ENTREPRENEURIAL ACTIVITY – A MATTER OF MICROECONOMIC CONDITIONS OR MACROECONOMIC FREEDOMS?

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Abstract:
In this paper, the implications of economic freedoms and entrepreneurial conditions for the level of early-stage entrepreneurship are under study. The purpose is to rank-order microeconomic entrepreneurial conditions and (macro)economic freedoms under which companies are established, i.e., to find the most important factors affecting entrepreneurial activity. The used data on entrepreneurial conditions is acquired from Global Entrepreneurship Monitor (GEM) and the data on economic freedoms from the Heritage Foundation. Both micro and macro perspectives are featured by 12 factors constructing an index making up the total of 24 individual predictors plus 2 indices. The target variable is the early-stage entrepreneurial activity from GEM, which is categorised into three categories of low, medium, and top level of entrepreneurial activity. The used methods to process the data and to analyse the predictive power are a multilayer artificial neural network, ANN, supported by a multiple correspondence analysis, MCA. Firstly, the MCA is used for descriptive purposes by plotting the most important factors with countries related to them. Secondly, the ANN will be optimised for the best possible network performance i) to demonstrate the effectiveness of neural networks by showing the model performance for each category of entrepreneurial activity and ii) to reveal and order the most important factors needed to achieve a high prediction accuracy of the model. The results from MCA and ANN are combined and their implications are discussed. Finally, some potential future research steps are suggested.

INTRODUCTION

This paper addresses the implications of economic freedoms and entrepreneurial conditions for the early-stage level of entrepreneurship. The dataset consists of 49 countries analysed from micro and macro perspectives with help of 27 variables, among which the class variable is the early-stage entrepreneurial activity. This class variable has three categories, according to the division of its values in three intervals, determined by the 25th and the 75th percentiles.
Verheul et al. (2002) gives several definitions and measurements of entrepreneurship including business ownership and self-employment. Business ownership refers to small and medium companies or, in a dynamic perspective, start-up activities. On the other hand, self-employment means a business owner and not a job-seeking person. Further, the same paper develops a discussion of the determinants of entrepreneurship at the micro, meso and macro level. At the micro level the main determinants of entrepreneurship are motivational and psychologic, at the meso level, they are market-specific, such as profit opportunities; the macro level aggregates the micro and meso levels, referring to cultural, technological and economic factors.
In this study, we use total entrepreneurial activity (TEA) as the target variable, which is a measure of the age 18-64 population, who are either a nascent entrepreneur or owner-manager of a new business (cf. Bosma et al., 2020). Bjørnskov and Foss, (2008) discuss theories of entrepreneurship and its determinants focusing on the relation between economic freedom and entrepreneurship measured by TEA. The empirical part of the paper contains a statistical analysis of a large-scale questionnaire, conducted in 29 countries and having 77000 respondents. They find that the size of government is strongly positively correlated with TEA, while GDP was negatively correlated with TEA. The lack of taxation was found positively impacting the entrepreneurship opportunities. Hall et al. (2013) found that economic freedom has a positive influence on entrepreneurship by increasing economic freedom, the climate for new businesses is encouraged. There is strong evidence of the positive relationship of economic freedoms and economic activity measured by GDP (cf. Gwartnery et al., 2019; Miller et al., 2020; Georgescu et al., 2018).
Several other drivers of entrepreneurial activity have been found in the literature. Nyström (2008) contains an empirical study in which the fixed effects model is chosen, when total self-employment is statistically significant influenced by size of government, legal structure, property rights and regulation of labour, business and credit. Kreft and Sobel (2005) study the Granger causality of capital venture and entrepreneurial activity and reach the conclusion that VC Granger causes entrepreneurial activity for 50 US states. Mandic et al. (2017) discusses how the institutional framework of 11 capitalist countries which belonged to EU before the 2004 expansion influenced the entrepreneurial activity. In their model, TEA is taken as dependent variable, while the explanatory variables are GDP per capita, GDP per capita rate, economic freedom index and age dependency ratio. They found strong positive and statistically significant impact of economic freedom to TEA in line with Hall et al. (2013).
The paper is structured as follows. Section 2 describes the dataset and the way the 49 countries are classified in the top, medium and low entrepreneurial activity. Section 3 is dedicated to the applied methods; in section 3.1 the

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multiple correspondence analysis is applied to categorised data. It was noticed that by applying principal component analysis, the first two components explain 31.7% of the total variance, which is dominated by the variables Entrepreneurial condition index, R&D transfer, Financing for entrepreneurs, Governmental programmes, Governmental support and policies, Internal market openness, Freedom index and Rule of law. In section 3.2 neural networks are applied to classify the countries into total entrepreneurial activity (TEA) categories, achieving an accuracy of 97.3% for the train set, respectively 83.3% for the test set. It will be noticed that property rights are the most important variable in classification followed by fiscal health, cultural and social norms, investment freedom and labour freedom. Discussion with future research suggestions conclude the paper.

DATA DESCRIPTION

In total, twenty-seven variables will be analysed. The dependent target variable is Early-stage total entrepreneurial activity (TEA) denoted as variable 0 (V0) in Table 1. Global Entrepreneur Monitor (GEM) defines TEA as the percentage of 18-64 years old population, who are either a nascent entrepreneur or owner-manager of a new business (cf. sources in Table 1). GEM provides twelve individual variables on entrepreneurial conditions, V2-V13, and an index constructed on them, V1, seen on the left column of Table 1. V1-V13 characterise the micro perspective in this this study; the macro perspective, on the other hand is featured by Economic freedoms obtained from the Heritage foundation, HF (right column of Table 1). V14 is the Economic Freedom Index and its underlying variables V15-V26 can be divided into *Rule of law* (V15-V17), *Government size* (V18-V20), *Regulatory efficiency* (V21-V23), and *Market openness* (V24-V26) as classified by HF.

Table 1. Dependent and independent variables

Target variable	
V0 – Early-stage entrepreneurial activity (TEA)	
Entrepreneurial conditions	**Economic freedoms**
V1 - Entrepreneurial conditions Index	V14 - Freedom index
V2 - Financing for entrepreneurs	V15 - Property rights
V3 - Governmental support and policies	V16 - Judicial effectiveness
V4 - Taxes and bureaucracy	V17 - Government integrity
V5 - Governmental programs	V18 - Tax burden
V6 - Basic school entrepreneurial education	V19 - Government spending
V7 - Post school entrepreneurial education	V20 - Fiscal health
V8 - R&D transfer	V21 - Business freedom
V9 - Commercial & professional infrastructure	V22 - Labor freedom
V10 - Internal market dynamics	V23 - Monetary freedom
V11 - Internal market openness	V24 - Trade freedom
V12 - Physical and services infrastructure	V25 - Investment freedom
V13 - Cultural and social norms	V26 - Financial Freedom

Sources: For V0-V13: Global Entrepreneurial Monitor, https://www.gemconsortium.org/;
for V14-V26: The Heritage Foundation, https://www.heritage.org/

Forty-nine (49) countries has/have available most-recent data for all the above 27 variables for year 2019. We divide all the variables into further 3 categories, i.e., *top, medium*, and *low categories:* a country falls into top category of each variable, if the value is larger or equal to 3rd quartile limit (75th percentile), medium category, when the value is between the 1st and 3rd quartile limits (25th – 75th percentiles), and into low category, when the value is less than the 25th percentile limit.

Table 2 shows the top-12 countries ordered by total entrepreneurial activity (TEA-V0): the top-6 countries are Latin American countries Chile, Ecuador, Guatemala, Brazil, Panama, and Colombia. The only European countries in top-TEA category are Armenia (7th) and Latvia (12th). Canada and the United States are 9th and 10th most-active entrepreneurial countries, respectively. Madagascar (8th) and United Arab Emirates (11th) are the other countries in top-TEA category. Table 2 also shows the Economic freedom index (V14) and Entrepreneurial conditions index (V1) for these countries as they summarise our macro and micro perspectives. The averages for the three key variables are: TEA = 22.8%, Freedom index = 68.0, and Entrepreneurial conditions index = 2.8.

Table 2. Countries in the top entrepreneurial category

Country	TEA (V0)	Freedom index (V14)	Entrepreneurial conditions index (V1)
1. Chile	36.7	76.8	2.8
2. Ecuador	36.2	51.3	2.6
3. Guatemala	25.1	64.0	2.4
4. Brazil	23.3	53.7	2.6
5. Panama	22.7	67.2	2.6
6. Colombia	22.3	69.2	2.7
7. Armenia	21.0	70.6	2.8
8. Madagascar	19.5	60.5	2.4
9. Canada	18.2	78.2	3.1
10. USA	17.4	76.6	3.1
11. UAE	16.4	76.2	3.4
12. Latvia	15.4	71.9	3.0
Average	*22.8*	*68.0*	*2.8*

Table 3 shows the same data and averages for 25 medium-TEA countries. The medium group is the largest and most diverse group. At this point, we only note that the average TEA = 11.2%, Freedom index = 69.3, and Entrepreneurial conditions index = 2.9. Interestingly, the TEA is only half of the top-TEA category, but both Economic freedoms and Entrepreneurial conditions do not show significant differences to the top-TEA categories; they are, in fact, slightly higher.

Table 3. Countries in the medium entrepreneurial category

Country	TEA (V0)	Freedom index (V14)	Entrepreneurial conditions index (V1)
13. India	15.0	56.5	3.4
14. South Korea	14.9	74.0	3.1
15. Qatar	14.7	72.3	3.4
16. Saudi Arabia	14.0	62.4	3.0
17. Slovakia	13.3	66.8	2.6
18. Mexico	13.0	66.0	2.9
19. Portugal	12.9	67.0	2.6
20. Israel	12.7	74.0	2.9
21. Ireland	12.4	80.9	2.9
22. Cyprus	12.2	70.1	2.8
23. Morocco	11.4	63.3	2.5
24. South Africa	10.8	58.8	2.4
25. Iran	10.7	49.2	2.1
26. Australia	10.5	82.6	2.9
27. Croatia	10.5	62.2	2.4
28. Netherlands	10.4	77.0	3.5
29. Luxembourg	10.2	75.8	3.1
30. Switzerland	9.8	82.0	3.5
31. UK	9.3	79.3	2.9
32. Russia	9.3	61.0	2.6
33. Jordan	9.1	66.0	3.1
34. China	8.7	59.5	3.4
35. Taiwan	8.4	77.1	3.3

36. Norway	8.4	73.4	3.2
37. Sweden	8.3	74.9	3.0
Average	*11.2*	*69.3*	*2.9*

Table 3 shows the same data for the 12 low-TEA countries. Interestingly this category is dominated by European countries (7/12) and close Belarus, three Islamic countries, Oman, Egypt and Pakistan, and Japan. Italy is entrepreneurially the least active (49th) of the countries under analysis, while Mediterranean Greece (38th) and Spain (44th) are not doing much better, just alike Germany (40th) as of year 2019.

Table 4. Countries in the low entrepreneurial category

Country	TEA (V0)	Freedom index (V14)	Entrepreneurial conditions index (V1)
38. Greece	8.2	59.9	2.6
39, Slovenia	7.8	67.8	2.8
40. Germany	7.6	73.5	3.0
41. Oman	6.9	63.6	2.8
42. Egypt	6.7	54.0	2.7
43. North Macedonia	6.2	69.5	2.5
44. Spain	6.2	66.9	3.2
45. Belarus	5.8	61.7	2.7
46. Poland	5.4	69.1	2.7
47. Japan	5.4	73.3	2.9
48. Pakistan	3.7	54.8	2.5
49. Italy	2.8	63.8	2.7
Average	*6.0*	*64.8*	*2.8*

The comparable averages for the low-TEA counties are: TEA = 6.0%, Freedom index = 64.8, and Entrepreneurial conditions index = 2.8. Total entrepreneurial activity is about half of the medium-TEA countries on average, Economic freedoms also show significantly lower average as the medium- and top-TEA group, but again Entrepreneurial conditions do not make a significant difference to other groups and is about the same as in the top-TEA group on average.

It is clearly seen that by looking at the index-level variables V1 and V14, and the group averages of the target V0, we are not able to draw any revealing conclusions on whether economic freedoms or entrepreneurial conditions work as drivers of entrepreneurial activity. We need to study the individual factors and whether countries are individually related to certain freedoms and conditions, which could further explain the early-stage entrepreneurial activity, TEA.

ANALYSIS

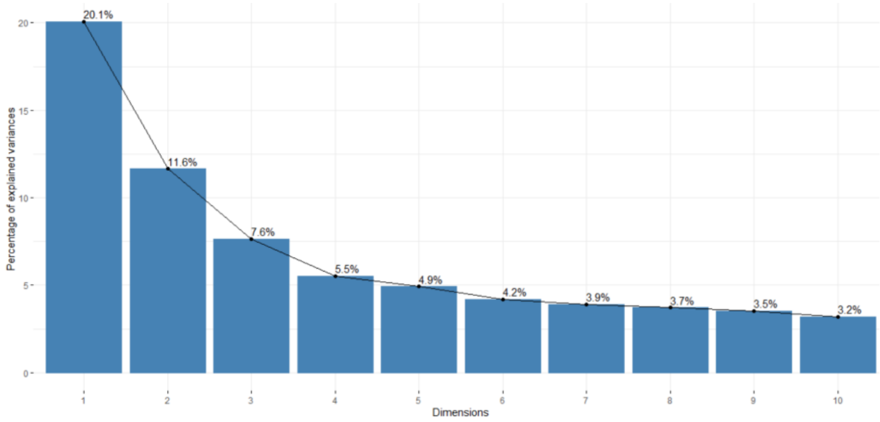
In this analysis part of the study, we will analyse qualitative data, i.e. the 27 variables categorised into top, medium, and low classes (as explained in the previous section), by multiple correspondence analysis in section 3.1. This will reveal which countries are related to which independent variables. We find the method most valuable for descriptive purposes, while the neural network analysis of section 3.2 is used to find the more complex connections of the numerical independent variables, V2-V13 and V15-V26, and the categorised target variable, TEA (V0).

Multiple Correspondence Analysis

Multiple correspondence analysis, MCA, using the R code provided by Kassambara (2017) is applied to categorised data (top, medium and low categories for each variable). The purpose is to get a high-level description of related factor classes and to imply, which factors play the greatest role in explaining the total variation in the dataset. MCA is a principal component approach applied to qualitative/categorical data in a similar way as principal component analysis, PCA, is to numerical data (cf. Tharwat, 2016; Kassambara, 2017).

The principal components are represented by dimensions so that the first and second ones (bars 1 and 2 in Figure 1; Dim1 and Dim2 in Figures 2 and 3) explain most of the variation of the data. Figure 1 shows that the first two dimensions explain 31.7% (20.1% for Dim1 and 11.6% for Dim2) of the total variation. In MCA associations between variables are obtained by computing distances between the variable categories and between countries.

Figure 1. Total variance explained by each dimension in MCA



These associations are visualised firstly in Figure 2, which plots the squared correlations between variables, while the dimensions are used as coordinates (Dim1 on vertical axis and Dim2 on horizontal axis). The plot identifies the variables that are the most correlated with each dimension 1 and dimension 2. The squared correlations between variables and the dimensions are used as coordinates. It is seen that the variables Entrepreneurial condition index (V1) is the most correlated with both dimensions 1 and 2; similarly, also the other variables seen on the top-right corner, R&D transfer (V8), Governmental programmes (V5), Governmental support and policies (V3), Internal market openness (V11) and Freedom index (V14) are very highly correlated with both the two most important dimensions. On the right side, the variables are most correlated with dimension 1. These include, among the above mentioned, the Rule of law variables (V15-V17) (Property rights, V15, Judicial effectiveness, V16, and Government integrity, V17) as well, as Financing for entrepreneurs (V2). On the top of Figure 2, in addition to the top-right corner variables, Post-school entrepreneurial education (V7), Financial (V26) and Investment freedoms (V25) are the most correlated with dimension 2. These variables can be expected to coincide also in the neural network analysis of the subsequent section.

Figure 2. The most correlated/contributing factors of the first two dimensions

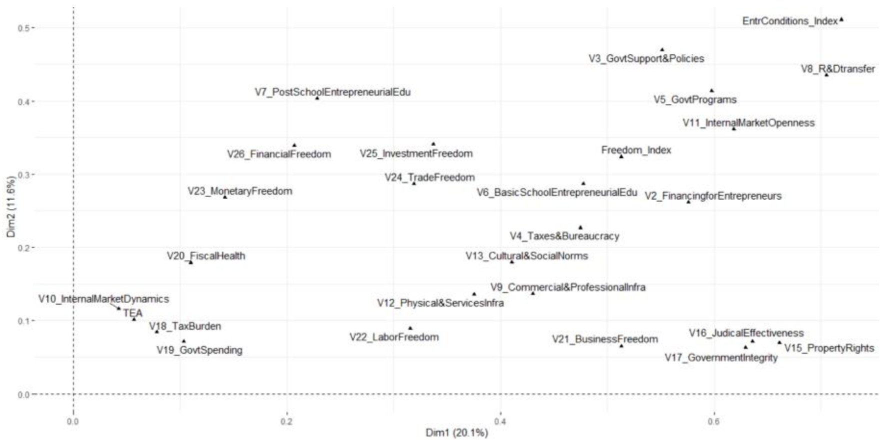
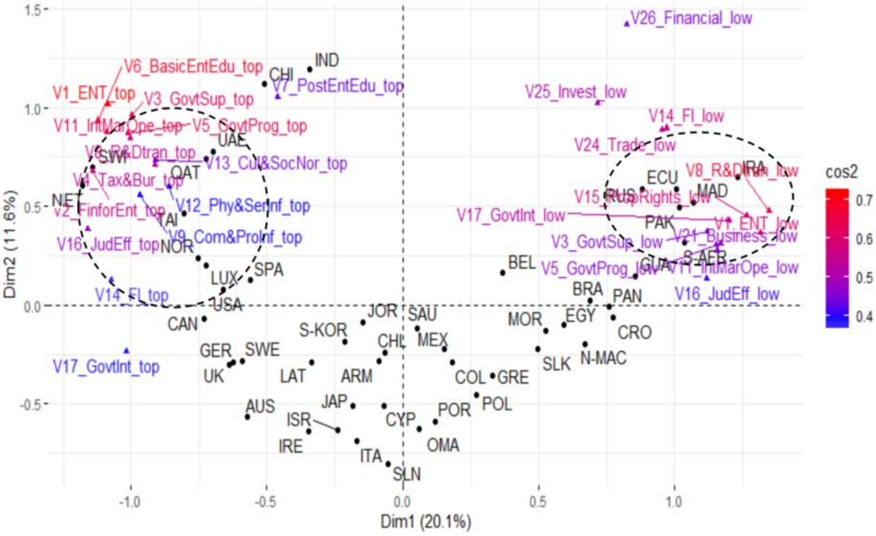


Figure 3 shows all the 49 countries and the top-third variable classes, i.e. 28 the most correlated classes out of the total 81 classes (27 variables times 3 classes each). The largest contributions, measured by correlation (cor2) with dimensions 1 and 2, are seen on red and the smallest contributions on blue. We may visually note two clusters showing up.

On the top-left quadrant, the largest contributions are shown by *top-class* of Basic entrepreneurial education (V6), *top-class* of Entrepreneurial conditions index (V1), *top-class* of Governmental support and policies (V3), Internal market openness (V11), *top-class* of R&D transfer (V8), *top-class* of Taxes and bureaucracy (V4) and *top-class* of Finance for entrepreneurs (V2). The countries close to these variables are *related* to these *top-class* variable categories. These countries include Switzerland (SWI), Netherlands (NET), Taiwan (TAI), Qatar (QAT) and

United Arab Emirates (UAE) together with a bit further down on the plot, Norway (NOR), Luxembourg (LUX) and the United States (USA).
On the top-right quadrant, the largest contributions are shown, specifically, by *low-class* of R&D transfer (V8), *low-class* of Entrepreneurial conditions index (V1), *low-class* of Property rights (V15), and in less extent the *low-class*es of Economic freedom index (V14), Trade freedom (V24), and Governmental integrity (V17), Investment freedom (V25). The countries related to these rather disastrous conditions include Ecuador (ECU), Iran (IRA), Russia (RUS), Pakistan (PAK), Madagascar (MAD), and South Africa (S-AFR).

Figure 3. MCA biplot of 49 countries and top-third contributing variable classes



Interestingly, the “top-cluster” of the top-left quadrant is clearly dominated by features of entrepreneurial conditions (micro perspective), while the “low-cluster” of the top-right quadrant also by Entrepreneurial conditions index and specifically R&D transfer, other factors with largest contributions are seen in economic freedom factors (macro perspective)

Neural Network Analysis

To neural network (NN) analysis is conducted using IBM SPSS v20 statistical software. The programme allows running the built-in multilayer perceptron (MLP) neural network. Neural networks have better predictive power than most of the other classification methods, e.g. Yim and Michell (2005) show NN beating logit models and discriminant analysis, Saboo et al. (2016) show the superiority of NN approach over linear regression models, and Anwar and Mikami (2011) show NN’s predictive ability over logistic regression and time-series, GARGH models. Our dataset of 49 countries was divided into the training set (75.5% of the cases) and the test set (24,5%) as seen in Table 5.

Table 5. Case processing summary

		N	Percent
Sample	Training	37	75.5%
	Testing	12	24.5%
Valid		49	100.0%

To construct the neural network, we chose hyperbolic tangent as the hidden layer activation function and softmax as the activation function for the output layer. After several trials, we ended up using back-propagation based on scaled conjugated optimisation to obtain the weights through cross-entropy error minimisation, and the structure was of only one hidden layer with 4 neurons (plus the bias), as was suggested by automatic architecture, which proved more efficient as multilayer NN, as shown in Figure 4. As the activations of the output layer add up to one (1), the softmax layer is interpreted as a probability distribution with estimated probabilities for the classification by the inputs (Zacharis, 2016)
The target variable is total entrepreneurial activity (TEA, V0) as was noted in Table 1. TEA is categorised to the three classes of top, medium and low, as is seen in Figure 4. Similar categorisation was done to entrepreneurial conditions, V2-V13, and economic freedoms, V15-V26, which are set as the predictors in the NN of Figure 4.

Figure 4. Architecture of the neural network

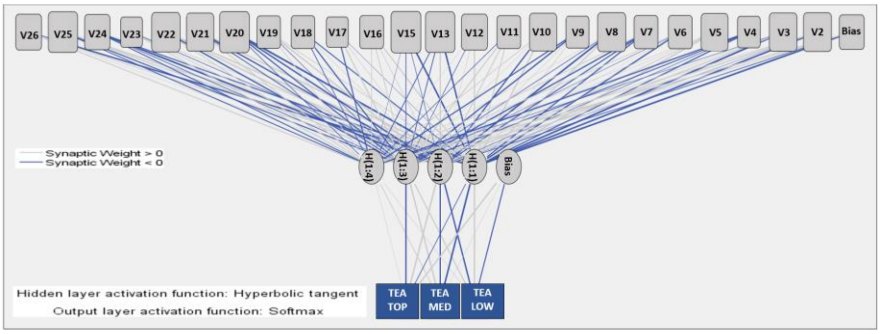


Table 6 shows the areas under the ROC curves, when plotting the trade-off of sensitivity (true positive rate) and specificity (false positive rate). It is seen that even in top-TEA category the area is 0.953, which implies that the neural network performance is great in classifying countries into TEA categories.

Table 6. Area under ROC curve

		Area
TEA_cat3	TEA_low	.995
	TEA_med	.980
	TEA_top	.953

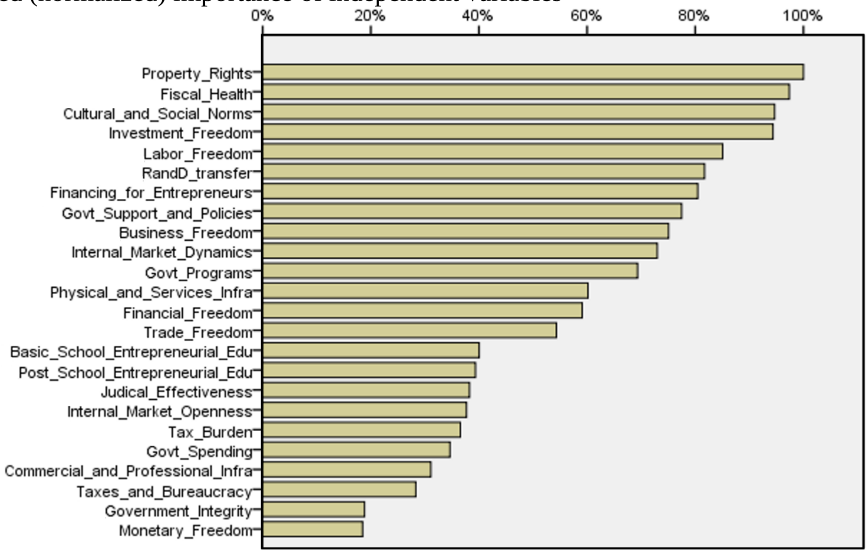
The highly accurate performance of the NN is seen in the model summary of Table 7. The overall accuracy in the train set was as high as 97.3%, but as the NN achieved 83.3% accuracy also with the test set, the model seems to have been overfitted in the training.

Table 7. Accuracy of classification

Sample	Observed	Predicted			
		TEA_low	TEA_med	TEA_top	Percent Correct
Training	TEA_low	9	0	0	100.0%
	TEA_med	0	19	0	100.0%
	TEA_top	1	0	8	88.9%
	Overall %	*27.0%*	*51.4%*	*21.6%*	*97.3%*
Testing	TEA_low	3	0	0	100.0%
	TEA_med	0	5	1	83.3%
	TEA_top	0	1	2	66.7%
	Overall %	*25.0%*	*50.0%*	*25.0%*	*83.3%*

The NN analysis is completed by obtaining the importance bar-plot of Figure 5. It is seen that property rights (V15) is / are the most important variable in the classification, i.e. it has the greatest effect on how the NN classifies the countries into top, medium and low categories. The other most-important factors, in this order, are Fiscal health (V20), Cultural and social norms (V13), Investment freedom (V25), Labor freedom (V22), R&D transfer (V8), Financing for entrepreneurs (V2), Governmental support and policies (V3), Business freedom (V21), and Internal market dynamics (V10).

Figure 5. Ordered (normalized) importance of independent variables



To summarise, out of the top-10 meaningful factors to predict entrepreneurial activity category, the half (5/10) were economic freedom factors and the other half (5/10) were the factors of entrepreneurial conditions. In general, the effects of property rights is not surprising as it has been shown in many studies the greatest or one of the greatest economic-freedom predictor of economic activity and well-being in advanced economies of OECD (Georgescu and Kinnunen, 2019; Kinnunen et al., 2017) and EU (Georgescu et al., 2018), as well as, less developed countries-in-transition (Kinnunen, 2018; Kinnunen et al., 2019), while Mandić et al. (2017) had shown importance of economic freedom index directly on entrepreneurial activity in selected EU countries; similarly, specifically, the importance of R&D is imminent (cf. Kiselakova et al., 2018; Duľová et al., 2017). Most interesting important factors are Fiscal health and Cultural and social norms, the 2nd and 3rd important factors, respectively. Fiscal health has often been found one of the less-important economic freedoms, when predicting economic activity and well-being (e.g., Georgescu et al., 2018), while Cultural and social norms is a complex phenomenon and possible the hardest entrepreneurial condition (V2-V13) to manage by governmental actions. This will lead to some future research suggestions in the following concluding section.

DISCUSSION AND CONCLUSIONS

Early-stage entrepreneurial activity is a crucial driver for wider economic activity and an important field to provide dynamism, which are increasingly important under turbulent times leading to diverse economic shocks requiring resilience and dynamism to overcome them. Drivers of entrepreneurial activity were studied from a combination of macro and micro perspectives in terms of (macro)economic freedoms and entrepreneurial conditions. The methods of neural network analysis and multiple correspondence analysis were applied to capture effects of categorical data (MCA) and complex relationships of independent variables and the dependent total entrepreneurial activity (TEA).

Multiple correspondence analysis revealed two clusters in section 3.1, when considering the two most important dimensions (explaining 31.7% of the total variation of our 27 variables): the "top-cluster" characterised by highest entrepreneurial conditions including the index and R&D transfers, governmental support and policies, supporting taxation and bureaucracy, financing for entrepreneurs and internal market openness and the "low-cluster" characterised also by entrepreneurial conditions index and R&D transfers, but otherwise mainly only by economic freedoms. Only handful of countries were closely related to these two clusters, but these implied that on the top level, micro perspective and entrepreneurial conditions are what matter, while on lowest level, macro perspective plays an equal or larger role. It must be noted that, while the medium-level countries were not related to most important factors on the first two dimensions, neither were the countries with highest entrepreneurial activity (by TEA), except USA and United Arab Emirates, while Ecuador and Madagascar, which belonged to the highest quartile by TEA, popped up related to the countries and low-class factors or economic freedoms and entrepreneurial conditions.

By neural network analysis in section 3.2, the economic freedoms and entrepreneurial conditions were shown both to include important predictors of TEA. Thus, the question of a matter of economic freedoms or economic conditions cannot be answered either or, but the results imply that both are crucial. Not surprising, property rights, investment, labour and business freedoms were on the top of the importance list of the economic freedom variables; similarly R&D transfers, entrepreneurial financing, governmental support and policies, as well as, internal market dynamics in the (early-stage) entrepreneurial activity may be expected; on the other hand, fiscal health (of governments related to balanced budgets and limited debt) was less expected; also, cultural and social norms were found as one of the most important of the entrepreneurial conditions, which does not offer easy policy implications as such norms are utterly difficult to manage by political decisions.

The used data source of this study, Global Entrepreneurial Monitor, provides another large dataset on entrepreneurial attitudes and our results (cf., the role of cultural and social norms) call for extending the research using also this data. Other suggestions for future studies arise from the use of only 2019 data for both economic freedoms and entrepreneurial conditions, which may not give well-generalisable results. Thus, a longer study period is suggested. It may detect, e.g. if certain economic freedoms are a prerequisite for entrepreneurial conditions, or vice versa, leading to increasing entrepreneurial activity, and it may lead to more generalisable and stable results as the neural network results may be unstable with a small dataset. Logistic regression or discriminant analysis may offer support for neural network approach.

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