The Impact of Patent Applications in the Context of the ESG Model at World Level

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Abstract

In the following article, we estimate the value of Patent Applications-PA in the context of the Environmental, Social and Governance-ESG model at world level. We use data from World Bank for 193 countries in the period 2011-2021. We found that PA is positively associated, among others, to "CO_2 *Emissions*" and "*Mammal Species Threated*", and negatively associated among others to "*Hospital Beds*" and "*Research and Development Expenditures*". Furthermore, we found that at aggregate level PA is negatively associated to each macro component of the ESG model i.e.: Environment, Social and Governance. Furthermore, we have applied eight different machine-learning algorithms for the prediction of the future value of PA. We found that the best predictive algorithm is the Simple Regression Tree in terms of minimization of MAE, RMSE and MSE and maximization of R-squared. The value of PA is predicted to growth by an average of 9.82% for the analysed countries.

Keywords: Analysis of Collective Decision-Making; General; Political Processes: Rent-Seeking; Lobbying; Elections; Legislatures; and Voting Behaviour; Bureaucracy; Administrative Processes in Public Organizations; Corruption; Positive Analysis of Policy Formulation; Implementation.

JEL Codes: D7, D70, D72, D73, D78.

1. Introduction-Research Question

In the following article, we analyse the relationship between patenting and the adoption of ESG-Environmental, Social and Governance model worldwide. The metric analysis, carried out with a mix of regressions and machine learning, is achieved using World Bank's ESG dataset. Technological innovation is an essential variable for the economic development and economic growth of countries and companies. In our analysis, technological innovation is approximated by Patent Applications-PA. At the same time, the adoption of the ESG model is also necessary to allow for the sustainability of production systems both at company and country level. However, it is not clear what the relationships are between

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PA, as an approximation of innovation, and the applications of the ESG approach. In our research hypothesis there is no contrast between PA and ESG. Conversely, the hypothesis is that the ESG model is compatible with technological innovation, approximated by the PA. The positive connection between technological innovation and the ESG model can certainly be demonstrated at a theoretical level, as the very possibility of applying ESG models depends on companies' investment in technological innovation and R&D. The relationship between ESG and I is so connected that it would be necessary to introduce a new variant of the ESG model, i.e. the ESG+I model where I is precisely the technological innovation, approximated by PA. There are various reasons that can lead an ESG model to be compatible with technological innovation. In fact, the application of new technologies can make it possible to develop production and consumption models that are more compatible with the environment, i.e. component E of the ESG model. Furthermore, the new technologies also offer the opportunity to act in improving the sociality, health and education of the population by offering the opportunity to improve the performance of the variable S of the ESG model, through social media, e-health and e-learning. Finally, new technologies can also improve governance through the application of big data and machine learning to the evaluation of public policies.
The article continues as follows: the second section presents a brief analysis of the scientific literature, the third section shows the results of the econometric model, the fourth section discusses the results of the predictive analysis with machine learning algorithms, the fifth section concludes. The appendix presents further data, tables and images elaborated during the analysis.

2. Literature Review

A brief analysis of the scientific literature is presented below which is not intended to be exhaustive but rather to introduce some elements of reflection regarding the relationship between PA and ESG models.

ESG scores, innovations and patent applications. The relationship between ESG models and patenting tends to be positive. The application of ESG models tends to be a driver for pushing companies to apply further technological innovations especially in the green technologies sector. In fact, in general, the most efficient companies tend to be both more innovative and better performing in terms of ESG score. Managers who are more sensitive to the application of ESG principles are also more inclined to support technological innovation and patenting. Furthermore, the need to effectively apply ESG models drives companies to invest more in technological innovation, especially connected to green technologies, to reduce energy costs and increase corporate sustainability. However, the motivations that push companies to invest both in technological innovation and in the application of ESG models are not only ethical and moral. In fact, it is also a matter of economic-financial reasons. In fact, companies that appear to be more dynamic in terms of technological innovation and the ability to apply ESG models are also more likely to obtain financing from specialized funds. Furthermore, the company's image on the market and towards consumers also tends to improve significantly, allowing companies to have positive results in terms of brand value, market power and consumer retention.
There is a positive relationship between ESG rating and green innovations in China [1]. Digital finance is positively associated to ESG performance and green innovation evaluated through patent applications [2]. ESG disclosure has a positive impact on technological innovation in the case of China’s A-share listed companies from 2011 to 2019 [3]. There is a positive relationship between the investment in R&D, patent applications and ESG performance in a set of firms operating in the industrial sector in France, Germany, Italy, Spain, the UK and the USA [4]. High ESG-scores companies innovate sub-optimally

through patenting in USA [5]. Green innovation measured though patenting and ESG performance growth together in a set of A-shared listed companies in Shanghai and Shenzhen from 2011-2019 [6]. European MNES have better ability in respect to US MNEs to invest in R&D in performing ESG model even if they have lower levels of governance in comparison with their counterparts [7]. The application of ESG models improve the ability to introduce innovations in a set of 320 Japanese companies in the period 2008-2016 [8]. There is a positive relationship between the adoption of ESG models and the performance in green innovation for China's A-share listed companies in the period 2009-2021 [9]. There is a positive correlation between patent application and ESG model in a subgroup of 12 countries in a set of 16 nations [10]. There is a positive relationship between the adoption of the ESG model and green innovation in a set of companies listed in the China's Growth Enterprise Market (GEM) [11]. ESG performance and green innovation grew together in Sichuan province in China during the period 2016-2020 [12]. The energy sector shows the presence of a declining relationship between ESG and green patenting i.e. in yet another patent generates a less than proportional increase in the value of ESG score [13]. Firms that apply the ESG model have also good results in improving patenting as showed in a set of A-share listed companies in China in the period 2001-2020 [14]. Managers that have an ESG orientation tend to promote also green innovation and patenting in a set of Chinese listed companies in the period 2010-2019 [15]. The Environmental Cooperation System of Shenzhen-Dongguan-Huizhou Metropolis (ECS-SDHM) has a positive impact in promoting either ESG performance either green corporate innovation [16]. There is a positive relationship between ESG rating and green patenting in a set of firms listed in the Shanghai and Shenzhen Stock Connect [17]. There is a positive relationship between ESG performance and green technological innovation in A-shared listed companies in China [18]. ESG score has a positive impact on green technological innovation for Chinese listed companies during the period 2010-2019 [19]. The ESG model promotes green technological innovation in China [20]. The ESG model has a positive impact on patenting and innovation in high-tech global corporations [21].

ESG, fiscal policies, regulation and green patenting. Tax policies and the creation of regulated markets can improve both the effectiveness of the application of ESG models and the orientation of companies towards patenting. In fact, taxing polluting companies constitutes a powerful incentive to ensure that companies are committed to applying new management and administrative models inspired by the ESG model. It also follows an investment in technological innovation and research and development with the aim of finding methodologies that allow companies to be more sustainable at low cost and maintaining high levels of productivity. The adoption of an environmental protection tax in China has increased either the ESG orientation of firms either the ability of companies to invest in green patenting [22]. Environment Trade System-ETS has a positive impact either on ESG either on green patenting in China [23].

ESG models, patenting and green finance. The possibility for companies to be remunerated and financed using green finance models is a further incentive for companies that are driven either to apply the ESG model either to technological innovation, especially with reference to green technologies. There are positive relationships among ESG models, patenting and green finance in Japan, China and South Korea [24].

Patent applications and SDG. The ESG model is one of the cultural products generated in the context of the SDG-Sustainable Development Goals. Therefore, it is possible to obtain similar results, in terms of relationship with technological innovation, both in the case in which the companies use the ESG model and in the case in which the companies are inspired by the SDG principles. There is a positive relationship between SDG-Sustainable Development Goals and the ability of MNEs-Multinational Enterprises to promote patent applications in the green economy [25].

Startups, ESG models and patent applications. Start-ups are very sensitive to the application of ESG models especially for purposes related to the opportunity to acquire funding. In this sense, start-ups have many financial incentives to combine the application of the ESG model with technological innovation. Startups that are ESG compliant have better patent utilization [26].

Furthermore, it must be considered that alongside the scientific literature there are many patents that have been developed from an ESG perspective, such as for example in the case of [27] .

3. Econometric Model for the Estimation of the Value of Patent Applications

In the following analysis, we have considered an econometric model for estimating the value of Patent Applications in the context of the ESG model with World Bank data. Specifically, we analysed 193 countries for a period between 2011 and 2021. The data were analysed with the following econometric techniques, i.e. Panel Data with Random Effects, Panel Data with Fixed Effects, Pooled OLS. In particular, we have divided the entire dataset into three different components, each for each element of the ESG model. We then carried out the regressions of PA on each sub-group of variables, i.e. the sub-group of E, S, and G respectively. Finally, we obtained the econometric results reported in the appendix. To summarize the value of the econometric results, we considered the average value of the coefficients obtained respectively with the Panel Data Random Effects, Panel Data with Fixed Effects and Pooled OLS models.

The impact of PA on the E-Environment component in the ESG model. Below we have analysed the application of the variable PA in the context of the variables related to the E components within the ESG model. In particular, we have estimated the following equation:

$$\boldsymbol{E-Component}: \boldsymbol{PatentApplications_{it}} = \boldsymbol{\alpha_1} + \boldsymbol{\beta_1}(\boldsymbol{CO2E})_{it} + \boldsymbol{\beta_2}(\boldsymbol{EPCS})_{it} + \boldsymbol{\beta_3}(\boldsymbol{MST})_{it}$$

Where $i = 193$ and $t = [2011; 2021]$.

We found that Patent Applications is positively associated to:

- *CO2E:* carbon dioxide emissions are those deriving from the combustion of fossil fuels and the production of cement. They include carbon dioxide produced during the burning of solid, liquid and gaseous fuels and gas flaring. There is a positive relationship between the value of PAs and the value of CO2E. In fact, the countries that produce the most patents worldwide are also the countries that have the highest levels of CO_2 emissions. In fact, we can see that many of the countries that have high levels in terms of CO_2 also have very high values in terms of PA. Among these, it is necessary to consider, for example, the United States which did not total around 269,586 patent applications in 2020 with a value of CO2E equal to an amount of 13.03 However, there are also other countries that have high levels of PA and also CO2E such as for example

China with an amount of 1,344,817 of PA and 7.75% of CO2E, Japan with values respectively equal to 227,348 and 8.03, South Korea with 180,477 PA and 10.99 CO2E, the Russian Federation with 180,477 PA and 10.99%. The positive relationship between PA and CO2E might seem paradoxical. In fact, generally the supporters of the theory of human capital highlight the fact that investment in human capital is more compatible with the environment. However, it must also be considered that PA is a variable connected to the size of the industrial economy. In fact, they are generally the large industrial groups to propose and implement the patents. Such industrial groups tend to have a very negative impact in terms of the environment. The positive relationship between PA and CO2E can therefore be better understood considering that the firms that have the greatest interest in patenting are precisely those firms engaged in highly polluting industrial sectors [28].

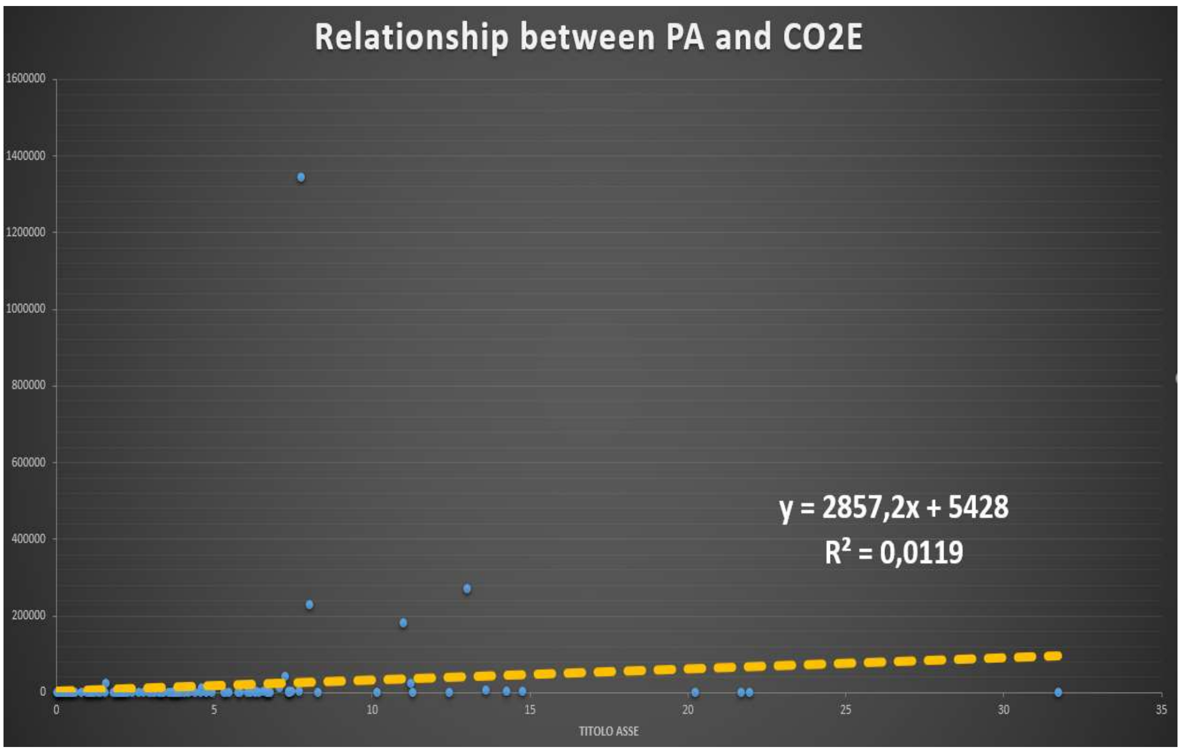

Figure 1. Relationship between PA and CO2E.

- *EPCS:* calculates the percentage of electricity obtained using coal. Electricity sources refer to the inputs used to generate electricity. Coal is all coal and lignite, both primary fuels (including hard coal and lignite-lignite) and derived fuels (including proprietary fuels, coke oven coke, gas coke, coke oven gas and blast furnace gas). Peat is also included in this category. There is a positive relationship between the PA value and the EPCS value. This relationship is because countries that have high levels of patents also tend to have highly polluting industrial systems both from the point of view of industrial production and from the point of view of energy production. In fact, if we consider the top ten countries by value of PA, it turns out that these countries also have a significant percentage of energy produced with coal. Relevant cases in this sense are: China with a PA value equal to 968,252 units and an EPCS value equal to 70.30%, the United States with a PA value equal to 288,335 and an EPCS amount equal to an value 34, 23%, Japan with 258,839 in terms of PA and 33.15% in terms of EPCS, South Korea with a value of 167,275 in terms of PA and a value of 43.07 in terms of EPCS, Germany with a value of 47,384 in terms of PA and 44.26% in terms of EPCS, Russia with a value of 29,269 in terms of PA and an EPCS value equal to an amount of 14.82%, United Kingdom with a value of 14,867 in PA and EPCS equal to 22.80%, France with a value of 14,306 in terms of PA and an EPCS value equal to 2.16%, India with PA equal to 12,579 and EPCS equal to 75.30%, Turkey with 5,352 in terms of PA and 29.09% in terms of EPCS. It follows therefore that many countries that have invested significantly in human capital still have a very significant pollution structure in the production of electricity.

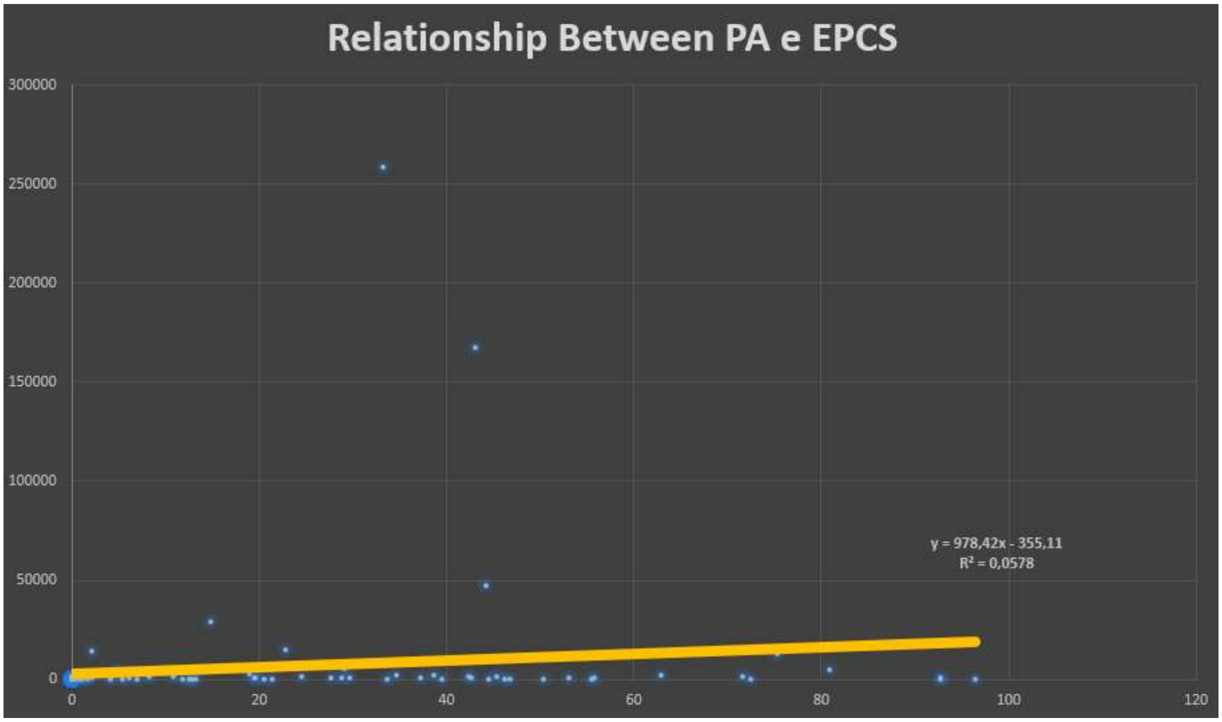

Figure 2. Relationship between PA and EPCS at world level.

- *MST:* considers mammal species are mammals excluding whales and porpoises. Threatened species are the number of species classified by the IUCN as threatened, vulnerable, rare, undetermined, endangered or insufficiently known. There is a positive relationship between the MST value and the PA value. Specifically, 7 of the top 10 countries by PA value also have an MST value above the average, i.e.: China with 1,393,815 and a MST value equal to an amount of 73, United States with a PA amount equal to 285,095 and an MST value equal to a value of 40, Japan with a PA value equal to a value of 253,630 units and an MST value equal to 29, Russian Federation with a PA value equal to an amount of 24,926 units and a value of MST equal to a value of 34, India with a PA value equal to an amount of 16,289 units and an MST value equal to 93, Iran with a PA value equal to 11,908 units and an MST value equal to a value of 18.

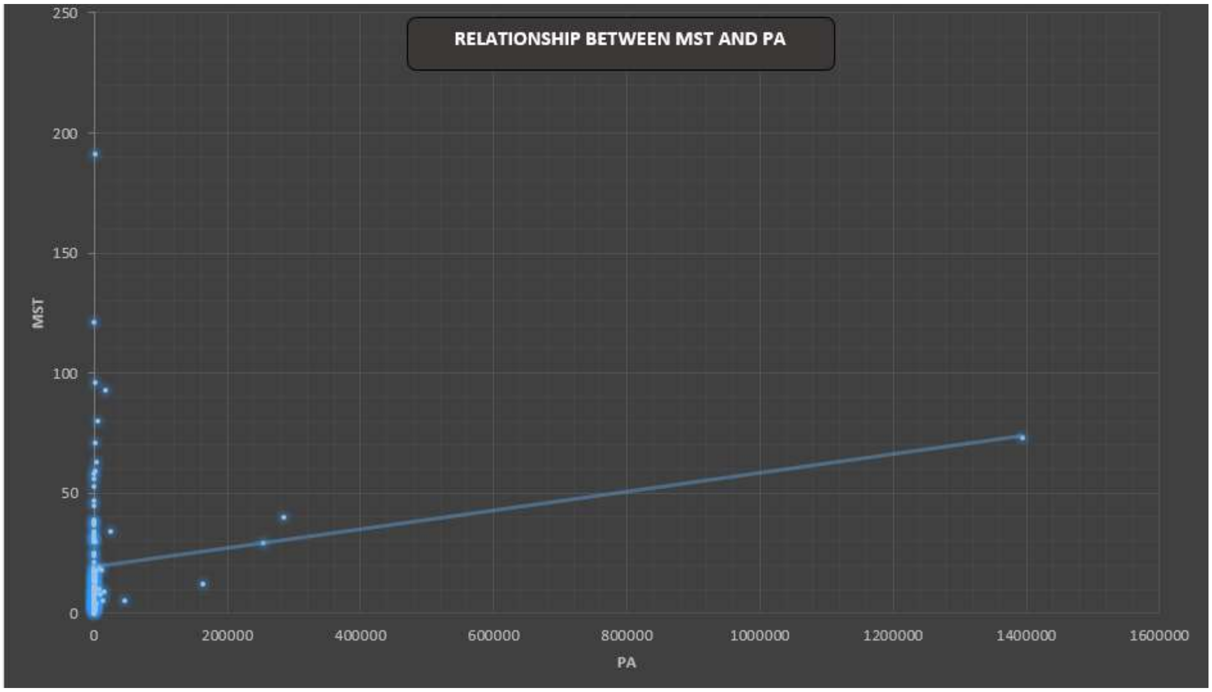

Figure 3. Relationship Between MST and PA.

Overall, we can therefore note that there is a negative relationship between the development of PA and the green variables i.e. the E-Environmental component of the ESG model. In fact, the development of patent applications tends to be positively connected with the emission of CO_2, with the growth of the percentage of electricity produced from coal, and with the presence of a risk of extinction for mammals at the country level. It follows that countries that have the highest levels of PA also are countries that have insufficient economic policies in terms of environmental protection. However, it must be considered that most of the patents are made in China and the United States, i.e. two countries that have developed a certain scepticism towards green economic policies. However, it is probable that in the future the value of the relationship between PA and environmental variables will tend to become positive following the introduction of new green-oriented technologies and thanks to the application of economic policies that are able to reduce the environmental impact of industrial production. Certainly, it is the USA and China that will have to improve the environmental sustainability of their production systems also to guide a deeper industrial green revolution at world level.

The impact of PA on the S-Social component in the ESG model. Below we analyse the impact of PA within the S-Social component in the ESG model. Specifically, we estimated the following equation, i.e.:

$$\boldsymbol{S-Component}: \boldsymbol{PatentApplications_{it}} = \boldsymbol{a_1} + \boldsymbol{b_1}(\boldsymbol{LEB})_{\boldsymbol{it}} + \boldsymbol{b_2}(\boldsymbol{LR})_{\boldsymbol{it}} + \boldsymbol{b_3}(\boldsymbol{HB})_{\boldsymbol{it}}$$

Where $\boldsymbol{i = 193}$ and $\boldsymbol{t = [2011; 2021]}$.

We found that the level of PA is negatively associated to the level of:

- *LR:* adult literacy rate is the percentage of people aged 15 and older who can read and write by understanding a short simple statement about their daily lives. There is a negative relationship between the LR value and the PA value. This relationship indicates that the fact that a country is at the forefront in the production of patents does not necessarily imply a medium-high cultural level of the population. This proposition might seem counterfactual, however, it is necessary to consider that the school-institutional system that is required for the formation of the population is divergent with respect to the development of university and post-graduate systems necessary to acquire the professional knowledge aimed at creating patents. In fact, even countries where there are serious problems of mass education for the population still have high levels of patents. To demonstrate that it is possible to create a scientific and intellectual elite even within countries that remain substantially backward from a cultural point of view.

- *HB:* include inpatient beds available in public, private, general, and specialized hospitals and rehabilitation centres. In most cases, beds for both acute and chronic care are included. There is a negative relationship between the HB value and the PA value. In fact, if we calculate the average of the HB value, it turns out that on average worldwide there are about 3.9 beds per 1000 inhabitants. However, considering the top 15 countries by PA value, it appears that the HB value is lower than the average value in the following countries, i.e.: United States with 2.87, Iran with 1.56, India with 0.53, United Kingdom with 2.54, Italy with 3.18, Turkey with 2.81, Brazil with 2.09, and Canada with 2.53. It follows therefore that many countries that invest significantly in the value of PA have a still reduced HB value compared to the world average. In particular, it is mainly some western countries that have a reduced level of HB as in the case of the USA, UK, Italy and Canada. These countries show that it is possible to invest successfully in the creation of an efficient system in the production of PA even having a reduced health expenditure in terms of HB.

We also found that the level of PA is positively associated to the level of:

- *LEB*: indicates the number of years a newborn would live if the prevailing patterns of mortality at the time of its birth remained the same throughout life. There is a positive relationship between the LEB value and the PA value. Countries that have a high LEB level also have a high PA value. Life expectancy is positively connected with the growth in the value of patents. In particular, life expectancy in China is equal to an amount of 78 years, in the United States it is 76.98 years, in Japan it is 84.56 years, in South Korea it is 83.43 years, in Germany 81.04 years, in Russia 71.34 years, in India with 70.15 years, France with 82.18 years, United Kingdom with 80.35 years, Iran with 74.83 years, Italy with 82.20 years, Turkey with 75.85 years old. However, this positive relationship is due to general factors external to the patent issue. Specifically, the value of patents and life expectancy tend to grow as a generalized effect of globalization and international trade. In other words, both the growth of patents and the growth in the value of life expectancy are positively connected with the development of globalization and could obviously also suffer the negative consequences of a reduction in the intensity of international trade.

If we consider the impact of the PA on the S-Social component of the ESG model, the n the presence of a substantially negative trend is evident. That is, the negative impact of the LR and HB variables on PA exceeds the positive impact of LEB on PA, considering the aggregated average values. Countries that have high levels of public administration may also be countries with a low capacity to generate positive outcomes in social terms. In fact, PA can grow even in the reduction of LR and HB, i.e. without having positive effects either on the trend of the general cultural level, or on the provision of hospital services that are in the interest of citizens. Furthermore, at the aggregate level, the positive impact of LEB on the

PA is due to exogenous factors, and in particular to the growth of globalization and widespread economic development at the regional level in countries with low per capita income.

The impact of PA on the G-Governance component in the ESG model. Below we consider the impact of the PA variable within the G-Governance component of the ESG model. Specifically, we estimated the following equation:

$$\boldsymbol{G-Component: PatentApplications_{it} = a_1 + b_1(GDPG)_{it} + b_2(IUI)_{it} + b_3(RFTM)_{it} + b_4(SLRI)_{it} + b_5(RDE)_{it}}$$

Where $\boldsymbol{i = 193}$ and $\boldsymbol{t = [2011; 2021]}$.

We found that the level of PA is positively associated to:

- *RFTM:* is the percentage of the population aged 15 and over who are economically active: all people who provide work for the production of goods and services during a given period. The ratio of female to male labour force participation rate is calculated by dividing the female labour force participation rate by the male labour force participation rate and multiplying by 100. We can see that the value of PA is positively associated with the value of RFTM extension. That is, the countries in which women participate more in the labour force are also the countries in which the level of public administration tends to increase. In fact, we can see that the countries that have higher levels of PA also have high levels of RFTM. In particular, we can note that within the ranking of the top ten countries by PA value, there are at least eight that have an RFTM value higher than the world average. The average value of RFTM is equal to an amount of 71.65%. Below we indicate the countries that have high levels of PA and RFTM, namely: China has a PA value equal to 1,344,817 and a RFTM value equal to a value of 83.58, the United States with 269,586 PA and a value of RFTM equal to 82.99%, Japan with a PA value of 227,348 with an RFTM value of 74.51%, South Korea with a PA value of 180,477 with an RFTM value of 73, 10%, Germany with a PA value equal to an amount of 42,260 units and an RFTM value equal to an amount of 84.25%, Russian Federation with a PA value equal to an amount of 23,759 units and an amount of 78 .54% of RFTM, France with a PA value of 12,771 and an RFTM value of 86.08%, United Kingdom with an RFTM value of 11,990 and a PA value of 87.25 [29].

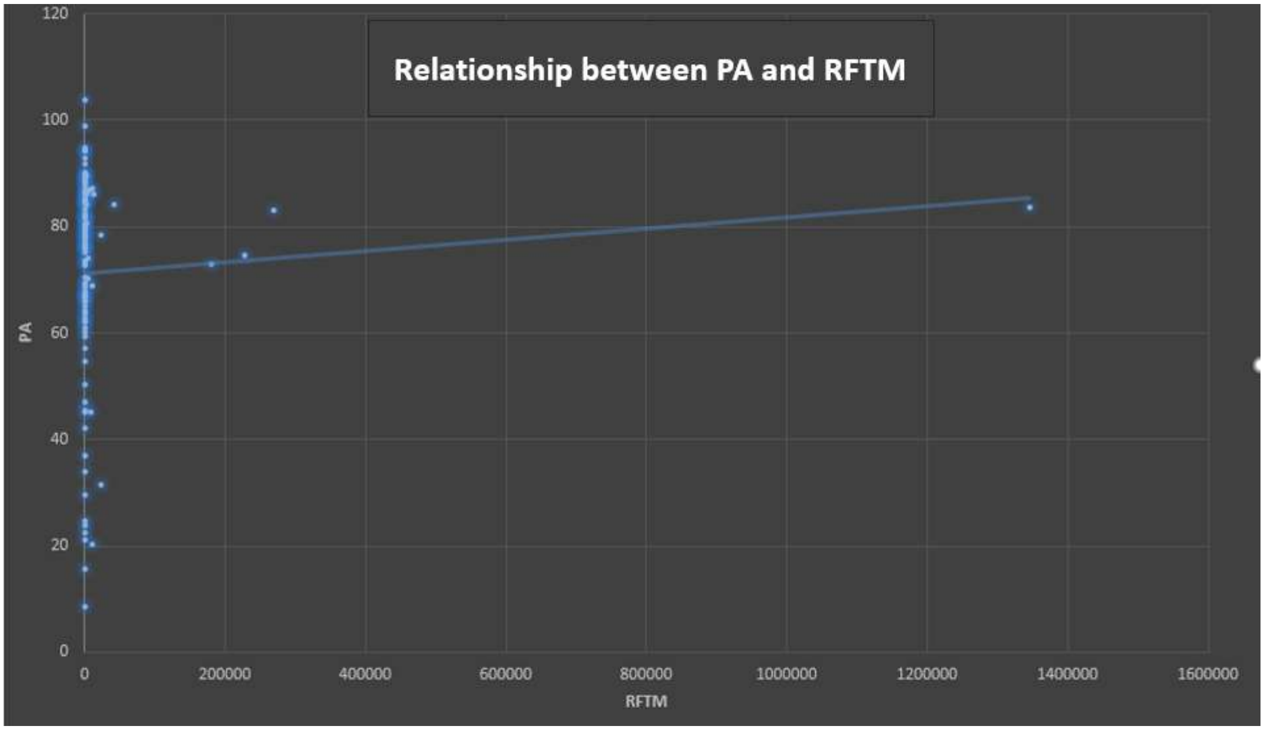

Figure 4. Relationship between PA and RFTM.

- *SLRI*: measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and creditors and thereby facilitate lending. The index ranges from 0 to 12, with higher scores indicating these laws are better designed to expand access to credit. SLRI has a positive relationship with BP value. That is, with the growth of the value of PA, the value of SLRI also grows. However, it must be considered that the value of SLRI tends to be quite low i.e. equal to a value of 0.006 units on average. It follows that the impact of SLRI in the determination of PA, however positive it may be, tends to be marginal from the point of view of the overall impact, with a value of the coefficient very close to zero in the Panel Data regression with Fixed Effects, in Panel Data with Random Effects and Pooled OLS.

We also found that the level of PA is negatively associated to:

- *GDPG:* Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2015 prices, expressed in US dollars. GDP is the sum of the gross value added of all resident producers in the economy plus any taxes on products and minus any subsidies not included in the value of products. It is calculated without making any deductions for depreciation of manufactured assets or depletion and degradation of natural resources. The GDPG value is negatively correlated with the PA value. Indeed, we can see that many of the countries that have a high PA value also have a low or negative GDPG value. In fact, if we consider the 2020 data, we can see that the United States has a number of PAs equal to a value of 269.58 units and a GDPG value equal to a value of -2.77%, Japan has a PA value equal to a amount of 227.35 units and a GDPG value equal to an amount of -4.28%, South Korea has a PA value equal to an amount of 180.50 units and a GDPG value equal to an amount of -0.71% , Germany has a value of 42.30 units and a GDPG value equal to an amount of -3.70%, Russia has a PA value equal to 23.80 and a GDPG value equal to an amount of -2.65%, India has a PA value equal to an amount of 23.80 and a GDPG value equal to an amount of -5.83%, France has a PA value equal to an amount of 12.80 units and a GDPG value equal to an amount of 7.78%, UK has a value of 11.99 units and a GDPG equal to -11.03%. However, it must be considered that many of these countries had a negative GDPG value, in 2020, due to the negative consequences of the Covid 19 pandemic crisis. However, the negative relationship between PA and GDPG must also be considered in a long-term perspective. In fact, since the countries that have high PA levels are also Western countries, which also have very low GDP growth rates, there is a negative relationship between PA and GDPG [30].

- *IUI:* Internet users are individuals who have used the Internet (from any location) in the last 3 months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV etc. There is a negative relationship between the BP value and the IUI value. Countries that have higher levels of internet access also have lower levels of patent applications. Indeed, if we consider the top 10 countries by value of IUI we can see that the same countries have quite low PA levels. In fact, considering the top ten countries by IUI value in 2020, we can see that the same countries have reduced values in terms of PA, namely: United Arab Emirates with an IUI value of 100.00 and a PA value of 39 , Bahrain with 99.67% and PA equal to 7, Qatar with 99.65% and PA equal to 81, Iceland with 99.53% and PA equal to 44, Luxembourg with IUI equal to 98.82 and PA equal to 129 , Saudi Arabia with 97.86% IUI and 1294 BP, Norway with 97% and 880, Denmark with 96.55 and 1261, South Korea with 96.51 IUI and 180,477 BP, Australia with 96.39 IUI at 2368 PA. The only country in the IUI top ten that also has a high PA value is South Korea [31].
- *RDE*: is the gross domestic expenditure on research and development (R&D), expressed as a percentage of GDP. They include both capital and current expenditures in the four main sectors: Enterprise, Government, Higher Education and Private Non-Profit. R&D covers basic research, applied research and experimental development. The RDE value is negatively associated with the PA value. The PA value should be positively associated with the RDE value. However, in this case the data appear to be counterfactual and the RDE value is negatively associated with the PA value [32].

The Impact of Patent Applications on ESG Components			
	Patent Applications	*PA*	Patent applications are worldwide patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office for exclusive rights for an invention--a product or process that provides a new way of doing something or offers a new technical solution to a problem. A patent provides protection for the invention to the owner of the patent for a limited period, generally 20 years [33].

E	*CO2 Emissions*	*CO2E*	Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring [34].
	Electricity Production from Coal Sources	*EPCS*	Sources of electricity refer to the inputs used to generate electricity. Coal refers to all coal and brown coal, both primary (including hard coal and lignite-brown coal) and derived fuels (including patent fuel, coke oven coke, gas coke, coke oven gas, and blast furnace gas). Peat is also included in this category [35].
	Mammal Species Threated	*MST*	Mammal species are mammals excluding whales and porpoises. Threatened species are the number of species classified by the IUCN as endangered, vulnerable, rare, indeterminate, out of danger, or insufficiently known [36].
S	*Life Expectancy at Birth*	*LEB*	Life expectancy at birth indicates the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life [37].
	Literacy Rate	*LR*	Adult literacy rate is the percentage of people ages 15 and above who can both read and write with understanding a short simple statement about their everyday life [38].
	Hospital Beds	*HB*	Hospital beds include inpatient beds available in public, private, general, and specialized hospitals and rehabilitation centers. In most cases, beds for both acute and chronic care are included [39].
G	*GDP Growth*	*GDPG*	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2015 prices, expressed in U.S. dollars. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources [40].
	Individuals Using the Internet	*IUI*	Internet users are individuals who have used the Internet (from any location) in the last 3 months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV etc [41].
	Ratio of Female to Male Labor Force Partecipation Rate	*RFTM*	Labor force participation rate is the proportion of the population ages 15 and older that is economically active: all people who supply labour for the production of goods and

			services during a specified period. Ratio of female to male labour force participation rate is calculated by dividing female labour force participation rate by male labour force participation rate and multiplying by 100 [42].
	Strenght of Legal Right Index	*SLRI*	Strength of legal rights index measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders and thus facilitate lending. The index ranges from 0 to 12, with higher scores indicating that these laws are better designed to expand access to credit [43].
	Research and Development Expenditures	*RDE*	Gross domestic expenditures on research and development (R&D), expressed as a percent of GDP. They include both capital and current expenditures in the four main sectors: Business enterprise, Government, Higher education and Private non-profit. R&D covers basic research, applied research, and experimental development [44].

4. Machine Learning and Predictions for the Estimation of the Future Value of PA

In the following analysis, we compare eight different machine-learning algorithms for predicting the future value of PA. The algorithms have been evaluated based on their ability to maximize R-squared and minimize Mean Average Error-MAE, Mean Squared Error-MSE, Root Mean Squared Error-RMSE based on the following formulas:

- $\boldsymbol{R^2 = 1 - \frac{SumSquaredRegression}{TotalSumOfSquares} = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)(y_i - \bar{y}_i)}}$
- $\boldsymbol{MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} = \frac{\sum_{i=1}^{n} |e_i|}{n}}$
- $\boldsymbol{MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)\left(Y_i - \hat{Y}_i\right)}$
- $\boldsymbol{RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)(\hat{y}_i - y_i)}}$

The algorithms have been classified according to their ability to maximize the R-squared and to minimize the statistical errors, i.e. MAE, MSE, and RMSE. A ranking was created for each statistical indicator. The ranking of the algorithms in the various rankings has been added up. The algorithm that reported the lowest value within the set of rankings considered is considered the best predictor algorithm. The algorithms were trained using 80% of the data while the remaining 20% was used for prediction. The following ordering of the clusters is therefore identified, i.e.:

- Simple Regression Tree with a payoff value equal to 4;
- Gradient Boosted Trees with a payoff value of 7;
- Tree Ensemble Regression with a payoff value of 12;
- Random Forest Regression with a payoff value of 13;
- ANN-Artificial Neural Network with a payoff value of 16;

- Polynomial Regression with a payoff value of 19;
- Linear Regression with a payoff value equal to 22;
- PNN-Probabilistic Neural Network with a payoff value of 26.

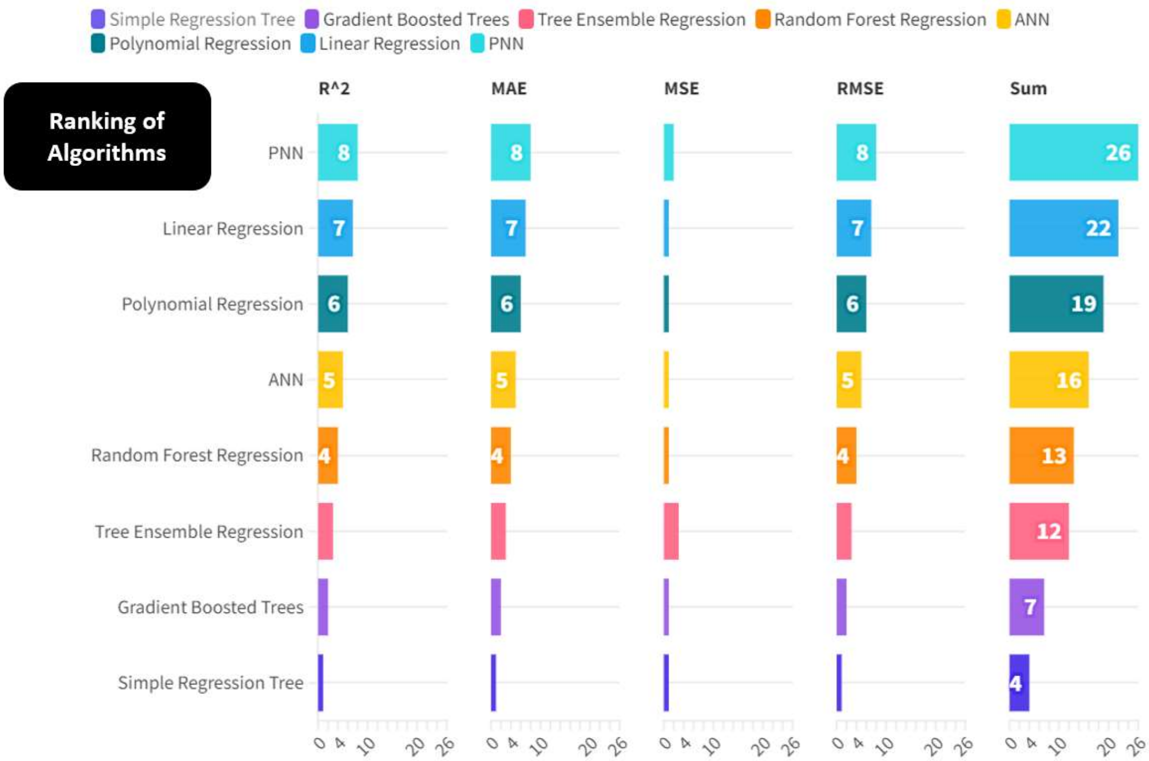

Figure 5. Ranking of algorithms based on their ability to maximize R-Squared, and minimize MAE, MSE and RMSE.

It follows that based on the proposed analysis the most relevant algorithm for the prediction is the Simple Regression Tree. Applying the Simple Regression Tree, it is possible to efficiently predict the future value of PA. Specifically we divide the set of countries for which we have a prediction into two categories i.e. winning countries and losing countries. By winning countries, we mean the set of countries for which a growth in the value of PA is predicted. By losing countries, we mean the countries for which a reduction in the value of PA is predicted.

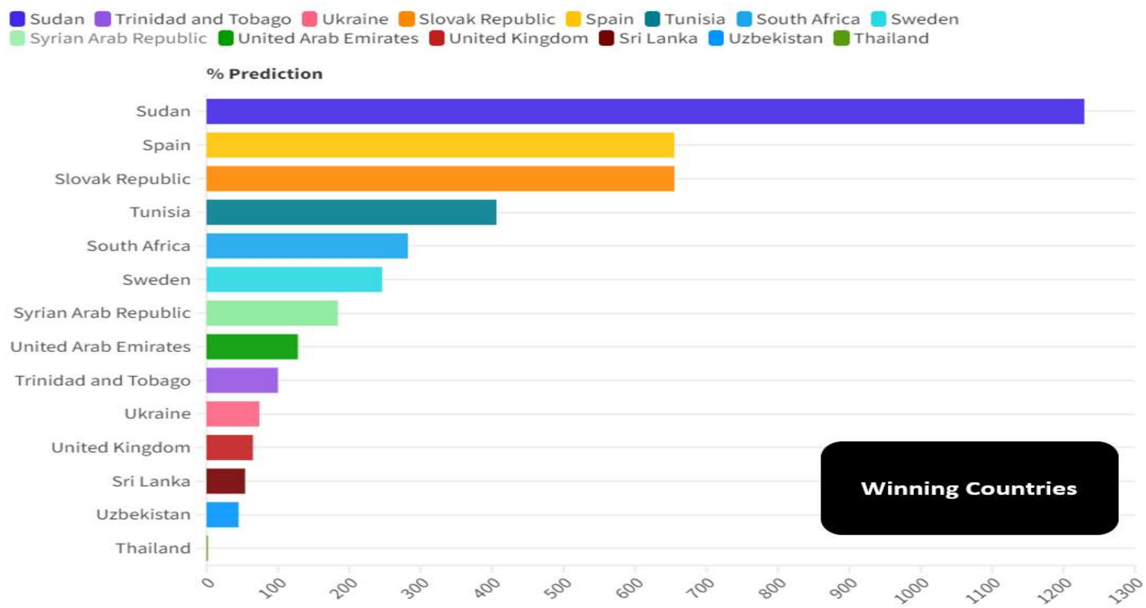

Figure 6. Winning countries based on the prediction with Simple Regression Tree.

Winning countries. The countries for which a growth in the value of PA is predicted are indicated below: Sudan with a value of +122.9%, Trinidad and Tobago with a value of +100.00%, Ukraine with a value of +74 .00%, Slovakia and Spain with a value of +65.5%, Tunisia with a growth of +40.6%, South Africa with a value of +28.2%, Sweden with a growth of +24.6%, Syrian Arab Republic with a growth of +18.4%, United Arab Emirates with a value of +12.8%, United Kingdom with an amount of +6.5%, Sri Lanka with a value of +5.4% , Uzbekistan with a growth of +4.5%, Thailand with +2.0%.

Losing countries. There are countries that are losing countries or countries for which a reduction in the value of PA is expected. These countries are: United States with -15.7%, Switzerland with -18.2%, Saudi Arabia with -24.4%, Zambia with -25.00%, Yemen Rep. with -26.7%, Singapore with -29.1%, Uganda with -30.8%, St. Lucia with -33.3%, Serbia with -34.8%, Vietnam with -37.8%, Turkey with -49.4%.

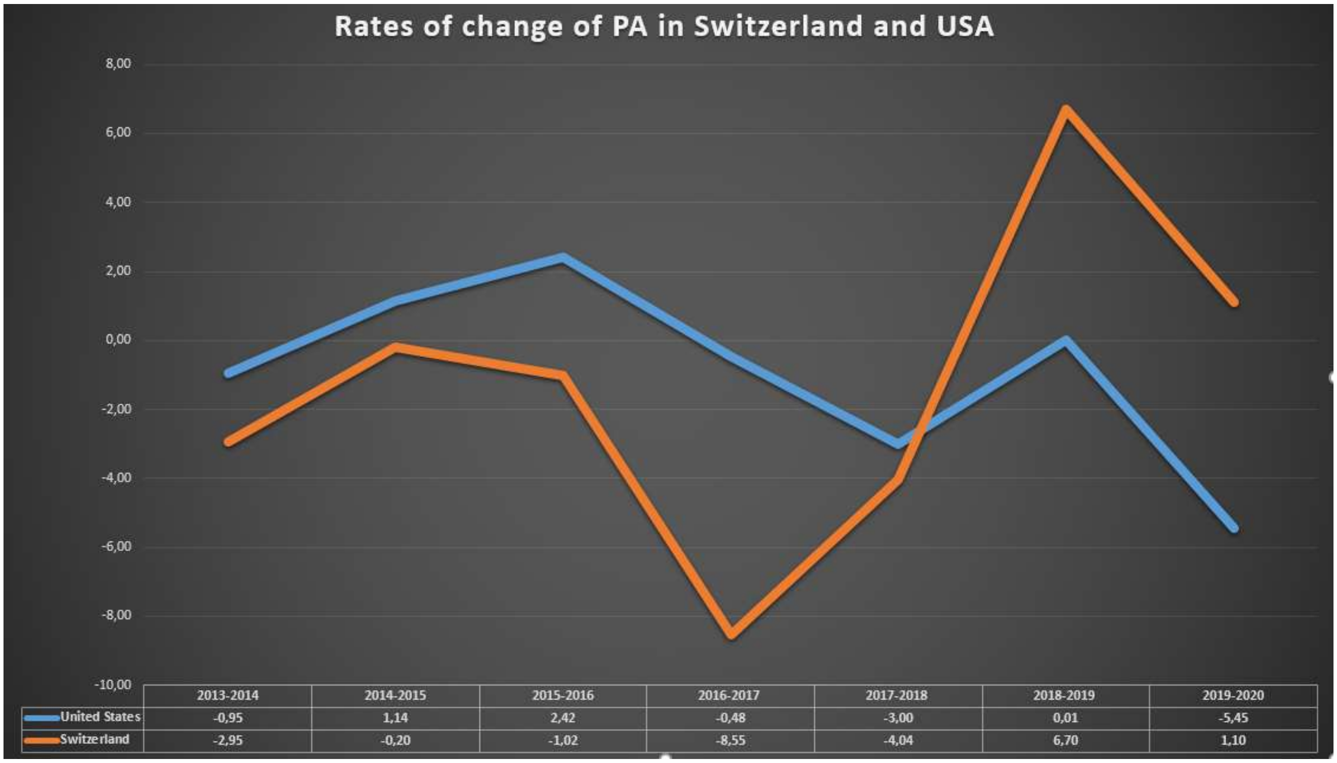

Figure 7. Rates of Change of PA in Switzerland and USA.

In this sense, it is necessary to consider that the prediction for the USA and Switzerland could be wrong. The prediction of a reduction in the PA value for Switzerland and the USA could simply be the projection by the algorithm of a decreasing trend present in the data, as indicated in Fig. 7. In fact, it is highly probable that for these countries, on the contrary, there will be a growth in the value of PA, above all because of the friction between the USA and China on the subjects of scientific research and technology. In fact, the possibility by the USA and in the broad sense of Western countries to increase their competitive capacity against China will require a further investment in the knowledge economy and in technology, which can also be measured through the growth of patents.

Figure 8. Losing countries based on the prediction with Simple Regression Tree.

5. Conclusions

In this article, we have estimated the value of PA in the context of the ESG model worldwide. We have used data from the World Bank's ESG database for 193 countries over the period 2011-2021. We have analysed the impact of PA on each of the three components of the ESG model, namely E-Environment, S-Social, and G-Governance. The aggregated results show that the value of PA tends to be negatively associated with both the E-component, the S-component and the G-component. However, these relationships are significantly affected by the role of China and the USA, which are the leading countries in terms of PA and which have medium-low values in terms of ESG. We then compared eight machine-learning algorithms to predict the future value of PA. The algorithms have been evaluated according to the ability to maximize R-squared and to minimize MAE, RMSE and MSE. The results show that the Simple Regression Tree algorithm is the best algorithm for the prediction and that the future value of PA is expected to grow by an average of 9.82% for the analysed countries.

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7. Declarations

Data Availability Statement. The data presented in this study are available on request from the corresponding author.

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Declaration of Competing Interest. The authors declare that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication.

Software. The authors have used the following software: Gretl for the econometric models, Orange for clusterization and network analysis, and KNIME for machine learning and predictions. They are all free version without licenses.

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8. Appendix

Lists of Acronyms	
Acronym	**Meaning**
SDG	Sustainable Development Goals
ESG	Environmental, Social and Governance
MNEs	Multinational Enterprises
ECS-SDHM	Environmental Cooperation System of Shenzhen-Dongguan-Huizhou Metropolis
ETS	Environment Trade System
WB	World Bank
PA	Patent Applications
CO2E	CO_2 Emissions
EPCS	Electricity Production from Coal Sources

MST	Mammal Species Threated
LEB	Life Expectancy at Birth
LR	Literacy Rate
HB	Hospital Beds
GDPG	GDP Growth
IUI	Individuals Using the Internet
RFTM	Ratio of Female to Male Labour Force Participation Rate
SLRI	Strength of Legal Right Index
RDE	Research and Development Expenditures
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
MAE	Mean Average Error
R^2	R-squared
ANN	Artificial Neural Network
PNN	Probabilistic Neural Network

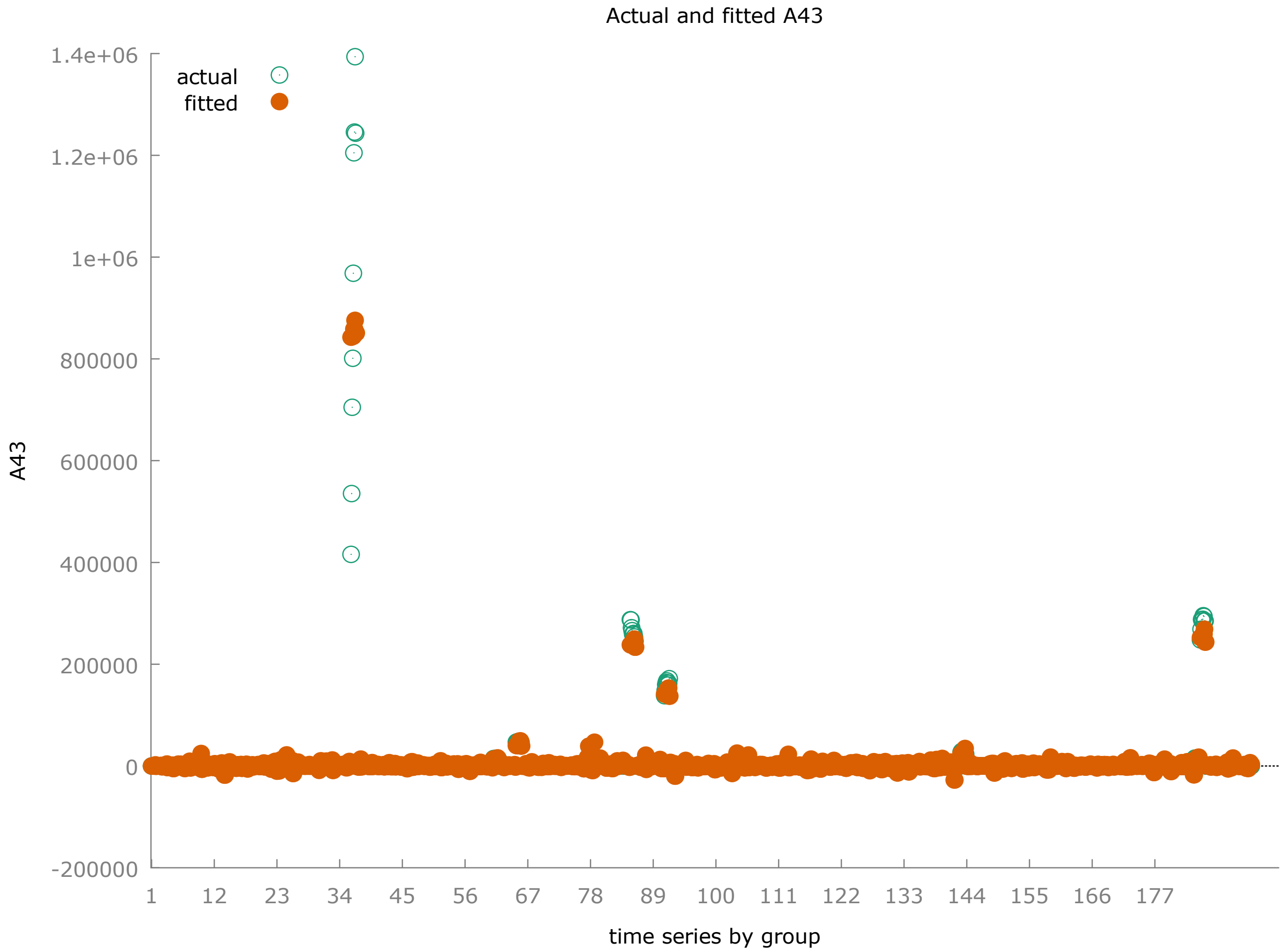
References by Themes	
Themes	**References**
ESG scores, innovations and patent applications	[1], [2], [3], [4], [5], [6], [7], [8] , [9], [10], [11], [12], [13] , [14], [15], [16], [17], [18], [19], [20], [21]
Patent applications and SDG	[25]
Startups, ESG models and patent applications	[26]
ESG models, patenting and green finance	[24]
ESG, fiscal policies, regulation and green patenting	[22], [23]

List of Variables and Average Value of the Regressions	
Variables	*Average Value*
CO_2 Emissions	1203,103
Electricity Production from Coal Sources	64,904
Mammal Species Threated	386,479
Life Expectancy at Birth	0,074
Literacy Rate	-0,025
Hospital Beds	-0,947
GDP Growth	-0,069

Individuals Using the Internet	-0,017
Ratio of Female to Male Labor Force Partecipation Rate	0,081
Strength of Legal Right Index	0,006
Research and Development Expenditures	-1,527

E-COMPONENT

Model 93: Fixed-effects, using 1930 observations					
Included 193 cross-sectional units					
Time-series length = 10					
Dependent variable: A43					
	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	5816.30	1228.60	4.734	<0.0001	***
A11	1055.52	298.124	3.541	0.0004	***
A16	−198.024	63.5911	−3.114	0.0019	***
A36	232.484	87.4586	2.658	0.0079	***
Mean dependent var	8614.651	S.D. dependent var	73790.77		
Sum squared resid	1.91e+12	S.E. of regression	33226.87		
LSDV R-squared	0.817740	Within R-squared	0.016593		
LSDV F(195, 1734)	39.89680	P-value(F)	0.000000		
Log-likelihood	−22728.66	Akaike criterion	45849.32		
Schwarz criterion	46940.11	Hannan-Quinn	46250.56		
rho	0.406942	Durbin-Watson	1.005053		
Joint test on named regressors -					
Test statistic: F(3, 1734) = 9.75245					
with p-value = P(F(3, 1734) > 9.75245) = 2.21614e-06					
Test for differing group intercepts -					
Null hypothesis: The groups have a common intercept					
Test statistic: F(192, 1734) = 38.8029					
with p-value = P(F(192, 1734) > 38.8029) = 0					

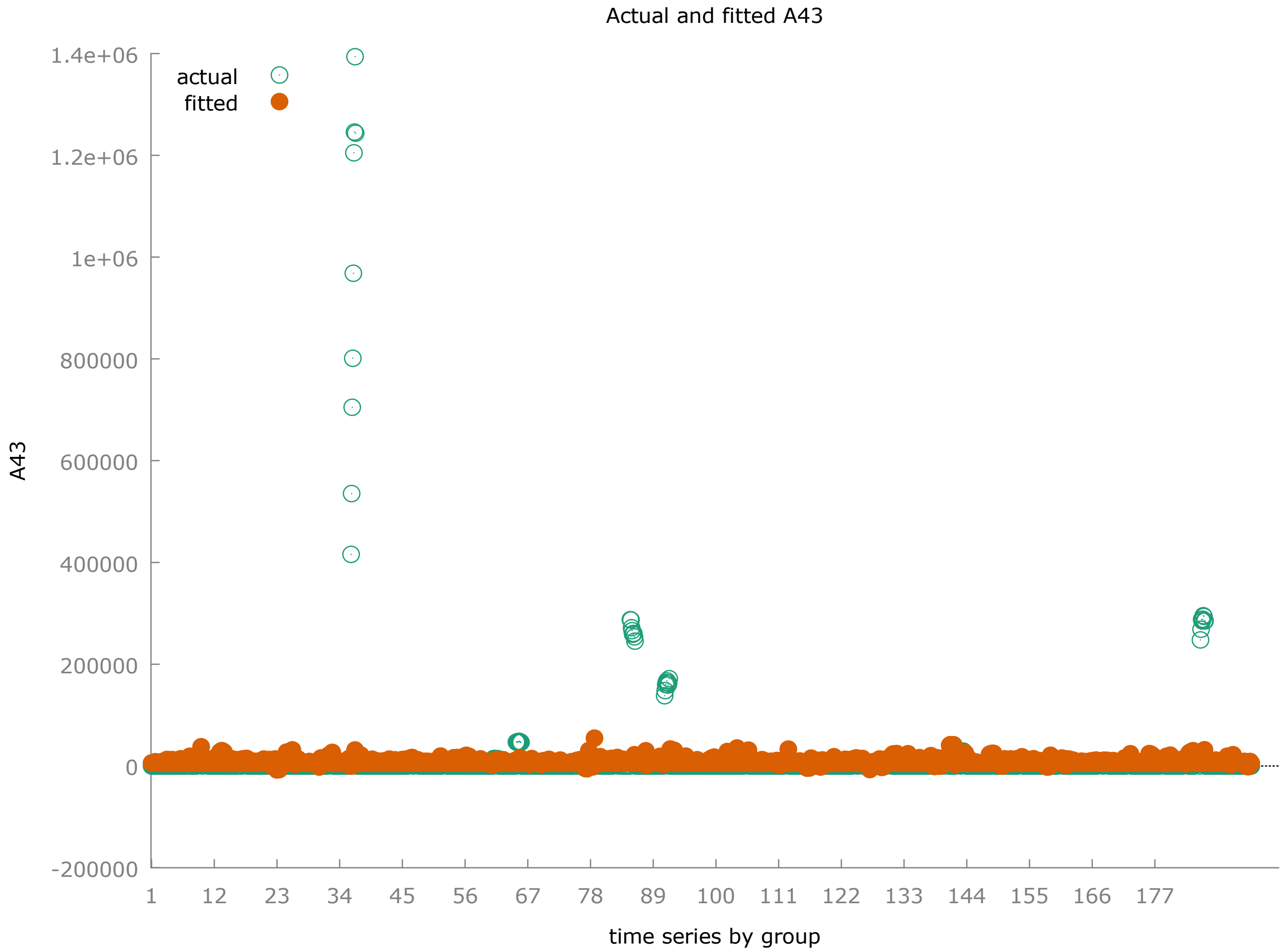


Model 94: Random-effects (GLS), using 1930 observations					
Using Nerlove's transformation					
Included 193 cross-sectional units					
Time-series length = 10					
Dependent variable: A43					
	Coefficient	*Std. Error*	*z*	*p-value*	
const	5528.76	5183.82	1.067	0.2862	
A11	1088.85	288.946	3.768	0.0002	***
A16	−169.247	62.6353	−2.702	0.0069	***
A36	245.759	86.8094	2.831	0.0046	***

Mean dependent var	8614.651	S.D. dependent var	73790.77
Sum squared resid	1.05e+13	S.E. of regression	73662.68
Log-likelihood	−24367.05	Akaike criterion	48742.09

Schwarz criterion	48764.35	Hannan-Quinn	48750.28
rho	0.406942	Durbin-Watson	1.005053

'Between' variance = 4.46267e+009
'Within' variance = 9.91906e+008
theta used for quasi-demeaning = 0.852543
Joint test on named regressors -
Asymptotic test statistic: Chi-square(3) = 29.6595
with p-value = 1.62741e-06
Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 5140.65
with p-value = 0
Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(3) = 17.4657
with p-value = 0.000566773

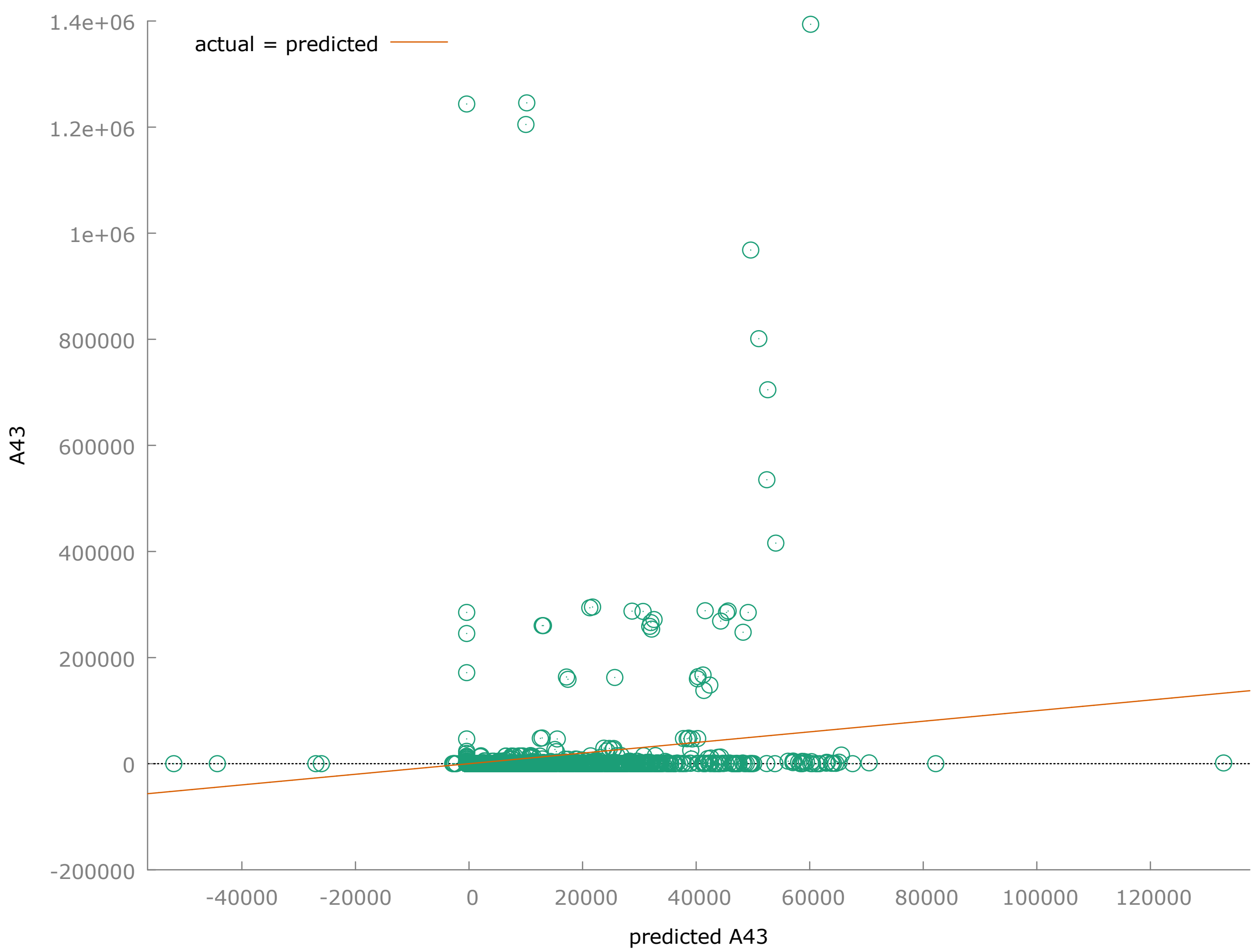


Model 95: Pooled OLS, using 1930 observations
Included 193 cross-sectional units
Time-series length = 10
Dependent variable: A43

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−411.461	2061.73	−0.1996	0.8418	
A11	1464.94	355.021	4.126	<0.0001	***
A16	561.984	103.135	5.449	<0.0001	***
A36	681.195	182.724	3.728	0.0002	***

Mean dependent var	8614.651	S.D. dependent var	73790.77
Sum squared resid	1.01e+13	S.E. of regression	72557.23
R-squared	0.034658	Adjusted R-squared	0.033154

F(3, 1926)	23.04906	P-value(F)	1.17e-14
Log-likelihood	−24337.36	Akaike criterion	48682.72
Schwarz criterion	48704.98	Hannan-Quinn	48690.91
rho	0.880002	Durbin-Watson	0.209560



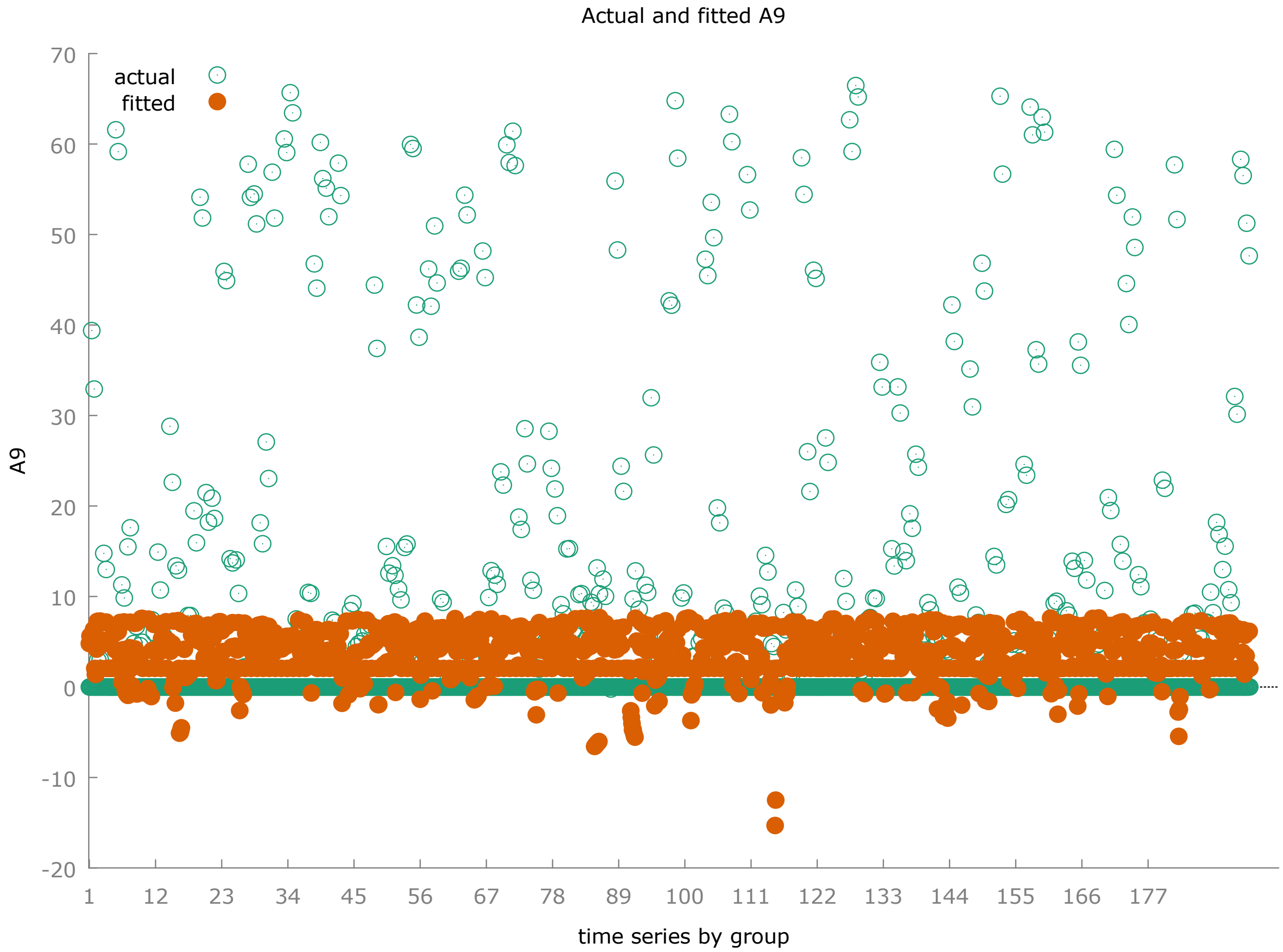
S-COMPONENT

Random-effects (GLS), using 1930 observations					
Included 193 cross-sectional units					
Time-series length = 10					
Dependent variable: A9					
	Coefficient	*Std. Error*	*z*	*p-value*	
const	2.05428	0.676812	3.035	0.0024	***
A34	0.0666591	0.0110094	6.055	<0.0001	***

A35	−0.0284312	0.00757483	−3.753	0.0002	***
A30	−1.05492	0.121372	−8.692	<0.0001	***

Mean dependent var	4.070476	S.D. dependent var	11.99643
Sum squared resid	265030.7	S.E. of regression	11.72755
Log-likelihood	−7488.596	Akaike criterion	14985.19
Schwarz criterion	15007.45	Hannan-Quinn	14993.38
rho	−0.223953	Durbin-Watson	2.396016

'Between' variance = 0
'Within' variance = 139.118
theta used for quasi-demeaning = 0
Joint test on named regressors -
Asymptotic test statistic: Chi-square(3) = 91.421
with p-value = 1.08471e-19
Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 2.54531
with p-value = 0.110622
Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(3) = 23.8747
with p-value = 2.65313e-05



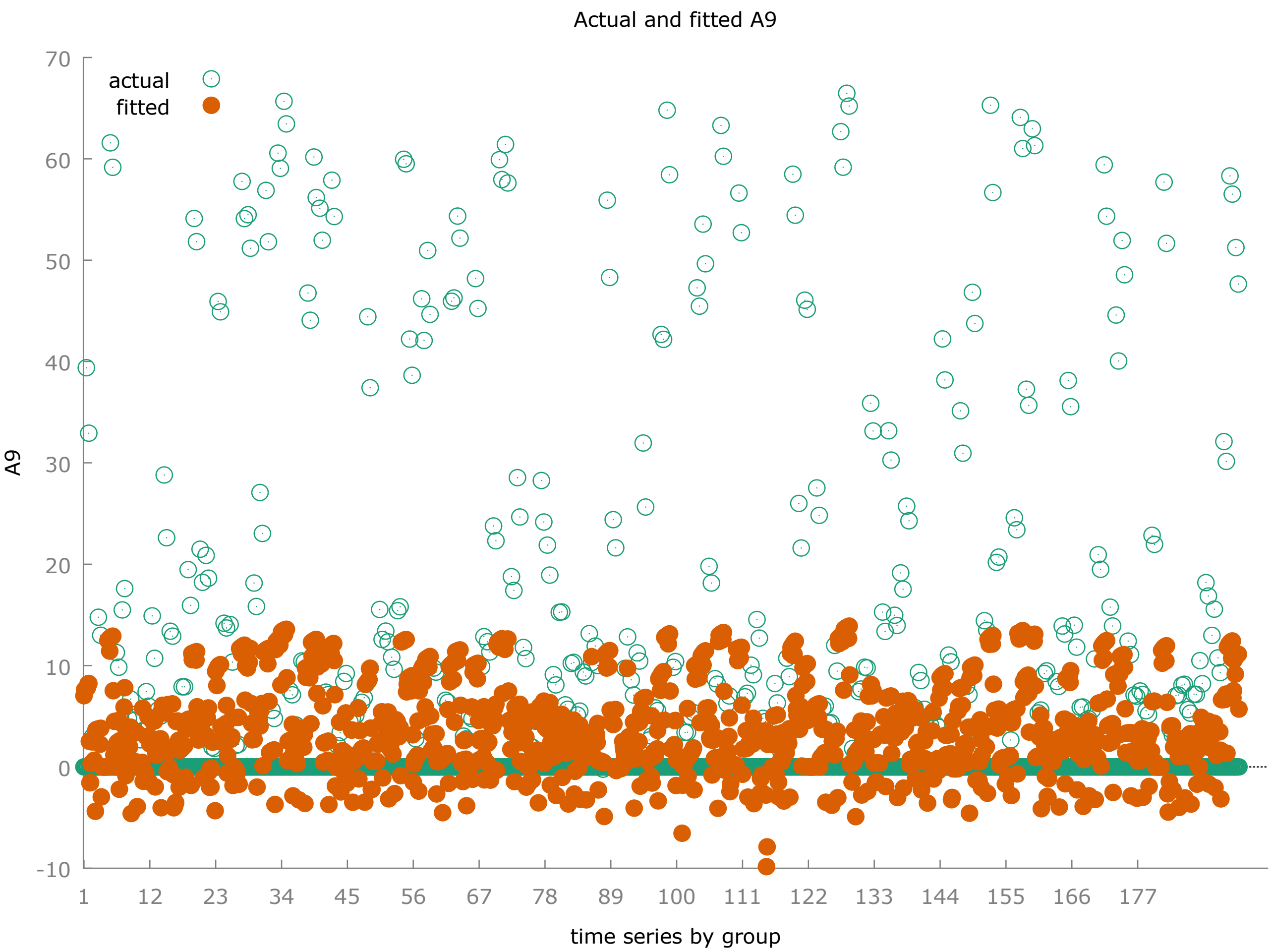
Fixed-effects, using 1930 observations
Included 193 cross-sectional units
Time-series length = 10
Dependent variable: A9

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.111038	0.824105	0.1347	0.8928	
A34	0.0880780	0.0136229	6.465	<0.0001	***
A35	−0.0191354	0.00947901	−2.019	0.0437	**
A30	−0.732587	0.185365	−3.952	<0.0001	***

Mean dependent var	4.070476	S.D. dependent var	11.99643
Sum squared resid	241230.7	S.E. of regression	11.79483
LSDV R-squared	0.131047	Within R-squared	0.026459
LSDV F(195, 1734)	1.341052	P-value(F)	0.001965

Log-likelihood	−7397.797	Akaike criterion	15187.59
Schwarz criterion	16278.39	Hannan-Quinn	15588.83
rho	−0.223953	Durbin-Watson	2.396016

Joint test on named regressors -
Test statistic: F(3, 1734) = 15.7088
with p-value = P(F(3, 1734) > 15.7088) = 4.41674e-10
Test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: F(192, 1734) = 0.891028
with p-value = P(F(192, 1734) > 0.891028) = 0.847811



Model 117: Pooled OLS, using 1930 observations
Included 193 cross-sectional units
Time-series length = 10

Dependent variable: A9					
	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	2.05428	0.676812	3.035	0.0024	***
A34	0.0666591	0.0110094	6.055	<0.0001	***
A35	−0.0284312	0.00757483	−3.753	0.0002	***
A30	−1.05492	0.121372	−8.692	<0.0001	***

Mean dependent var	4.070476	S.D. dependent var	11.99643
Sum squared resid	265030.7	S.E. of regression	11.73059
R-squared	0.045316	Adjusted R-squared	0.043829
F(3, 1926)	30.47368	P-value(F)	3.04e-19
Log-likelihood	−7488.596	Akaike criterion	14985.19
Schwarz criterion	15007.45	Hannan-Quinn	14993.38
rho	−0.119410	Durbin-Watson	2.212349

G-Component

Random-effects (GLS), using 1930 observations

Included 193 cross-sectional units

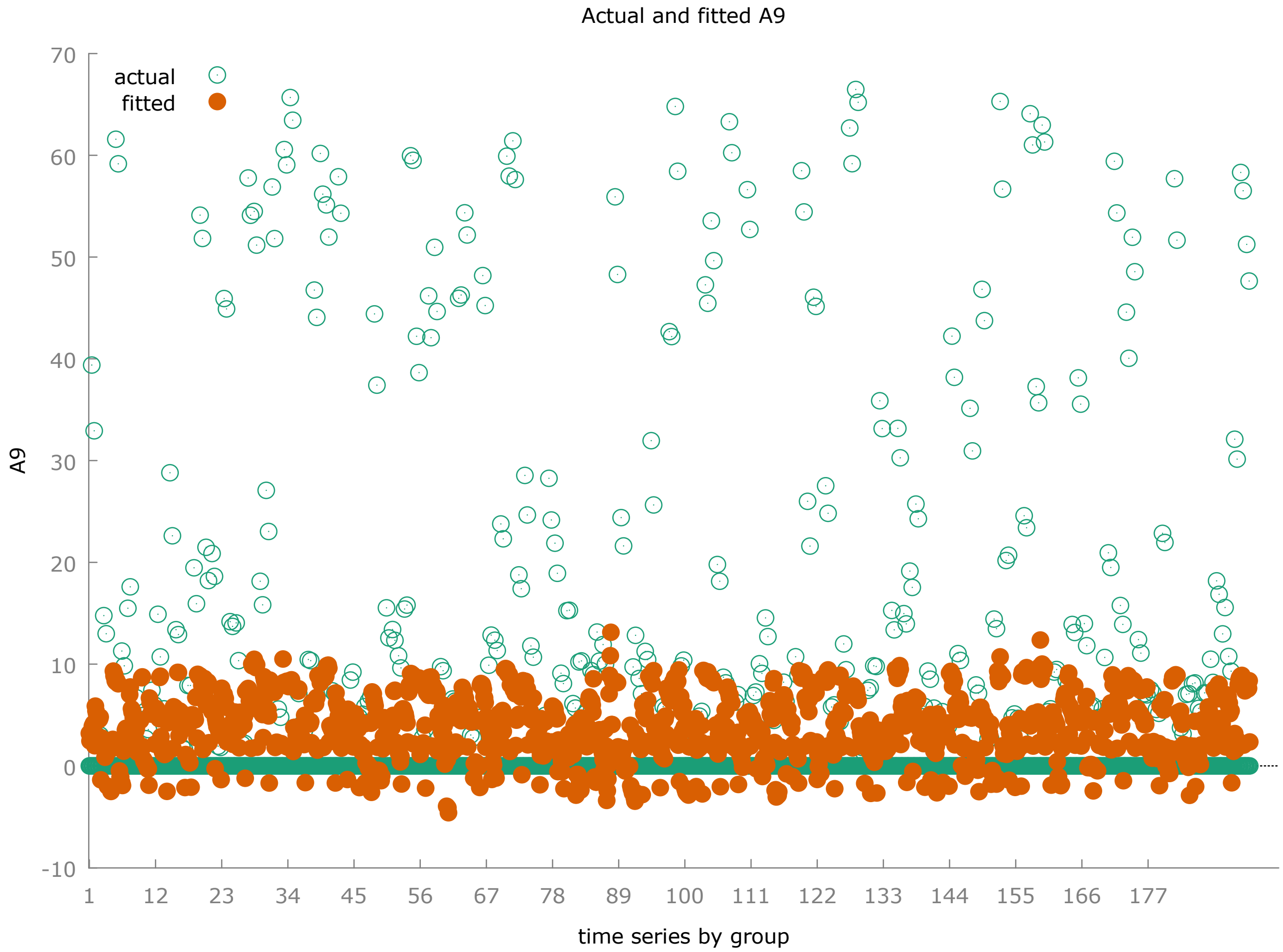
Time-series length = 10

Dependent variable: A9

	Coefficient	*Std. Error*	*z*	*p-value*	
const	1.85518	0.628298	2.953	0.0031	***
A24	−0.0627228	0.0367353	−1.707	0.0877	*
A32	−0.0474745	0.00914425	−5.192	<0.0001	***
A54	0.0815739	0.00870394	9.372	<0.0001	***
A63	0.00516276	0.00144719	3.567	0.0004	***
A58	−1.45109	0.368197	−3.941	<0.0001	***

Mean dependent var	4.070476	S.D. dependent var	11.99643
Sum squared resid	259436.8	S.E. of regression	11.60915
Log-likelihood	−7468.010	Akaike criterion	14948.02
Schwarz criterion	14981.41	Hannan-Quinn	14960.30
rho	−0.218613	Durbin-Watson	2.388508

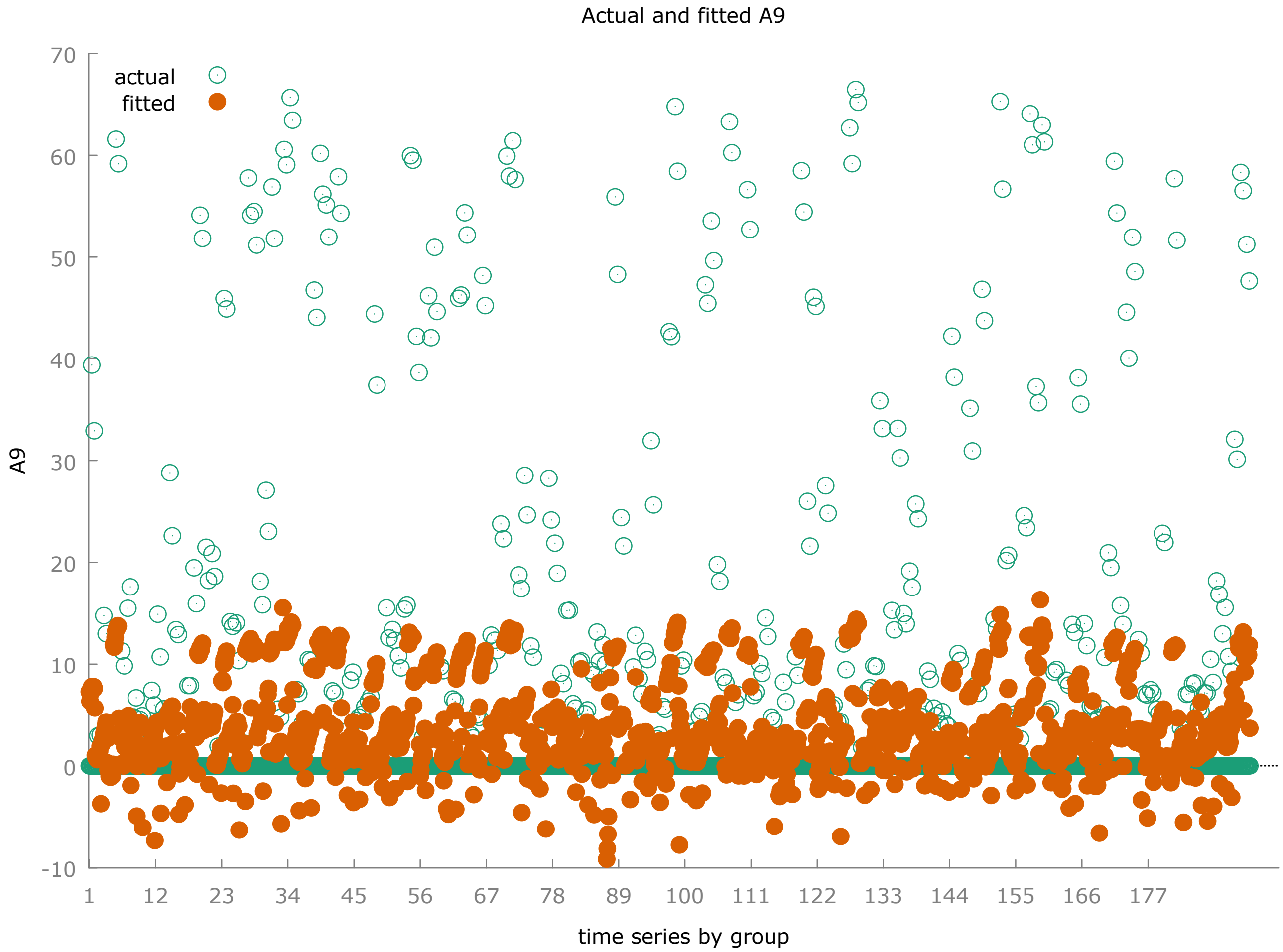
'Between' variance = 0
'Within' variance = 139.063
theta used for quasi-demeaning = 0
Joint test on named regressors -
Asymptotic test statistic: Chi-square(5) = 134.78
with p-value = 2.30008e-27
Breusch-Pagan test -
Null hypothesis: Variance of the unit-specific error = 0
Asymptotic test statistic: Chi-square(1) = 21.3365
with p-value = 3.85321e-06
Hausman test -
Null hypothesis: GLS estimates are consistent
Asymptotic test statistic: Chi-square(5) = 53.1026
with p-value = 3.20412e-10



Fixed-effects, using 1930 observations					
Included 193 cross-sectional units					
Time-series length = 10					
Dependent variable: A9					
	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−1.56238	0.935248	−1.671	0.0950	*
A24	−0.0811150	0.0431200	−1.881	0.0601	*
A32	0.0432827	0.0169656	2.551	0.0108	**
A54	0.0802668	0.0141111	5.688	<0.0001	***
A63	0.00639062	0.00234564	2.724	0.0065	***
A58	−1.67732	0.590161	−2.842	0.0045	***
Mean dependent var	4.070476	S.D. dependent var	11.99643		

Sum squared resid	240856.9	S.E. of regression	11.79249
LSDV R-squared	0.132394	Within R-squared	0.027967
LSDV F(197, 1732)	1.341610	P-value(F)	0.001863
Log-likelihood	−7396.300	Akaike criterion	15188.60
Schwarz criterion	16290.53	Hannan-Quinn	15593.93
rho	−0.218613	Durbin-Watson	2.388508

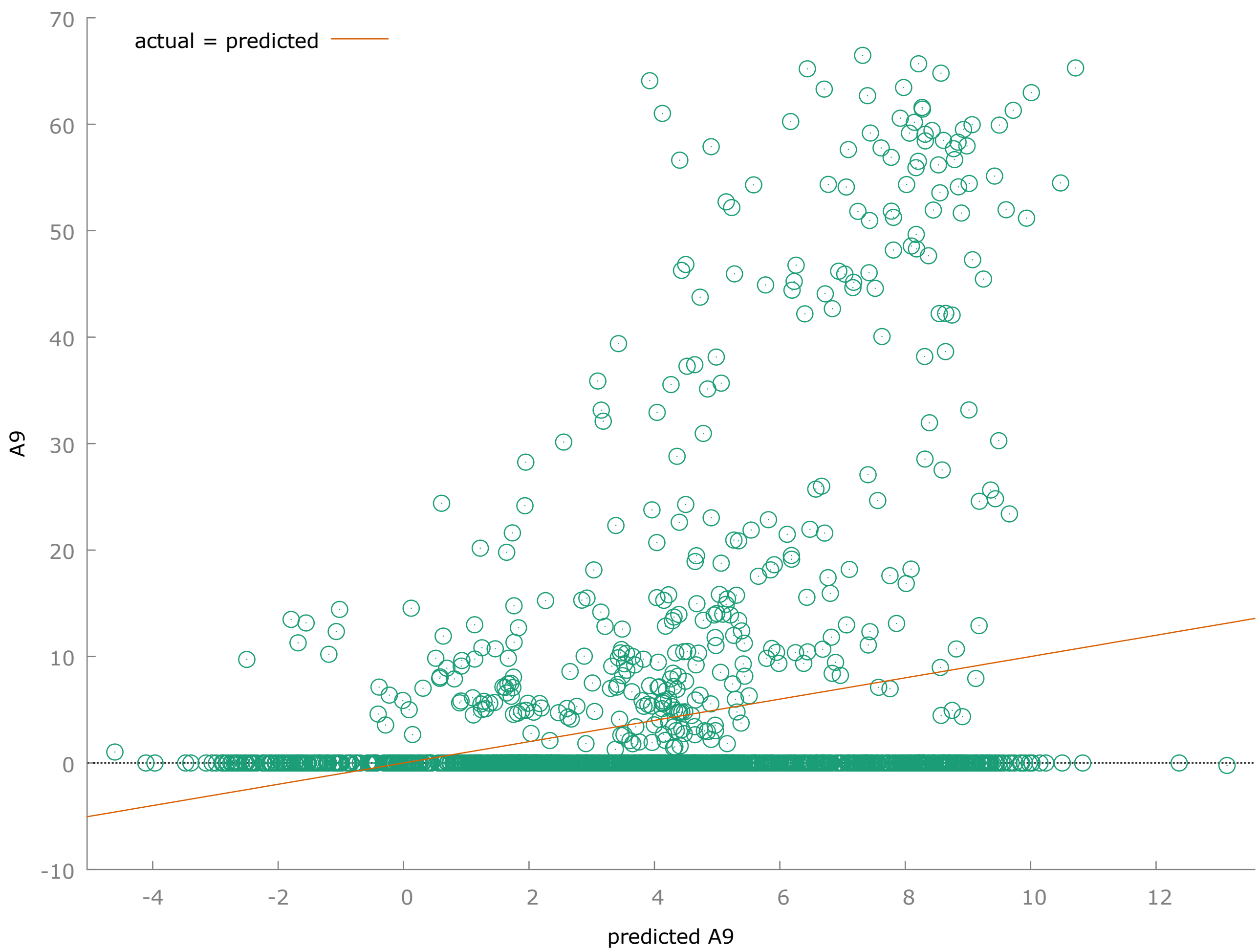
Joint test on named regressors -
Test statistic: F(5, 1732) = 9.96665
with p-value = P(F(5, 1732) > 9.96665) = 2.04644e-09
Test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: F(192, 1732) = 0.695873
with p-value = P(F(192, 1732) > 0.695873) = 0.999269

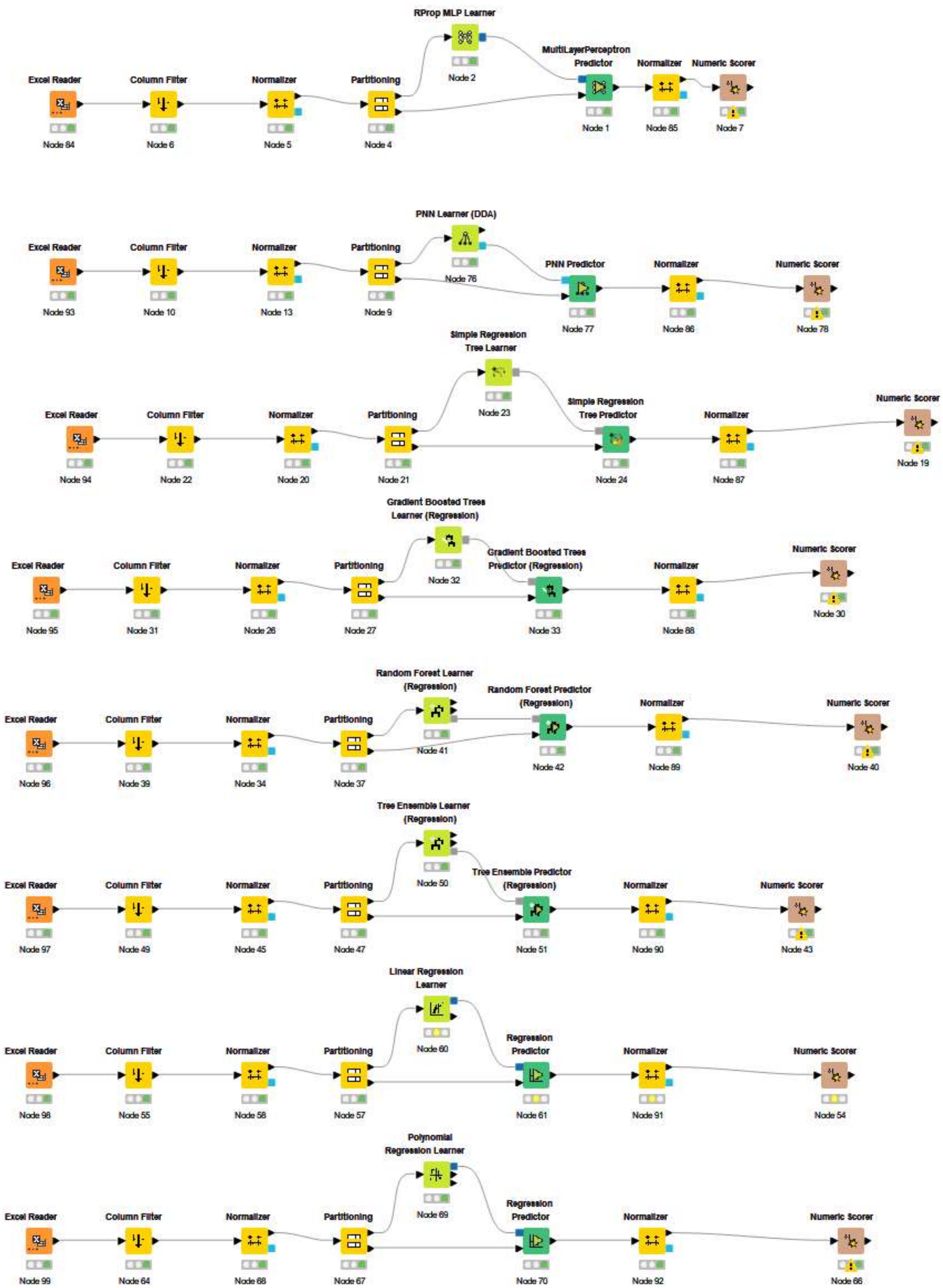


Model 135: Pooled OLS, using 1930 observations					
Included 193 cross-sectional units					
Time-series length = 10					
Dependent variable: A9					
	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	1.85518	0.628298	2.953	0.0032	***
A24	−0.0627228	0.0367353	−1.707	0.0879	*
A32	−0.0474745	0.00914425	−5.192	<0.0001	***
A54	0.0815739	0.00870394	9.372	<0.0001	***
A63	0.00516276	0.00144719	3.567	0.0004	***
A58	−1.45109	0.368197	−3.941	<0.0001	***

Mean dependent var	4.070476	S.D. dependent var	11.99643

Sum squared resid	259436.8	S.E. of regression	11.61217
R-squared	0.065466	Adjusted R-squared	0.063037
F(5, 1924)	26.95604	P-value(F)	1.99e-26
Log-likelihood	−7468.010	Akaike criterion	14948.02
Schwarz criterion	14981.41	Hannan-Quinn	14960.30
rho	−0.144875	Durbin-Watson	2.255470




RProp MLP Learner
Node 2
Excel Reader
Node 84
Column Filter
Node 6
Normalizer
Node 5
Partitioning
Node 4
MultiLayerPerceptron Predictor
Node 1
Normalizer
Node 85
Numeric Scorer
Node 7
PNN Learner (DDA)
Node 76
Excel Reader
Node 93
Column Filter
Node 10
Normalizer
Node 13
Partitioning
Node 9
PNN Predictor
Node 77
Normalizer
Node 86
Numeric Scorer
Node 78
Simple Regression Tree Learner
Node 23
Excel Reader
Node 94
Column Filter
Node 22
Normalizer
Node 20
Partitioning
Node 21
Simple Regression Tree Predictor
Node 24
Normalizer
Node 87
Numeric Scorer
Node 19
Gradient Boosted Trees Learner (Regression)
Node 32
Excel Reader
Node 95
Column Filter
Node 31
Normalizer
Node 26
Partitioning
Node 27
Gradient Boosted Trees Predictor (Regression)
Node 33
Normalizer
Node 88
Numeric Scorer
Node 30
Random Forest Learner (Regression)
Node 41
Excel Reader
Node 96
Column Filter
Node 39
Normalizer
Node 34
Partitioning
Node 37
Random Forest Predictor (Regression)
Node 42
Normalizer
Node 89
Numeric Scorer
Node 40
Tree Ensemble Learner (Regression)
Node 50
Excel Reader
Node 97
Column Filter
Node 49
Normalizer
Node 45
Partitioning
Node 47
Tree Ensemble Predictor (Regression)
Node 51
Normalizer
Node 90
Numeric Scorer
Node 43
Linear Regression Learner
Node 60
Excel Reader
Node 98
Column Filter
Node 55
Normalizer
Node 58
Partitioning
Node 57
Regression Predictor
Node 61
Normalizer
Node 91
Numeric Scorer
Node 54
Polynomial Regression Learner
Node 69
Excel Reader
Node 99
Column Filter
Node 64
Normalizer
Node 68
Partitioning
Node 67
Regression Predictor
Node 70
Normalizer
Node 92
Numeric Scorer
Node 66