The Impact of Venture Capital Expenditures on Innovation in Europe

Leogrande, Angelo and Costantiello, Alberto and Laureti, Lucio

Lum University Giuseppe Degennaro, Lum University Giuseppe Degennaro, Lum University Giuseppe Degennaro

25 September 2021

Angelo Leogrande[1], Alberto Costantiello[2], Lucio Laureti[3]

The Impact of Venture Capital Expenditures on Innovation in Europe

Abstract

We investigate the relationship between "*Venture Capital Expenditures*" and innovation in Europe. Data are collected from the European Innovation Scoreboard for 36 countries in the period 2010-2019. We perform Panel Data with Fixed Effects, Panel Data with Random Effects, Pooled OLS, WLS, Dynamic Panel. Results show that the level of Venture Capitalist Expenditure is positively associated to "*Foreign Doctorate Students*" and "*Innovation Index*" and negatively related to "*Government Procurement of Advanced Technology Products*", "*Innovators*", "*Medium and High-Tech Products Exports*", "*Public-Private Co-Publications*". In adjunct, cluster analysis is realized with the algorithm k-Means and the Silhouette coefficient, and we found the presence of four different clusters for the level of "*Venture Capital Expenditures*". Finally, we propose a confrontation among 8 different algorithms of machine learning to predict the level of "*Venture Capital Expenditures*" and we find that the linear regression generates the best results in terms of minimization of MAE, MSE, RMSE.

JEL CODE: O31, O32, O33, O34, O36, O38.

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

1. Introduction

In this article we investigate the role of "*Venture Capital Expenditure*" in respect to innovation in European countries[4] in the period 2010-2019. The role of innovation is essential to economic growth either in the short run either in the long run as showed in traditional economic theory [1], [2], [3]. The question of the financing of innovation is relevant since innovation is positively associated to human resources [4] [5], firms' sales [6], private investments [7], the presence of innovators [8], finance-firm nexus [9]. Furthermore, innovation also requires a cultural and social environment pro-actively oriented toward technology and Research and Development [10]. Innovation has positive effects on employment [11]. The attractiveness of research systems at national level can improve innovation [12], [13]. The investment in innovation and Research and Development has positive effect on firm performance [14]. For these reasons it is necessary to analyze if the presence of venture capitalists can improve the level of innovation. Venture capitalists tend to invest in new technologies considering the financial returns. But there are sectors in which innovations are not sufficiently profitable such as for example in the case of cleantech [15]. In this case the investment of venture capitalists could be

[1] Assistant Professor of Economics at LUM University-Giuseppe Degennaro.
[2] Professor of Economics and International Economics at LUM University-Giuseppe Degennaro.
[3] Professor of Economics at LUM University-Giuseppe Degennaro.
[4] Countries are 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.

inferior to the social optimal level and this situation can open a space for public intervention. But, in other cases, such as for example in the health sector, the investment of venture capitalists in innovation is either profitable either social relevant [16]. There is a positive relationship between public expenditure in Research and Development and venture capital especially in countries with low level of infrastructure [17]. More innovative economies that generate intellectual capital offer deeper investment opportunities for venture capitalists [18]. The investment of venture capital in Chinese start up has showed a controversial effect: at early-stage venture capitalists inhibit the investments of start ups in innovation while in the medium run the presence of external finance can promote a deeper technological innovation [19]. But, in the US, the investment of venture capitalists in start ups is positively associated to an increase in innovation and intellectual property rights [20]. Geographical locations have a role in creating the possibility of a connection between innovation and venture capital firms since both tend to distribute among urban districts [21]. Venture capitalists can promote the production of intellectual capital with greater efficiency in respect to traditional investment in Research and Development [22]. There is a positive relationship between venture capital and open innovation [23]. The role of venture capital is relevant in the case of countries that use startups to develop innovation systems [24]. Venture capitalists reduce the ability of young startups to develop deeper alliances tech-oriented [25]. If venture capital enterprises have a human capital with hard skills in STEM, then there are greater probabilities of a positive effect on the innovation abilities of the invested firms [26]. Venture capital invested firms improve their ability to innovate of 23% in Sweden [27]. Venture capitalists generate higher returns from innovation [28]. Venture capital can have a positive role to promote innovative start up especially in connection with high social capital and low taxation [29]. The relationship between startups and venture capital is more efficient when both share a common entrepreneurial culture that can work either as a scenario either as a model for commercial practices such as in the case of creative destruction in Silicon Valley [30]. Venture capital enterprises lack the ability to implement innovation in the long run with the industrialization of new products and services especially in comparison with start ups that receive public founding [31]. Venture capitalist enterprises promote deeper business innovation especially in the case of weak intellectual property rights regimes [32]. Researchers and entrepreneurs in innovation technology should consider the strategic role of venture capitalist firms in providing financial resources even considering the shortermism associated to a more profit-oriented management of intellectual assets in a knowledge economy [33]. Venture capital private enterprises are more efficient in respect to state-owned venture capital organizations in promoting innovation in China [34]. But the positive relationship between innovation and venture capital also shows the characteristics of non-linearity [35]. The development of an institutional framework for venture capital enterprises is positively associated to the digitalization of the entire economy [36].

The article continues as follows: the second paragraph presents the econometric model, the third paragraph contains the clusterization with k-Means algorithm, the fourth paragraph show a comparison among eight different algorithms of machine learning to predict the value of “Venture Capital Expenditures”, the fifth paragraph concludes. The appendix contains further materials on regressions, clusterization, machine learning and prediction.

2. The econometric model

We have estimated the sequent model:

$$\begin{aligned}
&\boldsymbol{VentureCapitalExpenditures_{it}}\\
&\quad = \boldsymbol{a_1 + b_1(ForeignDoctorateStudents)_{it}}\\
&\quad + \boldsymbol{b_2(GovernmentProcurementOfAdvacedTechnologyProducts)_{it}}\\
&\quad + \boldsymbol{b_3(InnovationIndex)_{it} + b_4(Innovators)_{it}}\\
&\quad + \boldsymbol{b_5(MediumAndHighTechProductExports)_{it}}\\
&\quad + \boldsymbol{b_6(PublicPrivateCoPublications)_{it}}
\end{aligned}$$

The level of "*Venture Capital Expenditures*" is defined as « *[…] private equity being raised for investment in companies. Management buyouts, management buy-ins, and venture purchase of quoted shares are excluded. Venture capital includes early-stage (seed + start-up) and expansion and replacement capital.* [11]» The variable is a proxy of the ability of a country to finance risks through capital accumulation either in traditional asset management either in innovative firms such as start ups and newcos. We estimate the value of "*Venture Capital Expenditures*" with the following econometric models i.e.: Panel Data with Random Effects, Panel Data with Fixed Effects, WLS, Pooled OLS, Dynamic Panel. Data are collected for 36 European countries in the period 2010-2019 from the European Innovation Scoreboard promoted by the European Commission. Results show that the level of "*Venture Capital Expenditures*" is positively associated to:

- "*Foreign Doctorate Students*": is defined as the percentage of foreign doctorate students as a percentage of all doctorate students. Is a measure of student international mobility. The variable has also a role in capturing the diffusion and dissemination of knowledge. Countries that are interested in improving the quality and quantity of human resources in Research and Development can augment the level of "*Foreign Doctorate Students*". There is a positive relationship between "*Foreign Doctorate Students*" and the level of "*Venture Capital Expenditures*". The positive relationship can be understood considering that generally the countries with more developed venture capital markets also have deeper international relationships and these relationships can also improve the presence of foreign students. In this case both the variables can be associated to a positive presence of the country in the international scenario.
- "*Innovation Index*": is a variable that describe the global ability of a country to innovate. There is a positive relationship between "*Innovation Index*" and "*Venture Capital Expenditures*". This positive relationship let us infer that the level of "*Venture Capital Expenditures*" captures an essential financial element of innovational capability of a country i.e., the ability to generate financial institutions, financial organizations and financial markets that can sustain risks either in innovation technology, start ups and newcos. A country that is interested in performing better in terms of innovation should promote reforms able to strengthen the role of venture capital markets and organizations.

Variables in the Model with Label, Definitions and Main Relations			
Label	**Variables**	**Definitions**	**Relations**
A59	y	*Venture Capital Expenditures*	
A19	x_1	*Foreign Doctorate Students*	Positive
A22	x_2	*Government Procurement of Advanced Technology Products*	Negative
A24	x_3	*Innovation Index*	Positive
A28	x_4	*Innovators*	Negative
A35	x_5	*Medium and High-Tech Product Exports*	Negative
A45	x_6	*Public-Private Co-Publications*	Negative

We also found that the level of "*Venture Capital Expenditures*" is negatively associated to:

- *"Government Procurement of Advanced Technology Products":* is a measure of the ability of a government to foster the supply of innovation technology through procurement and public demand. The variable is measured in a range between 1 and 7 in which in the case of 1 the choice of public procurement is based on price-based considerations while in the case of 7 the

State choice based on the qualitative characteristics of the innovation technology produced. There is a negative relationship between "*Venture Capital Expenditures*" and "*Government Procurement of Advanced Technology Products*". This negative relationship shows the presence of a negative trade-off between the State-centered financing of innovation technology and the "*Venture Capital Expenditures*" methodologies that are more oriented to financial markets and the private sectors.

- *"Innovators":* is a complex variable that measure the ability of SMEs to innovate. Specifically, the variable "*Innovators*" is based on three different sub-variables that are "*SMEs with Product or Process Innovations", "SMEs with Marketing or Organisational Innovations*", "*SMEs Innovating In-House*". There is a negative relationship between "*Innovators*" and "*Venture Capital Expenditures*". The negative relationship can be explained because in many European Countries the role of Venture Capital Market is under-developed i.e., in Southern and Eastern Europe.
- *"Medium and High-Tech Product Exports":* is a measure of the ability of a country to export products and services that are generated because of Research and Development expenditure and investments in innovation technology. Countries that are successful in implementing political economies oriented to innovation tend to have higher levels of "*Medium and High-Tech Product Exports*". There is a positive relationship between the increasing degree of "*Medium and High-Tech Product Exports*" and the economic growth in connection to productivity and high levels of human resources. There is a negative relationship between "*Medium and High-Tech Product Exports*" and "*Venture Capital Expenditures*". The negative relationship ca be better understood considering that many European countries that have well developed market for innovation technology and products based on Research and Development, also are characterized by financial systems that are more oriented to banks rather than venture capital markets. The preference for banking systems in respect to financial systems have a role in reducing the ability to develop an efficient institutional environment for venture capital in association with high levels of innovation technology.
- *"Public-Private Co-Publications":* is a measure of the ability of collaboration between the private and the public sector captured as academic publications. Generally, the presence of a positive and collaborative linkages between the public and the private sector in Research and Development can be considered positively as a signal of the efficiency of the innovation system. Our results show the presence of a negative relationship between the presence of "*Public-Private Co-Publications*" and the level of "*Venture Capital Expenditures*". Also this relationship can seem counterfactual for the fact that an efficient innovation system based on a collaboration between the public and the private sector should also be associated to a greater presence of venture capital organizations. But, as we discussed before, many European countries that have higher scores in terms of innovation systems do lack to develop financial institutions able to promote venture capitalism.

Synthesis of the Main Results of the Econometric Model to Estimate the Value of Venture Capital Expenditures. Source: EIS.																
	Random Effects			**Fixed Effects**			**WLS**			**Pooled OLS**			**Dynamic Panel**			
	Coefficient	**P-Value**		**Coefficient**	**P-Value**		**Coefficient**	**P-Value**		**Coefficient**	**P-Value**		**Coefficient**	**P-Value**		**Mean**
const	-1,62699	0,8011		-1,71181	0,679		-2,83458	0,3913		-1,21441	0,7984		8,86477	0,0926	*	
A19	0,440021	<0,0001	***	0,434459	<0,0001	***	0,442011	<0,0001	***	0,448861	<0,0001	***	0,360208	0,0009	***	0,42511
A22	-1,92811	<0,0001	***	-1,91873	<0,0001	***	-1,50959	<0,0001	***	-1,92372	<0,0001	***	-2,1116	<0,0001	***	-1,8784
A24	1,61066	<0,0001	***	1,64568	<0,0001	***	1,2422	<0,0001	***	1,54652	<0,0001	***	1,42184	<0,0001	***	1,49338
A28	-0,471011	<0,0001	***	-0,487285	<0,0001	***	-0,328202	<0,0001	***	-0,441353	<0,0001	***	-0,325622	0,0002	***	-0,4107
A35	-0,287397	0,0029	***	-0,299902	0,0091	***	-0,150725	0,0013	***	-0,268766	0,0002	***	-0,517182	0,0432	**	-0,3048
A45	-0,400998	<0,0001	***	-0,404364	<0,0001	***	-0,346997	<0,0001	***	-0,394264	<0,0001	***	-0,295887	0,0173	**	-0,3685
A59(-1)													-0,248649	0,0028	***	

Figure 1. Synthesis of the Main Results of the Econometric Model to Estimate the Value of Venture Capital Expenditures. Source: EIS.

We can also consider the mean value of the single variables to create an order of variables in the sense of impact. Our results show that "*Innovation Index*" has the main positive impact on "*Venture Capital Expenditures"* with a mean value of 1,49. "*Government Procurement of Advanced Technology Products"* has the most relevant negative impact of "*Venture Capital Expenditure*" with a mean value equal to -1,87.

Ranking of the Mean Value of the Results of Five Models Used to Estimate the Value of Venture Capital Expenditures.				
Rank	**Variable**		**Mean**	**Impact**
1	***A24***	*Innovation Index*	1,4934	**Positive Effects**
2	***A19***	*Foreign Doctorate Students*	0,4251	
3	***A35***	*Medium and High-Tech Product Exports*	-0,3048	**Negative Effects**
4	***A45***	*Public-Private Co-Publications*	-0,3685	
5	***A28***	*Innovators*	-0,4107	
6	***A22***	*Government Procurement of Advanced Technology Products*	-1,8784	

Figure 2. Ranking of the Mean Value of the Results of Five Models Used to Estimate the Value of Venture Capital Expenditures.

Finally, we can observe that the value of "*Venture Capital Expenditure*" is not clearly and positively associated to many determinants of innovation. The negative relationships among "*Venture Capital Expenditure*" and other variables, should not be considered as a manifestation of a theoretical model, but as a particular case for European countries. Since European countries are, in large part, based on banking systems, they also suffer more for the lack of external finance and venture capitalism. If policy makers, are interested in promoting "*Venture Capital Expenditures*", then they also should consider to reform financial institutions and organizations and opening markets to venture capital organizations and enterprises.

3. **Clusterization**

In adjunct we perform a cluster analysis with the algorithm k-Means optimized with the Silhouette coefficient. We find four different clusters i.e.:

- *Cluster 1*: Ukraine, Slovakia, Czechia, Greece, Slovenia, Serbia, Poland, Bulgaria, Croatia, Romania, Austria;
- *Cluster 2*: Spain, Sweden, Finland, Norway, Belgium, Estonia, Portugal, Ireland, Denmark, Germany, Hungary, Netherlands, Lithuania, Cyprus, Switzerland, Italy;
- *Cluster 3*: Malta, Latvia;
- *Cluster 4*: France, Luxembourg, United Kingdom.

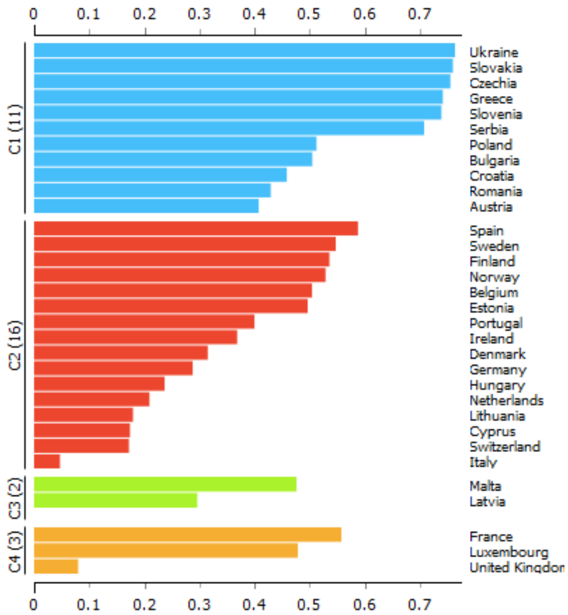


Figure 3. Synthesis of the main results of the cluster analysis with the algorithm k-Means optimized with the Silhouette Coefficient

We find that the four clusters perform in very different ways. Specifically, the fourth cluster-C4, has a mean value of "*Venture Capital Expenditure*" equal to 300,3 and it is at the highest rank among clusters. Cluster 2-C2 follows with a mean value of "*Venture Capital Expenditures*" equal to 193,7. Cluster 1 is at the third place with a level of the mean value of "*Venture Capital Expenditures*" equal to 50,89. Finally, Cluster 3-C3 has the lowest level of mean value of "*Venture Capital Expenditures*" with a mean value of 15,3. The order of cluster for mean value of "*Venture Capital Expenditures*" is C4>C2>C1>C3.

Ranking of Clusters for Mean Value

Rank	Cluster	MIN	MAX	MEAN
1	C4	292,8	304,1	300,3
2	C2	85,66	304,1	193,7
3	C1	7,48	122	50,89
4	C3	7,87	22,72	15,3

Figure 4. Ranking of clusters for Mean Value.

Finally, we can observe that there is a great gap among the four different clusters. Specifically, the second cluster-C2 has a mean value of "*Venture Capital Expenditures*" equal to 64,51% of the correspondent value C4, while the same value of C1 is equal to 16,9% of the value of C4. In the end countries in the third cluster-C3 have a mean value of "*Venture Capital Expenditures*" equal to 5,09% of the value of the correspondent value of the leading Cluster 4-C4.

4. Predictions

We use eight different machine learning algorithms to predict the level of "*Venture Capital Expenditures*". We divide the dataset in two parts using the node in KNIME named "*Partitioning*": 70% of train and 30% of test. We compare the efficiency of the machine learning algorithms using three different measures of errors i.e.: Mean Squared Error-MSE, Mean Absolute Error-MAE and Root Mean Squared Error-RMSE.

Rank	Algorithms	Mean Squared Error	Rank	Algorithms	Mean Absolute Error	Rank	Algorithms	Root Mean Squared Error
1	*Linear Regression*	0,025606	1	*Linear Regression*	0,110690	1	*Linear Regression*	0,160018
2	*ANN*	0,032685	2	*ANN*	0,120775	2	*ANN*	0,180791
3	*Tree Ensemble Regression*	0,047914	3	*Random Forest Regression*	0,130767	3	*Tree Ensemble Regression*	0,218892
4	*Random Forest Regression*	0,049777	4	*PNN*	0,167717	4	*Random Forest Regression*	0,223107
5	*PNN*	0,053763	5	*Tree Ensemble Regression*	0,198501	5	*PNN*	0,231869
6	*Polynomial Regression*	0,072156	6	*Polynomial Regression*	0,205896	6	*Polynomial Regression*	0,268619
7	*Simple Regression Tree*	0,116145	7	*Simple Regression Tree*	0,221881	7	*Simple Regression Tree*	0,340800
8	*Gradient Boosted Trees Regression*	0,138305	8	*Gradient Boosted Trees Regression*	0,260648	8	*Gradient Boosted Trees Regression*	0,371894

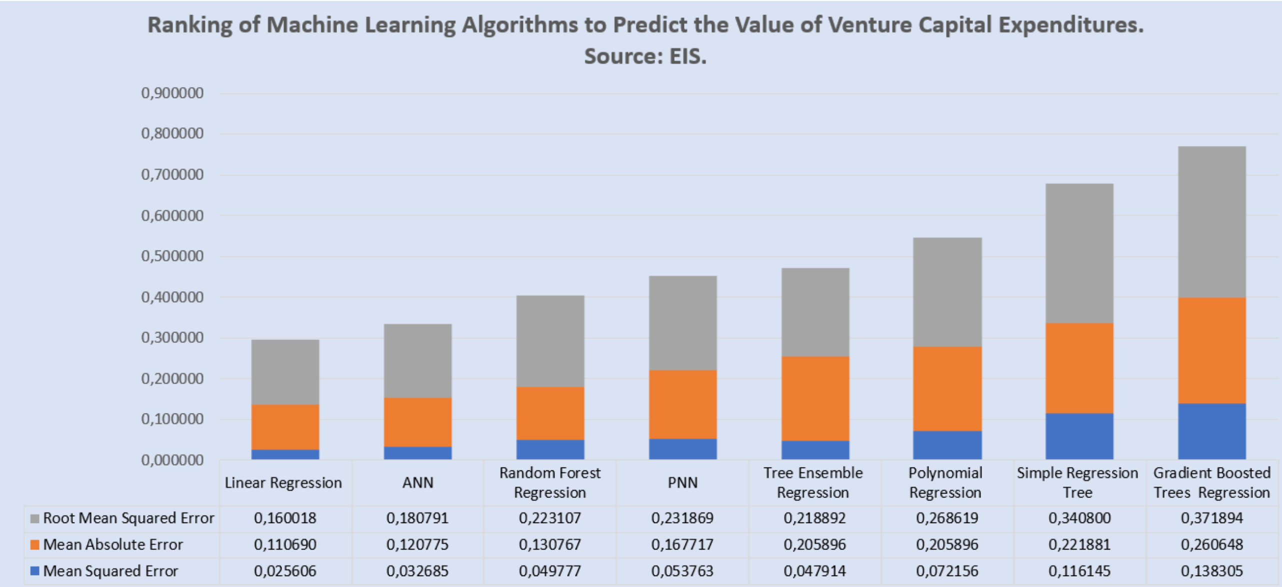
We choose the best algorithm considering the minimization of errors. We use the following algorithms i.e.:

- *Linear Regression;*
- *ANN-Artificial Neural Networks;*
- *Tree Ensemble Regression;*
- *Random Forest Regression;*
- *Probabilistic Neural Networks-PNN;*
- *Polynomial Regression;*
- *Simple Regression Tree;*
- *Gradient Boosted Tree Regression.*

We find that the best algorithm to predict the level of "*Venture Capital Expenditures*" is "*Linear Regression*", followed in order by "*Artificial Neural Network-ANN*", "*Tree Ensemble Regression*", "*Random Forest Regression*", "*Probabilistic Neural Network-PNN*", "*Polynomial Regression*", "*Simple Regression Tree*", "*Gradient Boosted Trees Regression*".

Ranking of Algorithm Based on the Minimization of MSE, MAE and RMSE					
Rank	**Algorithm**	**Mean Squared Error**	**Mean Absolute Error**	**Root Mean Squared Error**	**Total**
1	*Linear Regression*	1	1	1	3
2	*ANN*	2	2	2	6
3	*Tree Ensemble Regression*	3	5	3	11
3	*Random Forest Regression*	4	3	4	11
4	*PNN*	5	4	5	14
5	*Polynomial Regression*	6	6	6	18
6	*Simple Regression Tree*	7	7	7	21
7	*Gradient Boosted Trees Regression*	8	8	8	24

Figure 5. Ranking of machine learning algorithms based on the minimization of MSE, MAE and RMSE.



	Linear Regression	ANN	Random Forest Regression	PNN	Tree Ensemble Regression	Polynomial Regression	Simple Regression Tree	Gradient Boosted Trees Regression
Root Mean Squared Error	0,160018	0,180791	0,223107	0,231869	0,218892	0,268619	0,340800	0,371894
Mean Absolute Error	0,110690	0,120775	0,130767	0,167717	0,205896	0,205896	0,221881	0,260648
Mean Squared Error	0,025606	0,032685	0,049777	0,053763	0,047914	0,072156	0,116145	0,138305

Figure 6. Ranking of machine learning algorithms to predict the value of "Venture Capital Expenditures".

5. Conclusions

We investigate the relationship between "*Venture Capital Expenditures*" and innovation in Europe. We collect data from the European Innovation Scoreboard for 36 countries in the period 2010-2019. In the first paragraph we have analyzed different articles from the scientific literature that positively associate "Venture Capital Expenditures" to innovation. But, in the following part, when we have realized the econometric analysis, we found some counterfactual results. In our econometric analysis we have applied different models: Panel Data with Fixed Effects, Panel Data with Random Effects, Pooled OLS, WLS, Dynamic Panel. Results show that the level of Venture Capitalist Expenditure is positively associated to "*Foreign Doctorate Students*" and "*Innovation Index*" and negatively related to "*Government Procurement of Advanced Technology Products*", "*Innovators*", "*Medium and High-Tech Products Exports*", "*Public-Private Co-Publications*". Contrary to our expectations we found that the presence of "*Venture Capital Expenditures*" is not able to promote that deep impact on innovation that we have encountered in the literature. The gap between the theoretical framework and our results can be understood considering that in many European countries the markets for venture capital lack the necessary institutions and infrastructure. In adjunct, we must note that many European countries are banking-oriented instead of market oriented and tend to reduce the impact of external finance especially in the case of Central and Southern European countries. These facts can explain why we do not find a so deep connection between "*Venture Capital Expenditures*" and innovation in European countries. In the third paragraph we have realized a clusterization with k-Means algorithm optimized with Silhouette coefficient and we show the presence of four different clusters in Europe based on the level of "*Venture Capital Expenditures*". Finally, we propose a confrontation among 8 different algorithms of machine learning to predict the level of "*Venture Capital Expenditures*" and we find that the linear regression generates the best results in terms of minimization of MAE, MSE, RMSE.

Bibliography

[1] R. M. Solow, «A Contribution to the Theory of Economic Growth,» *The Quarterly Journal of Economics,* vol. 70, n. 1, pp. 65-94, 1956.

[2] P. M. Romer, «The Origins of Endogenous Growth,» *Journal of Economic Perspectives,* vol. 8, n. 1, pp. 3-22, 1994.

[3] J. Schumpeter, The Theory of Economic Development: an Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle, New Brunswick: Transaction Books, 1934.

[4] A. Leogrande e A. Costantiello, «Human Resources in Europe. Estimation, Clusterization, Machine Learning and Prediction,» *American Journal of Humanities and Social Sciences Research (AJHSSR),* vol. 5, n. 9, pp. 240-259 , 2021.

[5] A. Leogrande, A. Massaro e A. M. Galiano, «The Determinants of Human Resources in European Countries During the Period 2010-2019,» *American Journal of Humanities and Social Sciences Research (AJHSSR),* vol. 4, n. 9, pp. 145-171, 2020.

[6] A. Costantiello, L. Laureti e G. L. A. De Cristoforo, «The Innovation-Sales Growth Nexus in Europe,» *University Library of Munich,* 2021.

[7] A. Costantiello, L. Laureti e A. Leogrande, «The Determinants of Firm Investments in Research and Development,» *International Virtual Academic Conference Education and Social Sciences Business and Economics,* 2021.

[8] A. Costantiello, L. Laureti e A. Leogrande, «The SMEs Innovation in Europe,» *FEMIB ,* pp. 23-32, 2021.

[9] L. Laureti, A. Costantiello e A. Leogrande, «Finance-Innovation Nexus in Europe,» *JISET -International Journal of Innovative Science,Engineering & Technology,* vol. 7, n. 12, 2020 .

[10] A. Leogrande, A. Costantiello e A. Laureti, «The Innovation-Friendly Environment in Europe,» *ICSET-International Conference on Science, Engineering & Technology (ICSET-2021),* 2021.

[11] A. Costantiello e A. Leogrande, «The innovation-employment nexus in Europe,» *American Journal of Humanities and Social Sciences Research (AJHSSR),* vol. 4, n. 11, pp. 166-187, 2020.

[12] A. Leogrande, A. Massaro e A. M. Galiano, «The Attractiveness of European Research Systems,» *American Journal of Humanities and Social Sciences Research (AJHSSR) ,* vol. 4, n. 10, pp. 72-101, 2020.

[13] A. Leogrande, A. Massaro e A. M. Galiano, «The Determinants of Innovation in European Countries in the period 2010-2019,» *American Journal of Humanities and Social Sciences Research (AJHSSR),* vol. 4, n. 8, pp. 91-126, 2020.

[14] A. Leogrande e A. G. A. M. Massaro, «The Impact of R&D Investments on Corporate Performance in European Countries,» *American Journal of Humanities and Social Sciences Research (AJHSSR),* vol. 4, n. 7, pp. 186-201, 2020.

[15] B. E. Gaddy, V. Sivaram, T. B. Jones e L. Wayman, «Venture capital and cleantech: The wrong model for energy innovation,» *Energy Policy,* vol. 102, pp. 385-395, 2017.

[16] F. A. Frimpong, E. K. Akwaa-Sekyi e R. Saladrigues, «Venture capital healthcare investments and health care sector growth: A panel data analysis of Europe,» *Borsa Istanbul Review,* 2021.

[17] H. Herrera-Echeverry, «Public Expenditure in Research and Development and Venture Capital Commitments,» *Engineering Economics,* vol. 28, n. 3, pp. 240-252, 2017.

[18] Y. Lu, Z. Tian, G. A. Buitrago, S. Gao, Y. Zhao e S. Zhang, «Intellectual capital and firm performance in the context of venture-capital syndication background in China,» *Complexity,* 2021.

[19] H. Qiao, S. Zhang e Y. Xiao, «Modeling the Impacts of Venture Capital Investment on Firm Innovation,» *Discrete Dynamics in Nature and Society,* 2021.

[20] J. H. Park e Z. T. Bae, «When are 'sharks' beneficial? Corporate venture capital investment and startup innovation performance,» *Technology Analysis & Strategic Management,* vol. 30, n. 3, pp. 324-336, 2018.

[21] R. Florida e K. M. King, «Urban start-up districts: Mapping venture capital and start-up activity across ZIP codes,» *Economic Development Quarterly,* vol. 32, n. 2, pp. 99-118, 2018.

[22] M. Schnitzer e M. Watzinger, «Measuring the spillovers of venture capital,» *The Review of Economics and Statistics,* pp. 1-48, 2017.

[23] R. Yi, H. Wang, B. Lyu e Q. Xia, «Does venture capital help to promote open innovation practice? Evidence from China,» *European Journal of Innovation Management,* 2021.

[24] C. Norrby e S. Åslund, he Role of Venture Capital in Innovation Systems-A Case Study Comparing the Possible Risks and Rewards for Volvo Group Venture Capital Between Initiating Investments in China, India, Japan, Singapore, South Korea, and Taiwan, vol. Sweden, Gothenburg: Master's Thesis in Management and Economics of Innovation Chalmers Univerisity of Technology, 2021, p. Gothenburg.

[25] T. L. Galloway, D. R. Miller, A. Sahaym e J. D. Arthurs, «Exploring the innovation strategies of young firms: Corporate venture capital and venture capital impact on alliance innovation strategy,» *Journal of Business Research ,* vol. 71, pp. 55-65, 2017.

[26] X. Jin, P. Zheng, Z. Zhong e Y. Cao, «The Effect of Venture Capital on Enterprise Benefit According to the Heterogeneity of Human Capital of Entrepreneur,» *Frontiers in Psychology,* vol. 11, p. 1558, 2020.

[27] E. Dahlberg e S. Sörling, The Money of Innovation: The Impact of Venture Capital on Innovation in Sweden, Uppsala : Uppsala University, 2019.

[28] J. González-Uribe, «Exchanges of innovation resources inside venture capital portfolios,» *Journal of Financial Economics,* vol. 135, n. 1, pp. 144-168, 2020.

[29] L. Grilli, B. Mrkajic e G. Latifi, «Venture capital in Europe: social capital, formal institutions and mediation effects,» *Small Business Economics,* vol. 5, n. 12, pp. 393-410, 2018.

[30] S. Hogarth, «Valley of the unicorns: consumer genomics, venture capital and digital disruption,» *New Genetics and Society,* vol. 36, n. 3, pp. 250-272, 2017.

[31] M. Da Rin e M. F. Penas, « Venture capital and innovation strategies,» *Industrial and Corporate Change,* vol. 26, n. 5, pp. 781-800, 2017.

[32] A. Safari, «Venture capital and intellectual property rights effects on innovation in different socio-economic environments: a systematic review and exploration of various contradictive studies,» *International Journal of Economics and Business Research,* vol. 15, n. 3, pp. 373-397, 2018.

[33] M. Rossi e E. Martini, «Venture capitalists and value creation: The role of informal investors in the growth of smaller European firms,» *International Journal of Globalisation and Small Business,* vol. 10, n. 3, pp. 233-247, 2019 .

[34] W. Sun, Y. Zhao e L. Sun, «Big data analytics for venture capital application: towards innovation performance improvement,» *International Journal of Information Management,* vol. 50, pp. 557-565, 2020.

[35] J. Wen, D. Yang, G. F. Feng, M. Dong e C. P. Chang, «Venture capital and innovation in China: The non-linear evidence,» *Structural Change and Economic Dynamics,* vol. 46, pp. 148-162, 2018.

[36] R. P. Pradhan, M. B. Arvin, M. Nair, S. E. Bennett e S. Bahmani, «Short-term and long-term dynamics of venture capital and economic growth in a digital economy: A study of European countries,» *Technology in Society,* vol. 57, pp. 125-134, 2019.

[37] H. Hollanders, N. Es-Sadki, D. Vértesy e G. Damioli, «European Innovation Scoreboard 2017– Methodology Report,» European Commission, Bruxelles , 2017.

6. Appendix

6.1 Regression Analysis

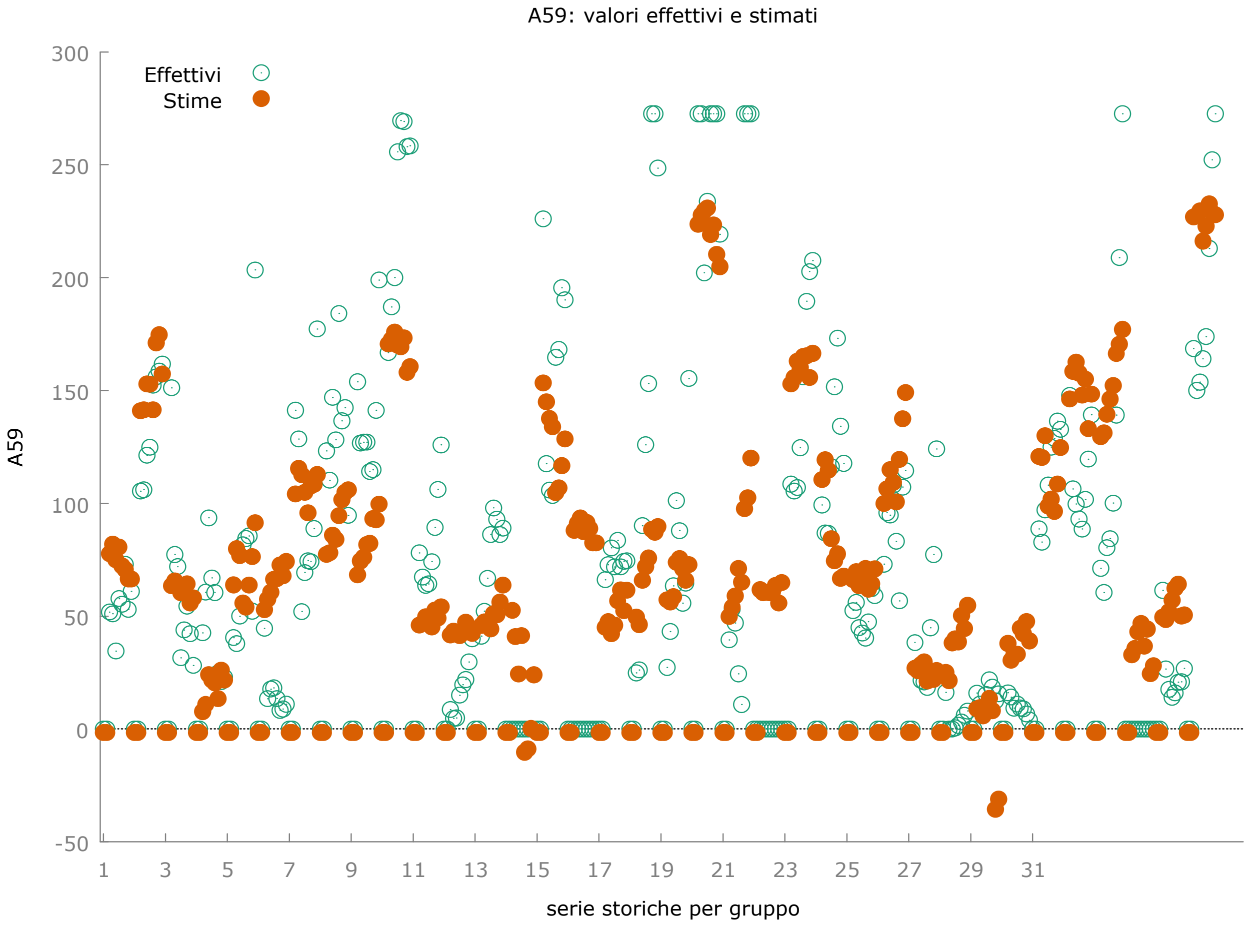
Effetti casuali (GLS), usando 360 osservazioni
Incluse 36 unità cross section
Lunghezza serie storiche = 10
Variabile dipendente: A59

	Coefficiente	*Errore Std.*	*z*	*p-value*	
const	−1,62699	6,45866	−0,2519	0,8011	
A19	0,440021	0,0499974	8,801	<0,0001	***
A22	−1,92811	0,297818	−6,474	<0,0001	***
A24	1,61066	0,187872	8,573	<0,0001	***
A28	−0,471011	0,102440	−4,598	<0,0001	***
A35	−0,287397	0,0965637	−2,976	0,0029	***
A45	−0,400998	0,0590096	−6,795	<0,0001	***

Media var. dipendente	68,38460	SQM var. dipendente	75,57819
Somma quadr. residui	731499,4	E.S. della regressione	45,45748
Log-verosimiglianza	−1881,832	Criterio di Akaike	3777,665

Criterio di Schwarz	3804,868	Hannan-Quinn	3788,481
rho	0,636696	Durbin-Watson	0,698379

Varianza 'between' = 925,392
Varianza 'within' = 1324
Theta usato per la trasformazione = 0,646211
Test congiunto sui regressori -
Statistica test asintotica: Chi-quadro(6) = 558,115
con p-value = 2,51333e-117
Test Breusch-Pagan -
Ipotesi nulla: varianza dell'errore specifico all'unità = 0
Statistica test asintotica: Chi-quadro(1) = 206,224
con p-value = 9,15688e-047
Test di Hausman -
Ipotesi nulla: le stime GLS sono consistenti
Statistica test asintotica: Chi-quadro(6) = 0,499397
con p-value = 0,997846



Effetti fissi, usando 360 osservazioni
Incluse 36 unità cross section
Lunghezza serie storiche = 10
Variabile dipendente: A59

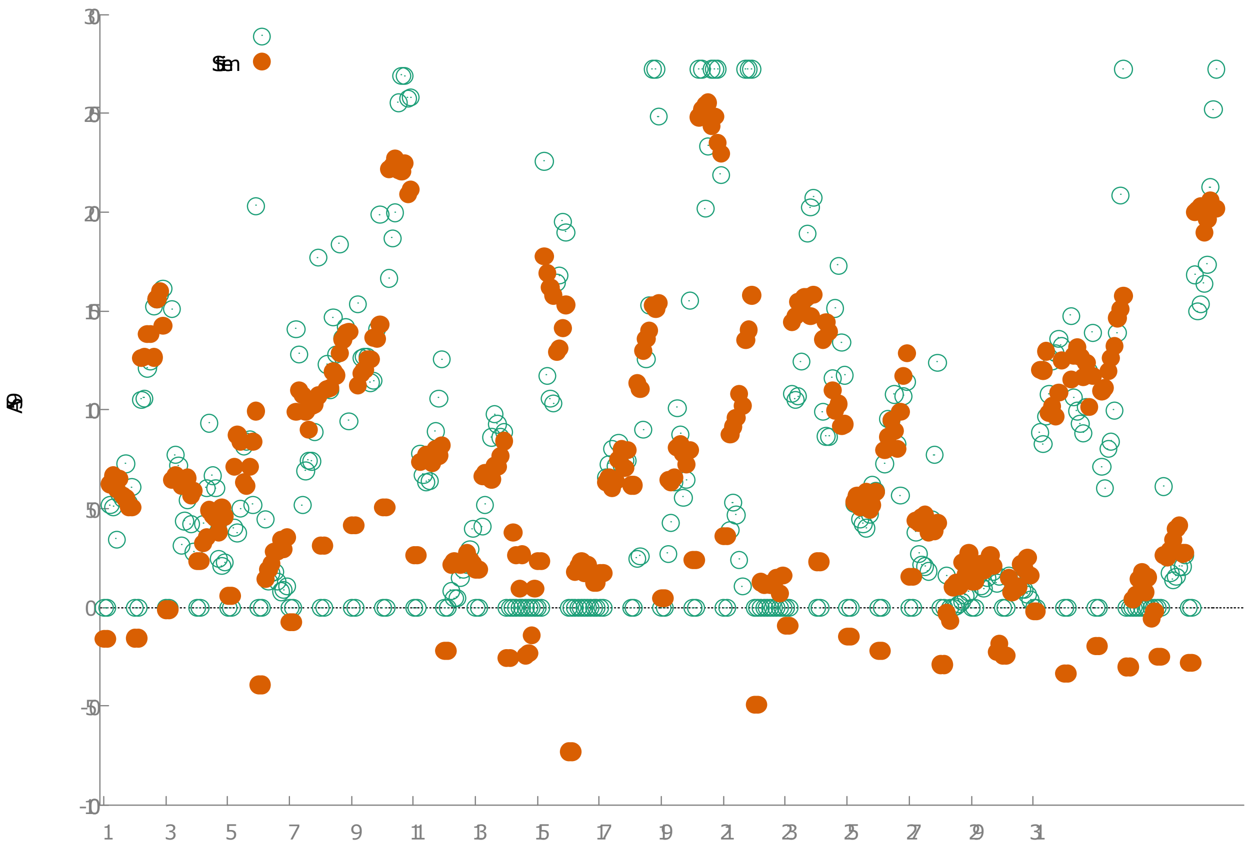
	Coefficiente	*Errore Std.*	*rapporto t*	*p-value*	
const	−1,71181	4,13336	−0,4141	0,6790	
A19	0,434459	0,0589763	7,367	<0,0001	***
A22	−1,91873	0,345522	−5,553	<0,0001	***
A24	1,64568	0,216642	7,596	<0,0001	***
A28	−0,487285	0,117971	−4,131	<0,0001	***
A35	−0,299902	0,114325	−2,623	0,0091	***
A45	−0,404364	0,0701948	−5,761	<0,0001	***

Media var. dipendente	68,38460	SQM var. dipendente	75,57819
Somma quadr. residui	421032,5	E.S. della regressione	36,38683
R-quadro LSDV	0,794681	R-quadro intra-gruppi	0,604278

LSDV F(41, 318)	30,01982	P-value(F)	2,90e-86
Log-verosimiglianza	−1782,403	Criterio di Akaike	3648,806
Criterio di Schwarz	3812,022	Hannan-Quinn	3713,704
rho	0,636696	Durbin-Watson	0,698379

Test congiunto sui regressori -
Statistica test: F(6, 318) = 80,9325
con p-value = P(F(6, 318) > 80,9325) = 4,5806e-061

Test per la differenza delle intercette di gruppo -
Ipotesi nulla: i gruppi hanno un'intercetta comune
Statistica test: F(35, 318) = 6,6554
con p-value = P(F(35, 318) > 6,6554) = 5,22738e-022

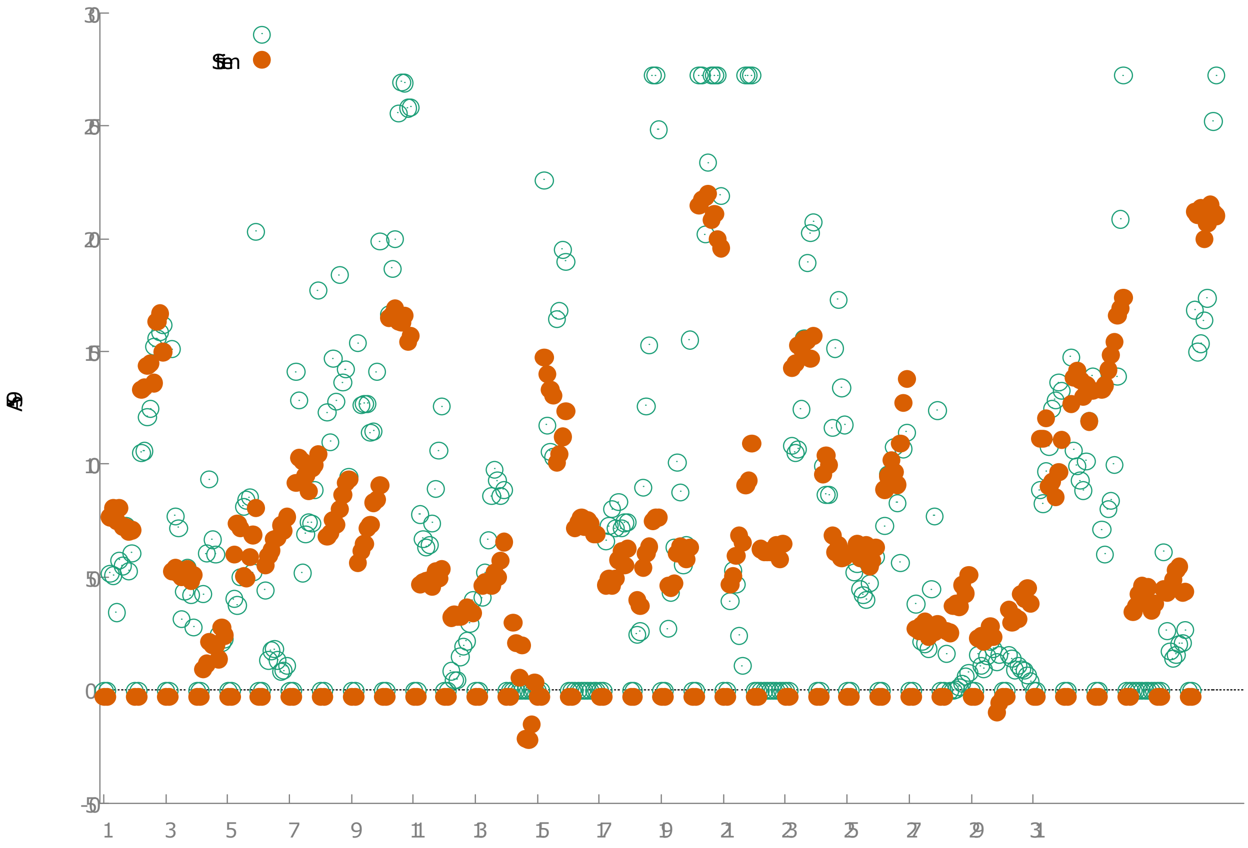


Modello 59: WLS, usando 360 osservazioni
Incluse 36 unità cross section

Variabile dipendente: A59					
Pesi basati sulle varianze degli errori per unità					
	Coefficiente	*Errore Std.*	*rapporto t*	*p-value*	
const	−2,83458	3,30222	−0,8584	0,3913	
A19	0,442011	0,0312081	14,16	<0,0001	***
A22	−1,50959	0,160217	−9,422	<0,0001	***
A24	1,24220	0,106511	11,66	<0,0001	***
A28	−0,328202	0,0490830	−6,687	<0,0001	***
A35	−0,150725	0,0465266	−3,240	0,0013	***
A45	−0,346997	0,0330522	−10,50	<0,0001	***

Statistiche basate sui dati ponderati:			
Somma quadr. residui	341,0139	E.S. della regressione	0,982876
R-quadro	0,738162	R-quadro corretto	0,733712
F(6, 353)	165,8605	P-value(F)	1,66e-99
Log-verosimiglianza	−501,0653	Criterio di Akaike	1016,131
Criterio di Schwarz	1043,333	Hannan-Quinn	1026,947

Statistiche basate sui dati originali:			
Media var. dipendente	68,38460	SQM var. dipendente	75,57819
Somma quadr. residui	749835,0	E.S. della regressione	46,08881



Modello 58: Pooled OLS, usando 360 osservazioni

Incluse 36 unità cross section

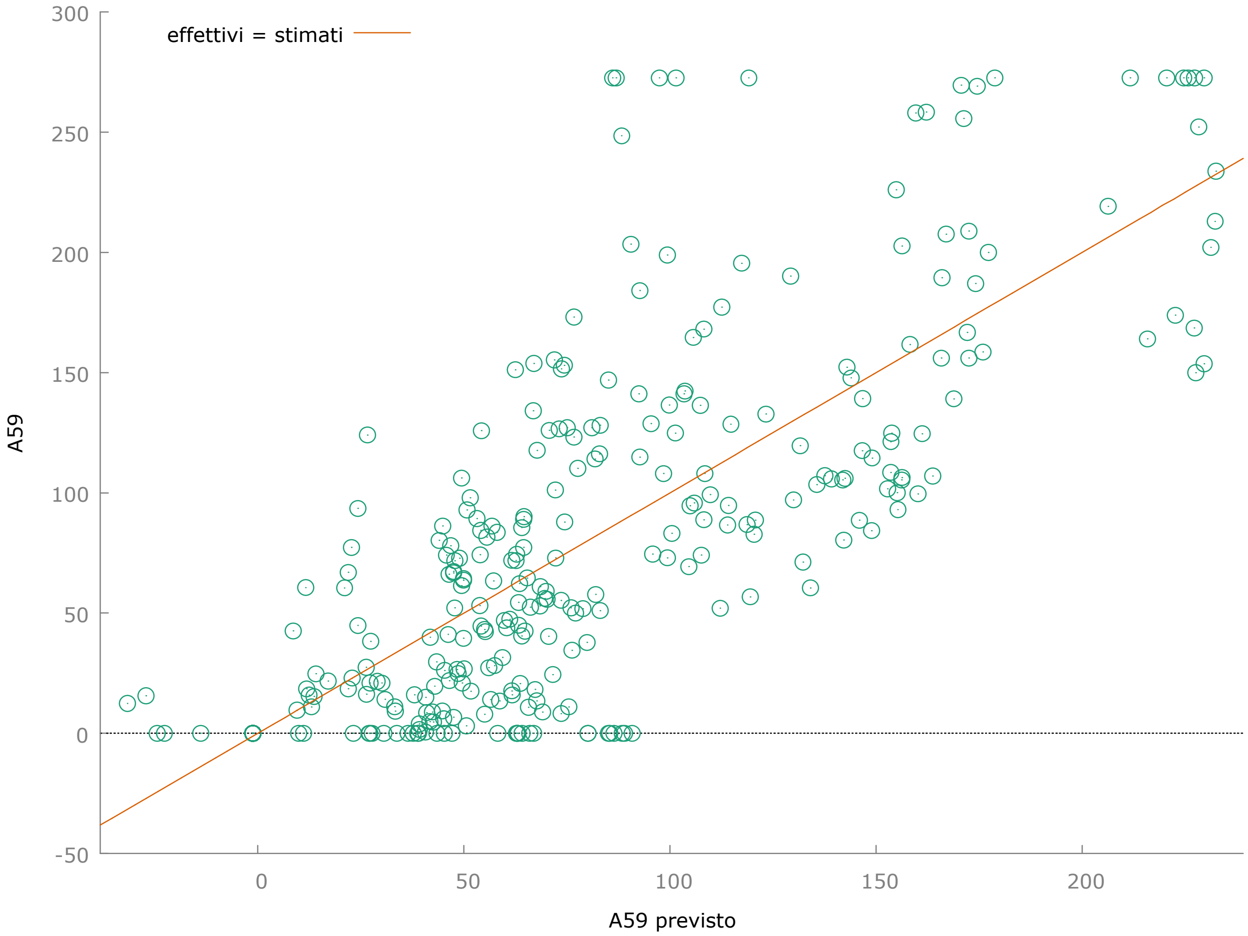
Lunghezza serie storiche = 10

Variabile dipendente: A59

	Coefficiente	*Errore Std.*	*rapporto t*	*p-value*	
const	−1,21441	4,75104	−0,2556	0,7984	
A19	0,448861	0,0374034	12,00	<0,0001	***
A22	−1,92372	0,233785	−8,229	<0,0001	***
A24	1,54652	0,151529	10,21	<0,0001	***
A28	−0,441353	0,0796777	−5,539	<0,0001	***
A35	−0,268766	0,0714984	−3,759	0,0002	***
A45	−0,394264	0,0442359	−8,913	<0,0001	***

Media var. dipendente	68,38460	SQM var. dipendente	75,57819
Somma quadr. residui	729444,0	E.S. della regressione	45,45782
R-quadro	0,644283	R-quadro corretto	0,638237
F(6, 353)	106,5603	P-value(F)	3,90e-76
Log-verosimiglianza	−1881,326	Criterio di Akaike	3776,652

Criterio di Schwarz	3803,855	Hannan-Quinn	3787,468
rho	0,875333	Durbin-Watson	0,402276

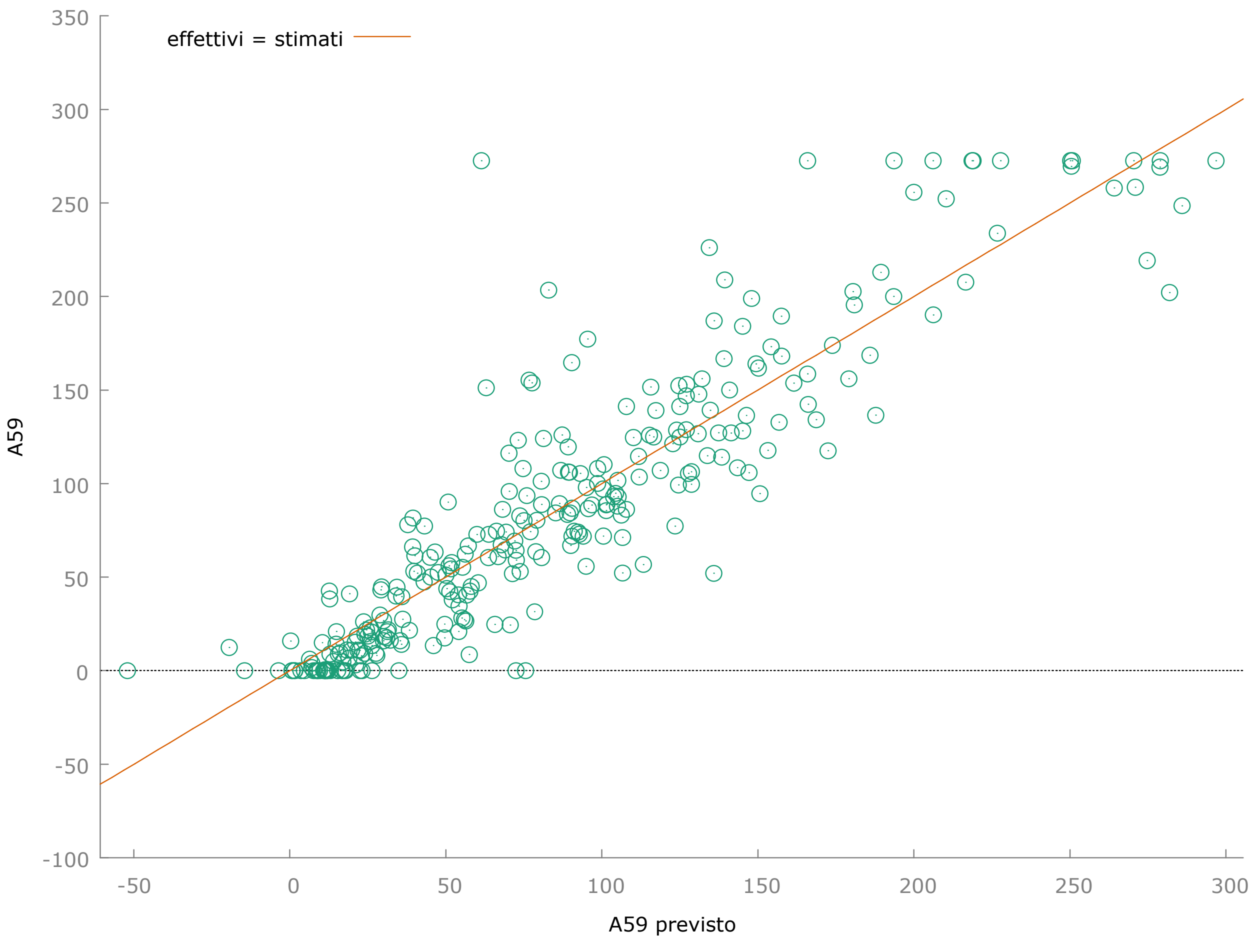


Modello 57: Panel dinamico a un passo, usando 288 osservazioni
Incluse 36 unità cross section
Matrice H conforme ad Ox/DPD
Variabile dipendente: A59

	Coefficiente	*Errore Std.*	*z*	*p-value*	
A59(-1)	−0,248649	0,147827	−1,682	0,0926	*
const	8,86477	2,66323	3,329	0,0009	***
A19	0,360208	0,0923127	3,902	<0,0001	***
A22	−2,11160	0,537316	−3,930	<0,0001	***
A24	1,42184	0,376609	3,775	0,0002	***
A28	−0,325622	0,161091	−2,021	0,0432	**
A35	−0,517182	0,217259	−2,380	0,0173	**
A45	−0,295887	0,0991691	−2,984	0,0028	***

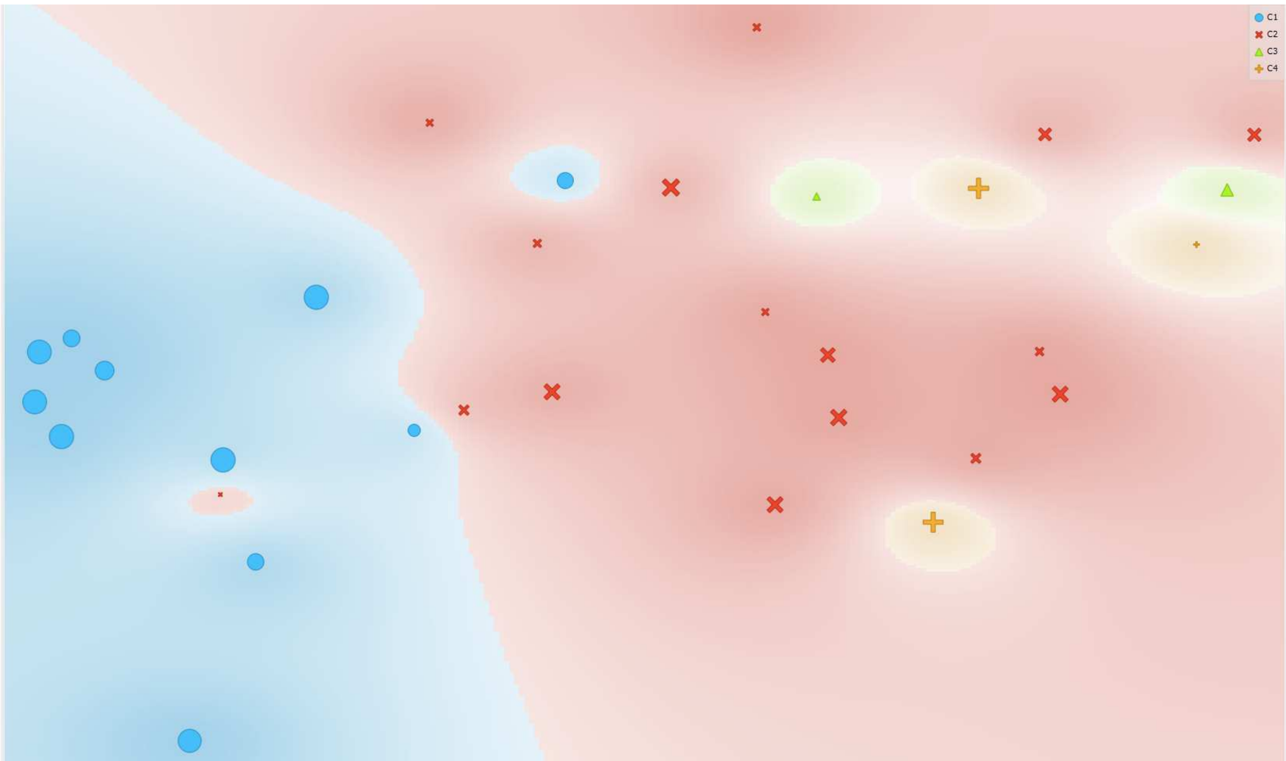
Somma quadr. residui	282954,2	E.S. della regressione	31,78916

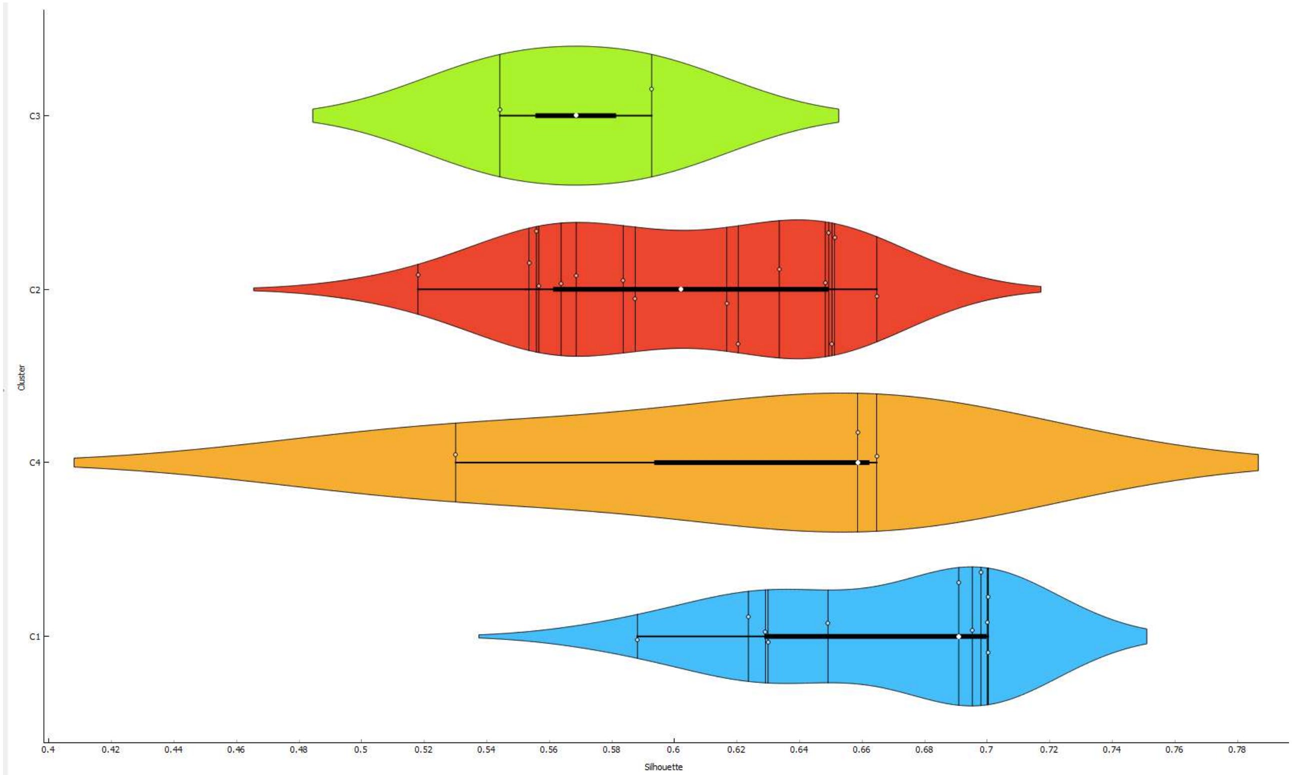
Numero di strumenti = 28
Test per errori AR(1): z = 0,99328 [0,3206]
Test per errori AR(2): z = -1,28794 [0,1978]
Test di sovra-identificazione di Sargan: Chi-quadro(20) = 49,7443 [0,0002]
Test (congiunto) di Wald: Chi-quadro(7) = 153,719 [0,0000]

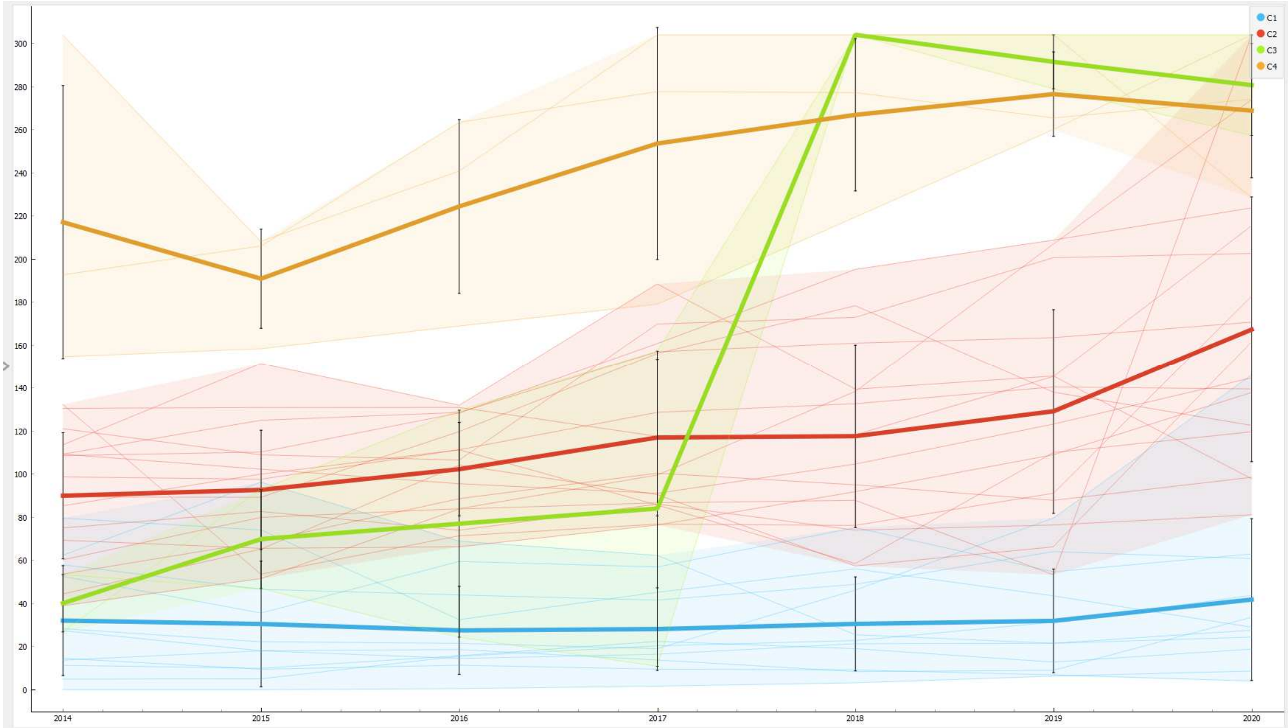


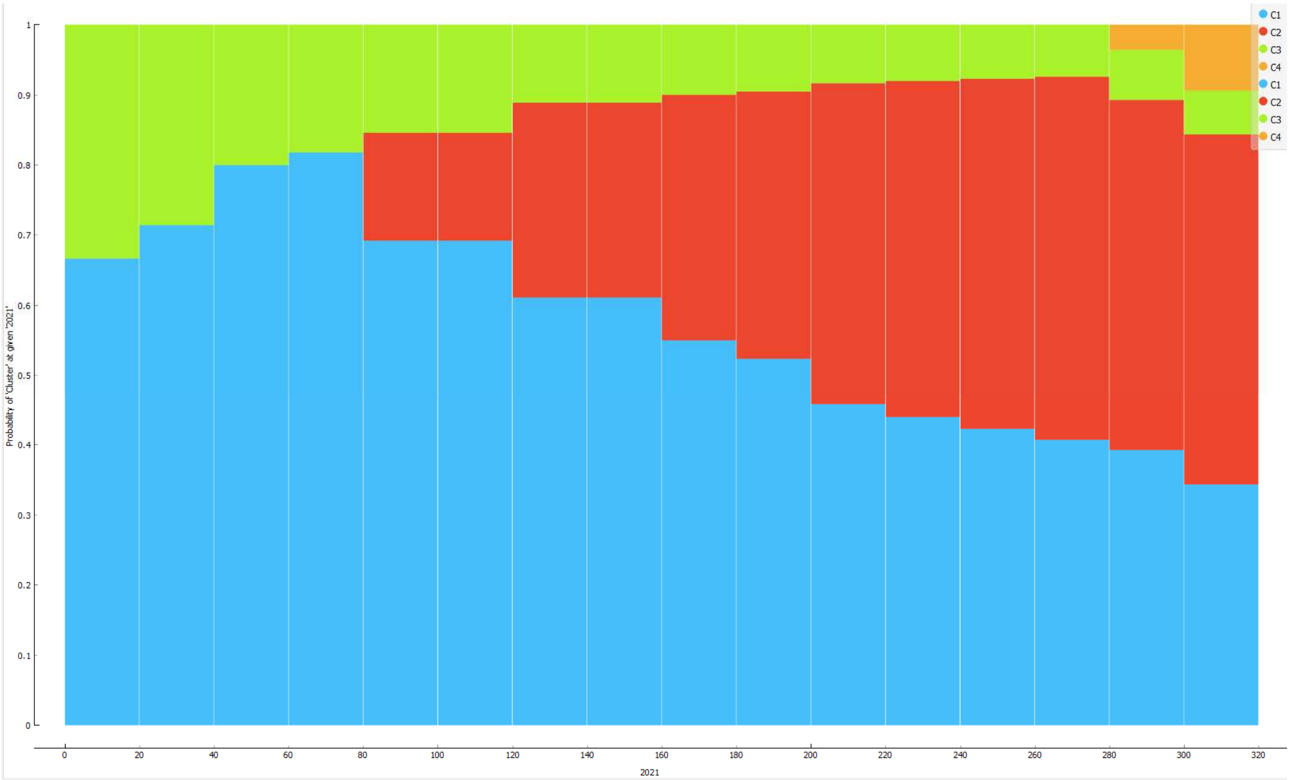
6.2 Clusterization with k-Means

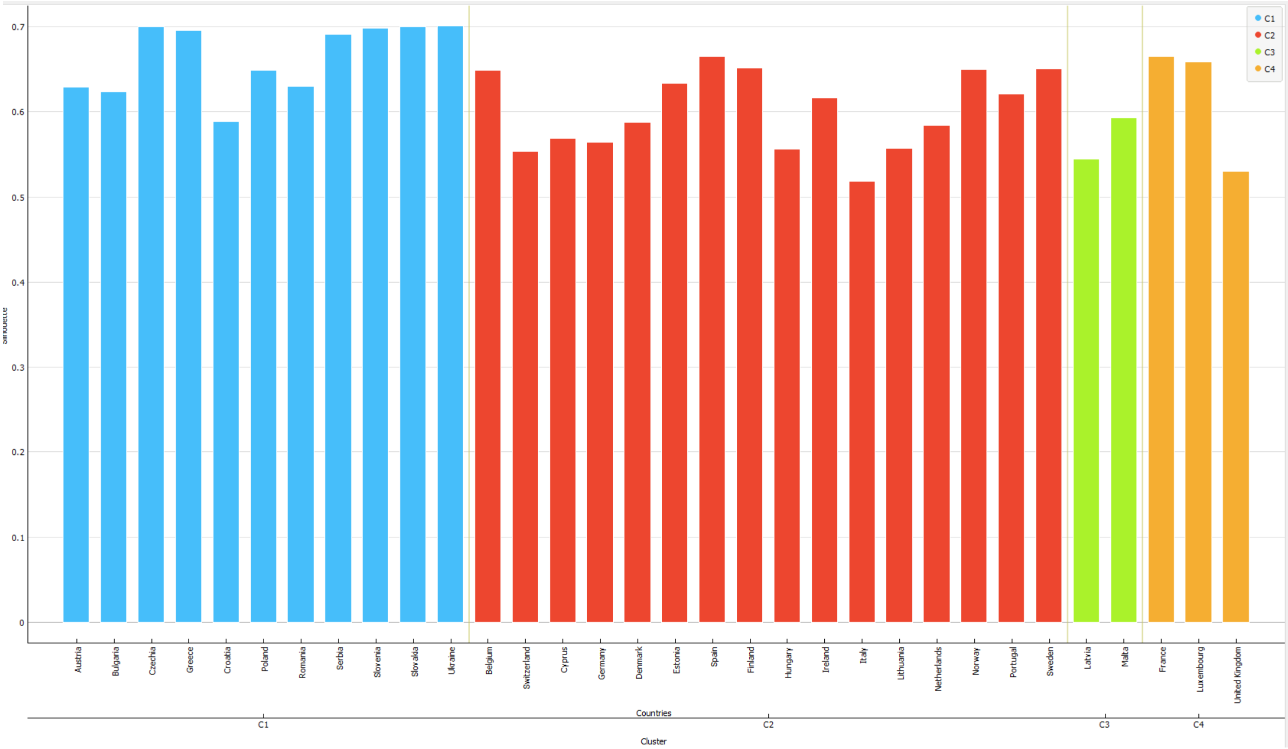
	2021	Countries	Cluster	Silhouette
1	58.6266	Austria	C1	0.629212
3	21.3567	Bulgaria	C1	0.623759
14	121.914	Croatia	C1	0.588289
6	37.5492	Czechia	C1	0.700122
10	48.8906	Greece	C1	0.695353
24	61.9455	Poland	C1	0.649205
26	122.035	Romania	C1	0.630038
27	11.69	Serbia	C1	0.691003
30	25.0394	Slovakia	C1	0.700366
29	7.48219	Slovenia	C1	0.698102
31	41.2647	Ukraine	C1	0.700439
2	194.025	Belgium	C2	0.648336
5	304.065	Cyprus	C2	0.568723
8	212.122	Denmark	C2	0.587588
9	253.895	Estonia	C2	0.633624
12	304.065	Finland	C2	0.651303
7	136.424	Germany	C2	0.563887
15	124.254	Hungary	C2	0.555966
16	203.655	Ireland	C2	0.61683
17	85.6627	Italy	C2	0.518113
18	165.112	Lithuania	C2	0.556738
22	231.243	Netherlands	C2	0.583754
23	99.0682	Norway	C2	0.649441
25	124.069	Portugal	C2	0.620526
11	172.509	Spain	C2	0.664799
28	219.863	Sweden	C2	0.650471
4	269.751	Switzerland	C2	0.553598
20	22.7196	Latvia	C3	0.544285
21	7.87253	Malta	C3	0.592851
13	292.787	France	C4	0.664752
19	304.065	Luxembourg	C4	0.658654
32	304.065	United Kingdom	C4	0.530179

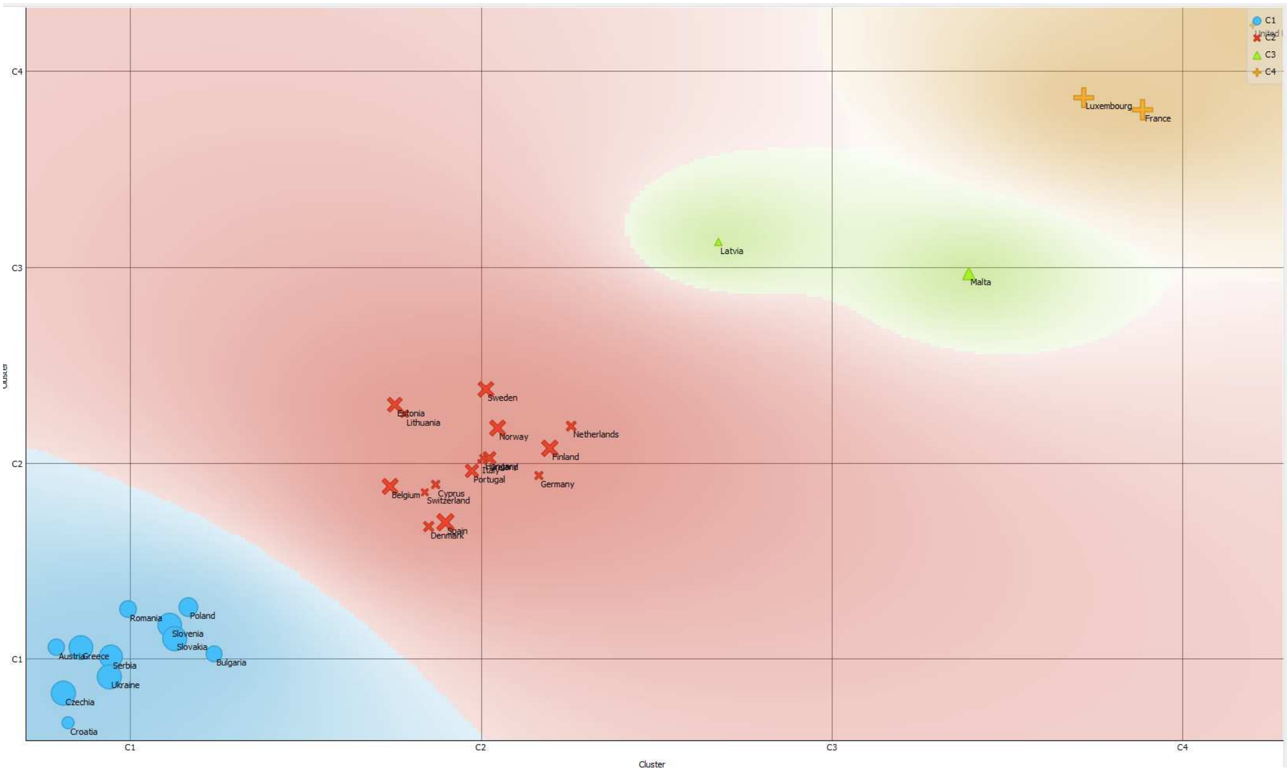

C1
C2
C3
C4


C3
C2
C4
C1
Cluster
0.4 0.42 0.44 0.46 0.48 0.5 0.52 0.54 0.56 0.58 0.6 0.62 0.64 0.66 0.68 0.7 0.72 0.74 0.76 0.78
Silhouette

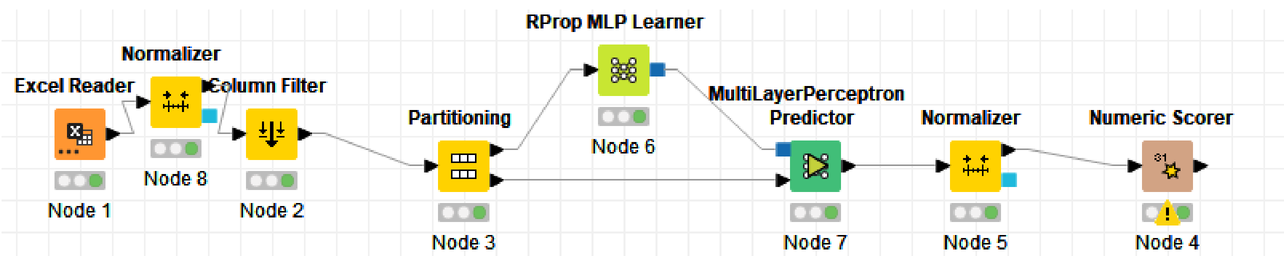

C1
C2
C3
C4
2014
2015
2016
2017
2018
2019
2020

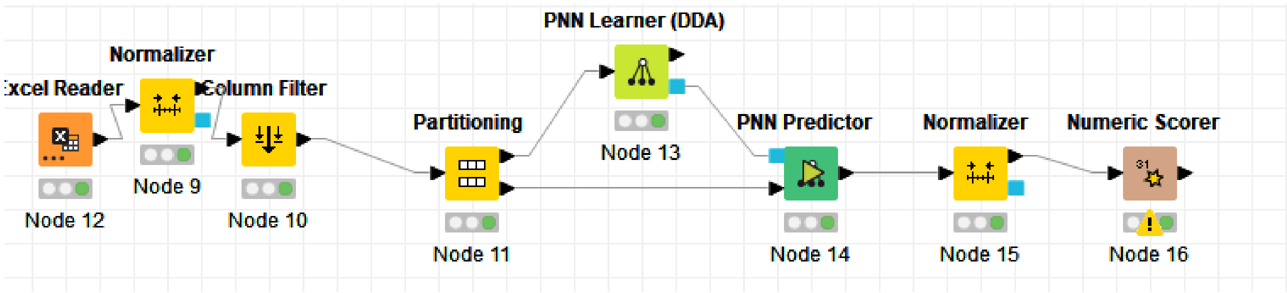

C1
C2
C3
C4
C1
C2
C3
C4
Probability of 'Cluster' at given '2021'
2021

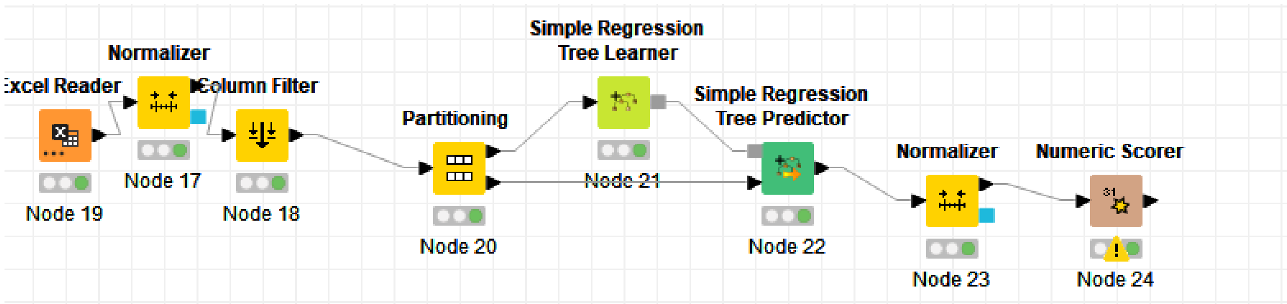


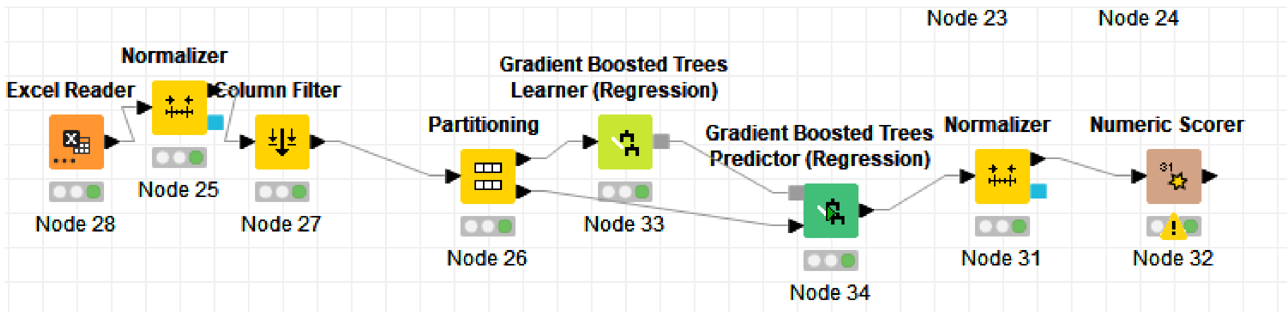


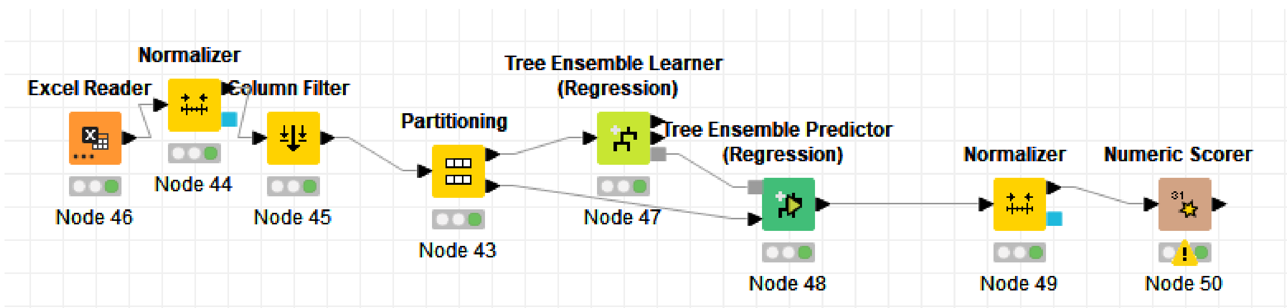
6.3 Machine Learning and Predictions Outputs

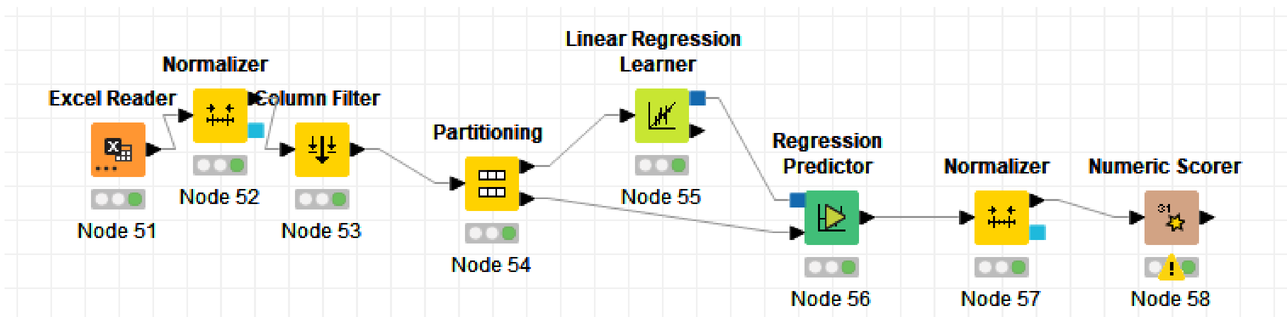


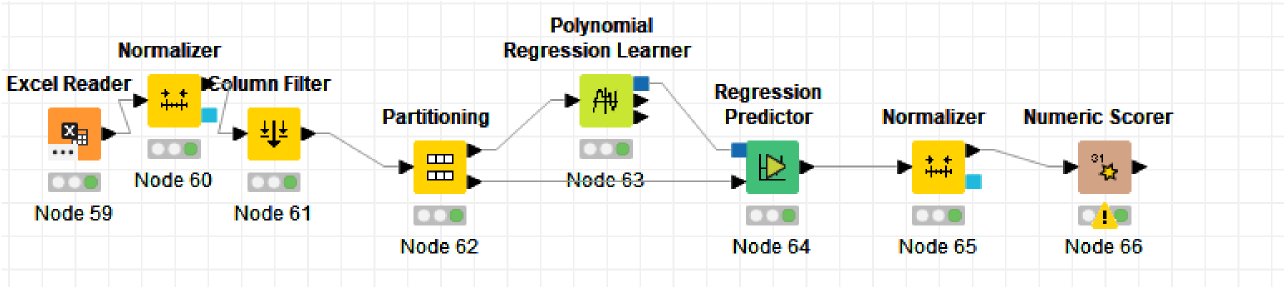

PNN Learner (DDA)
Normalizer
Excel Reader
Column Filter
Partitioning
Node 13
PNN Predictor
Normalizer
Numeric Scorer
Node 9
Node 12
Node 10
Node 11
Node 14
Node 15
Node 16


Simple Regression
Tree Learner
Normalizer
Excel Reader
Column Filter
Partitioning
Simple Regression
Tree Predictor
Normalizer
Numeric Scorer
Node 17
Node 21
Node 19
Node 18
Node 20
Node 22
Node 23
Node 24


Node 23
Node 24
Normalizer
Gradient Boosted Trees
Learner (Regression)
Excel Reader
Column Filter
Partitioning
Gradient Boosted Trees
Predictor (Regression)
Normalizer
Numeric Scorer
Node 25
Node 28
Node 27
Node 33
Node 26
Node 31
Node 32
Node 34


Normalizer
Tree Ensemble Learner
(Regression)
Excel Reader
Column Filter
Partitioning
Tree Ensemble Predictor
(Regression)
Normalizer
Numeric Scorer
Node 44
Node 46
Node 45
Node 47
Node 43
Node 48
Node 49
Node 50


Linear Regression
Learner
Normalizer
Excel Reader
Column Filter
Partitioning
Regression
Predictor
Normalizer
Numeric Scorer
Node 52
Node 55
Node 51
Node 53
Node 54
Node 56
Node 57
Node 58


Excel Reader
Node 59
Normalizer
Node 60
Column Filter
Node 61
Partitioning
Node 62
Polynomial
Regression Learner
Node 63
Regression
Predictor
Node 64
Normalizer
Node 65
Numeric Scorer
Node 66