5 CROSS-COUNTRY EVALUATION OF FINANCIAL REPORTING AND GOVERNANCE PRACTICES THROUGH FUZZY C-MEANS AND TOPSIS ALGORITHMS

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Abstract

In an era of ever-evolving global economic dynamics and governance frameworks, this study aims to cluster OECD countries based on their similarities in terms of their compliance with International Financial Reporting Standards (IFRS) and evaluates the performance of the countries in these clusters regarding their adoption of IFRS. For this purpose, 11 indicators as countries adopted IFRS, which essentially measure the quality of governance, were used in Fuzzy C-Means (FCM) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) algorithms. The FCM algorithm captures the dynamic interrelations among the indicators, allowing for comprehensive modeling of complex systems. The TOPSIS algorithm further facilitates a sophisticated analysis by ranking countries, providing a clear and insightful classification that reflects their proximity to an idealized spectrum of financial and governance excellence. The findings reveal significant insights into the drivers of financial performance and governance quality.

Keyword: Financial performance, Governance, IFRS, FCM, TOPSIS
JEL Classification: M41; G34; C38; F21; H25; O16

1. Introduction

In an era where the global economic and governance landscapes are continuously evolving, the importance of empirical research cannot be overstated. Scholars and practitioners alike delve into the intricate web of financial performance, governance quality, and sustainability to offer insights that not only contribute to the academic discourse but also provide practical guidance for policymakers and stakeholders. This paper stands at the forefront of this endeavor, presenting a groundbreaking study that leverages a broad spectrum of financial and governance indicators.

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We aim to unravel the complex dimensions that define and influence the global economic and governance landscapes, marking a significant milestone in the field.

The realm of global economics and governance is shaped by myriad factors, each playing a pivotal role in determining the overall health and efficiency of economies and governance structures. Financial indicators such as the International Financial Reporting Standards (IFRS) and governance metrics including measures of better governance practices are critical in this context. These indicators serve as vital tools for evaluating financial performance, governance quality, and the sustainability of economic practices. Empirical studies have extensively explored the effects of these indicators on economic fundamentals, yet the integration and comparative analysis of these indicators remain largely uncharted territories.

This paper introduces an innovative empirical approach by employing the **F**uzzy **C**-**M**eans (FCM) and **T**echnique for **O**rder **P**reference by **S**imilarity to **I**deal **S**olution (TOPSIS) algorithms. These algorithms are utilized for the first time in this area to measure and categorize countries based on their performance with a comprehensive set of financial and governance indicators. The application of the FCM algorithm allows for the modeling of complex systems where indicators and their interrelations can be dynamically adjusted based on expert knowledge and empirical data. Meanwhile, the TOPSIS algorithm facilitates the ranking of countries by comparing each country's performance to an ideal solution, providing a clear and insightful classification based on the studied indicators.

The adoption of IFRS has been widely debated in the literature, with many studies affirming its positive impact on the transparency, comparability, and quality of financial reporting across countries (Soderstrom, 2007; Barth et al., 2008; Guidara et al., 2022; Elhamma, 2023). Similarly, the implementation of better governance practices is associated with enhanced economic outcomes, including higher investment levels, stronger financial markets, and improved economic stability (La Porta et al., 2000; Holmberg et al. 2009). By integrating these indicators into our analysis, we aim to shed light on their collective impact on economic indicators, offering a holistic view that transcends the insights provided by isolated studies. The findings of the research have profound implications for policymakers and practitioners. Within the scope of financial performance and governance quality indicators associated with IFRS, identifying relatively good country clusters and relatively good countries in these clusters serves as a reference for countries in the development of policies aimed at increasing the effectiveness of finance and governance. The classification of countries based on their performance offers a useful framework for benchmarking and identifying best practices, encouraging a proactive approach to improving economic and governance outcomes.

2. Literature review

There is an array of studies that leverage a broad spectrum of financial and governance indicators to unravel the complex dimensions of the global economic and governance landscapes. The research area lies within the wider academic discourse but also illuminates the multifaceted insights these variables provide across various domains such as financial performance, governance quality, and sustainability. The adoption of International Financial Reporting Standards (IFRS) serves as a pivotal benchmark for financial transparency and accountability, widely discussed across the literature. Barth et al. (2008) highlight the role of IFRS in enhancing the quality of financial reporting, which, in turn, facilitates better investor decisions. Concurrently, Soderstrom and Sun (2007) delve into the global implications of IFRS adoption, emphasizing its contribution to the harmonization of accounting practices and its profound impact on international investment flows.

Further, the role of foreign direct investment (FDI) in spurring economic growth, especially in emerging markets, has been a critical focus of research. Alfaro et al. (2004) elucidate the pathways through which FDI fosters economic development, underscoring the significance of the host country’s financial markets. Blonigen and Piger (2014) supplement this discourse with a meta-analysis on FDI’s determinants and effects, suggesting that political stability and governance quality are essential in attracting FDI. The intricate relationship between tax policies and economic behavior has also captured scholarly attention. Works by Devereux and Sørensen (2006) and Bird (2010) examine the influence of corporate tax rates on investment and financing decisions, and the complexities of tax revenue systems, respectively, highlighting their implications for fiscal policy and development.

In the realm of governance, corruption control, and political stability, a significant body of literature underscores their impact on economic performance and institutional trust. Foundational insights by Mauro (1995) and Alesina et al. (1996) explore how governance quality and political stability are pivotal for economic growth and investment climates. Recent discussions by Holmberg et al. (2009) further elaborate on governance's role in achieving sustainable development goals, emphasizing the importance of transparency and accountability. Research on corporate governance metrics, such as director liability, disclosure practices, and the strength of auditing standards, showcases their crucial role in enhancing market confidence and protecting investor interests. La Porta et al. (2000) and Hermalin and Weisbach (2012) delve into the global variations in corporate governance practices and their implications for financial markets. Lastly, the concept of sustainable competitiveness, which integrates economic, social, and environmental indicators, reflects an escalating interest in sustainability within academia and policymaking. Porter and Kramer (2006), along with reports from the World Economic Forum on global competitiveness, provide valuable insights into how sustainability considerations are integral to national competitiveness strategies. Together, these studies present a cohesive narrative that underscores the importance of a nuanced approach to financial governance and performance analysis, contributing significantly to the broader discourse on global economic stability and growth.

3. Theoretical background

The fusion of the FCM clustering with the TOPSIS algorithm forms a methodological nexus that stands at the forefront of decision-making research. The pertinent literature pivots on the dynamic interplay between the flexibility of fuzzy clustering and the incisiveness of TOPSIS ranking, harnessing their collective strength to unravel the complexities of data-centric environments.

Dunn’s introduction of the FCM algorithm in 1973, with subsequent enhancements by Bezdek in 1981, marked the genesis of soft clustering algorithms that now underpin various modern analytical frameworks (Dunn, 1973; Bezdek, 1981). These algorithms were designed to reflect the ambiguous nature of real-world data by allowing overlapping membership across clusters, a significant departure from the rigidity of traditional clustering algorithms.

The advancement of multi-criteria decision-making methodologies, epitomized by TOPSIS, owes much to the seminal works of Hwang and Yoon in the 1980s. Their contributions have laid the foundation for algorithms that assess alternatives by their geometric proximity to an ideal solution, effectively prioritizing options in a multitude of decision-making scenarios (Hwang and Yoon, 1981). In more recent developments, Azadnia et al. (2011) presented a compelling integration of the FCM with TOPSIS for a comprehensive appraisal of customer lifetime value – a critical parameter in customer relationship management. They underscore the versatility of TOPSIS in passing through FCM-derived clusters to identify customer segments meriting targeted marketing interventions. Bai et al. (2014) furthered this discourse by amalgamating FCM with TOPSIS advocating its efficacy in organizational performance evaluations. They posited that the synergy of these algorithms enhances the predictive accuracy for company resilience and viability, especially within e-commerce frameworks. Their methodology innovatively incorporates the

Balanced Scorecard approach, accommodating both financial and non-financial assessment criteria (Bai et al., 2014).

Given the contemporary relevance of the FCM-TOPSIS integration, the discourse has gravitated towards application-driven research. Swindiarto et al. (2018) exemplified this trend by deploying the combined approach for evaluating complex decision-making scenarios, such as company performance assessments. They underscored the efficacy of FCM-TOPSIS in providing a more comprehensive understanding of organizational strengths and areas for improvement by leveraging clustering for grouping similar countries and TOPSIS for ranking these groups in a performance hierarchy. This approach is particularly beneficial for competitive sectors, as it aids in identifying efficiency optimization opportunities to boost industry competitiveness. Moreover, the ranking landscape has been a fertile ground for this methodological confluence. The study by Purnomo et al. (2022) utilizes the FCM and TOPSIS algorithms to address the limitations in higher education institution rankings, which previously relied on a single criterion. By incorporating multiple criteria, including the number of lecturers and students, institutions were grouped more comprehensively. The FCM algorithm classified colleges into clusters, while TOPSIS ranked them based on a set of weighted criteria.

The academic community has embraced the FCM-TOPSIS amalgamation as a robust analytical tool. Its relevance extends to diverse fields, including marketing, finance, healthcare, and corporate governance. It has proven especially pivotal in situations where data ambiguity reigns and decision-making criteria are multifaceted. The integrative approach facilitates a deeper understanding of clustered data and the stratification of clusters, enabling decision-makers to draw actionable insights from complex datasets.

The FCM algorithm partitions the dataset into fuzzy clusters, where each data point belongs to each cluster with a certain degree of membership. This approach acknowledges the ambiguity and overlaps in real-world data. Following clustering, TOPSIS evaluates and ranks these clusters based on their attributes, utilizing criteria weights and the concept of ideal solutions to facilitate decision-making. The synergy of FCM and TOPSIS offers a comprehensive framework for analyzing data with inherent complexity and ambiguity, supporting nuanced decision-making in fields such as market segmentation, resource allocation, and performance evaluation.

3.1. Fuzzy c-means algorithm

Fuzzy clustering, also known as soft clustering, represents an advanced approach to data classification that eschews the rigid partitions characteristic of traditional clustering methods. This technique allows each data point to possess membership in multiple clusters to varying degrees, thereby more accurately reflecting the complex, often ambiguous realities encountered in real-world data. Such an approach proves particularly adept at navigating the inherent ambiguities and overlaps found in numerous datasets, providing a versatile and realistic framework for data organization.

The FCM algorithm emerged as a standout technique within the realm of fuzzy clustering. Developed by Dunn in 1973 and subsequently refined by Bezdek in 1981, the FCM algorithm parallels the k-means algorithm in several respects but distinguishes itself by incorporating the concept of membership degrees, thereby facilitating the creation of fuzzy clusters.

Let a fuzzy matrix U with n rows and c columns, where n is the number of data objects and c $(2 \leq c < n)$ is the number of clusters. The basis of the fuzzy clustering algorithm is the assignment of n objects $x = \{x_1, \ldots, x_n\}$ to c fuzzy clusters with $v = \{v_1, \ldots, v_c\}$ cluster centers. μ_{ij}, the element in the ith row and jth column in μ indicates the membership degree of the ith object with the jth cluster. The membership degrees, which fluctuate between 0 and 1, play a critical role in establishing the clusters' fuzzy boundaries $\left(u_{ij} \in [0,1],\ \forall i,j\right)$. Unlike hard clustering, where a data point's membership is strictly binary (indicating either complete inclusion or exclusion), fuzzy clustering introduces a spectrum of possible membership values. This level of flexibility allows for a more nuanced categorization of data, accommodating the indicator degrees of association that a data point can have with different clusters, thus mirroring the often-indeterminate nature of real-world categorization. The characters of u as follows:

$$\sum_{j=1}^{c} u_{ij} = 1, \forall i = 1, \dots, n;\ \forall j = 1, \dots, c \quad (1)$$

$$0 < \sum_{i=1}^{n} u_{ij} < n, \forall j = 1, \dots, c \quad (2)$$

The optimization process undergoes iterations to refine u_{ij} and v_j, utilizing steps such as initialization, centroid calculation, and iterative optimization for adjustments. In the initialization step, the algorithm commences by specifying the number of clusters, c, and assigning initial membership coefficients to each data point randomly, thereby indicating their preliminary affiliations with the clusters. Subsequently, the centroid of each cluster is computed as the weighted mean of all points assigned to the cluster, with weights corresponding to their membership degrees. This calculation is formally represented as follows:

$$v_j = \sum_{i=1}^{n} u_{ij}^{m} x_i / \sum_{i=1}^{n} u_{ij}^{m} \quad (3)$$

where $m > 1$ adjusts the fuzziness of the clustering. The iterative process seeks a local minimum or a saddle point of the objective function, with convergence criteria based on the change in cluster centers across iterations. The iteration continues until $\left\| v_j^{(new)} - v_j^{(old)} \right\| < \varepsilon$, where ε is a small threshold value.

In the third step, the optimization iteratively updates the membership μ_{ij} and the cluster centers v_j until the changes are within a predefined accuracy level ε, indicating convergence. This iterative refinement is guided by the formula:

$$u_{ij} = \left(\sum_{j=1}^{c} \left(\frac{d_{ij}}{d_{ik}} \right)^{2/(m-1)} \right)^{-1} \quad (4)$$

which recalculates the membership coefficients to reflect each data point's evolving relationship with the clusters.

The Euclidean distance $d_{ij} = \|x_i - v_j\|$ measures the closeness (or distance) between x_i and v_j, where v_j represents the center of cluster j, x_i denotes the ith data point. The FCM algorithm's objective is to minimize $J_m(U, v) = \sum_{j=1}^{c} \sum_{i=1}^{n} u_{ij}^{m} \left\| x_i - v_j \right\|^2$, a balance between the proximity of points to cluster centers and their degrees of membership. Like k-means, the FCM algorithm is prone to converge to a local minimum, and its effectiveness is contingent upon the initial selection of cluster centers. The iterative pursuit of a local minimum or a saddle point of the objective function, with convergence determined by the stabilization of cluster centers, underpins the algorithm's methodology. This process persists until the disparity between successive iterations of cluster centers diminishes to less than ε, a minor threshold (Bezdek et al. 1984; Ross, 2010: p. 352,353).

In essence, the FCM algorithm presents a methodology that allows data to affiliate with multiple clusters to varying extents, in stark contrast to hard clustering's binary approach. The ability of fuzzy clustering to assign data points to multiple clusters with differing degrees of membership furnishes it with a significant advantage over more rigid clustering techniques. This adaptability renders the FCM algorithm especially well-suited to analyzing datasets with ambiguous or overlapping cluster boundaries, facilitating a deeper and more nuanced exploration of complex data structures.

3.2. TOPSIS algorithm

Cluster analysis stands as a cornerstone in data mining and pattern recognition, enabling the aggregation of data points into meaningful groups or clusters based on their inherent similarities. However, the subsequent ranking of these clusters to identify the most representative or optimal ones remains a challenge, necessitating the adoption of a systematic and objective approach. TOPSIS emerges as a solution to this challenge, offering a methodology to rank clusters by evaluating their distance from theoretically ideal solutions.

In the seminal work by Hwang and Yoon (1981), the TOPSIS algorithm is introduced as a method for ranking objects based on their proximity to an ideal solution. TOPSIS seeks to discern the option that most closely aligns with the positive ideal solution while being most distant from the negative ideal solution, thereby providing a systematic approach to decision-making. This methodology is particularly relevant for evaluating clusters generated through methods such as the FCM algorithm, intending to identify clusters that best match an ideal profile based on predetermined criteria, such as customer value in marketing analysis.

The TOPSIS algorithm employs a systematic approach to assess and rank objects according to their proximity to an ideally formulated solution. This process entails a sequence of clearly defined steps designed to establish a framework within which objects can be compared against a positive ideal solution and a negative ideal solution.

Let $S = (U, C, V, f)$ be an information system where U is the universe and C is a indicator sets for U. Besides, $V = \cup_{a \in C} V_a$ indicates the indicator range of indicator a, and $f: \mu \times C \to V$ is an information function, $\forall x \in \mu$ then $f(x, a) \in V_a$ (Bai et al., 2014).

The initial step in the TOPSIS algorithm is the construction of a $n \times m$ dimensional decision matrix $U = (x_{ij})$ with n objects in the rows and m indicators in the columns. This data matrix, denoted by x_{ij}, is normalized to ensure comparability across diverse metrics. The normalization process is as follows:

$$v_{ij} = \frac{x_{ij} - \min_i t_{ij}}{\max_i x_{ij} - \min_i t_{ij}}, i = 1,2, \dots, n;\ j = 1, 2, \dots, m \tag{5}$$

Following the normalization step, the algorithm proceeds to identify the positive ideal solution and the negative ideal solution. The positive ideal solution (S^+), is constituted by the most favorable outcomes across all criteria, whereas the negative ideal solution (S^-), comprises the least favorable. Specifically, S^+ is determined by selecting the maximum score for benefit criteria, $\max_i v_{ij}$, and the minimum for cost criteria, $\min_i v_{ij}$, within the set of benefit, J_b, and cost, J_c, criteria respectively. Conversely, S^- is defined by the inverse, selecting the minimum scores for benefit criteria and maximum scores for cost criteria.

$$S^+ = \{v_1^+, \dots, v_m^+\} = \left\{\left(\max_i v_{ij} \mid j \in J_b\right), \left(\min_i v_{ij} \mid j \in J_c\right)\right\} \tag{6}$$

$$S^- = \{v_1^-, \dots, v_m^-\} = \left\{\left(\min_i v_{ij} \mid j \in J_b\right), \left(\max_i v_{ij} \mid j \in J_c\right)\right\} \tag{7}$$

The core of the TOPSIS algorithm lies in the calculation of the distances of each object from the positive ideal solution and the negative ideal solution. The distance to the positive ideal solution (d_i^+), and to the negative ideal solution (d_i^-), are computed, respectively, as the Euclidean distances from each object's score to the positive ideal solution and negative ideal solution scores, as follows:

$$d_i^+ = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^+\right)^2}, i = 1, \dots, n \tag{8}$$

$$d_i^- = \sqrt{\sum_{j=1}^{m}\left(v_{ij} - v_j^-\right)^2}, i = 1, \dots, n \tag{9}$$

These distances serve as the basis for determining the relative closeness of each object to the ideal solution, denoted by

$$RC_i = d_i^- / (d_i^+ + d_i^-) \tag{10}$$

Objects exhibiting higher RC_i values are considered closer to the ideal solution, thereby indicating a higher preference (Opricovic and Tzeng, 2004).

Through the application of these steps, the TOPSIS algorithm provides a rigorous and objective framework for evaluating clusters generated by algorithms such as the FCM algorithm, aligning them with an ideal cluster prototype based on specific evaluation criteria. This algorithm ensures a comprehensive and nuanced assessment of objects, facilitating informed decision-making grounded in quantitative analysis.

3.3. Sample of the study

In the current study, which aims to obtain the clustering and ranking of countries regarding their adoption of IFRS, the most up-to-date data of 38 OECD countries[4] on the indicators presented in Table 1 were used as a sample. In the selection of indicators, Elhamma (2023) and Guidara et al. (2022) studies were taken into account. In addition, the "tax revenue as of GDP" indicator, which was not mentioned in these studies, was also included in the analysis. Table 1 outlines the set of these indicators, each a cog in the larger mechanism of economic and regulatory analysis. The adoption year of IFRS marks a pivotal shift in accounting practices, offering a harmonized and transparent financial language for countries worldwide. Foreign direct investment (FDI) serves as a beacon of economic attraction and trust in a nation's potential, while profit tax rates (TaxRat) offer insights into the fiscal policies impacting commercial profitability. Tax revenue as a percentage of GDP (TaxRev) reflects a government's capacity to finance its obligations. The control of corruption (ConCorr) sheds light on the integrity and effectiveness of governance, and political stability (PolStab) signals the predictability and safety of the investment climate.

Table 1. Definition of data

Indicator	Description	Source
IFRS	Adoption year of international financial reporting standards*	IFRS
FDI	Foreign direct investment, net inflows (BoP, current US$), 2022	World Development Indicators database by World Bank
TaxRat	Profit tax (% of commercial profits), 2019	
TaxRev	Tax revenue as % of GDP, 2022p	Global Revenue Statistics Database by OECD
ConCorr	Control of Corruption, 2022	Worldwide Governance Indicators constructed by Kaufmann and Kraay (2023)
PolStab	Political stability and absence of violence/terrorism, 2022	

[4] *Australia* (x_1), *Austria* (x_2), *Belgium* (x_3), *Canada* (x_4), *Chile* (x_5), *Colombia* (x_6), *Costa Rica*(x_7), *Czechia*(x_8), *Denmark* (x_9), *Estonia* (x_{10}), *Finland* (x_{11}), *France* (x_{12}), *Germany* (x_{13}), *Greece* (x_{14}), *Hungary* (x_{15}), *Iceland* (x_{16}), *Ireland* (x_{17}), *Israel* (x_{18}), *Italy* (x_{19}), *Japan* (x_{20}), *Korea* (x_{21}), *Latvia* (x_{22}), *Lithuania* (x_{23}), *Luxemburg* (x_{24}), *Mexico* (x_{25}), *Netherlands* (x_{26}), *New Zealand* (x_{27}), *Norway* (x_{28}), *Poland* (x_{29}), *Portugal* (x_{30}), *Slovakia* (x_{31}), *Slovenia* (x_{32}), *Spain* (x_{33}), *Sweden* (x_{34}), *Switzerland* (x_{35}), *Türkiye* (x_{36}), *United Kingdom* (x_{37}), *United States* (x_{38}).

Indicator	Description	Source
DirLia	Protecting minority investors: Extent of director liability index, 2019	
Discl	Protecting minority investors: Extent of disclosure index, 2019	Doing Business database by World Bank
SharSuit	Protecting minority investors: Ease of shareholder suits index, 2019	
StrAud	Strength of auditing and accounting standards, 2019	World Economic Forum, Global Competitiveness Report
Comp	Sustainable Competitiveness Score, 2022	World Economic Forum, Global Sustainable Competitiveness Index

*: *IFRS optional adoption years of Switzerland and the United States are taken into account.*

The focus on corporate governance is evident in the analysis of director liability (DirLia), the extent of disclosure (Discl), and the ease of shareholder suits (SharSuit), which collectively offer a window into the protection and empowerment of minority investors. The strength of auditing and reporting standards (StrAud) ensures the reliability of financial statements, a cornerstone of investor confidence. Lastly, the sustainable competitiveness score (Comp) encapsulates the long-term viability of a nation's growth, balancing economic, social, and environmental factors. Each indicator, drawn from reputable sources like the World Bank, World Economic Forum, and the OECD, contributes to a comprehensive understanding of where countries stand and the broader implications of their financial and governance ecosystems.

4. Application

4.1. Summary statistics and correlations

Summary statistics of the indicators used within the scope of the study are shown in Table 2, and the correlation analysis is shown in Table 3. The average number of years for countries to adopt IFRS is 17 years, the lowest adoption year is in the United Kingdom in 2021, and the highest adoption year is in Costa Rica at 23 years. The standard deviation of 3.554 for this indicator indicates a wide dispersion from the sample average of countries. Similarly, the sample average value of the strength of auditing and accounting standards indicator is 5.446, the lowest value is in Greece at 3.794 and the highest in Finland at 6.529, the standard deviation value is 0.604; This standard deviation reveals minimal dispersion from country averages. Other indicators are interpreted similarly.

Table 2. Summary statistics

Indicator	Minimum	Q1	Mean	Median	Q3	Maximum	Std. Dev.
IFRS	3	17.5	17.474	19	19	23	3.554
FDI	-3.22E+11	3.68E+09	2.21E+10	1.40E+10	3.80E+10	3.88E+11	8.59E+10
TaxRat	0.2	9.325	15.153	14.550	20.3	29.9	7.172
TaxRev	16.927	30.629	34.045	34.459	39.128	46.076	7.312
ConCorr	17.453	74.646	79.717	83.726	94.929	100	19.394
PolStab	11.792	58.844	65.392	69.104	78.420	96.226	20.672
Dirlia	2	4	5.358	5	6	9	1.875
Discl	0	5.25	6.642	7	8	10	2.238

Indicator	Minimum	Q1	Mean	Median	Q3	Maximum	Std. Dev.
SharSuit	4	6	7.263	7.5	8	9	1.389
StrAud	3.794	5.167	5.446	5.486	5.892	6.529	0.604
Comp	41.589	51.192	53.162	53.600	56.102	60.668	4.099

The correlation analysis shown in Table 3 reveals that IFRS adoption exhibits a positive relationship with foreign direct investment, profit tax, extent of director liability, extent of disclosure index, ease of shareholder suits and strength of auditing and accounting standards. The fact that all correlation coefficients, except the 0.792 correlation coefficient between the sustainable competitiveness score and control of corruption indicators, are below 0.75 shows that the relationships between the indicators do not indicate the existence of multicollinearity.

Table 3. Correlation analysis

	IFRS	FDI	TaxRat	TaxRev	ConCorr	PolStab	DirLia	Discl	SharSuit	StrAud	Comp
IFRS	1.000										
FDI	0.165	1.000									
TaxRat	0.283	0.253	1.000								
TaxRev	-0.301	-0.138	-0.313	1.000							
ConCorr	-0.154	-0.035	-0.165	0.522	1.000						
PolStab	-0.337	-0.247	-0.232	0.375	0.714	1.000					
DirLia	0.410	0.198	0.195	-0.247	0.090	-0.136	1.000				
Discl	0.431	0.157	0.369	-0.106	-0.027	-0.281	0.215	1.000			
SharSuit	0.174	0.372	0.070	-0.132	0.192	0.102	0.422	0.160	1.000		
StrAud	0.024	-0.031	-0.011	0.210	0.658	0.399	0.169	-0.128	0.123	1.000	
Comp	-0.180	-0.040	-0.391	0.607	0.792	0.685	-0.077	-0.176	0.145	0.413	1.000

4.2. Implementling FCM clustering algorithm

In determining the clustering of OECD countries regarding IFRS adoption, Bai et al. (2014) study was taken as a reference. Firstly, the values of each indicator of the countries were normalized using equation (5). The normalized data represents a standardized score ranging from 0 to 1, with higher values indicating better performance or stronger adherence to the indicator. Besides, the norrmalized scores allow for comparisons across countries on each indicator, helping to identify patterns, strengths, and weaknesses in governance and financial performance. For policymakers, investors, and analysts, this data is crucial for making informed decisions, developing strategies, and implementing reforms to enhance financial stability and governance quality.

4.3. Results

Using the FCM algorithm, 38 OECD countries are associated with clusters within the scope of 11 reference indicators. The computational parts of the algorithm are performed using R Studio software. The "fclust" package is used in the FCM algorithm (Ferraro et al., 2019). The assignment of countries to clusters is through membership values representing a value in the range [0,1]. In this study, the analysis was continued by determining the number of clusters in the FCM algorithm as $c = 4$ and the order of fuzziness value as $m = 1.3$. The clusters to which each OECD country belongs are determined on the principle of assigning countries to the cluster with the highest membership value. A country's highest membership value within a cluster represents that country's strong relationship with the relevant cluster. Clusters formed based on meaningful country similarities and differences provide useful predictions about countries in terms of IFRS adoption. Table 4 presents the findings obtained as a result of applying the FCM algorithm. Each row in Table 4 corresponds to a different cluster (Cluster 1 through Cluster 4), while each column represents a country (x_1 through x_{38}) with its membership values across these clusters. The membership values range from 0 to 1 and indicate the degree of belonging of each country to the respective clusters. A higher value suggests a stronger association with that cluster. The algorithm assigns each country to the cluster for which it has the highest membership value, as highlighted by the bold numbers in the table.

Interpreting cluster membership necessitates a detailed examination through cluster analysis. Countries classified within Cluster 1, such as x_2, x_3 and x_{11} demonstrate a compelling alignment with strong governance indicators, including IFRS adherence and tax revenue efficiency. This cluster possibly represents countries that have established robust financial systems and governance mechanisms. The prominence of these countries in Cluster 1 could serve as a model for best practices, highlighting the importance of stringent financial reporting standards and effective tax governance in driving transparency and accountability. Policymakers and regulatory bodies could look to these countries for insights into the implementation of successful governance frameworks. Cluster 2 encompasses countries like x_{15} and x_{19} characterized by specific strengths or challenges in internal market dynamics and direct liability. This grouping suggests a set of countries that might be grappling with or excelling in areas such as internal controls, liability management, and corporate governance. The distinctive focus on internal dynamics within this cluster signals potential areas for targeted reforms or interventions aimed at enhancing internal governance structures. Corporations and regulatory agencies could benefit from understanding the factors that contribute to the strong performance or notable challenges within these countries. Characterized by a nearly exclusive membership of x_6 and x_{36}, Cluster 3 could represent outliers or countries with distinct characteristics not widely shared with others in the dataset, possibly due to unique political stability issues or control of corruption metrics. The isolation of these countries within their own cluster underscores the significant impact of external governance factors on financial performance and reporting. This insight is crucial for policymakers and international organizations, which may need to devise customized strategies to address the specific governance and stability issues affecting these countries. Dominated by countries like x_4, x_{18}, x_{32}, x_{37}, and x_{38}, Cluster 4 might encapsulate countries excelling in or facing challenges with direct liability, strong auditing practices, and political stability. The high membership values suggest a particular alignment with these governance indicators. This cluster could represent countries that are navigating complexities in governance and political stability, with their performance and reporting practices heavily influenced by these factors. The identification of these countries offers a valuable perspective on the challenges and opportunities inherent in maintaining robust governance in less stable environments. It suggests a need for adaptive governance frameworks that can withstand and adapt to political and economic fluctuations.

The delineation of countries into these clusters based on the FCM algorithm enables a nuanced understanding of their financial governance and policy environments. Countries grouped together share similar characteristics and challenges, offering insights into targeted policy interventions and reforms. For instance, countries in Cluster 1, with high adherence to international reporting standards and effective tax governance, might serve as benchmarks for best practices. Conversely, the unique characteristics of countries in Cluster 3 highlight the need for customized approaches to address their specific governance challenges.

Furthermore, the analysis underscores the diversity within the dataset, emphasizing the importance of tailored policy and regulatory frameworks to enhance financial governance across different countries. The clusters formed through this algorithm thus provide a foundational step for deeper analysis and understanding of the underlying patterns and governance profiles of the countries involved.

Table 4. Cluster formation by FCM algorithm

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
Cluster 1	**0.593***	**0.999***	**0.973***	0.001	0.015	0.000	0.012	0.031	**0.997***	**0.886***
Cluster 2	0.300	0.000	0.018	0.001	0.042	0.000	**0.972***	**0.949***	0.002	0.113
Cluster 3	0.002	0.000	0.000	0.000	0.078	**0.999***	0.000	0.000	0.000	0.000
Cluster 4	0.105	0.000	0.008	**0.998***	**0.864***	0.001	0.015	0.020	0.002	0.001
	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	x_{20}
Cluster 1	**0.998***	**0.826***	**0.959***	0.067	0.002	**0.972***	0.003	0.006	0.027	0.076
Cluster 2	0.001	0.171	0.037	**0.737***	**0.997***	0.022	0.005	0.012	**0.972***	0.006
Cluster 3	0.000	0.000	0.000	0.172	0.000	0.000	0.000	0.009	0.000	0.000
Cluster 4	0.001	0.003	0.003	0.024	0.000	0.006	**0.992***	**0.973***	0.001	**0.918***
	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}	x_{26}	x_{27}	x_{28}	x_{29}	x_{30}
Cluster 1	0.002	0.004	0.012	**0.942***	0.000	**0.997***	0.007	**0.994***	0.005	0.002
Cluster 2	0.005	**0.995***	**0.988***	0.052	0.000	0.002	0.002	0.002	**0.993***	**0.998***
Cluster 3	0.000	0.000	0.000	0.000	**1.000***	0.000	0.000	0.000	0.000	0.000
Cluster 4	**0.993***	0.002	0.000	0.006	0.000	0.000	**0.991***	0.004	0.002	0.000
	x_{31}	x_{32}	x_{33}	x_{34}	x_{35}	x_{36}	x_{37}	x_{38}		
Cluster 1	0.005	0.050	0.388	**1.000***	**0.845***	0.000	0.013	0.001		
Cluster 2	**0.995***	0.137	**0.598***	0.000	0.138	0.000	0.006	0.002		
Cluster 3	0.000	0.000	0.000	0.000	0.001	**1.000***	0.001	0.000		
Cluster 4	0.000	**0.812***	0.014	0.000	0.016	0.000	**0.980***	**0.997***		

**: The membership in bold indicates the cluster to which it belongs.*

The findings from Table 4, which details the cluster formation via the FCM algorithm, reveal intricate patterns of association among various countries based on a comprehensive set of financial governance and performance indicators. These clusters, delineated based on the countries' proximities to certain characteristics, underscore not only the diversity present within the dataset but also hint at underlying commonalities that may not be immediately apparent. Here, we delve deeper into the implications of these findings, attempting to extract more nuanced insights that could inform policy, regulatory frameworks, and strategic decision-making.

The nuanced analysis of clusters formed through the FCM algorithm provides a granular view of the financial governance landscape, revealing patterns and associations that transcend simple categorizations. For policymakers, regulators, and corporate leaders, these insights offer a strategic foundation for targeted interventions, reforms, and best practice implementations. By understanding the characteristics that define each cluster, stakeholders can tailor their strategies to address specific challenges, leverage strengths, and foster an environment conducive to sustainable financial governance and performance. Thus, the cluster analysis not only sheds light on the diverse governance profiles across countries but also emphasizes the critical role of tailored, informed approaches in addressing the multifaceted challenges and opportunities within the financial governance domain.

The ranking of country clusters obtained using the FCM algorithm is presented in Table 5. These rankings of the clusters were obtained with the help of the TOPSIS algorithm. The distances of the center of each cluster from the best solution to the worst solution were calculated with the help of equations (8) and (9). Then, with the help of equation (10), relative closeness values were obtained for each cluster. The TOPSIS algorithm evaluates each cluster based on three key metrics: the distance from the best solution, the distance from the worst solution, and the relative closeness, which ultimately informs their ranking. The number in the column of the distance from the best solution tells us how far each cluster is from the perfect scenario, where lower numbers would mean a cluster is closer to being ideal based on the chosen criteria (like financial performance, governance, etc.). Distance from the worst solution represents how far each cluster is from the least desirable outcome. Here, higher numbers are better because they mean the cluster is further away from the worst-case scenario. Relative closeness is a score that combines the two distances (from the best and worst solutions) to give us an idea of overall performance. A higher relative closeness suggests that a cluster is generally performing better, considering both how close it is to the ideal and how far it is from the worst. Rank, based on the relative closeness, assigns a numerical rank to each cluster, with 1 being the best-performing cluster and higher numbers indicating lower performance.

Table 5. Ranking of clusters by TOPSIS

	Distance from the best solution	Distance from the worst solution	Relative closeness	Rank
Cluster 1	0.593	0.073	0.109	1
Cluster 2	0.395	0.012	0.030	3
Cluster 3	0.407	0.000	0.000	4
Cluster 4	0.392	0.015	0.036	2

According to the output in Table 5, Cluster 1 ranks as the best-performing cluster. Despite having the greatest distance from the best solution (0.593), its distance from the worst solution (0.073) and the highest relative closeness (0.109) suggest it balances well between achieving desirable outcomes and avoiding undesirable ones better than the other clusters. This indicates that, while Cluster 1 is the furthest from the ideal solution in absolute terms, its relative proximity to the worst solution and its relative closeness suggest it is the closest to the ideal solution among the evaluated clusters. Countries within Cluster 1, overall, have a good mix of the analyzed characteristics, making them relatively ideal. Cluster 2 is placed third. It's closer to the best solution than Cluster 1 (0.395) but has a lower relative closeness (0.030), impacted by its proximity to the worst solution. This implies that Cluster 2 is closer to the best solution than Cluster 1 in absolute terms but has a lower relative closeness due to its proximity to the worst solution, thus affecting its overall ranking negatively. Cluster 3 is ranked last (4th), with a distance from the best solution (0.407) like Cluster 2 but with the closest proximity to the worst solution (0.000) and no relative closeness. The absence of any distance from the worst solution suggests that Cluster 3 aligns most closely with the least desirable attributes among all the clusters, marking it as the one with the most areas for improvement. Cluster 4 comes in second, showing a performance closely competitive with Cluster 2 but with a slightly better relative closeness (0.036), thanks to its balance between not being too far from the best and not too close to the worst outcomes. Despite being near to the best solution, its slightly greater distance from the worst solution compared to Cluster 2, coupled with a higher relative closeness, allows it to achieve a better ranking.

The TOPSIS rankings provide a nuanced view of how each cluster stands in relation to ideal and less ideal outcomes based on the chosen criteria. For decision-makers, this analysis could guide where to focus improvement efforts or identify strengths. For example, examining why Cluster 1 performs well could uncover best practices, while understanding Cluster 3's challenges might highlight critical areas for development or intervention. Therefore, the TOPSIS rankings illuminate the relative performance of each cluster against the ideal and negative ideal solutions based on the defined criteria. Cluster 1, despite being the farthest from the ideal solution, ranks highest due to its overall performance metrics, underscoring the importance of the relative closeness in determining proximity to the ideal scenario. Clusters 2 and 4 show a competitive closeness to the best solution, but differences in their relative closeness and distances from the worst solution influence their final rankings. Cluster 3, closely aligned with the worst solution, ranks the lowest, indicating significant room for improvement based on the evaluation criteria. This analysis showcases the utility of TOPSIS in discerning the relative merits of clusters, guiding decision-makers in prioritizing areas for development or further investigation.

In determining the performance ranking for the adoption of IFRS by the OECD country within each cluster, the TOPSIS algorithm which was introduced to the literature by Hwang and Yoon (1981) and used by Bai et al. (2014) used. Using the centers of the indicators, the distances to the best and worst solutions for the countries in each cluster were used in equation (10) to obtain relative closeness values. Table 6 shows the findings regarding the clustering and ranking of OECD countries. Distance from best solution represents how far each country's performance is from the ideal scenario across the evaluated indicators. Lower distances are better, as they indicate closer alignment with the ideal. Distance from worst solution indicates how far each country is from the least desirable outcome. Greater distances are preferable, indicating that the country is far from the worst-case scenario. Relative closeness is a measure that combines the two distances to show how close overall a country is to the ideal scenario. A higher coefficient suggests better performance. Rank is the position of each country within its cluster, determined by its relative closeness. A lower rank number means a better position. Accordingly, it can be said that Sweden, Denmark, Finland, Austria, and the Netherlands, which are in the first cluster and have the highest relative closeness value of 0.370, are the best-performing countries in this cluster.

Table 6. Ranking of OECD countries within clusters by TOPSIS

	Distance from best solution	Distance from worst solution	Relative closeness	Rank
Cluster 1:				
x_{34} Sweden	1.485	0.874	0.370	1
x_2 Austria	1.485	0.874	0.370	2
x_{11} Finland	1.485	0.872	0.370	3
x_{26} Netherlands	1.484	0.871	0.370	4
x_9 Denmark	1.484	0.870	0.370	5
x_{28} Norway	1.482	0.867	0.369	6
x_3 Belgium	1.469	0.843	0.365	7

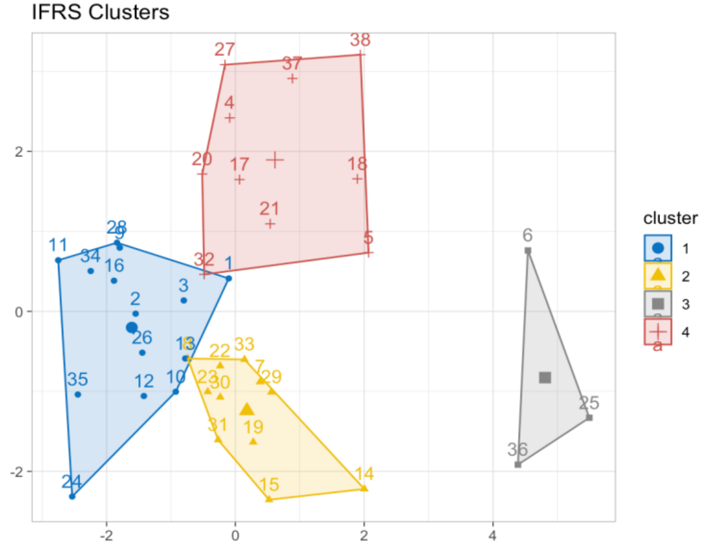
	Distance from best solution	Distance from worst solution	Relative closeness	Rank
x_{16} Iceland	1.469	0.843	0.365	8
x_{13} Germany	1.462	0.829	0.362	9
x_{24} Luxembourg	1.452	0.810	0.358	10
x_{10} Estonia	1.425	0.755	0.346	11
x_{35} Switzerland	1.404	0.709	0.336	12
x_{12} France	1.398	0.697	0.333	13
x_{1} Australia	1.316	0.460	0.259	14
Cluster 2:				
x_{30} Portugal	1.553	0.909	0.369	1
x_{15} Hungary	1.553	0.909	0.369	2
x_{31} Slovakia	1.551	0.906	0.369	3
x_{22} Latvia	1.551	0.905	0.369	4
x_{29} Poland	1.550	0.903	0.368	5
x_{23} Lithuania	1.546	0.898	0.367	6
x_{19} Italy	1.535	0.880	0.364	7
x_{7} Costa Rica	1.536	0.878	0.364	8
x_{8} Czechia	1.520	0.851	0.359	9
x_{14} Greece	1.400	0.686	0.329	10
x_{33} Spain	1.357	0.555	0.290	11
Cluster 3:				
x_{25} Mexico	1.523	1.125	0.425	1
x_{36} Türkiye	1.523	1.125	0.425	2
x_{6} Colombia	1.522	1.124	0.425	3
Cluster 4:				
x_{4} Canada	1.510	0.713	0.321	1
x_{38} United States	1.509	0.711	0.320	2
x_{21} Korea	1.506	0.707	0.319	3
x_{17} Ireland	1.505	0.705	0.319	4
x_{27} New Zealand	1.505	0.704	0.319	5
x_{37} UK	1.498	0.691	0.316	6
x_{18} Israel	1.494	0.686	0.315	7

	Distance from best solution	Distance from worst solution	Relative closeness	Rank
x_{20} Japan	1.458	0.618	0.298	8
x_5 Chile	1.430	0.586	0.291	9
x_{32} Slovenia	1.407	0.499	0.262	10

Interpretation of results by cluster shows some striking points. In Cluster 1, countries like Sweden (x_{34}) and Austria (x_2) top the list, showing they are relatively closer to the ideal performance across the selected indicators. This suggests strong governance, economic performance, or other positive characteristics measured by the analysis. Australia (x_1) ranks last in this cluster, indicating it's farthest from the ideal compared to other countries in Cluster 1, possibly due to specific challenges in the measured indicators. In Cluster 2, Portugal (x_{30}) and Hungary (x_{15}) lead, showing their performance is comparatively closer to what's considered ideal within this group. It highlights their strengths or improvements in the evaluated areas. Spain (x_{33}) is at the bottom, suggesting room for improvement to reach closer to the cluster's ideal performance. Cluster 3 includes countries like Mexico (x_{25}) and Türkiye (x_{36}), both sharing the top spot. The closeness to the ideal solution for these countries within their cluster suggests they are doing relatively well based on the analysis criteria. Canada (x_4) and United States (x_{38}) show strong performance within this Cluster 4, being closer to the ideal. It implies effective policies or favorable conditions in the areas being measured. Slovenia (x_{32}), being last, indicates that among the high-performing countries in Cluster 4, it's the furthest from the ideal, highlighting specific areas where it could improve.

The ranking of OECD countries within each cluster based on TOPSIS provides valuable insights into where each country stands in relation to an ideal set of conditions or policies as defined by the analysis criteria. Countries ranking higher within their clusters can serve as benchmarks or models in particular governance or performance aspects. Conversely, countries with lower rankings within their clusters have identifiable areas for improvement. Decision-makers and policymakers can use this analysis to target specific areas for development, learning from the strategies of higher-ranked countries to drive improvements.

Figure 1. IFRS clusters of OECD countries



In visualizing the clusters obtained for countries' adoption of IFRS, visualization was made in a 2-dimensional area using the fviz_cluster function in the R Studio program. In the theoretical background, dimensional reduction is carried out by principal component analysis to ensure that countries are represented as clusters in a 2-dimensional space (Kassambra, 2017). The variance ratios explained by the first two axes and the clustering of countries on IFRS and related indicators for $c = 4$ with the fviz_cluster function of the factoextra package are shown in Figure 1. Accordingly, while Cluster 1, Cluster 4, and Cluster 2 represent country clusters with similar characteristics due to some overlapping points, Cluster 3 is far from these areas, and this indicates that Cluster 3 is a country cluster with different characteristics.

5. Discussion and Conclusion

In this study, OECD countries were clustered based on their compliance with IFRS and their similarities in terms of financial and governance indicators related to IFRS, and the performances of the countries in these clusters were evaluated. Thanks to the FCM algorithm, a versatile view is provided of how countries comply with different financial and governance indicators associated with IFRS. Using the year in which countries adopted IFRS and 10 indicators related to IFRS, each country is assigned a cluster where it shows the strongest association based on a range from 0 (no association) to 1 (full association).

As a result of the FCM algorithm, where 4 clusters were obtained, countries with high values in Cluster 1 may represent well-governed regions with robust financial systems. Countries like Sweden, Austria, and Finland lead in this cluster, showcasing strong alignment with governance indicators such as adherence to international reporting standards and tax revenue efficiency. Cluster 2 countries like Hungary and Italy are characterized by particular strengths or challenges within their internal market dynamics and direct liability. These could suggest areas of strong internal controls or significant liability management issues. Cluster 3 stands out due to its outliers, like Mexico and Türkiye, suggesting unique characteristics, potentially in political stability or corruption control. These might indicate external governance factors significantly impacting financial performance. In Cluster 4, countries such as Canada and the United States demonstrate particular strengths or challenges related to direct liability, strong auditing, and political stability. This suggests navigation through complexities in governance, potentially requiring adaptive frameworks for stability.

The data presents a compelling narrative about the financial and governance health of various countries. By analyzing their alignment with critical indicators such as IFRS compliance, foreign direct investment levels, tax rates, and governance factors like political stability and corruption control, the FCM algorithm has clustered countries that exhibit similar characteristics. For instance, countries in Cluster 1 could serve as models, offering insights into successful financial governance mechanisms. On the other hand, the distinctive characteristics of Cluster 3 countries may require tailored strategies to address governance and stability issues. The differences in the rankings within and between clusters underscore the diversity of the dataset and highlight the significance of context-specific approaches to enhancing governance and financial performance. This methodical FCM clustering and subsequent ranking by the TOPSIS algorithm provide policymakers and corporate leaders with a nuanced view of where these countries stand in a complex landscape of financial and governance practices. For those at the helm of policy direction and corporate strategy, the insights gleaned from the clusters are invaluable. They reveal benchmarks against which best practices can be gauged and areas that necessitate improvement come to light. The top-performing countries, as determined by their closeness to an ideal solution and their distance from the worst-case scenario, serve as models of robust financial systems and governance mechanisms. They exemplify the high adherence to international reporting standards, effective tax governance, and a commitment to transparency and accountability. On the other end of the spectrum, countries that align closely with less favorable attributes – signified by their proximity to the 'worst' solution – highlight the pressing need for targeted interventions. It's here that customized strategies and policies must be crafted, taking into account the unique challenges of each cluster. Such a bespoke approach can significantly enhance financial governance and stability, addressing specific vulnerabilities or leveraging particular strengths.

In essence, these findings emphasize that while some countries are closely aligned with ideal characteristics, others might be closer to less desirable ones, and each has its path to achieving better governance and financial robustness. By employing innovative methodologies and offering comprehensive insights, this study not only contributes to the academic discourse but also serves as a practical guide for enhancing global economic stability and governance quality.

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