

The Determinants of Design Applications in Europe

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Abstract

In this article we estimate the level of “*Design Application*” in 37 European Countries in the period 2010-2019. We use data from the European Innovation Scoreboard-EIS of the European Commission. We perform four econometric models i.e., Pooled OLS, Panel Data with Random Effects, Panel Data with Fixed Effects, Dynamic Panel. We found that the level of Design Applications is negatively associated to “*Enterprise Births*”, “*Finance and Support*”, “*Firm Investments*” and positively associated with “*Venture Capital*”, “*Turnover share large enterprises*”, “*R&D expenditure public sector*”, “*Intellectual Assets*”. In adjunct we perform a cluster analysis with the application of the k-Means algorithm optimized with the Silhouette Coefficient and we found three different clusters. Finally, we confront eight different machine learning algorithms to predict the level of “*Design Application*” and we found that the Tree Ensemble is the best predictor with a value for the 30% of the dataset analyzed that is expected to decrease in mean of -12,86%.

Keywords: General; Innovation and Invention: Processes and Incentives; Management of Technological Innovation and R&D; Technological Change: Choices and Consequences; Intellectual Property and Intellectual Capital.

JEL Code: O30; O31; O32; O33; O34.

1. Introduction

In this article we investigate the determinants of design applications for 36 European countries⁵ in the period 2010-2019 from the European Innovation Scoreboard of the European Commission. Design applications are considered as a part of the Intellectual Assets in the definition of the European Innovation Scoreboard. Intellectual Assets are essential to innovation and Research and Development. The role of innovation and Research and Development is essential to promote economic growth as in the model Solow [1], in the endogenous growth theory [2] and in Schumpeterian economics [3]. Innovation is positively associated with venture capitalism [4], human resources [5], [6], sales [7], [8], and employment [9]. Innovation increases the level of the attractiveness of research systems [10].

Intellectual assets are positively related with profitability [11], productivity [12] and competitiveness [13], [14]. Intellectual capital, of which intellectual assets are an essential part, is positively associated to high performance at an organizational level [15]. Dynamic capability can strengthen intellectual assets and capital to promote innovation at firm level [16]. Intellectual capital can promote business performance for SMEs at a country level [17]. Intellectual assets, and especially patents, are positively associated with open innovation [18]. Intellectual capital promotes product innovation [19]. Informal Intellectual Assets protection can generate better outcomes in terms of open innovation [20].

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⁵ 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, Spain, Sweden, Switzerland, Turkey, Ukraine, UK.

Firms that are interested in maximizing the economic value of intellectual assets need to implement more efficient organizational structures able to engage high skilled employees in a generalized activity of process and product innovation [21]. There is a positive relationship between the ability of a firm to implement intellectual property rights and the ability of the firm to promote significant technological innovation at the frontier, even this relationship also depends on the know-how at a firm level [22]. Intellectual capital can improve the innovation performance in SMEs [23]. Intellectual assets improve the ability of firm to measure business performance [24]. There is a positive relationship between the financial performance of listed firms in India and the level of intellectual assets [25]. Even if design applications are a relevant tool to promote innovation, in some contexts such as Italy, the presence of informal relationships between manufacturing firms and designers, based on trust and cooperation, can generate better results for the counterparts in terms of innovativeness [26]. The efficacy in using intellectual capital and assets grows in the case of the application of the open innovation model for its ability to create the conditions for a better knowledge dissemination and a shared governance of intangible goods and services [27].

Intellectual property rights can express their higher potential in the sense of innovativeness in the case of the application in combination of complementary assets i.e. managerial methods that are appropriate in the knowledge economy [28].

The article continues as follows: the second paragraph contains the econometric model, the third paragraph presents the cluster analysis, the fourth paragraph shows the results of the machine learning algorithms used to predict the value of design application, the fifth paragraph concludes. The appendix contains the econometric results.

2. The Econometric Model

We estimate the determinants of Design Applications. Design application is a measure that evaluates the value of design application in terms of GDP. The definitions of the Design application and all the determinants of the estimated econometric model are officially produced by the European Commission in the European Innovation Scoreboard. Design applications are considered as intellectual creative products and services that are officially registered in the European Union Intellectual Property Office. Design applications are creative intellectual goods and services that are essentially related to industrial production either in the tangible or in the intangible sector. The knowledge economy requires design applications either in the sense of products, processes, and services.

$$\begin{aligned}
 \mathbf{DesignApplications}_{it} &= \mathbf{a}_1 + \mathbf{b}_1(\mathbf{EnterpriseBirth})_{it} + \mathbf{b}_2(\mathbf{FinanceAndSupport})_{it} \\
 &+ \mathbf{b}_3(\mathbf{FirmInvestment})_{it} + \mathbf{b}_4(\mathbf{IntellectualAssets})_{it} \\
 &+ \mathbf{b}_5(\mathbf{R\&DExpenditurePublicSector})_{it} \\
 &+ \mathbf{b}_6(\mathbf{TurnoverShareLargeEnterprises})_{it} + \mathbf{b}_7(\mathbf{VentureCapital})
 \end{aligned}$$

Where i is equal to 36 and $t=[2010;2019]$.

Our results show that design application is positively associated to:

- *Intellectual assets*: is a measure that captures different forms of Intellectual Property Rights-IPR such as patent applications, trademark application and design application. The positive relationship between design applications and intellectual assets can be understood either because design application is a component of intellectual assets either since there is a positive externality of design applications on patent applications and trademark applications.

- *R&D expenditure public sector*: is a measure of the value of the R&D of the government sector in terms of GDP. R&D expenditure is essential to promote the implementation of the knowledge economy at a national level. The possibility to promote high-tech industry either in the product and in the service sector requires the investment in R&D. R&D expenditures also has positive effects in terms of human resources and empowerment of human capital. R&D expenditure is the strategic investment to promote innovation, green sustainability, and a higher level of human capital. R&D expenditures are also positively associated to a high level of instruction and educational investments. The positive relationship between R&D expenditures and design applications is since design application is a typical output of R&D expenditures and is associated to patent application.
- *Turnover share of large enterprise*: is an indicator in which at the numerator there is the turnover of enterprises with 250 persons employed or more and in the denominator there is the turnover of enterprises of the total business economy. The indicator is a measure of relative relevance of large enterprises in respect to the total number of enterprises in the business sector except for the financial and insurance sector. There is a positive relationship between turnover share of large enterprises and the level of design application. This positive relationship can be better understood because generally big corporations have greater investments in Research and Development and intellectual assets and therefore also in design applications.
- *Venture Capital*: is the value of financial investments in startups and newcos in respect to the level of Gross Domestic Products. The greater the investment of venture capital in economic organizations that promote innovation technology the greater the dynamism of the entire business sector in producing new products and services. Furthermore, the greater the investment in venture capital the greater the ability of newcos and startups to afford risks and with higher perspective profits. There is a positive relationship between venture capital and design application that can be explained considering that the design applications require a high level of innovation technology and research and development that generally are financed with venture capitalism and external finance. The level of financial sophistication at a country level is positively associated to the ability of a country to promote Research and Development and innovation technology.

The level of design application is negatively associated to:

- *Enterprise Birth*: is the percentage of new firms with enterprise birth in respect to the total population of active enterprise in a certain period. In this indicator are computed all the business sectors except for the holding companies. There is a negative relationship between enterprise birth and design applications meaning that SMEs generally have not sufficient human capital, knowledge, and technology to promote intellectual assets such as design applications. Design applications are effectively the output of complex product systems that are generally associated to medium firms and big corporations.
- *Finance and Support*: is an indicator that measure the ability to finance innovation technology and research and development such as for example Venture Capital expenditures and the public expenditures in Research and Development. There is a negative relationship between finance and support and design application. This negative relationship can be better understood because in European countries the role of finance and support has a low impact on innovation technology and therefore on design applications. But this negative relationship is counterfactual. In effect, theoretically there should be a positive relationship between finance and support and design application.
- *Firm investments*: is a measure of the investments that firms finance either in the sense of Research and Development either in the sense of innovation technology to promote the skills of personnel. There is a negative relationship between firm investments and design applications. This negative relationship is counterfactual and shows the presence of a

difficulty of firms to promote an adequate level of human capital to produce high innovational goods and services such as intellectual assets and therefore design applications.

Synthesis of the Main Results of the Econometric Models									
Variables		Pooled OLS		Panel Data with Fixed Effects		Panel Data with Random Effects		Dynamic Panel	
		Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
y	<i>Design Applications</i>	A7							
	<i>Const</i>		★ 0,12348		★ -0,30207		★ -0,30808		★ 0,137 **
x_1	<i>Enterprise births (10+ employees)</i>	A14	★ -10,4577 ***	★ -8,32162 ***	★ -8,46137 ***			★ -1,22 *	
x_2	<i>Finance and support</i>	A17	★ -0,50054 ***	★ -0,53229 ***	★ -0,52437 ***			★ -7,64 ***	
x_3	<i>Firm investments</i>	A18	★ -0,36161 ***	★ -0,30952 ***	★ -0,31792 ***			★ -0,46 ***	
x_4	<i>Intellectual assets</i>	A29	★ 1,38345 ***	★ 1,307 ***	★ 1,31918 ***			★ -0,31 ***	
x_5	<i>R&D expenditure public sector</i>	A47	★ 0,25666 ***	★ 0,264578 ***	★ 0,260784 ***			★ 1,29 ***	
x_6	<i>Turnover share large enterprises</i>	A57	★ 0,23089 ***	★ 0,225737 ***	★ 0,227779 ***			★ 0,245 *	
x_7	<i>Venture capital</i>	A59	★ 0,163479 ***	★ 0,194419 ***	★ 0,189436 ***			★ 0,203 **	
x_8	<i>Design Applications</i>	A7(-1)						★ 0,164 **	

Figure 1. Synthesis of the Main Results of the Econometric Models.

The variables that have the greatest impact in terms of design applications are: intellectual assets in the positive sense, and enterprise birth negatively.

3. Cluster Analysis

In adjunct we perform a cluster analysis with the application of the k-Means algorithm optimized with the Silhouette Coefficient. We use data for 37 European countries in the period 2014-2021 from the European Innovation Scoreboard of the European Commission. We found three different clusters that are:

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

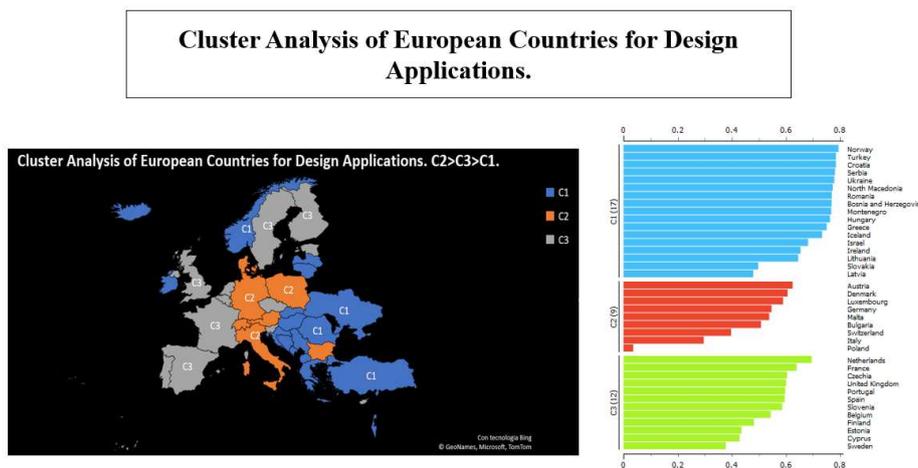


Figure 2. The cluster analysis with the algorithm k-Means optimized with the Silhouette Coefficient.

It is possible to realize a ranking of the three clusters based on the median value of the design application. C2 is the first cluster for the value of median of design application equal to 115,00, followed by the cluster 3 with a median value equal to 52,14, and cluster 1 with a median value of

14,00. The distribution of design applications among European countries shows the dominance of Central Europe with the adjunct of Italy and Hungary. France, Spain, UK, and Scandinavian countries have an intermediate level of design applications. While Eastern countries, Ireland, Iceland, and Norway have the lower level of design applications. As we can see, the level of design application can be low also in countries that traditionally have high levels of innovation technology such as Norway and Ireland. In this case the low level of design application is due to cultural, traditional, and strategical assets of the economy at a country level. For example, the case of Italy is essentially the case of country with a medium-low level of innovation technology that has a traditional international comparative advantage in the production of services in industrial design.

4. Machine Learning and Predictions

Finally, we apply eight different algorithms to predict the value of Digital Applications in European countries. We choose the algorithms based on their ability to maximize R-squared and minimize the following errors “Mean Absolute Error”, “Mean Squared Error”, “Root Mean Squared Error”, “Mean Signed Difference”. We use the 70% of the dataset for machine learning and the remaining 30% to prediction. Based on our analysis we have the following order of algorithms:

1. *Tree Ensemble* with a payoff of 5;
2. *Gradient Boosted Trees* with a payoff equal to 10;
3. *Simple Regression Tree* with a payoff of 16;
4. *Polynomial Regression Tree* with a payoff of 27;
5. *Random Forest*, *ANN-Multilayer* and *Linear Regression* with a payoff of 28;
6. *PNN-Probabilistic Neural Network* with a payoff of 38.

Rankings of Algorithms by Performance in Maximization R ² and Minimization of Errors							
Rank	Algorithms	R ²	Mean absolute error	Mean squared error	Root mean squared error	Mean signed difference	Sum
1	<i>Tree Ensemble</i>	1	1	1	1	1	5
2	<i>Gradient Boosted Trees</i>	2	2	2	2	2	10
3	<i>Simple Regression Tree</i>	3	4	3	3	3	16
4	<i>Polynomial Regression</i>	4	7	4	4	8	27
5	<i>Random Forest</i>	5	6	5	5	7	28
5	<i>ANN-MULTILAYER</i>	6	5	6	6	5	28
5	<i>Linear Regression</i>	7	3	7	7	4	28
6	<i>PNN</i>	8	8	8	8	6	38

Figure 3. Ranking of Algorithms by Performance in Maximization of R-squared and Minimization of Errors.

The *Tree Ensemble* algorithm is the best machine learning based predictor of the level of design application in European countries.

Specifically, the *Tree Ensemble* algorithm predicts the following values:

- *Belgium* with a predicted value equal to 46,58 equivalent to -5,95 in absolute value and -11,33 in percentage points;
- *Cyprus* with an increase in the level of design applications from 49,68 to 50,93 equivalent to 1,25 in absolute value and correspondent to +2,52%;
- *Denmark* with a reduction in the level of design applications from 160,30 to 125,91 equivalent to -34,39 in absolute value correspondent to -21,45%;
- *Spain* with a reduction of the design applications from 49,55 to 48,06 equivalent to an absolute variation of -1,49 and a correspondent value of -3,01%;
- *Finland* with a reduction of the design applications from 94,75 to 75,46 equivalent to an absolute variation of -19,29 and a correspondent value of -20,36%;
- *Israel* with an increase of the design applications from 22,16 to 26,53 equivalent to an absolute variation of 4,37 and a correspondent value of 19,72%;
- *Latvia* with a reduction of the design applications from 39,89 to 31,95 equivalent to an absolute variation of -7,95 and a correspondent value of -19,92%;

- *Netherlands* with a reduction of the design applications from 95,26 to 61,47 equivalent to an absolute variation of -33,79 and a correspondent value of -35,47%;
- *Romania* with a reduction of the design applications from 17,91 to 16,36 equivalent to an absolute variation of -1,55 and a correspondent value of -8,65%;
- *Slovenia* with an increase of the design applications from 42,56 to 52,64 equivalent to an absolute variation of 10,08 and a correspondent value of 23,68%;
- *Turkey* with an increase of the design applications from 2,05 to 4,97 equivalent to an absolute variation of 2,92 and a correspondent value of 142,24%;
- *United Kingdom* with a reduction of the design applications from 51,75 to 50,45 equivalent to an absolute variation of -1,30 and a correspondent value of -2,51%;

At an aggregate level the level of design application is expected to decrease in mean from the analyzed countries from 56,53 to 49,28 with an absolute variation equal to -7,26 correspondent to -12,84%.

Predictions with the Tree Ensemble Algorithm					
Countries	2021	Prediction	Absolute Variation	Percentage Variation	
Belgium	★ 52,53	★ 46,58	★ -5,95	-11,33	
Cyprus	★ 49,68	★ 50,93	★ 1,25	2,52	
Denmark	★ 160,30	★ 125,91	★ -34,39	-21,45	
Spain	★ 49,55	★ 48,06	★ -1,49	-3,01	
Finland	★ 94,75	★ 75,46	★ -19,29	-20,36	
Israel	☆ 22,16	☆ 26,53	☆ 4,37	19,72	
Latvia	★ 39,89	★ 31,95	★ -7,95	-19,92	
Netherlands	★ 95,26	★ 61,47	★ -33,79	-35,47	
Romania	☆ 17,91	☆ 16,36	☆ -1,55	-8,65	
Slovenia	★ 42,56	★ 52,64	★ 10,08	23,68	
Turkey	☆ 2,05	☆ 4,97	☆ 2,92	142,24	
United Kindgom	★ 51,75	★ 50,45	★ -1,30	-2,51	
Mean	★ 56,53	★ 49,28	★ -7,26	-12,84	

Figure 4. Predictions with the Tree Ensemble Algorithm.

Finally, we can observe that policy makers should contrast the predicted reduction of the value of design application with the implementation of political economies oriented to promote Research and Development, Intellectual Assets, Venture Capital, and Turnover Share of Large Enterprise as showed in our estimated econometric model.

5. Conclusions

In this article we estimate the level of “*Design Application*” in 36 European Countries in the period 2010-2019. We use data from the European Innovation Scoreboard-EIS of the European Commission. Design application in the context of the European Innovation Scoreboard is associated with patents and trademark application in the main category of intellectual assets. Intellectual assets area an essential tool to promote innovation and to improve human capital either at a firm level either at a country level. In the first paragraph we have synthesized the economic literature that relate the role of intellectual asset to economic growth and productivity. The second paragraph presents the econometric model. We perform four econometric models i.e., Pooled OLS, Panel Data with Random Effects, Panel Data with Fixed Effects, Dynamic Panel. We found that the level of Design Applications is negatively associated to “*Enterprise Births*”, “*Finance and Support*”, “*Firm Investments*” and positively associated with “*Venture Capital*”, “*Turnover share large enterprises*”, “*R&D expenditure public sector*”, “*Intellectual Assets*”. In the third paragraph we have performed a cluster analysis with the application of the k-Means algorithm optimized with the Silhouette Coefficient and we found three different clusters. The three clusters show a dominance of Italy and Central-Europe in offering services in the sector of design application. Finally, we confront eight

different machine learning algorithms to predict the level of “*Design Application*” and we found that the Tree Ensemble is the best predictor with a value for the 30% of the dataset analyzed that is expected to decrease in mean of -12,86%. Policy makers can promote design application by incentivizing the investments in Research and Development, in promoting venture capitalism and creating the legislative conditions to strengthen intellectual assets also in the context of open innovation.

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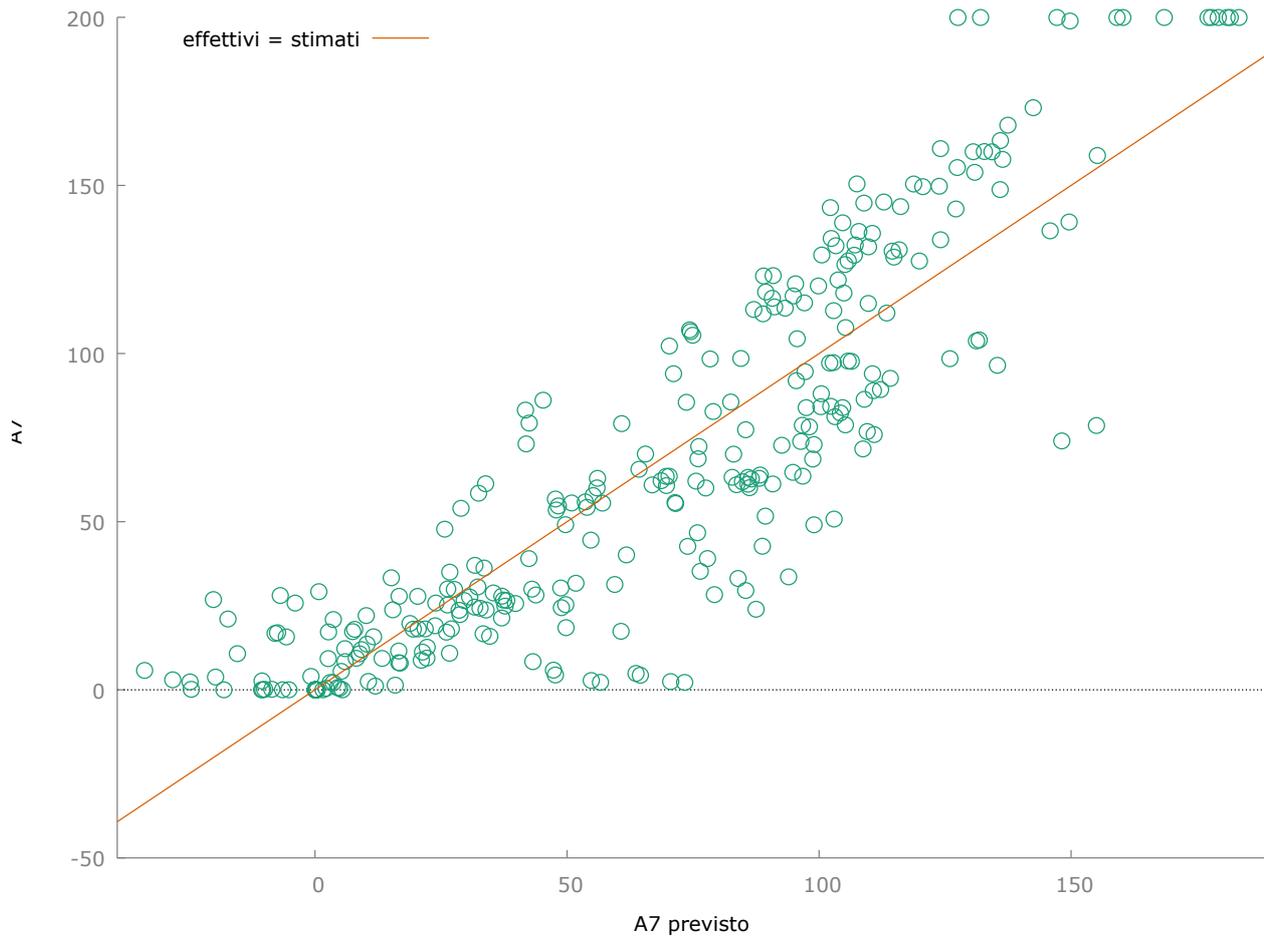
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1. Appendix

7.1 Econometric Results

Modello 225: Pooled OLS, usando 360 osservazioni					
Incluse 36 unità cross section					
Lunghezza serie storiche = 10					
Variabile dipendente: A7					
	<i>Coefficiente</i>	<i>Errore Std.</i>	<i>rapporto t</i>	<i>p-value</i>	
const	0,123480	2,22492	0,05550	0,9558	
A14	-10,4577	1,93187	-5,413	<0,0001	***
A17	-0,500543	0,0805274	-6,216	<0,0001	***
A18	-0,361613	0,0415250	-8,708	<0,0001	***
A29	1,38345	0,0439841	31,45	<0,0001	***
A47	0,256660	0,0528274	4,858	<0,0001	***
A57	0,230890	0,0888211	2,599	0,0097	***
A59	0,163479	0,0334049	4,894	<0,0001	***
Media var. dipendente					
54,29286		SQM var. dipendente		56,11276	
Somma quadr. residui					
190914,5		E.S. della regressione		23,28885	
R-quadro					
0,831103		R-quadro corretto		0,827745	
F(7, 352)					
247,4449		P-value(F)		9,2e-132	
Log-verosimiglianza					
-1640,044		Criterio di Akaike		3296,087	
Criterio di Schwarz					
3327,176		Hannan-Quinn		3308,449	
rho					
0,890178		Durbin-Watson		0,330137	



Modello 227: Effetti fissi, usando 360 osservazioni

Incluse 36 unità cross section

Lunghezza serie storiche = 10

Variabile dipendente: A7

	<i>Coefficiente</i>	<i>Errore Std.</i>	<i>rapporto t</i>	<i>p-value</i>	
const	-0,302070	1,65081	-0,1830	0,8549	
A14	-8,32162	1,48213	-5,615	<0,0001	***
A17	-0,532290	0,106751	-4,986	<0,0001	***
A18	-0,309520	0,0456645	-6,778	<0,0001	***
A29	1,30700	0,0497456	26,27	<0,0001	***
A47	0,264578	0,0666723	3,968	<0,0001	***
A57	0,225737	0,0770793	2,929	0,0037	***
A59	0,194419	0,0418643	4,644	<0,0001	***

Media var. dipendente	54,29286	SQM var. dipendente	56,11276
Somma quadr. residui	70904,22	E.S. della regressione	14,95569
R-quadro LSDV	0,937273	R-quadro intra-gruppi	0,855844

LSDV F(42, 317)	112,7773	P-value(F)	1,0e-165
Log-verosimiglianza	-1461,754	Criterio di Akaike	3009,509
Criterio di Schwarz	3176,611	Hannan-Quinn	3075,952
rho	0,473935	Durbin-Watson	0,871202

Test congiunto sui regressori -

Statistica test: $F(7, 317) = 268,857$

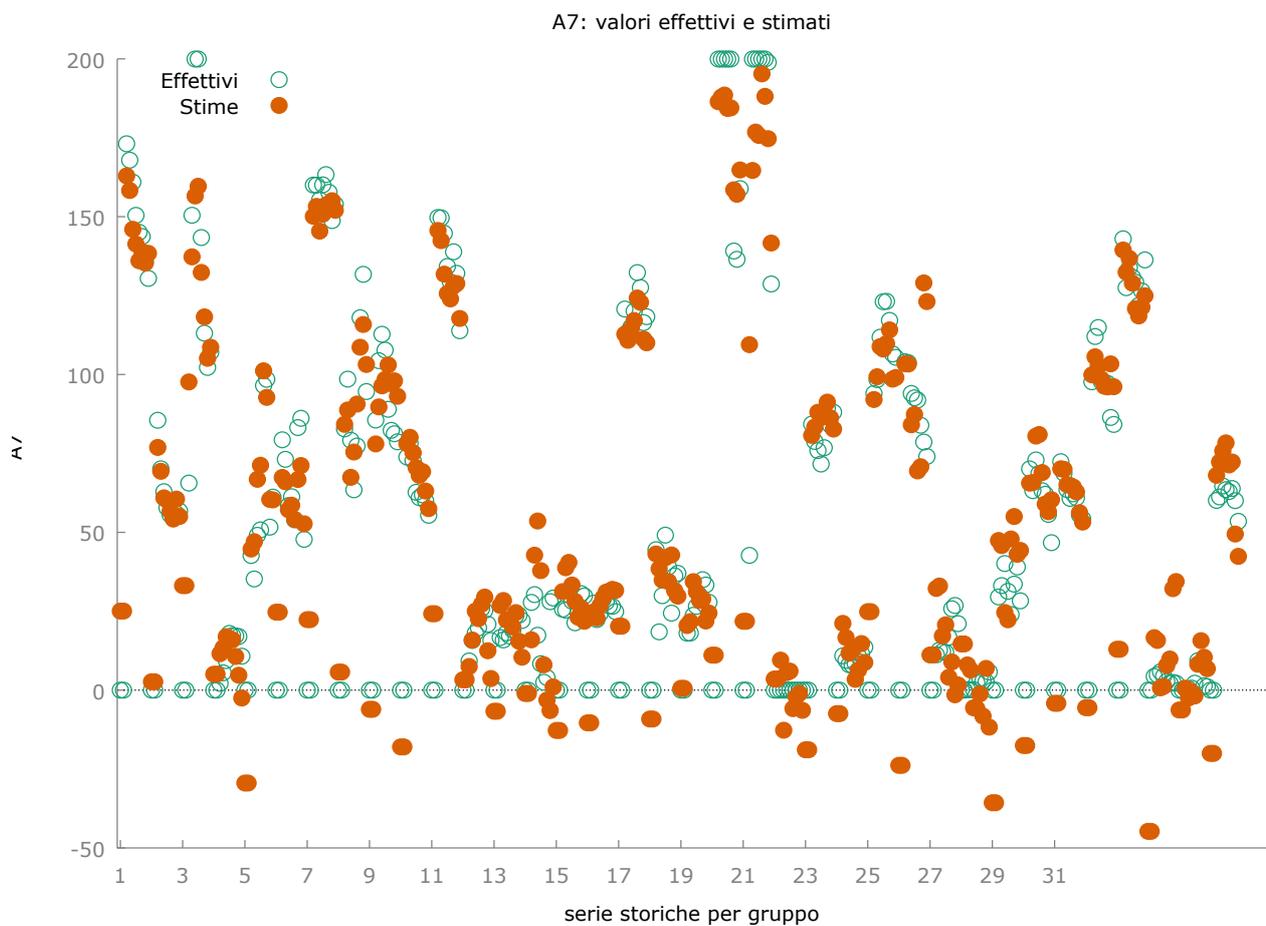
con p-value = $P(F(7, 317) > 268,857) = 3,14534e-129$

Test per la differenza delle intercette di gruppo -

Ipotesi nulla: i gruppi hanno un'intercetta comune

Statistica test: $F(35, 317) = 15,3298$

con p-value = $P(F(35, 317) > 15,3298) = 1,85816e-049$

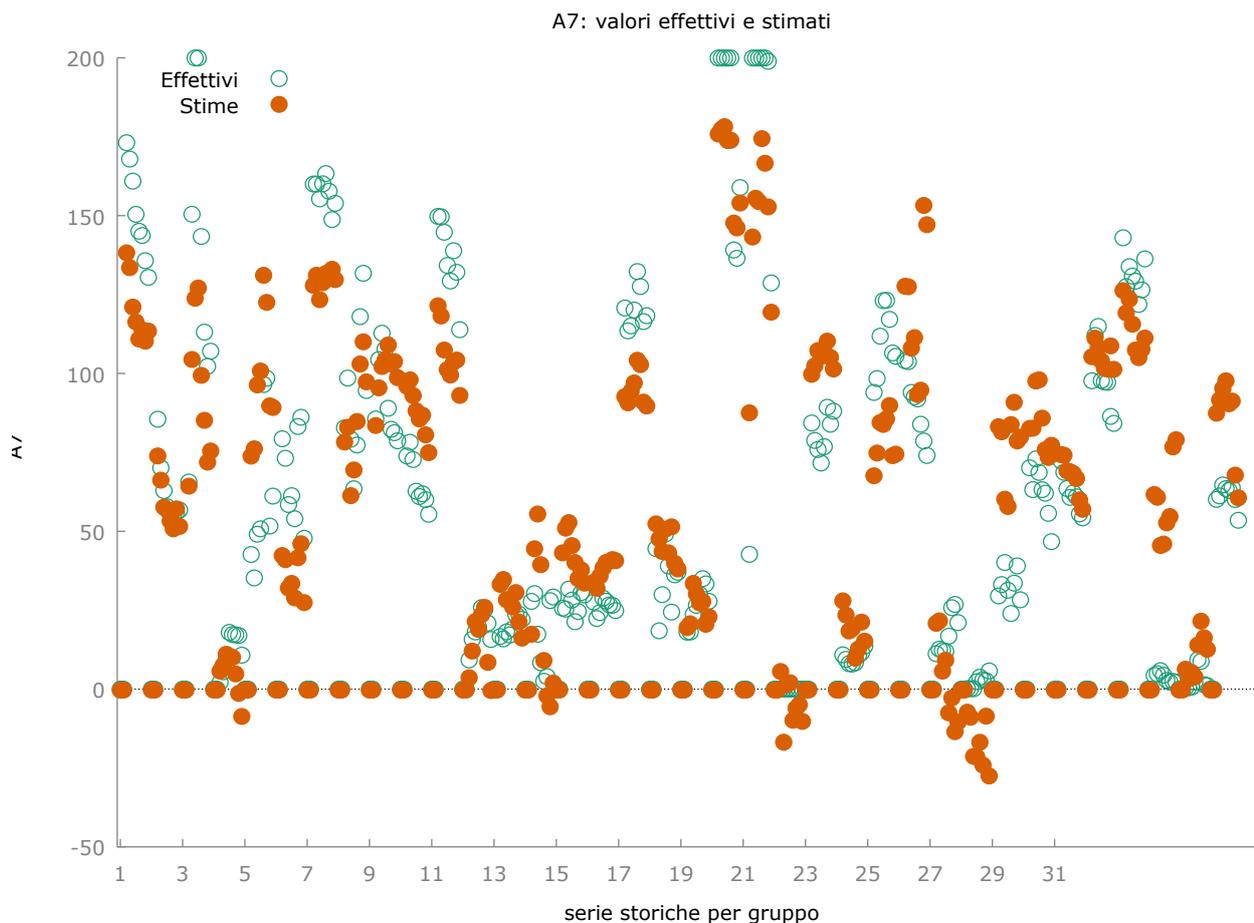


Modello 228: Effetti casuali (GLS), usando 360 osservazioni				
Incluse 36 unità cross section				
Lunghezza serie storiche = 10				
Variabile dipendente: A7				

	<i>Coefficiente</i>	<i>Errore Std.</i>	<i>z</i>	<i>p-value</i>	
const	-0,308082	3,50209	-0,08797	0,9299	
A14	-8,46137	1,45146	-5,830	<0,0001	***
A17	-0,524370	0,0971367	-5,398	<0,0001	***
A18	-0,317921	0,0428785	-7,414	<0,0001	***
A29	1,31918	0,0464605	28,39	<0,0001	***
A47	0,260784	0,0610960	4,268	<0,0001	***
A57	0,227779	0,0748395	3,044	0,0023	***
A59	0,189436	0,0383405	4,941	<0,0001	***

Media var. dipendente	54,29286	SQM var. dipendente	56,11276
Somma quadr. residui	193324,0	E.S. della regressione	23,40214
Log-verosimiglianza	-1642,301	Criterio di Akaike	3300,602
Criterio di Schwarz	3331,691	Hannan-Quinn	3312,964
rho	0,473935	Durbin-Watson	0,871202

Varianza 'between' = 348,064	
Varianza 'within' = 223,673	
Theta usato per la trasformazione = 0,754273	
Test congiunto sui regressori -	
Statistica test asintotica: Chi-quadro(7) = 2031,94	
con p-value = 0	
Test Breusch-Pagan -	
Ipotesi nulla: varianza dell'errore specifico all'unità = 0	
Statistica test asintotica: Chi-quadro(1) = 539,854	
con p-value = 2,02838e-119	
Test di Hausman -	
Ipotesi nulla: le stime GLS sono consistenti	
Statistica test asintotica: Chi-quadro(7) = 5,36729	
con p-value = 0,615235	



Modello 229: Panel dinamico a un passo, usando 288 osservazioni

Incluse 36 unità cross section

Matrice H conforme ad OLS/DPD

Variabile dipendente: A7

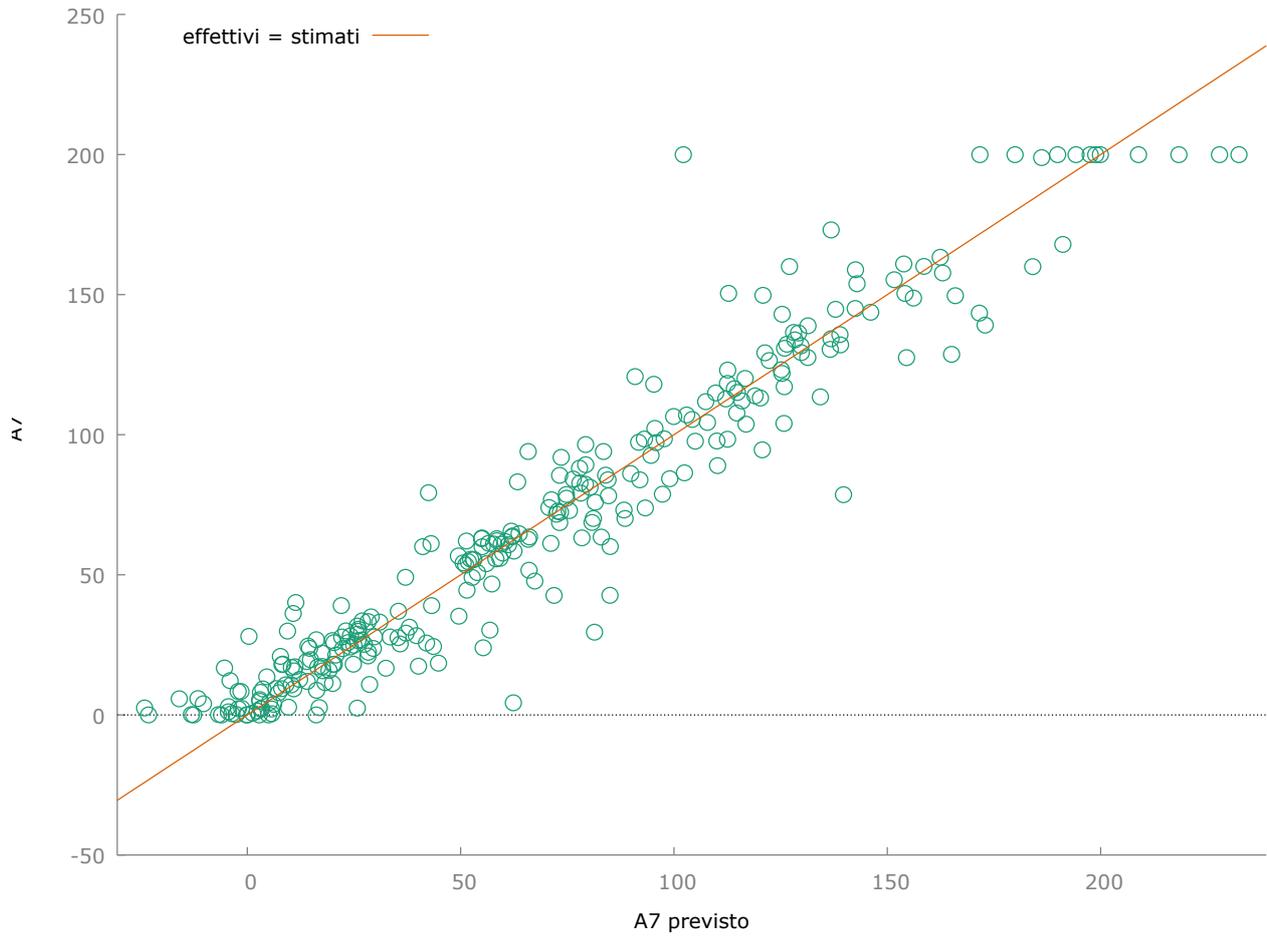
	<i>Coefficiente</i>	<i>Errore Std.</i>	<i>z</i>	<i>p-value</i>	
A7(-1)	0,137115	0,0625966	2,190	0,0285	**
const	-1,21842	0,680087	-1,792	0,0732	*
A14	-7,64157	2,36074	-3,237	0,0012	***
A17	-0,463252	0,177448	-2,611	0,0090	***
A18	-0,308810	0,0876711	-3,522	0,0004	***
A29	1,29009	0,136445	9,455	<0,0001	***
A47	0,244720	0,131756	1,857	0,0633	*
A57	0,203339	0,0928756	2,189	0,0286	**
A59	0,164169	0,0747277	2,197	0,0280	**

Somma quadr. residui	65634,29	E.S. della regressione	15,33781
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Numero di strumenti = 29

Test per errori AR(1): $z = -1,23332$ [0,2175]

Test per errori AR(2): $z = -1,70308$ [0,0886]
Test di sovra-identificazione di Sargan: Chi-quadro(20) = 37,9154 [0,0091]
Test (congiunto) di Wald: Chi-quadro(8) = 522,524 [0,0000]



1.2 Cluster Analysis

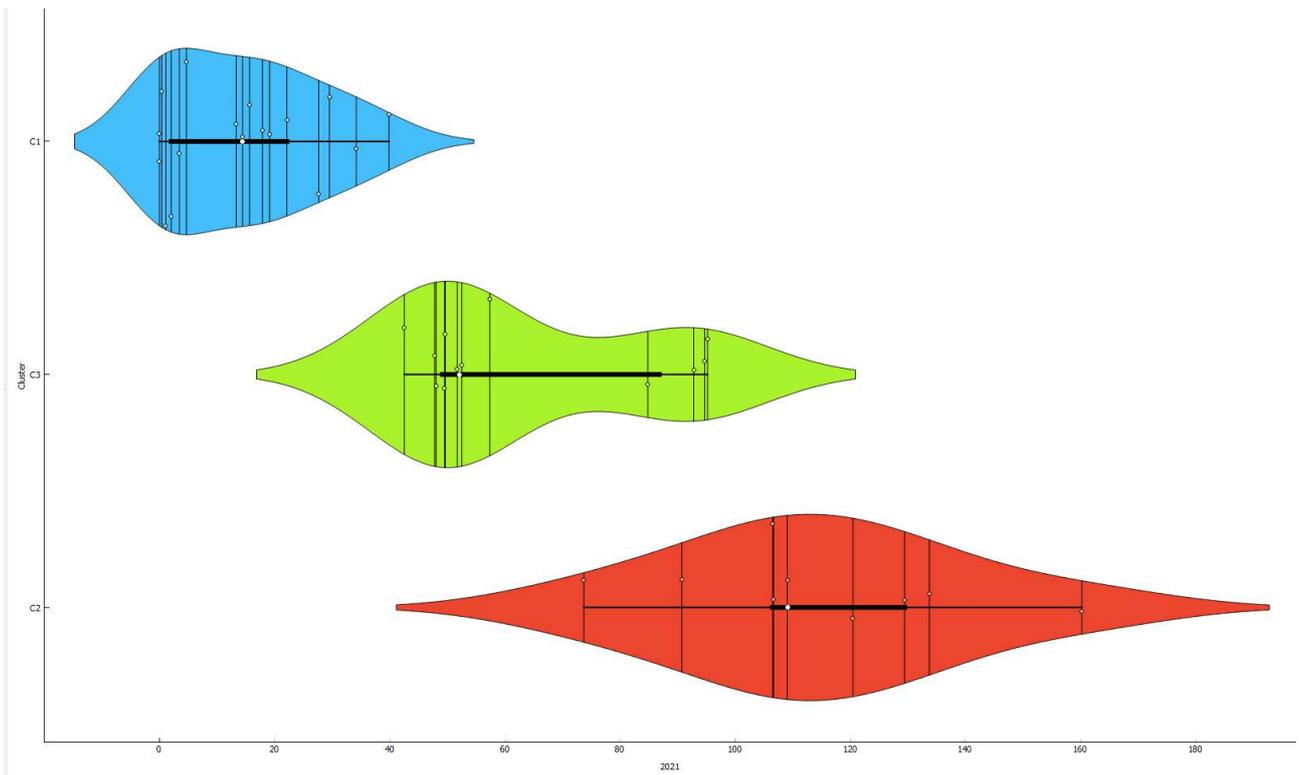
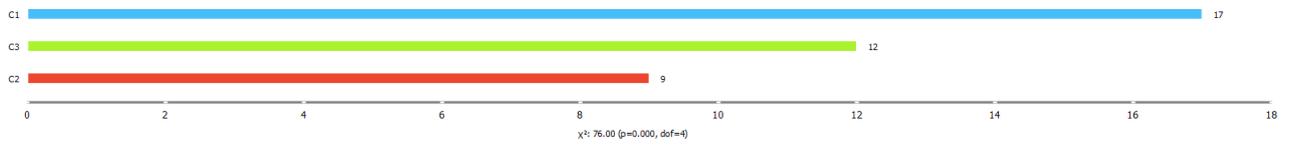
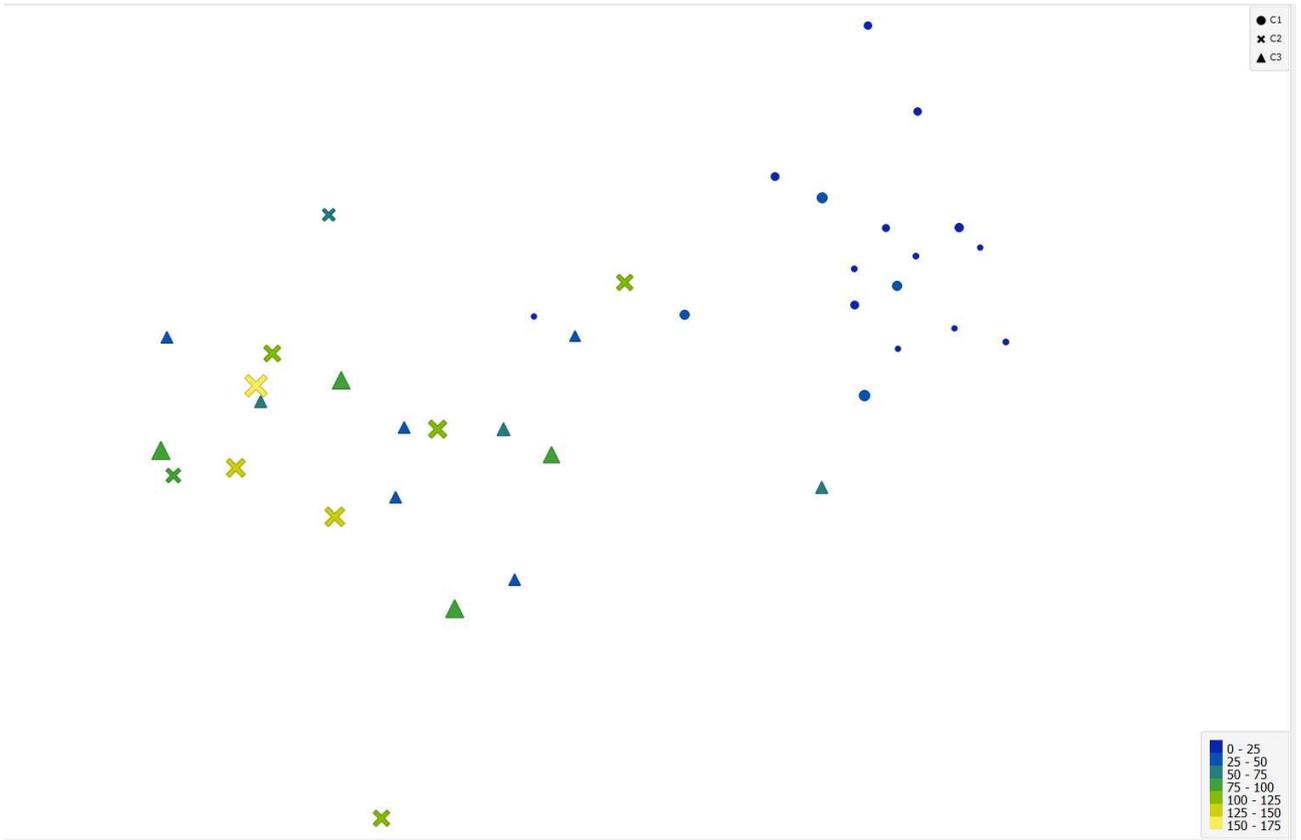
Number of clusters: 3
Optimization: initialize with KMeans++, 10 re-runs limited to 300 steps

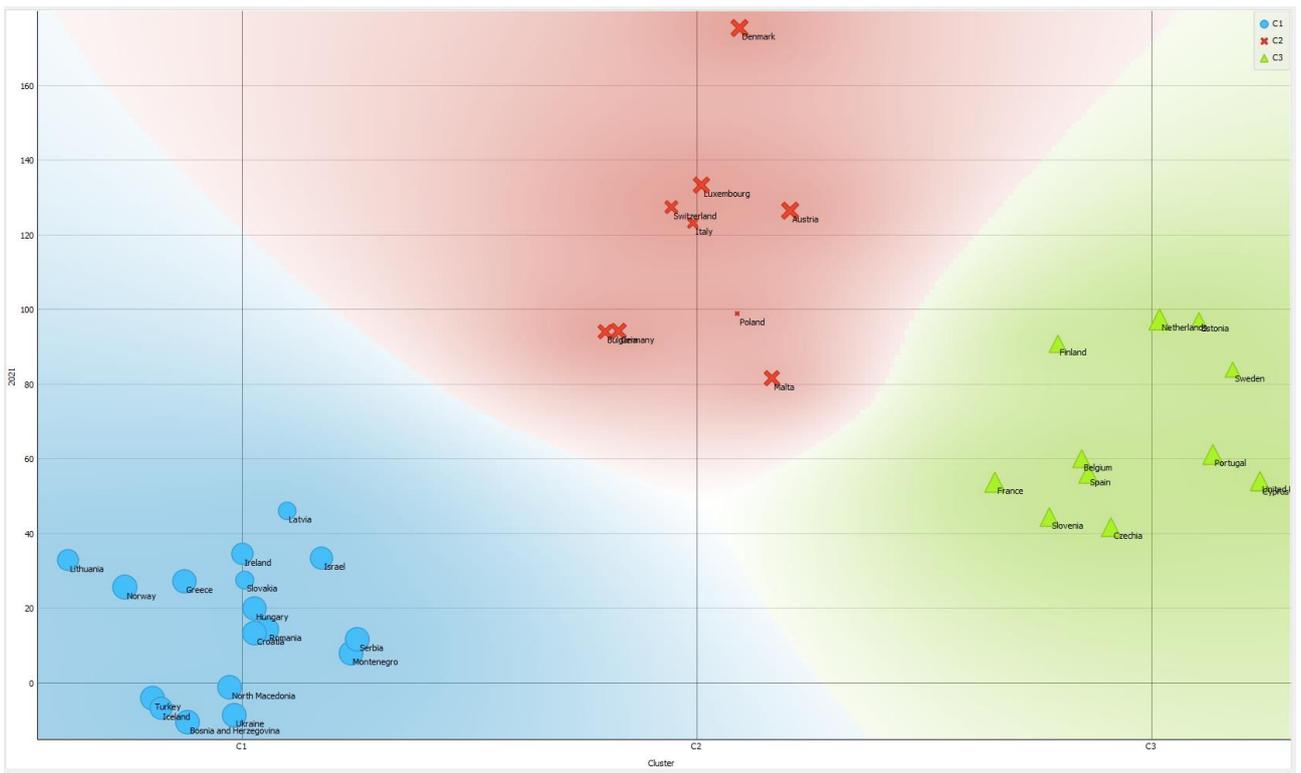
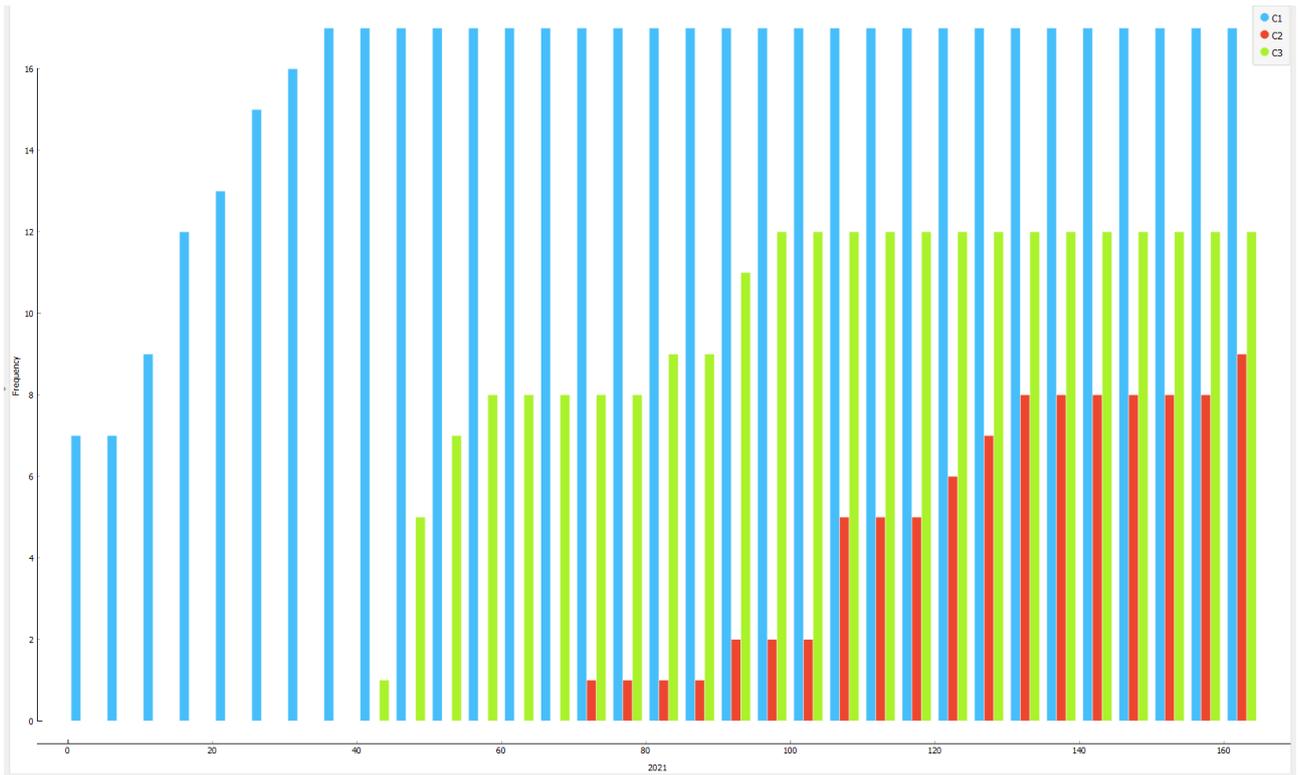
Data

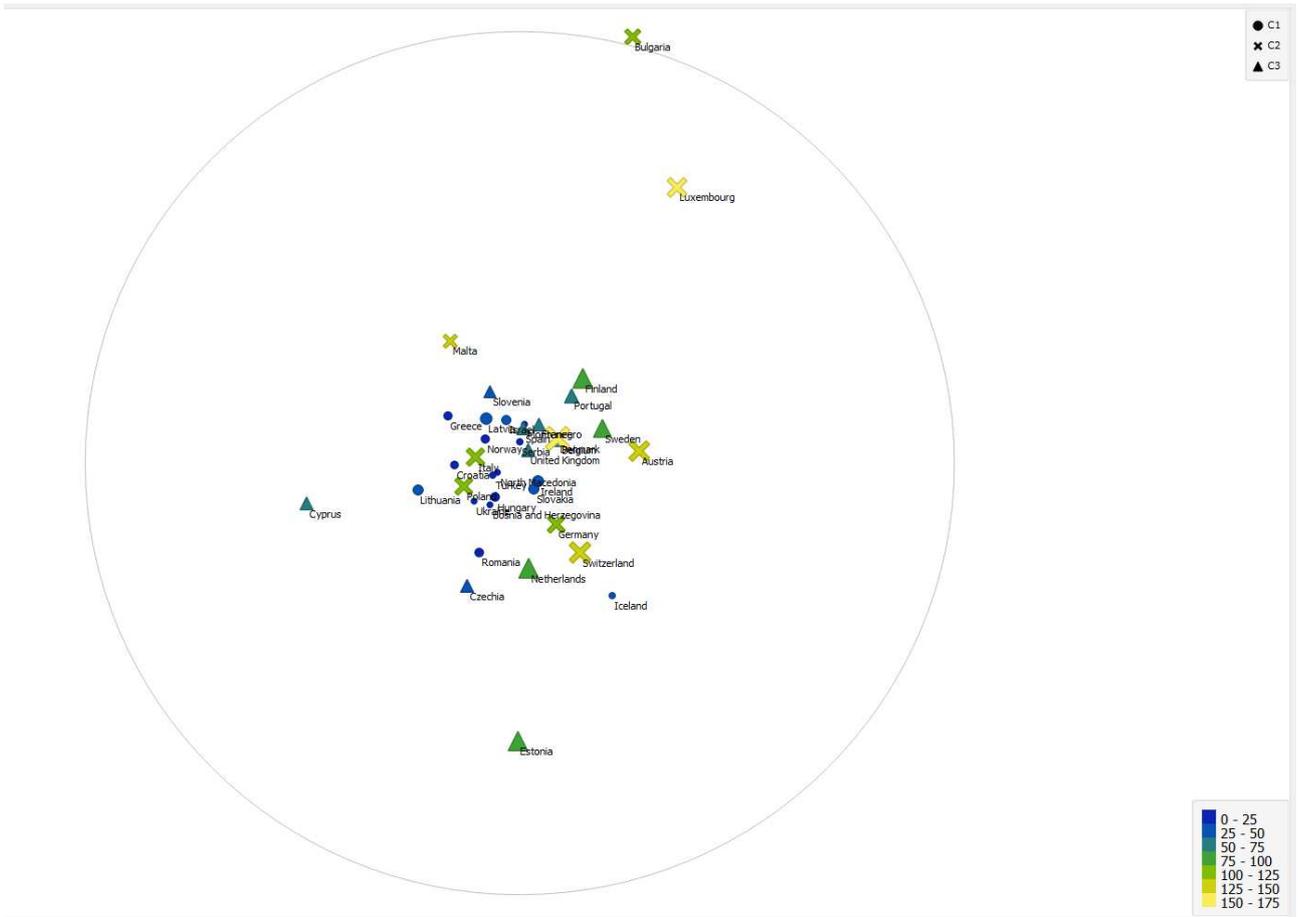
Data instances: 38
Features: 2014, 2015, 2016, 2017, 2018, 2019, 2020
Meta attributes: Feature 1
Target: 2021

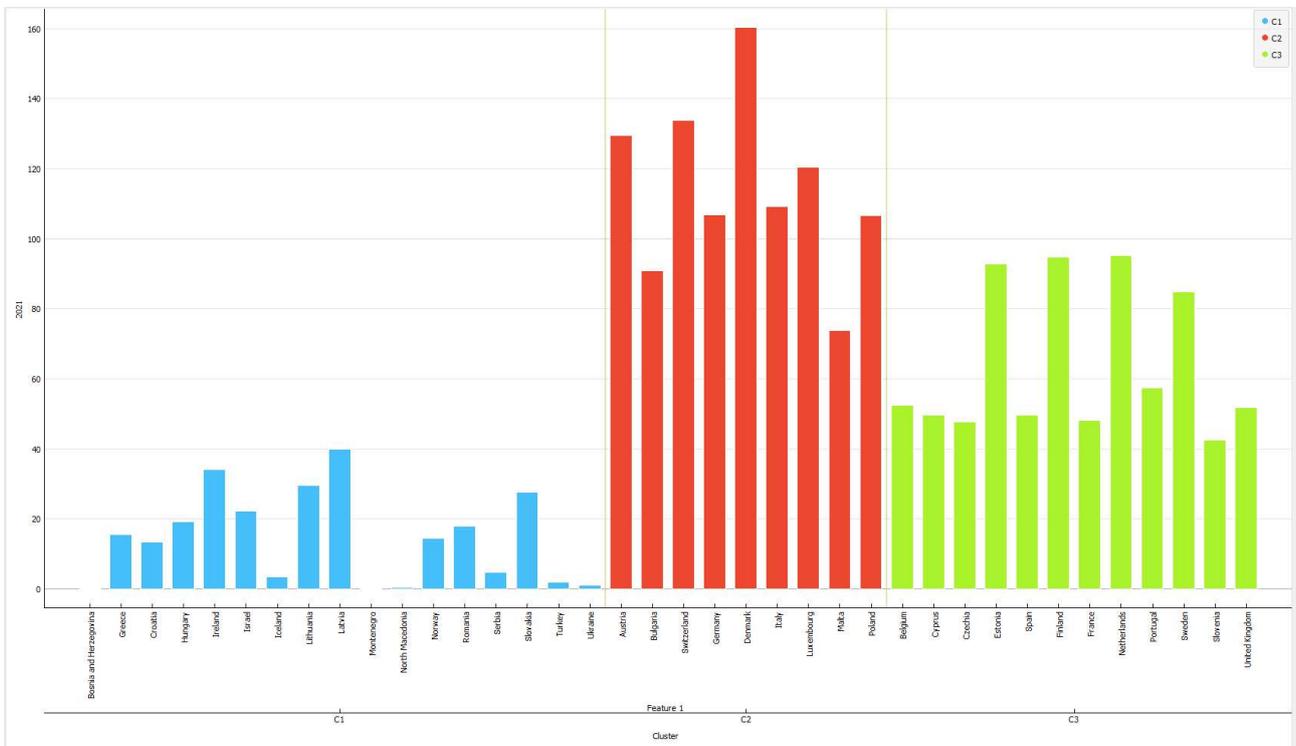
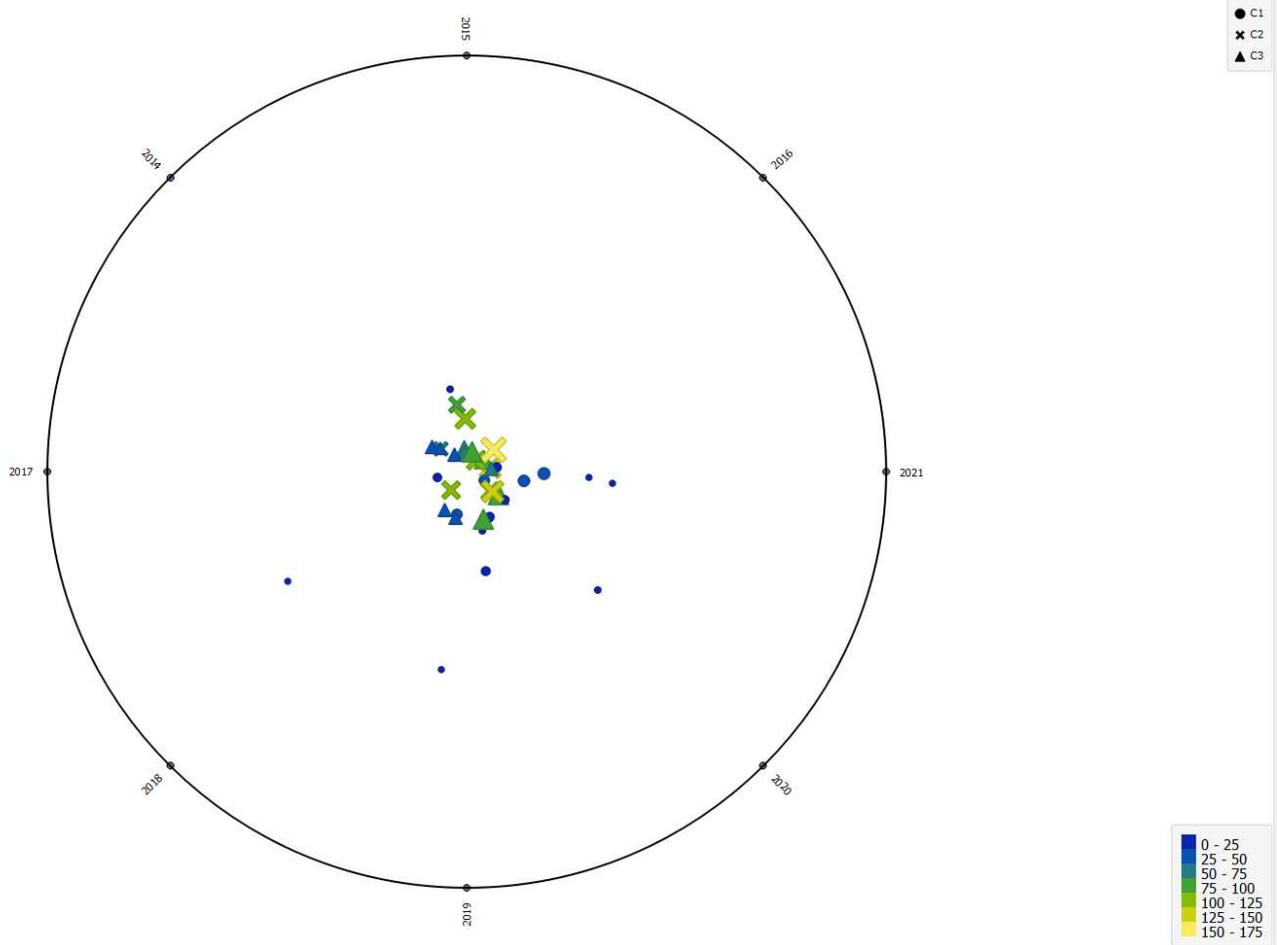
Silhouette scores for different numbers of clusters

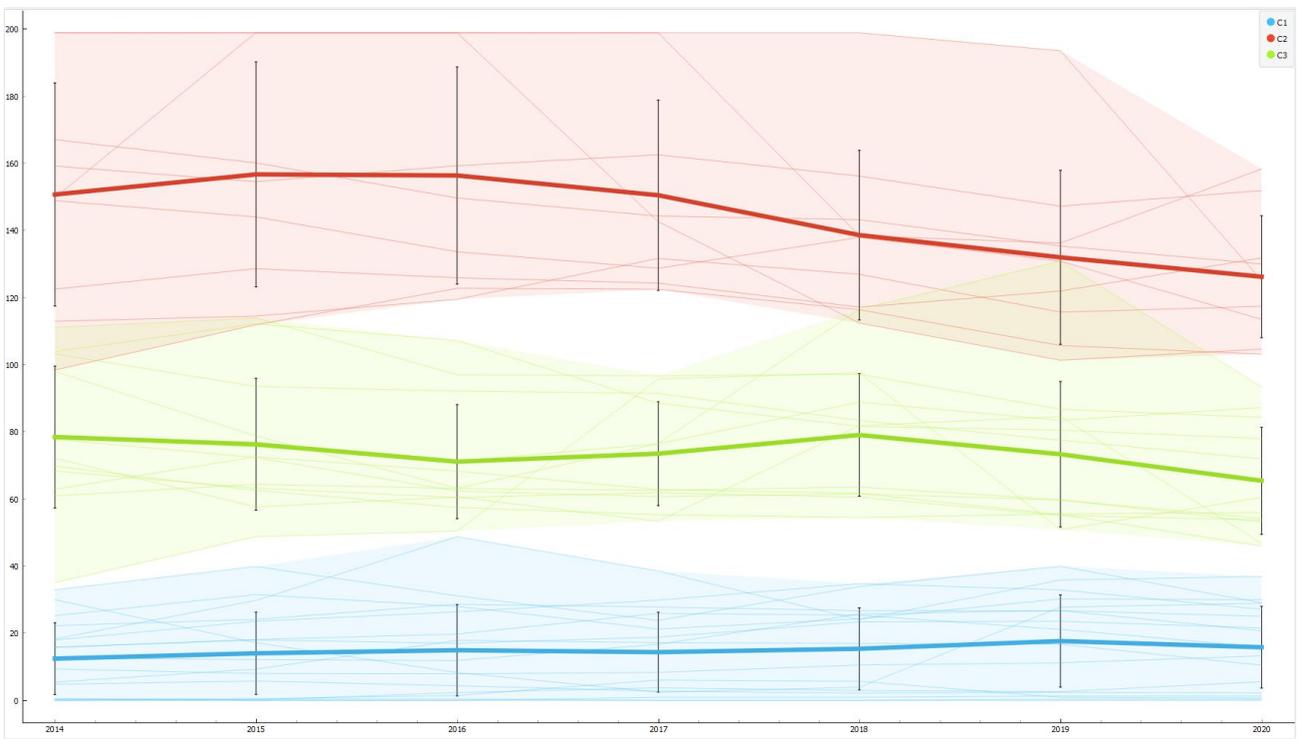
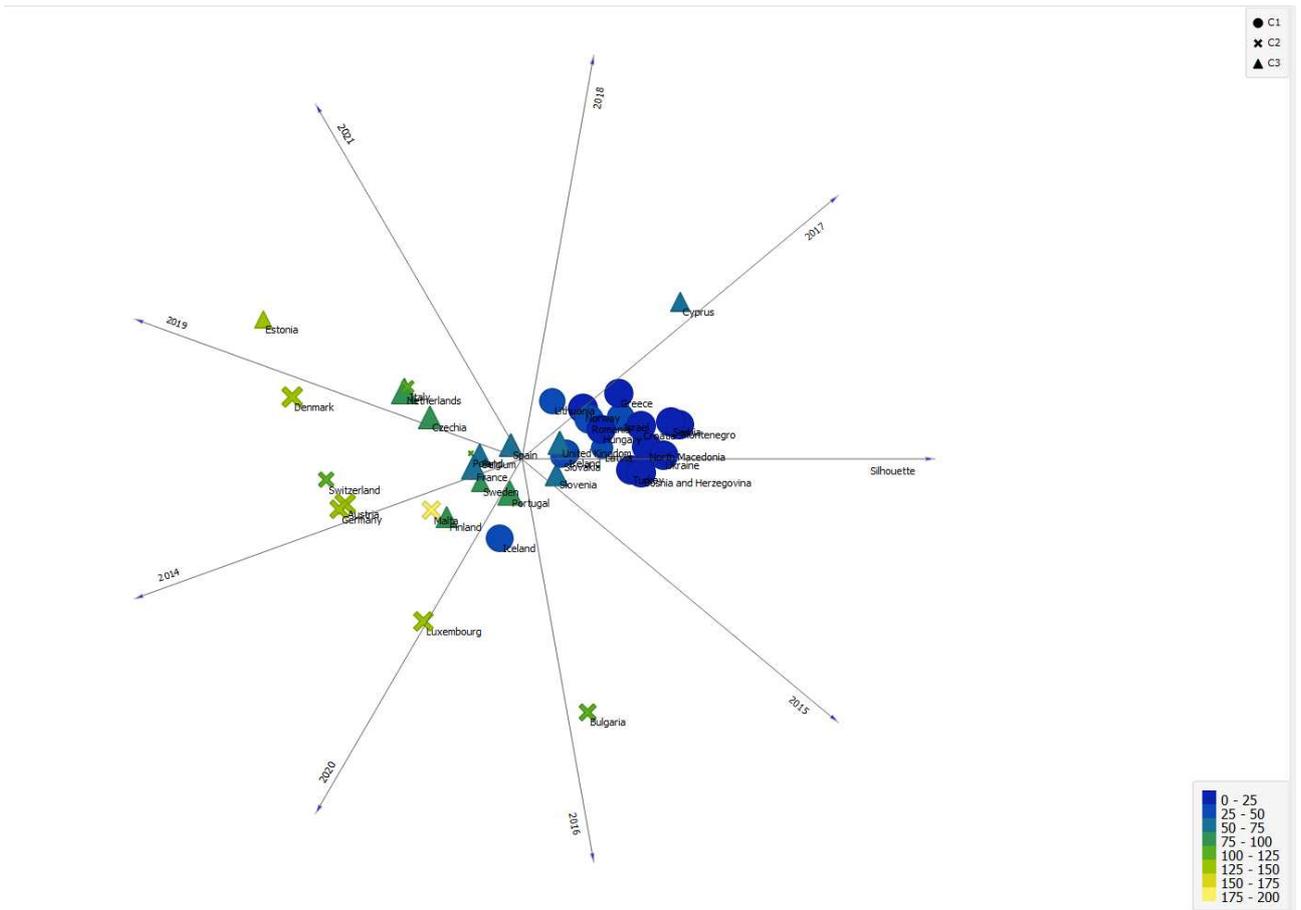
2	0.598
3	0.591
4	0.528
5	0.505
6	0.473
7	0.470
8	0.472
9	0.467
10	0.470
11	0.465
12	0.427
13	0.415
14	0.399
15	0.381
16	0.354
17	0.356

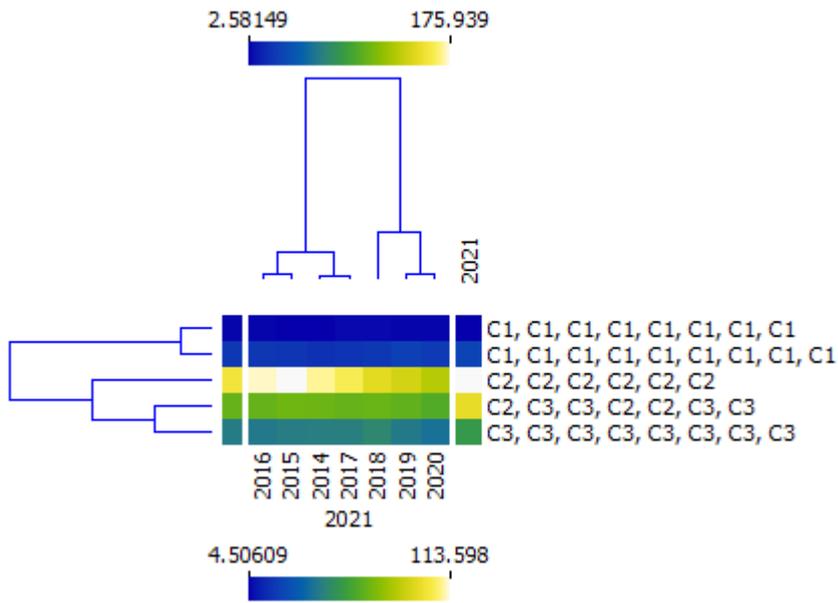












1.3 Machine Learning and Predictions

Results of Machine Learning Algorithms to Predict the Degree of Designs Applications				
	ANN-MULTYLAYER	PNN	Simple Regression Tree	Gradient Boosted Trees
R²	0,8958592781	0,7433889734	0,9290124843	0,9547292895
mean absolute error	0,0670943563	0,1155971707	0,0538746004	0,0424403747
mean squared error	0,0119709814	0,0301184888	0,0062839560	0,0040511874
root mean squared error	0,1094119803	0,1735467913	0,0792714074	0,0636489385
mean signed difference	0,0399276979	0,0465969350	0,0366078813	0,0360836451
	Random Forest	Tree Ensemble	Linear Regression	Polynomial Regression
R²	0,910210074	0,970976971	0,866657781	0,916686131
mean absolute error	0,069906422	0,041486123	0,051828093	0,071303191
mean squared error	0,009282988	0,002901757	0,013723895	0,009116712
root mean squared error	0,096348266	0,053867957	0,117149029	0,095481473
mean signed difference	0,048230153	0,003119281	0,038678825	0,055896804

