,0190131	16,90	<0,0001	***
A46	0,118728	0,0290984	4,080	<0,0001	***
A47	0,0963620	0,0414700	2,324	0,0201	**
A52	−0,0672924	0,0237171	−2,837	0,0045	***
A53	0,292701	0,0204158	14,34	<0,0001	***
A59	−0,0159627	0,00919791	−1,735	0,0827	*

Somma quadr. residui	4366,817	E.S. della regressione	3,999458

| Numero di strumenti = 34 |
|---|
| Test per errori AR(1): z = 1,19687 [0,2314] |
| Test per errori AR(2): z = 0,394814 [0,6930] |
| Test di sovra-identificazione di Sargan: Chi-quadro(20) = 23,8029 [0,2511] |
| Test (congiunto) di Wald: Chi-quadro(13) = 98446,2 [0,0000] |
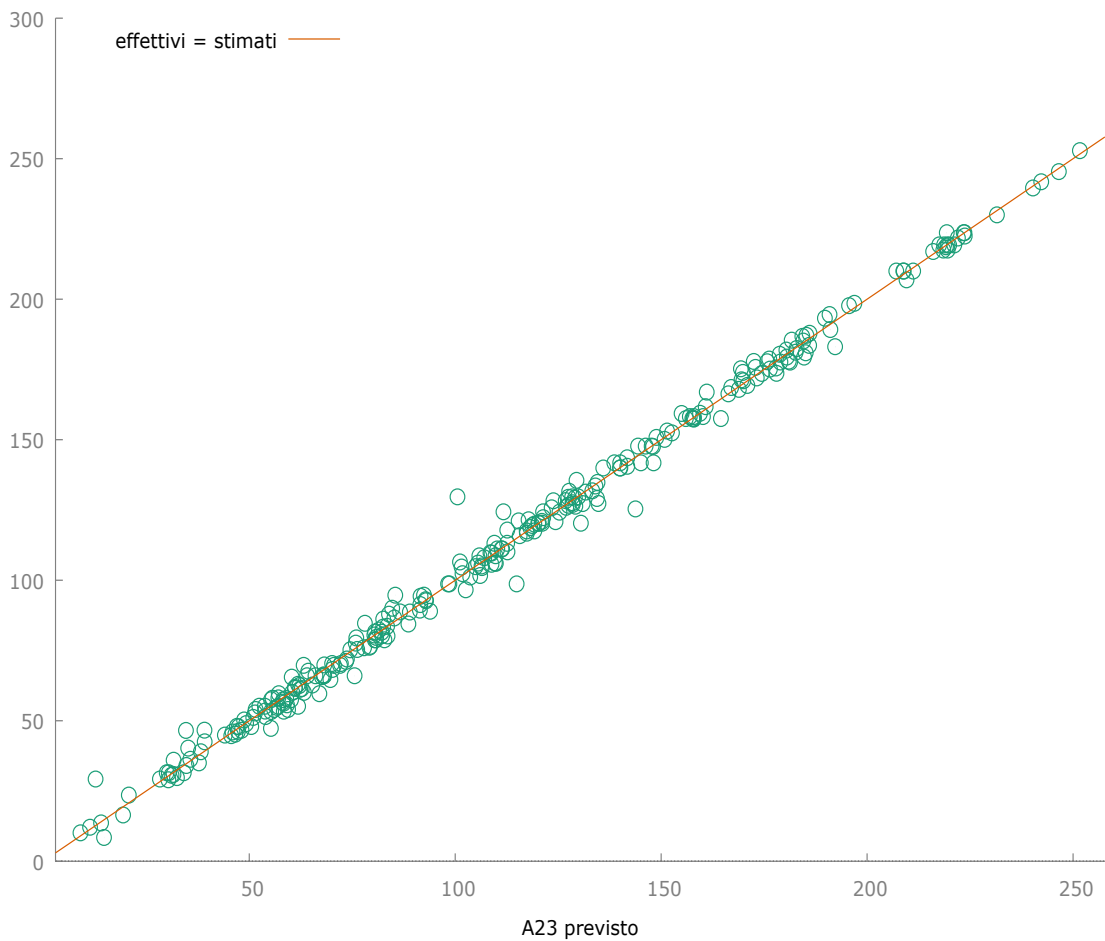
	Coefficiente	Errore Std.	rapporto t	p-value	
	Pooled OLS, usando 358 osservazioni				
	Incluse 36 unità cross section				
	Lunghezza serie storiche: minimo 8, massimo 10				
	Variabile dipendente: A23				
	Coefficiente	*Errore Std.*	*rapporto t*	*p-value*	
const	1,66348	0,764518	2,176	0,0302	**
A4	0,151388	0,0163032	9,286	<0,0001	***
A11	0,235696	0,0112219	21,00	<0,0001	***
A12	0,260197	0,0342445	7,598	<0,0001	***
A22	−0,534613	0,0327173	−16,34	<0,0001	***
A32	0,206297	0,00871573	23,67	<0,0001	***
A35	−0,0960481	0,0114040	−8,422	<0,0001	***
A37	0,273373	0,0116970	23,37	<0,0001	***
A46	0,101147	0,0164290	6,157	<0,0001	***
A47	0,168065	0,0163044	10,31	<0,0001	***
A52	−0,133505	0,0128597	−10,38	<0,0001	***
A53	0,276928	0,00810929	34,15	<0,0001	***
A59	−0,0308628	0,00807233	−3,823	0,0002	***

Media var. dipendente	91,00458	SQM var. dipendente	68,04448

Somma quadr. residui	18989,27	E.S. della regressione	7,418986
R-quadro	0,988512	R-quadro corretto	0,988112
F(12, 345)	2473,805	P-value(F)	0,000000
Log-verosimiglianza	−1218,806	Criterio di Akaike	2463,612
Criterio di Schwarz	2514,059	Hannan-Quinn	2483,675
rho	0,900327	Durbin-Watson	0,327024
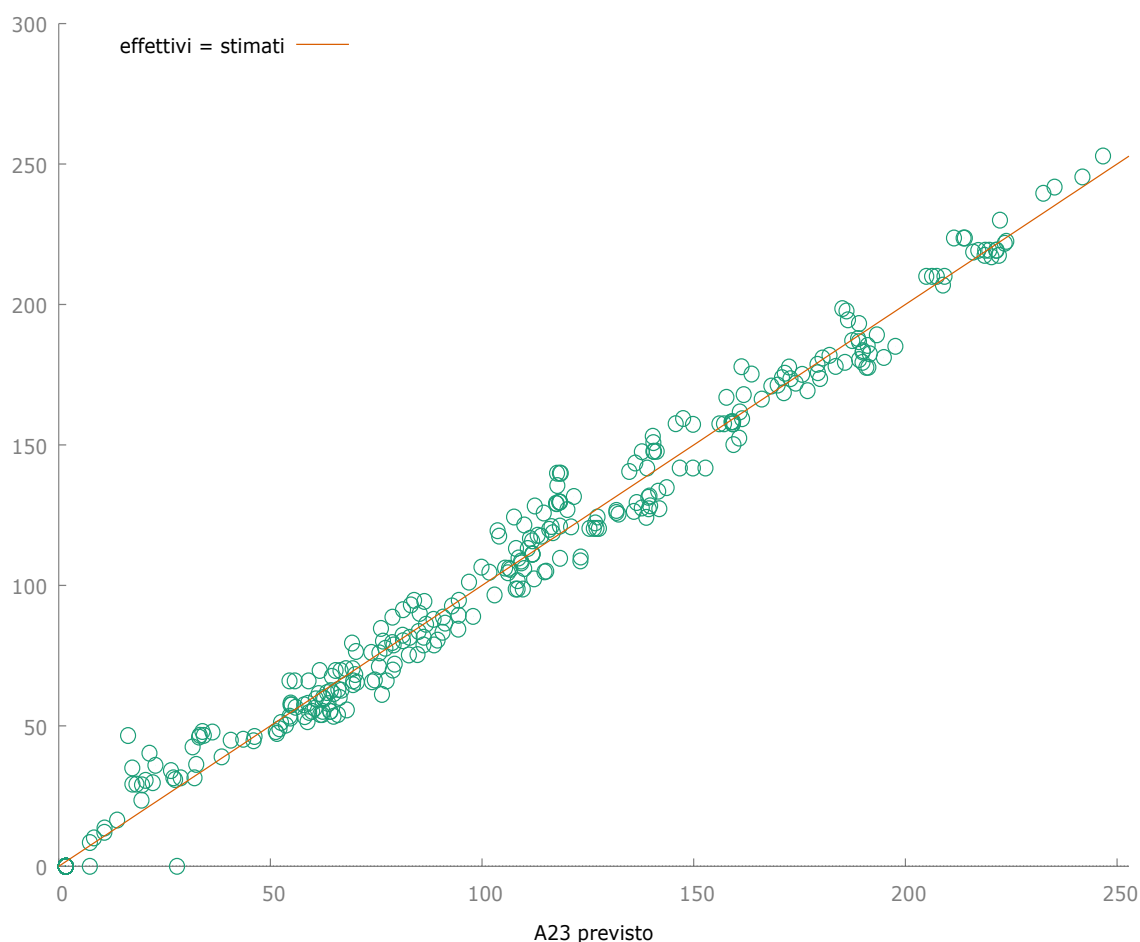
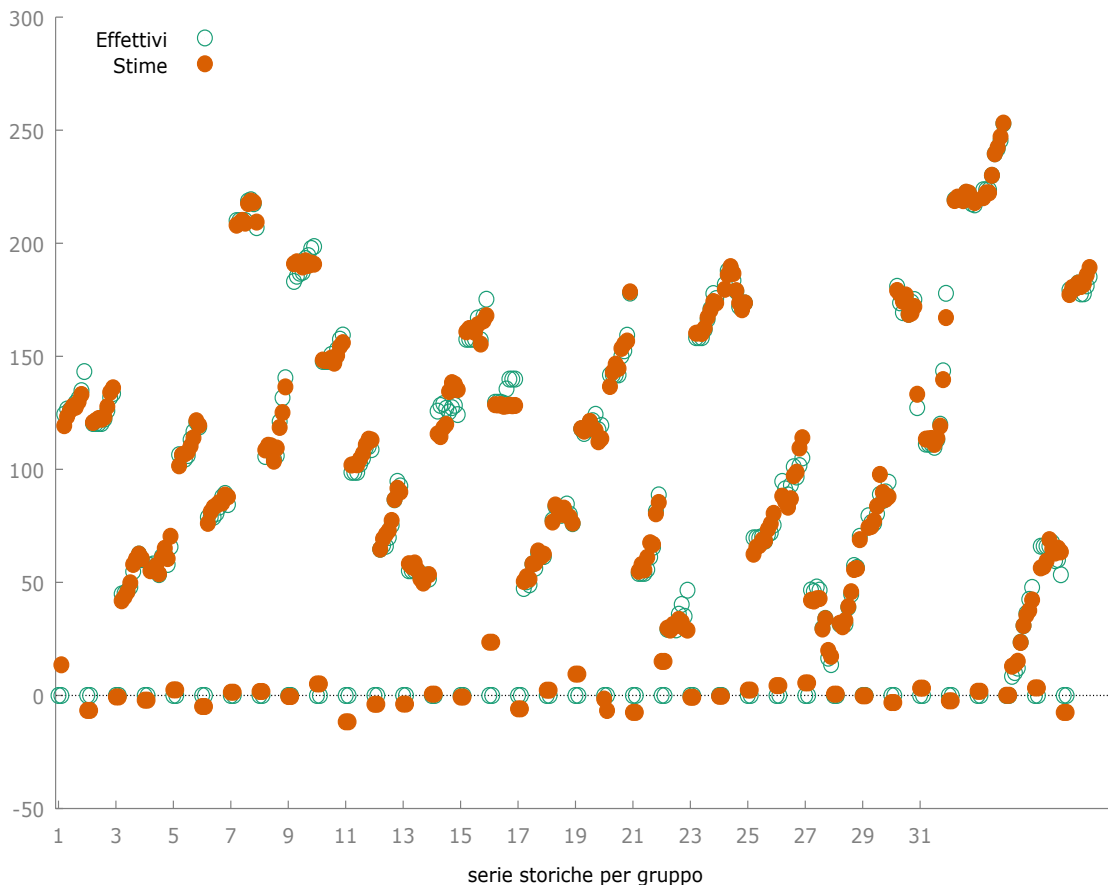| Effetti fissi, usando 358 osservazioni |
|---|
| Incluse 36 unità cross section |
| Lunghezza serie storiche: minimo 8, massimo 10 |
| Variabile dipendente: A23 |
| |

	Coefficiente	Errore Std.	rapporto t	p-value	
const	0,174644	0,568338	0,3073	0,7588	
A4	0,131767	0,0226674	5,813	<0,0001	***
A11	0,209329	0,0135921	15,40	<0,0001	***
A12	0,142652	0,0339725	4,199	<0,0001	***
A22	−0,464164	0,0401838	−11,55	<0,0001	***
A32	0,214497	0,0110444	19,42	<0,0001	***
A35	−0,0753852	0,0145905	−5,167	<0,0001	***
A37	0,306128	0,0134557	22,75	<0,0001	***

A46	0,0904869	0,0181675	4,981	<0,0001	***
A47	0,116663	0,0194239	6,006	<0,0001	***
A52	−0,0726980	0,0140301	−5,182	<0,0001	***
A53	0,265580	0,0102251	25,97	<0,0001	***
A59	−0,0139220	0,00744774	−1,869	0,0625	*

|			
Media var. dipendente	91,00458	SQM var. dipendente	68,04448
Somma quadr. residui	7728,774	E.S. della regressione	4,993148
R-quadro LSDV	0,995324	R-quadro intra-gruppi	0,991706
LSDV F(47, 310)	1404,015	P-value(F)	0,000000
Log-verosimiglianza	−1057,899	Criterio di Akaike	2211,798
Criterio di Schwarz	2398,063	Hannan-Quinn	2285,876
rho	0,601889	Durbin-Watson	0,624058

Test congiunto sui regressori -
Statistica test: F(12, 310) = 3088,84
con p-value = P(F(12, 310) > 3088,84) = 0
Test per la differenza delle intercette di gruppo -
Ipotesi nulla: i gruppi hanno un'intercetta comune
Statistica test: F(35, 310) = 12,9045
con p-value = P(F(35, 310) > 12,9045) = 2,369e-042

A23: valori effettivi e stimati

Effetti casuali (GLS), usando 358 osservazioni				
Incluse 36 unità cross section				
Lunghezza serie storiche: minimo 8, massimo 10				
Variabile dipendente: A23				
	Coefficiente	*Errore Std.*	*z*	*p-value*
const	0,258045	1,14649	0,2251	0,8219
A4	0,136655	0,0206005	6,634	<0,0001 ***
A11	0,215103	0,0126609	16,99	<0,0001 ***
A12	0,159500	0,0327649	4,868	<0,0001 ***
A22	−0,470201	0,0371905	−12,64	<0,0001 ***
A32	0,211251	0,0101975	20,72	<0,0001 ***
A35	−0,0795062	0,0134161	−5,926	<0,0001 ***
A37	0,300994	0,0127179	23,67	<0,0001 ***
A46	0,0900508	0,0172099	5,233	<0,0001 ***
A47	0,129266	0,0181918	7,106	<0,0001 ***
A52	−0,0822150	0,0133824	−6,144	<0,0001 ***
A53	0,267027	0,00944962	28,26	<0,0001 ***
A59	−0,0160321	0,00727203	−2,205	0,0275 **

Media var. dipendente	91,00458	SQM var. dipendente	68,04448
Somma quadr. residui	21608,36	E.S. della regressione	7,902652
Log-verosimiglianza	−1241,934	Criterio di Akaike	2509,868
Criterio di Schwarz	2560,315	Hannan-Quinn	2529,931
rho	0,601889	Durbin-Watson	0,624058

Varianza 'between' = 35,369

Varianza 'within' = 24,9315

theta medio = 0,742614

Test congiunto sui regressori -

Statistica test asintotica: Chi-quadro(12) = 38525,6

con p-value = 0

Test Breusch-Pagan -

Ipotesi nulla: varianza dell'errore specifico all'unità = 0

Statistica test asintotica: Chi-quadro(1) = 340,788

con p-value = 4,29828e-076

Test di Hausman -

Ipotesi nulla: le stime GLS sono consistenti

Statistica test asintotica: Chi-quadro(12) = 16,8662

con p-value = 0,154702

A23: valori effettivi e stimati
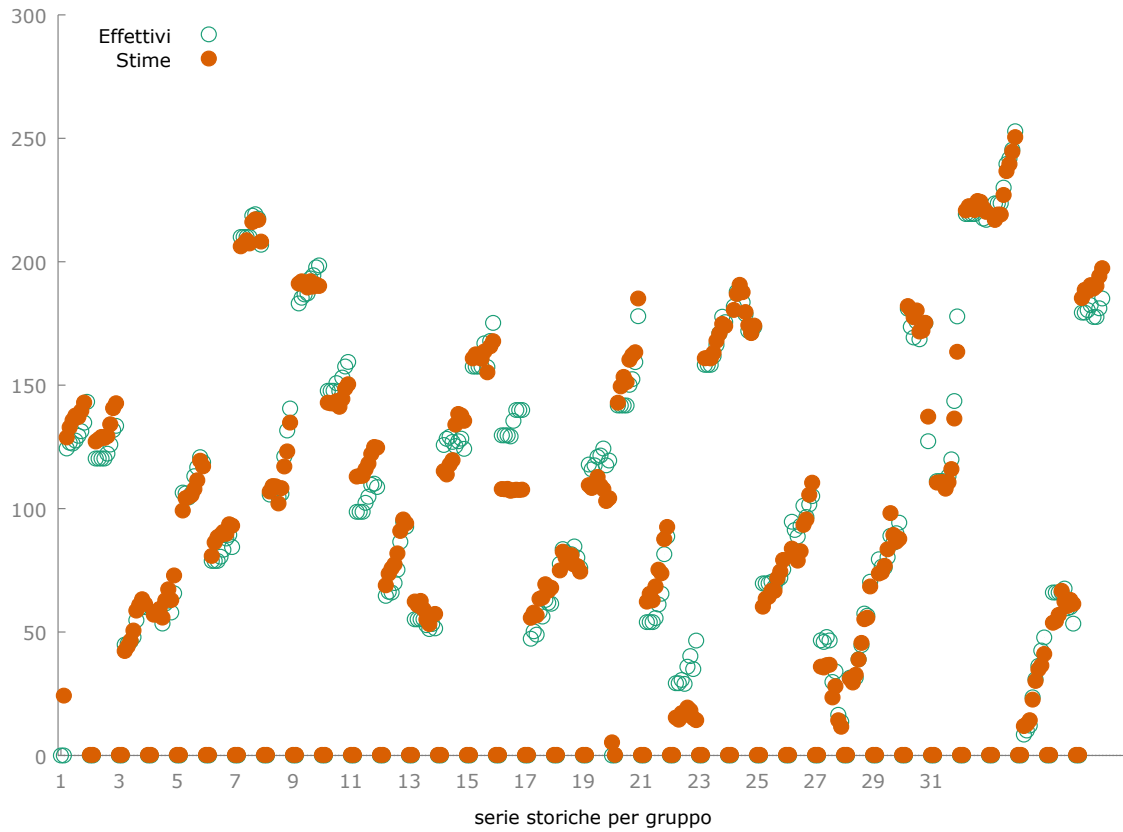
Modello 70: WLS, usando 358 osservazioni
Incluse 36 unità cross section
Variabile dipendente: A23
Pesi basati sulle varianze degli errori per unità

	Coefficiente	*Errore Std.*	*rapporto t*	*p-value*	
const	0,164731	0,386516	0,4262	0,6702	
A4	0,184460	0,0127293	14,49	<0,0001	***
A11	0,151996	0,00967149	15,72	<0,0001	***
A12	0,157114	0,0250899	6,262	<0,0001	***
A22	−0,410288	0,0243232	−16,87	<0,0001	***
A32	0,232997	0,00580705	40,12	<0,0001	***
A35	−0,0651772	0,00660499	−9,868	<0,0001	***
A37	0,305480	0,00730008	41,85	<0,0001	***
A46	0,0621947	0,00981435	6,337	<0,0001	***
A47	0,119997	0,0104281	11,51	<0,0001	***
A52	−0,0822811	0,00758662	−10,85	<0,0001	***
A53	0,299345	0,00495578	60,40	<0,0001	***
A59	−0,0127805	0,00424777	−3,009	0,0028	***

Statistiche basate sui dati ponderati:

|			
Somma quadr. residui	248,9142	E.S. della regressione	0,849406
R-quadro	0,997747	R-quadro corretto	0,997669
F(12, 345)	12733,68	P-value(F)	0,000000
Log-verosimiglianza	−442,9270	Criterio di Akaike	911,8540
Criterio di Schwarz	962,3009	Hannan-Quinn	931,9168

Statistiche basate sui dati originali:

| Media var. dipendente | 91,00458 | SQM var. dipendente | 68,04448 |
| Somma quadr. residui | 30178,93 | E.S. della regressione | 9,352816 |

A23: valori effettivi e stimati
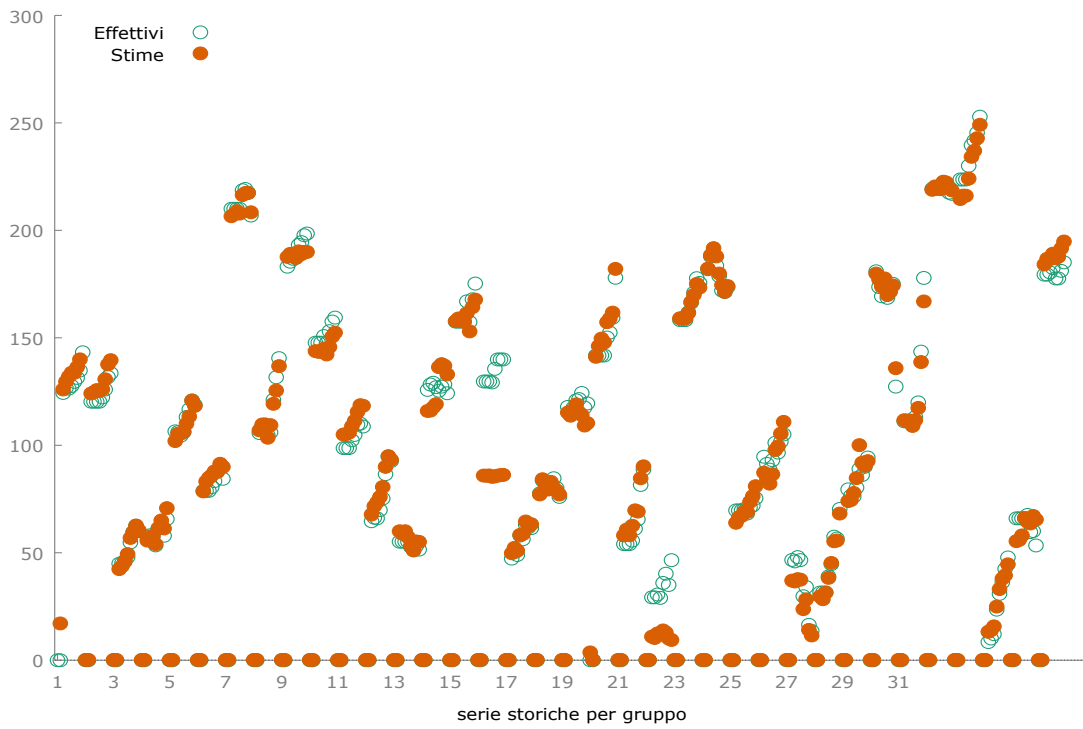
1.2 Clusterization Results with Orange

Feature 1	Cluster	Silhouette
Denmark	C1	0.680859
Finland	C1	0.641994
Norway	C1	0.5435
Sweden	C1	0.676786
Switzerland	C1	0.66847
United Kingdom	C1	0.611252
Bosnia and Her...	C2	0.67482
Bulgaria	C2	0.704253
Croatia	C2	0.701198
Czechia	C2	0.574372
Greece	C2	0.661046
Hungary	C2	0.701024
Italy	C2	0.695825
Latvia	C2	0.645645
Malta	C2	0.691334
Montenegro	C2	0.697911
North Macedonia	C2	0.6981
Poland	C2	0.66519
Portugal	C2	0.524934
Romania	C2	0.690453
Serbia	C2	0.699493
Slovakia	C2	0.653634
Turkey	C2	0.692918
Ukraine	C2	0.702027
Austria	C3	0.693186
Belgium	C3	0.686006
Cyprus	C3	0.635919
Estonia	C3	0.682315
France	C3	0.503773
Germany	C3	0.569479
Iceland	C3	0.630075
Ireland	C3	0.617829
Israel	C3	0.668625
Lithuania	C3	0.664668
Luxembourg	C3	0.636474
Netherlands	C3	0.669102
Slovenia	C3	0.602516
Spain	C3	0.67821

Human Resources in Europe in 2021. Source: European Innovatio Scoreboard.
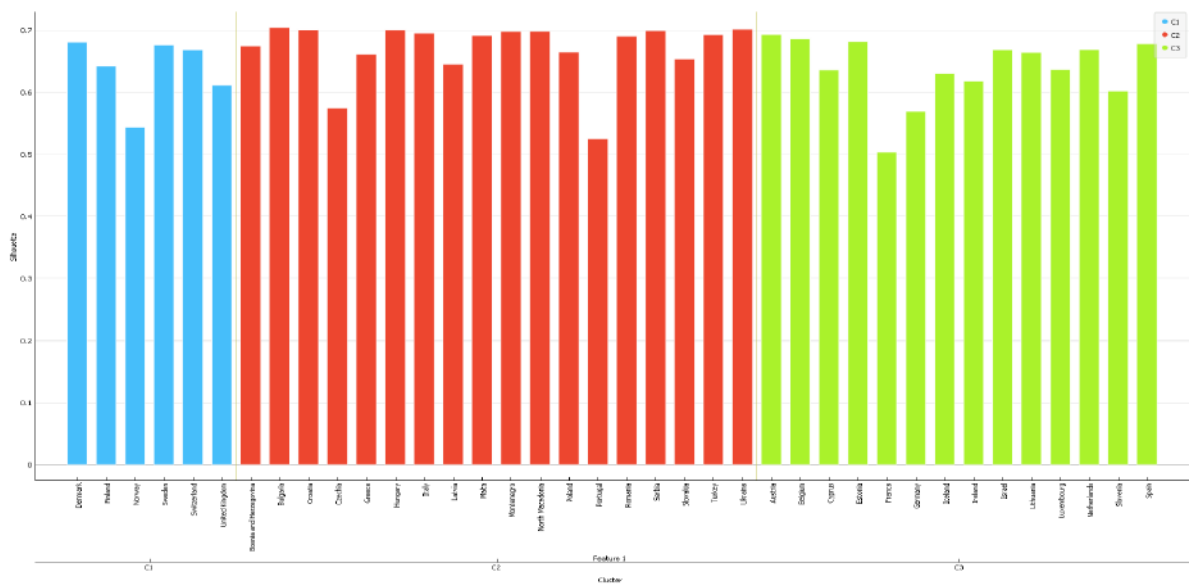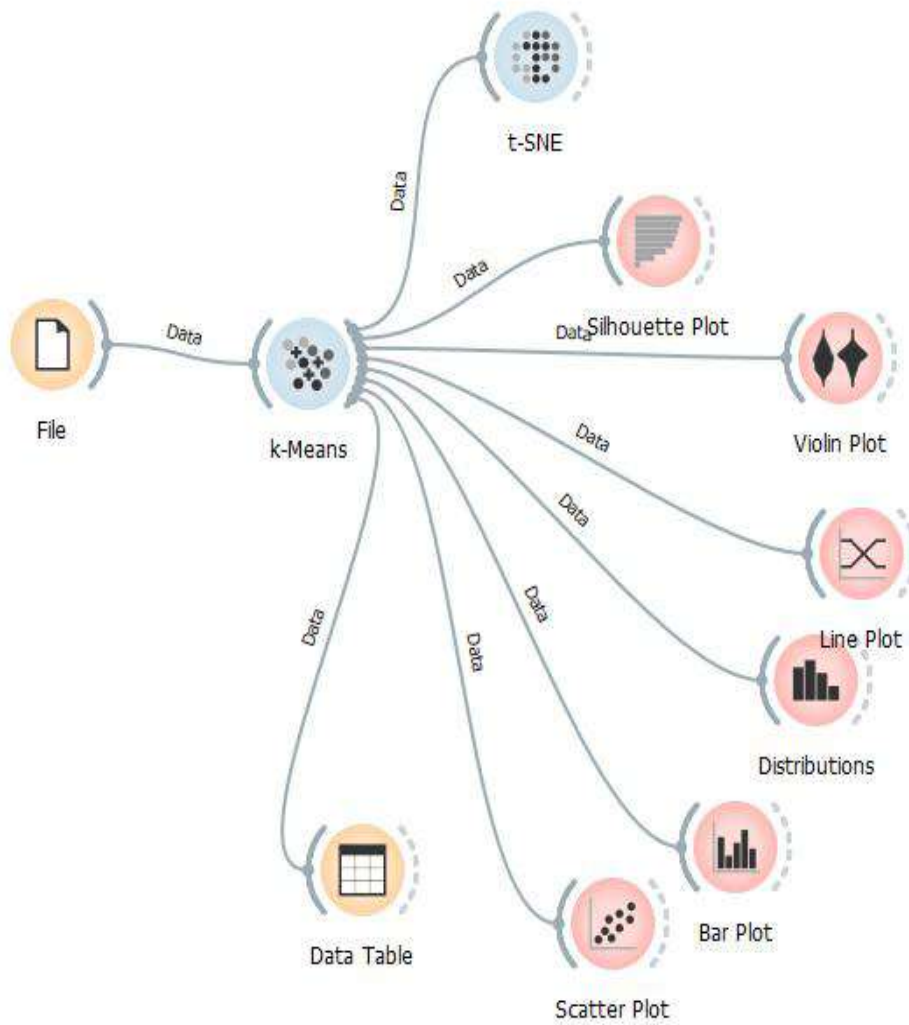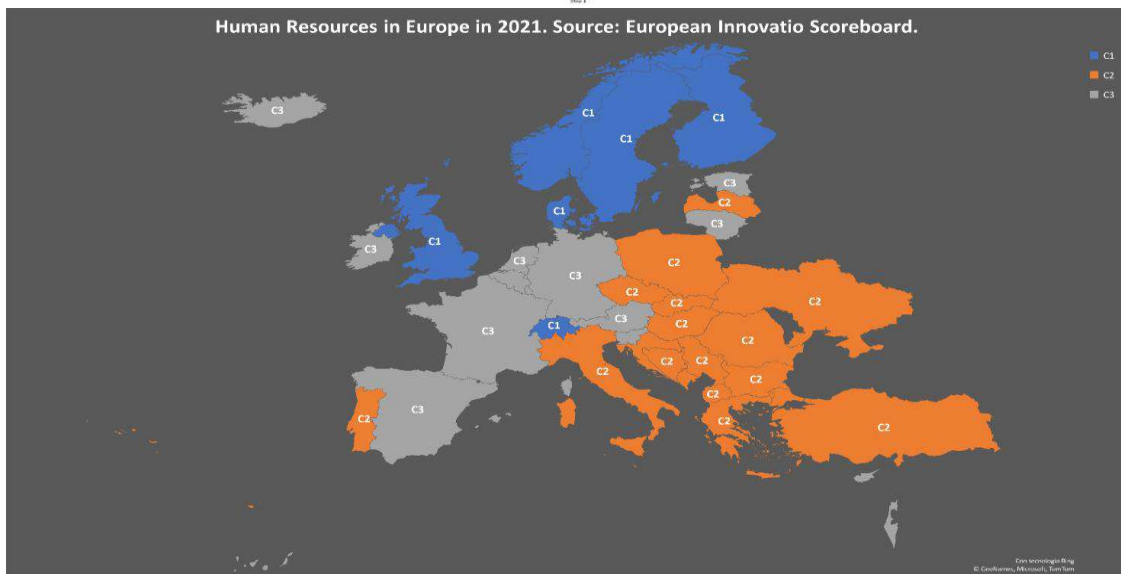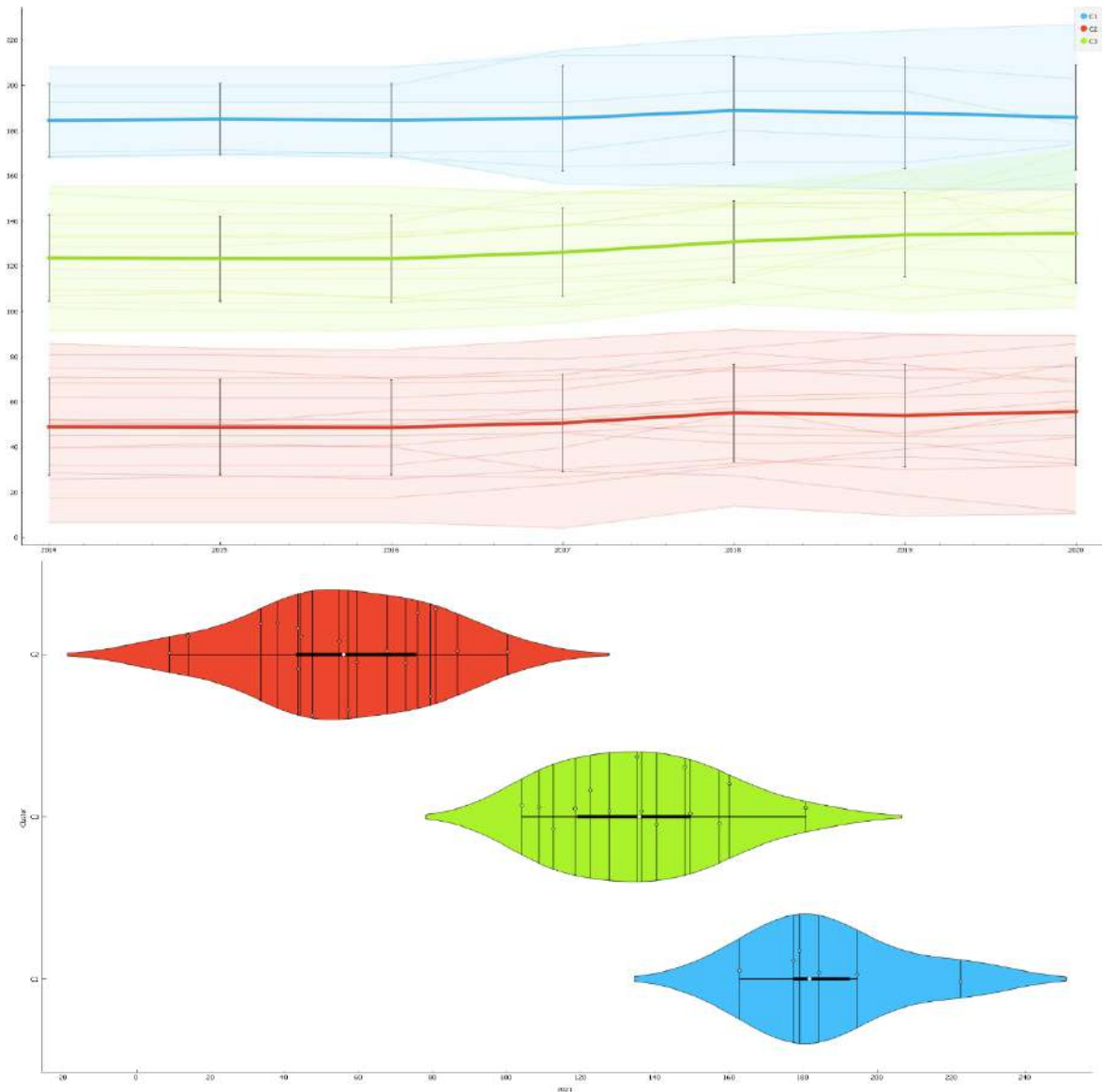
1.3 Machine Learning and Prediction with KNIME