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WHAT DRIVES THE PERFORMANCE OF THE SME SECTOR? EVIDENCE FROM SELECTED EUROPEAN COUNTRIES

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Abstract: Small and medium-sized enterprises (SME) are highly important for economic development of every nation. Recently, many experts and policymakers have been trying to measure the performance and efficiency of these businesses. However, the methods used so far are often idiosyncratic, subjective, or static. This paper suggests a new way to measure the success of these businesses using a data-driven method. More specifically, we combine decision-making techniques (namely, TOPSIS) and preference learning techniques. This innovative approach is flexible and can adapt to changes over time by iterative preference elicitation and TOPSIS calculation. As a part of the case-study of the proposed approach, we found that Ireland is a great example to follow and that the 'think-small-first' principle is the most important driver of the SME growth. The findings can help government officials and analysts, especially when they are planning policies for small and medium-sized enterprises.

Keywords: Small and medium-sized enterprises, performance measurement, TOPSIS, preference learning.

MSC: 68U35, 90B50.

1. INTRODUCTION

It has almost become a doctrinal phase to claim that small and medium-sized enterprises (SME) are the backbone of every economy [1]. On the one hand, in the European context, SMEs create 99 percent of the number of enterprises, 49 percent of persons employed, and 32 percent of turnover [2]. SMEs also provide accelerated innovation, improved exports, and a substantial contribution to gross domestic value growth. In addition, they drive digitization [3] and contribute to sustainable development [4]. On the other hand, this sector is vulnerable to external changes and requires governmental support in terms of both financial and non-financial aid [5].

Being at the same time highly important and fragile, the SME sector is subject to continuous monitoring and measurement of success. This stands for the level of economic subjects [6] and the sector as a whole [7]. Not surprisingly, in the last few decades, a colossal number of papers have dealt with the performance of the SME sector. Most of the concurrent body of knowledge is based on measuring idiosyncratic measures, using a single or a small number of parameters to claim how *entrepreneurial* successful a nation is [8].

Entrepreneurial success as such is an amorphous term. It might be viewed through the number of newly established companies, support for the second chance, ease of access to finance, implementation of the 'think small principle', internationalization of SMEs, development of entrepreneurial skills and innovation, environmental impact, or digitalization. Looking at only one or a few individual measures can create various biases. For instance, two countries can have the same percentage of businesses run as SMEs or even the same employment and GDP creation. Still, their performance regarding innovation, internationalization, or digitalization can vary significantly. One can find a possible explanation that entrepreneurship can sometimes be pure necessity rather than an opportunity seeking endeavours [9].

Having the above in mind, a single, comprehensive measure of entrepreneurial performance would be highly beneficial for both scholars and practitioners. Unfortunately, this field has only scarcely been investigated in the extent literature. This paper aims to provide a comprehensive measure of entrepreneurial performance. For this purpose, we first draw on the concepts of 'entrepreneurial nations' and algorithmic governance. The first one is used to explain how concurrent metrics have been used to measure performance of the SME sector. The later one is fundamental to our approach and explains how data-driven metric could utterly change the measurement paradigm.

From these two concepts, we develop our analytical framework as an innovative combination of two existing methodologies. More specifically, we used individual performance measurement scores retrieved from the *Small Business Act (SBA) factsheet*, which were combined using the TOPSIS method (a method within the MCDA/M family of methods). Furthermore, to allow for an objective weighting of individual measures, we used Preference Elicitation (as a machine learning technique). This combination of techniques has already been used in other policy-making fields, such as public procurement [10], or tax administration performance [11]. However, the area of SMEs has been below the research radars.

Our approach allows for:

- Comprehensive, rather than idiosyncratic, approach to measuring entrepreneurial performance. When using a single or limited number of performance measures, the measurement system can create either the *myopia* or *hyperopia* effect [12]. Thus, it might help policymakers and other stakeholders compare countries based on multiple criteria.

- Objective, rather than subjective, approach to weighing individual performance measures. Since the approach is data-driven, it provides algorithmic learning. Other approaches are usually based on expert-based weights, which are always the subject of disputes and discussions.
- The bootstrapping procedure, when combined with our approach, facilitates more thorough testing by enabling the comprehensive examination of variability and performance under a wider range of scenarios. One can understand that this approach can create the so-called *atrophic* or *hypertrophic* effect. [13].

The remainder of the paper is organized in the following order: Section 2 provides the theoretical root of the study by reviewing algorithmic governance as a fundamental approach and entrepreneurial success at the national level as a background to our study. Section 3 thoroughly delineates the methodology of our study – analytical framework based on the combination of machine learning and multiple-criteria decision-making techniques and data sources used for the empirical investigation. Section 4 elaborates on the results of our study by reporting on the most important drivers of entrepreneurial success and the role-model countries from the *Old Continent*. Section **??** contextualizes the findings and explains the main contributions and implications. Section 6 is reserved for concluding remarks, limitations, and further recommendations.

2. LITERATURE REVIEW

In this section, we first elaborate on the entrepreneurial performance of countries. Then, we explain the concept of algorithmic governance as an underlying concept for our analytical framework.

2.1. Entrepreneurial nations and drivers of entrepreneurship growth

Concurrent literature provides a myriad of examples of country rankings related to entrepreneurial activity and the performance of the SME sector. All these performance measurement approaches are either suited for policy-making purposes or simply scholarly approaches aimed at improving the soundness of the previous one.

From a policy-making point of view, important measures of entrepreneurial activity across national contexts are given in several annually conducted assessment projects ran by supranational agencies, such as *the Global Entrepreneurship Monitor (GEM)*, *EIM COMPENDIA Database*, and the *World Bank Group Entrepreneurship Survey Dataset* [14]. Out of these, The GEM survey has been the most broadly used in empirical studies, such as [15] or [16]. Datasets provided from these annual surveys provide rich and comparable evidence on entrepreneurship at the country level. Still, these rankings and metrics are subject to criticism since a number of performance measures capture necessity rather than opportunity seeking in entrepreneurship endeavors [17]. Also, these metrics reflect more on the development of the SME sector than the so-called 'Schumepterian entrepreneurship' [18]. The Schumepeterian theory of entrepreneurship refers to entrepreneurship not only by the dimension of organizing business (as a central concept of the Marshallian entrepreneurship theory), but by innovation and economic advancement [19]. Finally, these surveys are focused on singular comparative performances and do not provide a holistic assessment of entrepreneurial success.

From a scholarly point of view, a notable example of the performance measurement of entrepreneurship is the study of Stel, Carree and Thurik [7] who thoroughly elaborate on the effects of entrepreneurial activity on national wealth creation. The paper in general finds low entrepreneurial activity in European countries compared to their Asian or North American counterparts. Some studies tangentially explain the entrepreneurial success of nations by either examining the causes [20] or investigating the determinants of such success [21]. Nonetheless, none of these or similar studies have put upfront the methodological rigour in comparing countries regarding their entrepreneurial performance.

2.2. Algorithmic governance

The idea and the concept of algorithmic governance are only a decade old, although the roots and the idea have been present for much longer [22]. The concept refers to the use of algorithms, computational models, and automated decision-making processes in the management and regulation of various aspects of society.

This concept is particularly relevant in the context of modern digital technologies and the increasing reliance on algorithms to inform or automate decision-making in areas such as government, business, and social institutions. Algorithmic governance involves the use of algorithms to make decisions that were traditionally made by humans. These decisions can range from simple tasks, such as sorting and filtering data, to more complex decisions like resource allocation, policy enforcement, and risk assessment. The system heavily relies on data analysis to inform decision-making. Large datasets are processed to identify patterns, trends, and correlations, which can then be used to make predictions or optimize processes.

For the purpose of our study, value-neutral weighting of policy choices is particularly relevant feature of algorithmic governance. From a philosophical point of view, value-neutral strategy is 'restricted to data and decision outcomes, thereby omitting internal value-laden design choice points.' [23]. Traditional systems (such as the World Bank Ease of Doing Index, for instance) rely heavily on the subjective weighting of idiosyncratic performance measures. The algorithmic approach, however, allows for very efficient and expert-free, neutral decision-making.

However, algorithmic governance raises some concerns regarding the fairness of decisions, doubts related to the black box of the algorithm, or even the privacy of data. Governments, organizations, and researchers are exploring ways to create guidelines and standards for algorithmic systems. For instance, Issar and Aneesh [24] emphasize 'the growing institutional capabilities to move contestable issues to a space of reduced negotiability, raising questions of social asymmetry, inequity, and inequality. Thus, whenever the algorithm overtakes a human role in the decision-making process (or in our case weighting process), this should always be done with a precaution.

3. METHODOLOGY

In this section, we first explain the sources of data used in our framework. Afterwards, we delineate the analytical framework of our approach in a step-by-step manner.

3.1. Data sources

The main data source for our study comes from the *Small Business Act (SBA) Factsheet*. The SBA is a EU-funded initiative aimed at supporting SMEs. It aims to improve the overall business environment for SMEs, foster entrepreneurship, and encourage innovation [25]. Policymakers, government officials, and other stakeholders often rely on this factsheet to access summarized and relevant information on a particular topic.

As explained in detail in [26], the last edition of the SBA Factsheet calculates SBA profiles for the 27 EU member states plus 16 non-member states (part of the *COSME* program). In total, the list has 94 indicators that come from highly reliable sources such as the Eurobarometer, GEM, World Bank statistics, Eurostat Business Statistics, the Survey on the Access to Finance of Enterprises (SAFE), and others. It is worth stating that all the data was collected for the 2021 year. The SBA covers various areas, such as: entrepreneurship in general (entrepreneurial environment), "the second chance," implementation of the "think small first principle," access of SME to public procurement, access to finance, access to the EU single market, entrepreneurial skills and innovation, environmental friendliness of SMEs, internationalization, and digitization. Very little to no criticism has been put on the quality of these data, and they have been broadly used by scholars (i.e. [27] or [28]).

A complete set of criteria can be found in the Appendix A and it consists of ten groups of criteria. Those are, namely, *Entrepreneurship*, *Second Chance*, *Think small first*, *Public Procurement*, *Access to Finances*, *Single Market*, *Skills and Innovation*, *Internationalization*, and *Digitization*.

3.2. Analytical framework

In this paper, we explored an innovative approach to evaluate the performance of SMEs and entrepreneurship across different countries. Our method combines the TOPSIS method, a well-established technique in multi-criteria decision-making (MCDM), with a preference learning framework from machine learning. This blend of techniques aims to objectively weigh various performance measures of SMEs and entrepreneurship. Similar approach was used in [10] and the results were promising.

The use of machine learning, specifically preference learning, is a key aspect of our approach. Preference learning is particularly effective in reducing human bias in deciding the importance of different criteria, especially when these criteria are complex and potentially conflicting [29]. In our study, we applied this method to estimate weights by analyzing country rankings based on their business environments for SMEs and entrepreneurship, as outlined in existing research [30]. We transformed these rankings into pairwise comparisons, which were then used in a mathematical model to determine the weights for the TOPSIS method. This comparison helps us calculate the weights of various indicators, aiming to minimize the error between the input preferences and the outcomes.

The method of estimating criteria weights through preference learning offers several advantages over traditional methods of determining criteria weights. Usually, individual decision-makers or groups could use their expertise or group decision-making techniques to decide these weights. However, human reasoning has its limitations, and such processes need to be carefully managed to avoid introducing biases. These biases might manifest in various ways, such as giving undue importance to a criterion because it correlates with another or misjudging weights due to the complexity of making numerous comparisons [31].

Preference learning sidesteps some of these issues by relying on a more systematic, data-driven approach. Instead of relying solely on human judgment, which can be swayed by various cognitive biases, preference learning uses mathematical models and algorithms to derive weights. This method ensures a more objective and reliable process, reducing the likelihood of skewed weight assignments and enhancing the overall credibility and accuracy of the rankings. One might find this approach very similar to the Stochastic Multicriteria Acceptability Analysis (SMAA), which offers a family of methods designed to deal with uncertainty and imprecision in decision-making, particularly useful when decision makers' preferences are not precisely known or when there is variability in the criteria evaluations [32]. It assesses the acceptability of alternatives by considering possible weights and performances, providing a probabilistic interpretation of each alternative's potential to be the best choice. While SMAA excels in handling ambiguity and providing a broad, probabilistic overview of alternatives' acceptability, the TOPSIS and Preference Learning mix focuses on deriving explicit rankings based on observed data and the conceptual proximity to an ideal solution by utilizing human preferences to derive criteria weights.

One of the significant advantages of the proposed methodology is its efficiency and generalizability. By deriving weights from a limited set of pairwise comparisons, we can create a comprehensive ranking of countries without needing an exhaustive set of comparisons. This feature makes the method more practical and widely applicable.

Our analysis begins with a detailed explanation of the TOPSIS method. TOPSIS is renowned in MCDM for its ability to identify the best option by comparing it to an ideal solution [33]. It involves calculating a positive ideal solution (notated as $[S_i^+]$) and a negative ideal solution (notated as $[S_i^-]$). The ideal choice is the one closest to the positive solution and farthest from the negative one. The process starts with constructing a decision matrix, represented in the equation we will discuss next. Following this, we will delve into the mathematical model used for learning the criteria weights within the preference learning framework, which incorporates the outcomes from TOPSIS as inputs. This approach, previously used in public administration studies [10], is novel in the context of SME and entrepreneurship analysis. We will start by describing TOPSIS method and later describe the mathematical model that learns criteria weights using the preference learning framework using TOPSIS outcomes as inputs.

In our analysis, we arrange the data in a matrix format (denoted M), where each row represents a different country (these are our alternatives) and each column corresponds to a specific criterion we're evaluating. In this matrix, the element x_{ij} denotes the value of the j-th criterion for the i-th country. A general presentation of the data matrix is presented below.

$$M = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix} \tag{1}$$

To effectively compare these different criteria, which might be measured in various scales and units, we normalize the data matrix. This normalization is of immense importance because it allows comparison of values on a consistent scale. We use the $L2$ norm method for this purpose. This ensures that each criterion contributes equally to the final evaluation, providing a fair and balanced comparison of the countries' performances in different aspects.

$$\hat{x_{ij}} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{2}$$

The next step in our analysis involves calculating the weighted normalized matrix. This is a critical stage where we apply the weights to the normalized data. Each value in our normalized matrix is multiplied by its corresponding weight as presented below.

$$v_{ij} = w_j \hat{x_{ij}} \tag{3}$$

The key part of the TOPSIS method involves calculating the positive and negative ideal solutions. In simple terms, the positive ideal solution represents the best possible scenario, where each criterion has the most favorable value. Conversely, the negative ideal solution represents the least favorable scenario, with each criterion at its least desirable value. We determine these ideal solutions using a max-min approach for the positive ideal solution and a min-max approach for the negative ideal solution. This means we look for the highest values for each criterion in the positive ideal solution and the lowest values for each criterion in the negative ideal solution. The formulas are presented below.

$$IPS(v^+) = \{v_1^+, v_2^+, ..., v_m^+\} \tag{4}$$

where

$$v_j^+ = \{best_{i=1,\ldots,n}(v_{ij}), j \in J\} \tag{5}$$

with *best* being the highest value of criterion j if higher value is better or the lowest value of criterion j if lower value is better. Analog to this, we calculated the negative ideal solution $IPS(v^-)$ with a difference that the worst value is observed. The separation measures were calculated as follows:

$$S_i^+ = \sqrt{\sum_{j=1}^{m}(v_{ij} - v_j^+)^2} \qquad S_i^- = \sqrt{\sum_{j=1}^{m}(v_{ij} - v_j^-)^2} \tag{6}$$

where S_i^+ and S_i^- are distances from the positive ideal and negative ideal solution, respectively. In simple terms, we compared each country's performance against ideal solutions to assess how close or far they are from the ideal scenarios in the context of SMEs and entrepreneurship.

These coefficients are crucial because they help us understand how close each country's performance is to the ideal scenarios we've identified – both the best possible (positive) and the worst possible (negative) outcomes.

The next important step in our process is to calculate the closeness coefficients, denoted as CC_i (as presented below). These coefficients are crucial because they help us understand how close each country's performance is to the ideal scenarios we've identified – both the best possible (positive) and the worst possible (negative) outcomes.

$$CC_i = \frac{S_i^-}{S_i^- + S_i^+} \tag{7}$$

The idea is to measure the relative proximity of each country's performance to these ideal solutions. A higher closeness coefficient indicates that a country is closer to the positive ideal solution and further from the negative one, which implies a better overall performance in terms of the criteria we're evaluating. Theoretically, $CC_i = 1$ would be a positive ideal solution v_j^+, and $CC_i = 0$ would be a negative ideal solution v_j^-. Consequently, one can use CC to rank countries according to their performance and derive policies for improvement.

An additional problem we faced is the presence of 110 criteria. Combining all of them into a single model would result in a *curse of dimensionality* issues where every distance would tend to be similar due to the additive nature of the distance functions. To ameliorate the procedure, we divided the TOPSIS method into 10 separate subproblems. More specifically, one TOPSIS model per each group of attributes as presented in the previous section. Once all the TOPSIS models are concluded, we generate an additional TOPSIS model using the results of the first ten models. Addressing the problem of criteria hierarchies in MCDM methods is a task well known in the literature [34, 35]. The process of hierarchical TOPSIS was conducted in the same manner as in the [36] where a distance was calculated from the *Partial positive ideal and negative ideal solutions* for every hierarchical part prior to the calculation of *Relative closeness to partial positive ideal and negative ideal solutions and ranking.* In other words, the hierarchical TOPSIS was not only conducted at a comprehensive level, but to each of the non-elementary criterion denoted as a group in tables A.3, A.4, A.5, and A.6. However, there is a difference between [36] and the proposed approach. Both approaches are using preferences of the DM to derive a set of weights, but in our approach, preferences are presented in a goal function as a hinge function, while in the [36] they are presented as the constraint. In that sense, the proposed approach would yield a solution regardless of whether a set of preferences are satisfied or not, while the [36] approach would yield in an unfeasible solution. On the other side, [36] provides rank acceptability index and pairwise winning index due to SMAA methodology, while our approach utilizes bootstrap procedure to estimate expected utility score and its confidence interval.

To effectively integrate the TOPSIS method into our preference learning mathematical model, we need to conceptualize TOPSIS as a function. Let's denote this function as t. This function t requires two key inputs: firstly, x, which is a data vector representing the information for a specific entity, such as data pertaining to a single country; and secondly, w, which is a vector of weights reflecting the importance of each criterion in our analysis. This setup allows us to perform optimization procedure, making the entire method more streamlined.

With the TOPSIS model established and a set of preference relations denoted as P, we can now proceed to formulate our mathematical model. The essence of this model lies in its ability to link the outcomes from the TOPSIS method with the preference relations. The preference relations P represent our understanding of how different countries should ideally be ranked (more specifically, compared in pairs) based on their SME and entrepreneurship performance. These preferences are based on ranking of countries as given in [30]. More specifically, we transformed the ranking of countries into a set of pairwise comparisons, which are as preference relations for the mathematical model.

$$minf(W) = \sum_{P=(p_1,p_2)} max(t(x_{p_2}, W) - t(x_{p_1}, W), 0) \tag{8}$$
$$s.t. \tag{9}$$
$$\sum_q w_q = 1, \forall r \tag{10}$$
$$\sum_t w_r = 1 \tag{11}$$
$$0.01 \geq w_{rq} \geq 0.3 \tag{12}$$
$$0.01 \geq w_r \geq 0.3 \tag{13}$$

where P symbolizes a set of preference relations, expressed in the format $p_1 \succ p_2$. This denotes that an individual prefers country p_1 over country p_2. The function t, as previously described, is the TOPSIS function used to evaluate these countries. It is worth noting that the whole space of weights vectors is denoted with W where $W = \{(w_{1_1}, ..., w_{10_8}) \cup (w_1, ..., w_{10})\}$. More specifically, we have a set of hierarchical r denoting top level weights and q denoting second level weights. Our idea is to ensure that a set of weights is equal to 1 for each group of criteria, as well as for the top level criteria. In addition, we would like to limit the weights to a value between 0.01 and 0.3 so none of the criterion takes too much of the ranking importance, as well as to have every criterion of at least minor importance.

The objective function of our model resembles a hinge function commonly utilized in support vector machines [37]. It penalizes scenarios where the TOPSIS method assigns a higher utility value to a less preferred country. In other words, if the TOPSIS outcome aligns with our preference relations (meaning the preferred country gets a higher score), the hinge function contributes nothing to the goal function. However, if there's a discrepancy – if a less preferred country scores higher – the function quantifies this mismatch, reflecting the degree of dissatisfaction with the preference relation. Additionally, our mathematical model incorporates specific constraints inherent to the TOPSIS method. These constraints pertain to the weights used in the TOPSIS function: firstly, all weights must be positive, and secondly, they should sum up to one. These constraints are vital to ensure that the TOPSIS evaluations are balanced and correctly proportioned, allowing for a fair and meaningful comparison of the countries based on the established preference relations. To further restrict the criteria weight we added a constraint that weights should be between 0.01 and 0.3.

As an outcome of this process, we obtain a set of criteria weights w, which lead to the calculation of closeness coefficients (CC_i). These coefficients are tailored to optimize the preference relations we defined earlier. An important aspect of this result is its applicability: these weights and closeness coefficients can be used to rank countries. This ranking is not limited to just those countries included in our initial preference relations; it can also be extended to countries not previously considered in the preference set.

The model we've developed, despite initial appearances, presents a unique challenge in terms of its mathematical structure. At first glance, it might seem like a linear or convex model, primarily because the hinge function is essentially a combination of two linear functions, and the constraints involved are linear. However, the reality is more complex due to the nature of the TOPSIS function t that is integral to the objective function. A key point of complexity in our model arises from the TOPSIS methodology. Instead of a standard single TOPSIS model, our approach incorporates a total of 11 TOPSIS models. This includes ten models for different groups of criteria and an additional overarching model that combines these ten. This multi-layered structure significantly increases the complexity of the TOPSIS function within our overall model.

To tackle this complexity, we explored various optimization techniques. Evolutionary algorithms and several other population-based metaheuristics were tested. However, the most effective optimization procedure turned out to be Sequential Least Squares Programming (SLSQP) [38]. SLSQP is a method designed for solving constrained nonlinear optimization problems. It is grounded in the principles of sequential quadratic programming, which involves approximating the objective function and constraints with quadratic models and then solving a series of subproblems based on these approximations. The advantage of SLSQP over other methods lies in its least-squares approach to fitting the quadratic models. This approach allows SLSQP to handle more general constraints and sidestep some of the numerical issues that can arise in optimization problems.

In addition to the calculation of the TOPSIS closeness coefficient, we want to ensure that the findings are statistically significant. Thus, we performed bootstrap permutation tests to estimate the statistical significance of the ranking. Bootstrap permutation tests [39] are a robust, non-parametric approach to statistical testing that combines the principles of bootstrapping and permutation testing. More specifically, we repeatedly sampling from the dataset to estimate the distribution of a countries' rank. Then, by comparing the test statistic from the original data with the distribution of test statistics obtained from bootstrapped data, we can evaluate the statistical significance of the observed effect, thereby enhancing the robustness and reliability of inferential conclusions drawn from empirical data.

4. RESULTS

This section presents the results of the preference learning based TOPSIS method. The weights of the top-level criteria are presented in Table 1. For the sake of clarity, criteria names are replaced with C1-C10, where criteria are *Entrepreneurship*, *Second Chance*, *Think small first*, *Public Procurement*, *Access to Finances*, *Single Market*, *Skills and Innovation*, *Internationalization*, and *Digitization*. One can notice that not a single criterion is dominant in weights and that *Think small first* and *Entrepreneurship* have the greatest importance for the ranking, while *Second Chance* and *Internationalization* are of less important. As a result of the preference learning phase of our approach conducted using three experts in the area of finance and entrepreneurship, we obtained the criteria weights as obtained in the Table 1. More specifically, we obtained weights for the entire set of criteria both top level (presented in the table) and the bottom level (those sub-criteria presented in tables A.3, A.4, A.5, and A.6.)

Table 1: Criteria Weights

Attribute	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Weight	0.141	0.049	0.151	0.143	0.090	0.097	0.080	0.083	0.055	0.109

4.1. TOPSIS Results

In our study, we found that Ireland is doing the best in terms of SME performance according to the proposed method (as shown in Table 2 and Figure 1). Column $CC(Rank)$ represents the closeness coefficient, which is an output of the TOPSIS method and based on which one can rank countries (values in the brackets). They are followed by Latvia, Lithuania, Estonia, and the United Kingdom. On the other hand, the countries that are not doing as well are Romania, Bulgaria, Croatia, Greece, and Spain.

However, our method of ranking these countries had some unexpected results. For example, we thought Germany would be second, but it ended up sixth. Also, we expected Belgium to be third, but it came in eleventh. There are a couple of reasons for these surprises. First, some countries just couldn't rank higher because other countries were doing better in all aspects (a country is dominated by other country). This means that for every important factor we looked at, these countries were either doing worse or just as good as others. Second, trying to move one country up in the ranking would end up making the overall results less accurate. This is because improving one country's rank might not fit with how other countries are doing, based on the expressed preferences.

4.2. Robustness Analysis

One problem with the TOPSIS method is called *rank reversal* [40]. This means that the order of preferences between two countries can change if we use a different group of countries for ranking. For example, let's say we have 26 countries. Initially, country A might rank higher than country B (more specifically, we prefer A over B). But if we remove a non-optimal country C, the ranking can change, and now country B might rank higher than country A (we prefer B over A). This happens because the best possible scenario (ideal solution) might change, and some criteria might become less important in calculating the rankings. This issue can occur with any country that isn't completely outperformed by others (non-dominated) or doesn't completely outperform others (non-dominant), especially if it has the best or the worst score in one or more criteria.

To deal with this, we used a method called bootstrap permutation testing. We repeated the TOPSIS method 500 times by randomly selecting 20 countries. This helps us see if a country consistently ranks in the top 5 or bottom 5. Additionally, we calculate the expected value and confidence intervals of the TOPSIS

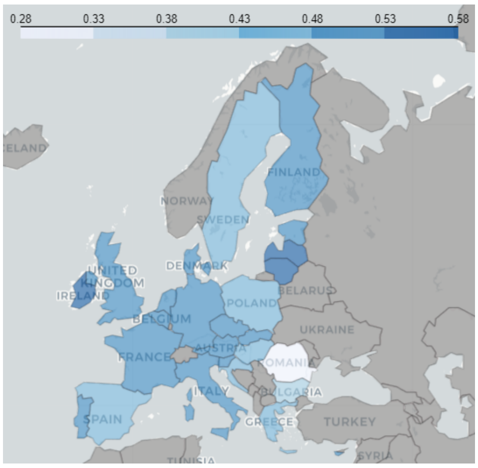

Figure 1: Map of the TOPSIS results

score using the percentile method. This gives us a better understanding of where countries really stand in the rankings. In addition, we calculated p-values for several questions we posed to ourselves. More specifically, what is a probability that a country belongs to the *top five* countries by the given ranking, as well as if a country belongs to the *bottom five* countries. A table with p values is presented in the Appendix B.

Based on the bootstrap analysis presented in columns Bootstrap CC (95% CI) and Bootstrap Rank in Table 2, there are only two countries that are consistently and statistically significant at the **top five** countries. Those are Ireland ($p \leq 0.0001$) and Lithuania ($p = 0.0128$). However, Latvia is close to be statistically significant at the top five with $p = 0.0686$, while Latvia and United Kingdom are commonly ranked among top five countries, but their p values are 0.1340 and 0.1865, respectively. In addition, we can be certain that Bulgaria, Romania, Greece, Croatia, Spain, Hungary, Poland, Cyprus, and Czech Republic are not within the top five countries as they never had that rank within 500 repetitions ($p = 0$), and we are close to certain that Sweden, Portugal, Slovenia, Netherlands, Slovakia, and Belgium are not within the top five countries as their p value is over 0.95.

On the other side of the ranking, situation with the **bottom five** countries is far clearer with Romania being the last ranked country every single time (consequently, $p = 0$) and Bulgaria being the penultimate or the worst ranked country if Romania was not selected in the experiment (consequently, $p = 0$). In addition, Greece and Croatia were most of the time among the bottom 5 ranked countries, thus having p values equal to 0.0053 and 0.0129, respectively. Spain was ranked among the bottom five most often. However, our analysis cannot confirm that Spain is within the bottom five countries as its p value is 0.1034. On the other side, we are certain that Austria, France, Finland, Germany, United Kingdom,

Table 2: Bootstrap based ranking of countries

Country	CC (Rank)	Bootstrap CC (95% CI)	Bootstrap Rank
Austria	0.5095 (10)	0.5105 (0.4871, 0.5360)	10
Belgium	0.5049 (11)	0.5018 (0.4699, 0.5284)	**12**
Bulgaria	0.3847 (25)	0.3874 (0.3642, 0.4093)	25
Croatia	0.4526 (24)	0.4521 (0.4203, 0.4801)	24
Cyprus	0.4871 (17)	0.4892 (0.4638, 0.5158)	17
Czech Republic	0.4922 (15)	0.4948 (0.4612, 0.5174)	**16**
Denmark	0.5119 (9)	0.5178 (0.4913, 0.5463)	**8**
Estonia	0.5278 (4)	0.5339 (0.5100, 0.5618)	4
Finland	0.5139 (8)	0.5215 (0.4945, 0.5629)	**7**
France	0.5159 (7)	0.5177 (0.4887, 0.5481)	**9**
Germany	0.5229 (6)	0.5252 (0.4951, 0.5516)	6
Greece	0.4548 (23)	0.4565 (0.4249, 0.4861)	23
Hungary	0.4724 (21)	0.4762 (0.4483, 0.5001)	**20**
Ireland	0.5820 (1)	0.5885 (0.5621, 0.6169)	1
Italy	0.5005 (13)	0.4991 (0.4603, 0.5368)	**14**
Latvia	0.5431 (2)	0.5467 (0.5167, 0.5736)	**3**
Lithuania	0.5404 (3)	0.5489 (0.5220, 0.5768)	**2**
Netherlands	0.4979 (14)	0.5037 (0.4801, 0.5323)	**11**
Poland	0.4778 (20)	0.4759 (0.4485, 0.4988)	**21**
Portugal	0.4834 (18)	0.4869 (0.4576, 0.5150)	**19**
Romania	0.2847 (26)	0.2855 (0.2605, 0.3089)	26
Slovakia	0.4912 (16)	0.4952 (0.4675, 0.5204)	**15**
Slovenia	0.5015 (12)	0.5014 (0.4707, 0.5297)	**13**
Spain	0.4703 (22)	0.4718 (0.4405, 0.4990)	22
Sweden	0.4814 (19)	0.4887 (0.4647, 0.5193)	**18**
United Kingdom	0.5249 (5)	0.5289 (0.5048, 0.5574)	5

Estonia, Latvia, Lithuania, and Ireland are not in the bottom five countries ($p = 1$), and we are close to certain that Slovakia, Denmark, and Netherlands are not in the bottom five countries ($p \geq 1$).

Finally, we calculate expected closeness coefficient (CC) and confidence intervals (CI), and recalculate rankings to inspect if there were changes. Changes in rank are denoted in bold letters. In total 16 countries changed their rank, however most of the changes are for one place in rank, either an improvement or deterioration. The biggest change happened to Netherlands that improved for three places and this is due to good results in *Entrepreneurship* and *Second Chance* criteria and very poor values in *Public Procurement*, *Access to Finance*, and *Digitization* criteria.

5. DISCUSSION

In this section, we summarize the main findings. Afterwards, we put the findings into a broader stream of concurrent research, accordingly explaining our contributions. Finally, we explain the main implications of our study.

5.1. Key findings

One should highlight Ireland as the best performing country with regards to SME performance. The Baltic countries, notably Latvia, Lithuania, and Estonia, frequently rank in the top five, with Latvia and Lithuania excelling in Entrepreneurship and Public Procurement, and Estonia performing well in areas like *Think Small First*, *Environment*, and *Internationalization.* The United Kingdom shows overall competence but falls short in *Public Procurement*, *Think Small First*, and *Single Market* criteria. Significantly, Ireland and Lithuania's positions in the top five are backed by a statistical significance greater than 95%.

Scandinavian countries — Denmark, Finland, and Sweden — although not the best, show good performance, especially in *Internationalization*, *Environment*, *Skills and Innovation*, and *Second Chance* criteria, along with decent scores in *Access to Finance.* However, their lower scores in *Entrepreneurship*, *Public Procurement*, and *Single Market* criteria place them in a relatively good position, except for Sweden, which ranks 19th out of 26.

France and Germany are above average performers with their own set of strengths and weaknesses. However, their performance is dragged down by below-average scores in *Entrepreneurship.* Italy shows proficiency in *Digitization* and *Single Market* criteria but is let down by low scores in *Entrepreneurship*, *Access to Finance*, and *Second Chance* criteria, resulting in an overall average performance.

The Czech Republic, Poland, and Slovakia are categorized as below-average performers, with notably poor results in *Second Chance* and *Internationalization* criteria. Belgium and the Netherlands show average performance, with Belgium slightly outperforming the Netherlands. Both countries do well in the *Second Chance* criterion but are below average in *Public Procurement* and *Access to Finance.*

Surprisingly, Spain is among the bottom five, with particularly poor results in *Public Procurement*, *Environment*, and *Access to Finance.* Portugal, while better than Spain, also performs poorly in *Public Procurement*, *Access to Finance*, and *Digitization* but scores well in the *Think Small First* criterion.

Finally, Balkan countries, particularly Romania, Bulgaria, Greece, and Croatia, are identified as poor performers, with their low rankings confirmed with 95% statistical significance.

5.2. Contributions

This paper contributes to the development of the knowledge base on SME performance in conceptual and methodological ways. From the conceptual point of view, this paper contributes as follows:

- First, we contribute in general to the enriching the concept of algorithmic governance [41] and providing an example of algorithmic governance use in the SME sector. Although this study is supportive to algorithmic governance, we recognize potential categorical pitfalls of the implementation of fully neutral and data-driven rankings in any policy-making fields [42].

- Second, the study findings explicitly show that (1) *Think small-first*, (2) *business environment*, and (3) *access to finance* are the most important contributors to the overall performance of the SME sector and entrepreneurship. Concurrent literature is ambiguous in presenting the most influential drivers of the SME and entrepreneurship growth. On the one side, recent studies see political and historical factors as the most important ones [43] which is close or identical to our findings. On the other side, some scholarly voices tend to put larger emphasis on innovation and digitization [44].

- Third, we provide an objective ranking of the selected European countries in terms of the goodness of their SME sector. Our ranking differs to some extent from both practice-led [45] and scholarly-made rankings [46]. Nonetheless, in a broader regional context - West Europe and Nordic countries are always seen as 'good' examples, whereas South and East Europe still require active policies to improve their entrepreneurial ecosystems. Still, those vague regional definitions should not be taken for granted, since our result (contrary to some recent scholalry advocations [47]) show that there is no clear division between Old and New Europe when it comes to SME development.

As seen through the methodological lens, this paper adds a contribution by combination of preference learning and TOPSIS method to obtain ranking of countries in the SME performance. This way we obtain human preferences about the ranking, but with significant drop of time to obtain weights needed for the TOPSIS method.

5.3. Implications

This study has twofold contributions: (1) to researchers and (2) to policyholders. As for the researchers, this paper adds to the growing field of data-driven non-stationary ranking in policy-making [48]. From a grand scheme of things, this is a contribution to algorithmic governance in the sense that ranking and policy-making are done in an objective manner. Also, it provides novelties regarding the sensitivity analysis of the PL-TOPSIS approach. Recent studies based on this approach [1] are inelastic in terms of sensitivity to the number units of observations and attributes.

Implications for policyholders are by far more important. First, the approach to SME sector performance measurement presented in this paper is comprehensive. Accordingly, it provides a holistic overview of the SME and entrepreneurship in a country, thus allowing for the "whole-of-government approach" advocated by various international organizations and financial institutions [49]. Second, this paper puts special emphasis on various performance measures to be monitored by governments. Specific emphasis should be given to the entrepreneurial environment (i.e. "Think-small-first" and access to finance for SME). This paper calls for innovative approaches to government-based facilitation in the SME sector. This is somewhat paradoxical since public administrations themselves are not prone to innovations [50].

6. CONCLUSIONS

In this paper, we analyze performance of the SME sectors in 26 European countries. To get a comprehensive measure of the entrepreneurial success of the country, we used a combination of TOPSIS and preference learning on individual measures retrieved from the SBA factsheet. Our study finds that Ireland can serve as a role model, whereas the *Think-small-first* measure is the most important driver of entrepreneurial success.

This approach can play a pivotal role in the ex-ante examination of policies related to the SME sector since it creates a 'clay pigeon shooting' effect. This means that once the policymakers in the observed European countries compare the efficiency of their policies towards the SME sector (after investing heavily in singular performance), the performance matrix recalculates the weights and forces them to push harder in other directions. Accordingly, this approach does not allow for any atrophia or hypertrophia in the entrepreneurial performance.

Even though our framework can be a solid foundation for policy analyses, a handful of limitations can jeopardize its practical implementation. First, we observed only data from a single period to generalize conclusions on the most important driver of SME performance. Even the first consecutive period can alter the weighting, thus diluting the importance of our findings. Second, our approach is sensitive to the original data from the $SBAfactsheet$ dataset. Some criticism has been posed to the use of such aggregated data [51], although proponents and advocates immensely outnumber the critics [52].

As a part of future work, we plan to employ SMAA as the proposed approach obtains weights that are static, thus obtaining a single ranking. SMAA could potentially offer a robust framework for addressing the multifaceted challenges of MCDM, balancing between probabilistic analysis and data-driven preference modeling to accommodate various decision-making contexts and uncertainty levels. In addition, the possibility to add rank acceptability index and pairwise winning index would increase the ability to interpret the obtained ranking.

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Appendix A. Criteria Set

The tables A.3, A.4, A.5, and A.6 present the set of attributes used in this research, their groups, and their orientation for the TOPSIS method.

Table A.3: TOPSIS Criteria - Entrepreneurship, Second Chance, and Think small first

Group	Criteria	Orientation
Entrepreneurship	Total early-stage Entrepreneurial Activity (TEA)	max
Entrepreneurship	Total early-stage Entrepreneurial Activity for Female Working Age Population	max
Entrepreneurship	Total early-stage Entrepreneurial Activity Established Business Ownership Rate	max
Entrepreneurship	Improvement-Driven Opportunity Entrepreneurial Activity: Relative Prevalence	max
Entrepreneurship	Entrepreneurial intentions	max
Entrepreneurship	Degree to which school education helped develop an entrepreneurial attitude	max
Entrepreneurship	Entrepreneurship as Desirable Career Choice	max
Entrepreneurship	High-status to successful entrepreneurship	max
Entrepreneurship	Media attention for entrepreneurship	max
Entrepreneurship	Education	max
Entrepreneurship	Share of high growth enterprises	max
Entrepreneurship	Employment share of high growth enterprises	max
Entrepreneurship	High Job Creation Expectation Rate	max
Second Chance	Time to resolve insolvency	min
Second Chance	Cost to resolve insolvency (% of the debtor's estate)	min
Second Chance	Degree of support for allowing for a second chance	max
Second Chance	Fear of Failure Rate	max
Second Chance	Strength of insolvency framework index (0-16)	max
Think small first	Time to start a business (days)	min
Think small first	Cost to start a business (% of income per capita)	min
Think small first	Paid-in minimum capital (% of income per capita)	min
Think small first	Time to register property (in days)	min
Think small first	Cost to register property (% of property value)	min
Think small first	Payment of taxes (number per year)	min
Think small first	Time to pay taxes (hours per year)	min
Think small first	Cost to enforce contracts (% of claim)	min
Think small first	Fast-changing legislation and policies are a problem when doing business (% of businesses who agree with the statement)	min
Think small first	The complexity of administrative procedures are a problem when doing business (% of businesses who agree with the statement)	min
Think small first	SMEs interacting online with public authorities	max
Think small first	Starting a business: Procedures (number)	min
Think small first	Burden of government regulation (1 worst-7 best)	max
Think small first	New firms can get most of the required permits and licenses in about a week (Likert scale 1-5)	max
Think small first	The people working for government agencies are competent and effective in supporting new and growing firms (Likert scale 1-5)	max

Table A.4: TOPSIS Criteria - Public Procurement and Access to Finances

Group	Criteria	Orientation
Public Procurement	SMEs' share in the total value of public contracts awarded	max
Public Procurement	Share of businesses having taken part in a public tender of public procurement procedure (%)	max
Public Procurement	Total aid earmarked for SMEs	max
Public Procurement	Average delay in payments - public authorities	min
Public Procurement	Enterprises submitting a proposal in a public electronic tender system (eProcurement)	max
Public Procurement	Percentage of awards of contract per country & year for which the winner was a SME	max
Public Procurement	Proportion of bids coming from SMEs	max
Public Procurement	Percentage of calls for competition per country & year which were split into lots	max
Access to Finances	Venture capital investments (% of GDP)	max
Access to Finances	Strength of legal rights index (0-12)	max
Access to Finances	Depth of credit information index (0-8)	max
Access to Finances	Total duration in days to get paid (no, of days)	min
Access to Finances	Bad debt loss (% of total turnover)	min
Access to Finances	Cost of borrowing for small loans relative to large loans	min
Access to Finances	Annual average of interest rate for small loans	max
Access to Finances	Rejected loan applications and loan offers whose conditions were deemed unacceptable (% of loan applications by SMEs)	min
Access to Finances	Access to public financial support including guarantees (% share that indicated a deterioration)	max
Access to Finances	Willingness of banks to provide a loan (% share of respondents who indicated a deterioration)	max
Access to Finances	Willingness of banks to provide a loan (% share of respondents who indicated a deterioration)	max
Access to Finances	Equity funding available for new and growing firms (Likert scale 1-5)	max
Access to Finances	Professional Business Angels funding available for new and growing firms (Likert scale 1-5)	max

Table A.5: TOPSIS Criteria - Single Market and Skills and Innovation

Group	**Criteria**	**Orientation**
Single Market	Number outstanding single market directives (directives not notified or not transposed into national legislation)	max
Single Market	Average transposition delay for overdue directives (in months)	max
Single Market	Number of pending infringement proceedings	max
Single Market	Public contracts secured abroad (by total value of contracts)	max
Single Market	Intra-EU exports of goods by SMEs in industry (% of SMEs)	max
Single Market	Intra-EU imports of goods by SMEs in industry (% of SMEs)	max
Single Market	Intra-EU online importers (% of SMEs)	max
Single Market	New and growing firms can easily enter new markets (Likert scale 1-5)	max
Single Market	New and growing firms can afford the cost of market entry (Likert scale 1-5)	max
Single Market	New and growing firms can enter markets without being unfairly blocked by established firms, (Likert scale 1-5)	max
Single Market	The anti-trust legislation is effective and well enforced (Likert scale 1-5)	max
Skills and Innovation	SMEs innovating in house (% of SMEs)	max
Skills and Innovation	Innovative SMEs collaborating with others (% of SMEs)	max
Skills and Innovation	SMEs introducing product innovations	max
Skills and Innovation	SMEs introducing business process innovations	max
Skills and Innovation	Sales of new to market and new to firm innovations as % of turnover	max
Skills and Innovation	Share of SMEs selling online	max
Skills and Innovation	Share of SMEs purchasing online	max
Skills and Innovation	Training enterprises as share of all enterprises	max
Skills and Innovation	Turnover from e-commerce	max
Skills and Innovation	Percentage of enterprises employing persons with ICT specialist skills (%)	max
Skills and Innovation	Share of SMEs provided training to their personnel to develop/upgrade their ICT skills	max
Skills and Innovation	R&D Transfer (average of 82-87)	max

Table A.6: TOPSIS Criteria - Internationalization and Digitization

Group	Criteria	Orientation
Internationalization	SMEs having done electronic sales to the rest of the world	max
Internationalization	Information availability	max
Internationalization	Involvement of trade community	max
Internationalization	Advance rulings	max
Internationalization	Formalities – automation	max
Internationalization	Formalities – procedures	max
Internationalization	Border Agency Co-operation (internal)	max
Internationalization	Documents to export (number)	min
Internationalization	Time to export (days)	min
Internationalization	Cost to export (US$ per container)	min
Internationalization	Documents to import (number)	min
Internationalization	Time to import (days)	min
Internationalization	Extra-EU exports of goods by SMEs in industry (% of SMEs)	max
Internationalization	Extra-EU imports of goods by SMEs in industry (% of SMEs)	max
Digitization	Enterprises sending e-invoices	max
Digitization	Enterprises having website-homepage	max
Digitization	Enterprises that buy cloud computing services	max
Digitization	Enterprises using their own websites or apps for sale	max
Digitization	Individuals who have used a programming language	max
Digitization	Enterprises having access internet ¡10 MBPS speed	max
Digitization	Online availability of info for business mobility	max
Digitization	Start-up environment	max

Appendix B. Bootstrap Statistical Testing

Our analysis revealed significant insights through the calculated p-values based on the 500 iterations of bootstrap sampling, addressing our research questions regarding country rankings. Specifically, these values provided a statistical measure of the likelihood that a given country would fall within the top five or bottom five in the rankings, offering a nuanced understanding of their comparative standing on a global scale. Values denoted in bold letters have p value less than 0.05, signaling that there exist a statistical significant association that a country is in the top five or bottom five countries, depending on the observed column.

Table B.7: Results of the Bootstrap Sampling

Country	**Top 5 (p value)**	**Bottom 5 (p value)**
Austria	0.9354	1.0000
Belgium	0.9640	0.9280
Bulgaria	1.0000	**0.0000**
Croatia	1.0000	**0.0129**
Cyprus	1.0000	0.7431
Czech Republic	1.0000	0.8939
Denmark	0.6762	0.9974
Estonia	0.1340	1.0000
Finland	0.5940	1.0000
France	0.6700	1.0000
Germany	0.3941	1.0000
Greece	1.0000	**0.0053**
Hungary	1.0000	0.2175
Ireland	**0.0000**	1.0000
Italy	0.8955	0.8881
Latvia	0.0686	1.0000
Lithuania	**0.0128**	1.0000
Netherlands	0.9767	0.9974
Poland	1.0000	0.2595
Portugal	0.9947	0.6561
Romania	1.0000	**0.0000**
Slovakia	0.9724	0.9548
Slovenia	0.9868	0.9180
Spain	1.0000	0.1039
Sweden	0.9975	0.5914
United Kingdom	0.1865	1.0000