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Entrepreneurial activity in the international trade in cultural goods: A fuzzy clustering analysis

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ABSTRACT

This study offers a novel country-level longitudinal investigation of conditions, including, income, urbanity, education, R&D, and entrepreneurial activity, driving international trade, for imports and exports. The configurational (clustering) approach places emphasis on country and year groupings, offering 'targeted' understanding on country level variations of international trade in cultural goods. The study explores context sensitive conditions affecting international trade in cultural goods, including environment for entrepreneurship, and entrepreneurial processes. Emphasis is given to configurational considerations of clusters of country-year observations based on conditions. Inferences inferred will be country groups-based perspectives. Using UIS and GEM datasets, fuzzy c-means clustering is employed for economic development-related conditions measuring, income, urbanity, education, R&D, and entrepreneurial activity, to establish clusters of country-year observations, based on differences in the condition values describing them. These clusters are defined to give qualitative understanding of their individuality. Validation of clusters is undertaken with consideration of differences on levels of international trade of cultural goods, in terms of forms of imports and exports. To complement the validation, cluster profiling is undertaken, with consideration of population age and poverty levels. The study contributes increased understanding concerning drivers (conditions) of trade in cultural goods, and impact of entrepreneurship in both imports and exports.

1. Introduction

The international trade of cultural goods is one reflection of the economic development state and cultural power for any country and is unsurprisingly, also included amongst the United Nations's Sustainable Development Goals. Van der Pol (2007) identified that cultural goods represented only 2.6 % of the EU economy and 3 % of gross domestic product (GDP) in Mercosur countries by 2003, but these industries tend to grow faster than the economy as a whole and provide higher quality employment opportunities than the economy generally. Disdier et al. (2010) noted a positive and significant influence of cultural flows on overall trade.

Wang (2019) uses the United Nations Educational, Scientific and Cultural Organization (UNESCO) definition of cultural goods as consumer products that spread ideas, symbols, and lifestyles, providing information and entertainment. In terms of trade, high added value and value transmission of cultural industries have also increased the importance of cultural goods in global trade over time, as well as contributing more to the national economy. Scavia et al.'s (2021) study addresses the relationship between trade in cultural goods and economic growth for 31 countries in Europe for 2004–2017, the results indicating that cultural exports and imports have a positive effect on GDP in the long run.

The topic is important and topical, therefore, because of the growth in the importance of the cultural goods sector economically and its potential for future growth. Currently, however, there is a lack of research in this area, with knowledge gaps regarding understanding the drivers of the cultural goods' trade. The novel, early reflection, in this study, thus offers a country-level investigation of conditions, including, income, urbanity, education, research and development (R&D), and entrepreneurial activity, which may drive such trade, in terms of both imports and exports. To offer a more comprehensive and rigorous approach in this initial study we utilise a longitudinal perspective, with data covering the years 2010 to 2019.

A configurational (clustering) approach is adopted in this study, placing emphasis on country and year groupings, to offer more

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'targeted' and nuanced understanding regarding behaviour and interactions (Ketchen and Shook, 1996; Crum et al., 2022). Moreover, fuzzy clustering is employed in this study (Bezdek, 1981; Bezdek et al., 1984; Andrews et al., 2017). Clusters of country-year observations (cases) are established based on associated 'clustering' variables describing income, urbanity, education, R&D, and entrepreneurial activity. The established clusters are defined, in terms of describing country-year observations Rich, Urban, Innovative, Educated, non-entrepreneurial and Poor, Rural, Non-innovation, Non-education and Start-up friendly. These clusters are further compared against external variables describing the export and import based cultural trade of the country-year observations. Certain statistically significant differences are identified on the considered forms of cultural trade across the newly established clusters.

The structure of the rest of the study is as follows; in the following Section 2, literature on culture and entrepreneurship is presented. Section 3 describes the data, as well as its origins. In Section 4, an initial fuzzy cluster analysis of the created culture-entrepreneurship data is undertaken. Section 5 considers the established clusters against export and import cultural trade of the countries over different years, as well as some profiling (including hierarchical regression). In Section 6, a discussion on the cluster-based findings is provided. Section 7 offers conclusions and directions for future research.

2. The theoretical drivers of trade in cultural goods

Considering the theoretical rationale supporting the complex interactions amongst the conditions included as drivers, it is notable that, whilst there is literature on the cultural drivers of entrepreneurship, the ways in which entrepreneurship can drive the cultural industries generally, and trade in cultural goods specifically, remains under researched. This study focuses on cultural goods production, and trade specifically, that is the outcome considered, with entrepreneurial culture theorised as one of a range of drivers of the import and export of cultural goods, which follow in many ways broader drivers of trade generally.

The spectrum of cultural goods is, however, wide and is effectively illustrated in the 2009 UNESCO framework for Cultural Statistics (see Fig. 1). Fig. 1 confirms the diversity of goods ranging from cultural craft goods associated with a particular country (e.g. cultural tourism goods from Australia, whisky from Scotland) to the existence of sophisticated film industries in specific countries and regions. The Welsh government, for example, noted that the film industry delivered a turnover of £459 million in 2022 through productions such as "His Dark Materials" such activity supporting many creative businesses and employment in Wales (Bowden, 2023). There are also, however, potential linkages between different types of cultural industries. In Northern Ireland for example, a significant tourism industry has developed from the "Game of Thrones" television series that was filmed in Northern Ireland. In 2018, this attracted one in six of visitors to the country (350,000 people) and over £50 million to the local economy (Tourism Northern Ireland, 2018). This diversity of cultural goods with their potentially disparate drivers, as well as the linkages between them, therefore gives rise to the following research question:

RQ1. Are there distinct groups of countries defined by different combinations (clusters) of cultural sector relevant, trade and entrepreneurship related, variables most likely to drive imports and exports of cultural goods?

Turning to the drivers themselves, as Park (2014) has identified, there are broad similarities between the trade in services and cultural goods. This means that theories used in the studies of service sector trade, such as Grünfeld and Moxnes's (2003), which utilised the gravity model approach (where trade is a function of the market size of importer and exporter country and the distance between them), are potentially of interest. Consequently, Park (2014) found, in the Korean context, the relative economic development of the exporting country and the market size of the importing country are important determinants of cultural trade, the results of which are generally consistent with traditional goods' trade. Salim and Mahmood (2015) also find that the size of Pakistan and its trading partner countries' markets as well as distance between them are also important determinants of exports in cultural

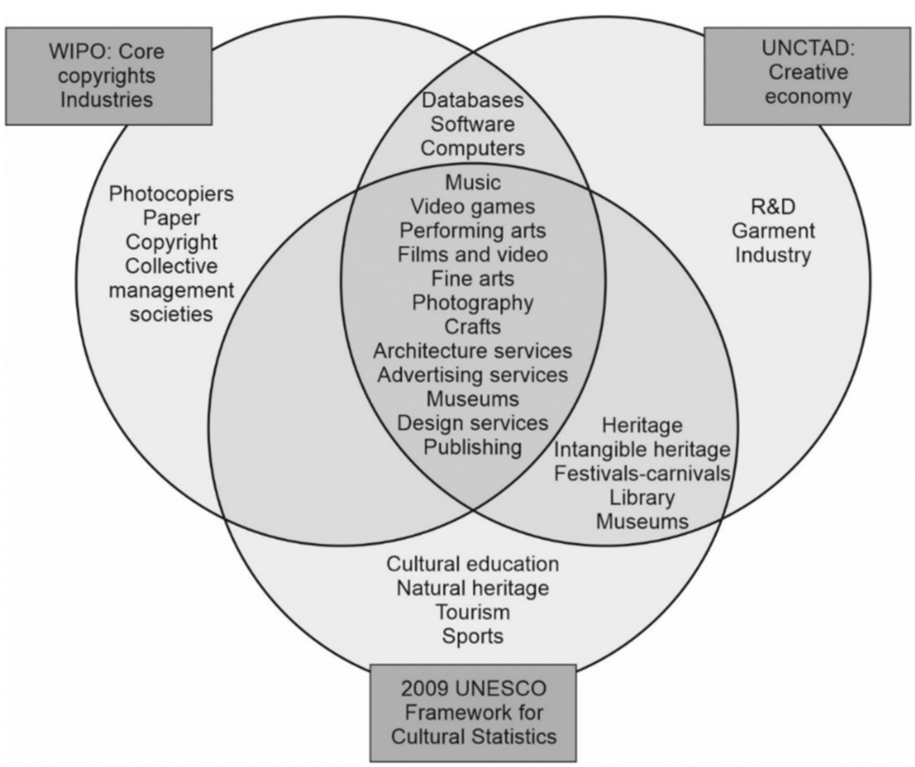

Fig. 1. 2009 UNESCO framework for Cultural Statistics (UNESCO, 2009).

goods. Specifically, cultural goods exports are strongly and positively influenced by the growth of GDP in Pakistan, whilst the trading partner countries' GDP growth negatively influence cultural goods' exports. Salim and Mahmood (2015) also highlight, however, that the gravity model has added impetus in the context of cultural goods because of the importance of cultural ties and commonalities which are often greater with physical proximity. Marvasti (1994, p. 136) also found that "Available statistics on trade in cultural industries suggest that highly populated countries have historically been leading exporters of cultural products." Following the gravity model, distance, representing transaction costs and trade barriers, negatively affect exports of cultural goods, whilst linguistics and cultural ties (Maghssudipour et al., 2023) including colonial ones, common borders, and land area of the trading partners positively influence the export of cultural goods. In many ways, therefore, the level and strength of economic development, measured in a variety of ways, can be seen as key drivers of imports and exports of cultural goods.

In addition, entrepreneurship can be seen to play a key role in driving the development of cultural industries, particularly those with strongly creative elements (Demetry, 2019), in newly growing sectors such as digital publishing (McMullen et al., 2021), in niche sectors of cultural industries where resource restrictions and bottom-up approaches often apply, and where cultural enterprises are particularly important to regions economically and socially (Ratten and Ferreira, 2017). Porfírio et al. (2016) also highlight the interconnectedness, in entrepreneurship theory, between the environment (providing opportunities for entrepreneurship), knowledge, education and networking. Linking economic development aspects with entrepreneurship Zukauskaite (2012) also found that R&D and highly qualified labour were also positively linked to the development of certain cultural industries, via the universities and their interactions with cultural businesses and entrepreneurs. In the area of entrepreneurship, the clustering of these important elements together has also been identified as being of relevance (Crum et al., 2022), driving organizational resilience and strategic renewal in SMEs (Herbane, 2019) and innovation (for example, in Portugal, see Vaz et al., 2014). Consequently, the following research question has been developed:

RQ1. Are there distinct groups of countries defined by different combinations (clusters) of cultural sector relevant, trade and entrepreneurship related, variables most likely to drive imports and exports of cultural goods?

RQ2. Do these clusters have significantly different impacts on imports and exports of cultural goods?

3. Data

In terms of sample characteristics and data collected, this study on the investigation of trade in culture, uses data collected from two sources, namely, UNESCO (UNESCO, 2022) and GEM (GEM, 2023). In terms of the UNESCO data, a description of the background to where the majority of the data came from can be clearly seen from their opening statements on the UNESCO (2022), website.

> "The UNESCO Institute for Statistics (UIS) is the official and trusted source of internationally comparable data on education, science, culture, and communication. As the official statistical agency of UNESCO, the UIS produces a wide range of state-of-the-art databases to fuel the policies and investments needed to transform lives and propel the world towards its development goals."

The entrepreneurship data comes from the Global Entrepreneurship Monitor (GEM), which advocates (GEM, 2023).

> "GEM carries out survey-based research on entrepreneurship and entrepreneurship ecosystems around the world. GEM is a networked consortium of national country teams primarily associated with top academic institutions. GEM is the only global research source that collects data on entrepreneurship directly from individual entrepreneurs. GEM tools and data are therefore unique and benefit numerous stakeholder groups."

Variables considered in this study are next described (how they are specifically used with be elucidated later), see Table 1.

In Table 1, the considered variables employed in this study are summarised. A total of 227 cases are considered (cases here are country-year observations), covering the years 2010 to 2019,[1] and 46 countries, see Table 2.

In Table 2, the number of occurrences of each country is shown,[2] in terms of number of times a country-year observation includes that country, ranging from 1 up to 10. Before explaining the methods used to cluster, we first elucidate the frequency of inclusion of countries, then the variable values of the country-year observations over the considered years, 2010 to 2019, see Figs. 2, 3 and 4.

In Fig. 2, each clustering variable, GDPprcap, RPOPprcnt, GERDprcnt, GETDprccnt and TEA, is described by a graph which includes 10 boxplots. These boxplots depict the spread of the case values on a clustering variable over the considered years 2010 to 2019. Viewing the sets of 10 boxplots allows an initial visualisation of the change in the clustering variable value over time. A statistical perspective can be given, by considering ANOVA tests (Hair et al., 2010), describing a test for the difference between two or more means. For each clustering variable, the ANOVA results are, GDPprcap ($F(1, 225) = 3.99$, $p = 0.047^*$), RPOPprcnt ($F(1, 225) = 1.74$, $p = 0.19$), GERDprcnt ($F(1, 225) = 0.35$, $p = 0.55$), GETDprccnt ($F(1, 225) = 5.08$, $p = 0.025^*$) and TEA ($F(1, 225) = 0.68$, $p = 0.41$). These tests show that for GDPprcap and GETDprccnt, there appears to be some variation in the associated case values over the respective years.

In Fig. 3, a similar set of sets of boxplots are given, here for the four external cultural trade variables, CGTExppc_1, CGTExppc_2, CGTImppc_1 and CGTImppc_2. A statistical perspective can be again given, by considering ANOVA tests. For each cluster variable the ANOVA results are, CGTExppc_1 ($F(1, 225) = 0.1$, $p = 0.75$), CGTExppc_2 ($F(1, 225) = 0.77$, $p = 0.38$), CGTImppc_1 ($F(1, 225) = 0.35$, $p = 0.77$) and CGTImppc_2 ($F(1, 225) = 0.53$, $p = 0.47$). These tests show there is not statistically significant across year variations on any of the considered culture trade external variables for the considered cases.

In Fig. 4, a similar set of sets of boxplots are given, here for the two profiling variables. A statistical perspective can be again given, by considering ANOVA tests. For each cluster variable the ANOVA results are, YTHprcnt ($F(1, 10.1) = 0.1$, $p = 0.002^{**}$) and PVTYprcnt ($F(1, 225) = 7.55$, $p = 0.007^{**}$). These tests show the considered profiling variables, for the considered cases, are statistically significant over the considered years.

A similar set of Figures are given for all the variables (clustering, external and profiling), but instead showing spread of values over the different countries, see Figs. A1 to A3, in appendix A. These country-based boxplots' graphs are interesting since they demonstrate where for some countries there appears changes to variables over the years they are included in, and some with no movement (for those countries with only a single year observation included, they will only be

[1] One restriction on years is the GEM data has three-year embargo on the data we are considering here.

[2] There is no need for a country to have year data for all considered years.

Table 1
Details of clustering, external and profiling variables.

Variable name	Variable description	Variable type	Relationship with review of the literature
Clustering variables			
GDPprcap	GDP per capita (current US$)	Economic Development	Overall income (output per head)
RPOPprcnt	Rural population (% of total population)	Economic Development	Level of rurality
GERDprcnt	GERD as a percentage of GDP	Economic Development	Commitment to R&D
GETDprccnt	Government expenditure on tertiary education as a percentage of GDP (%)	Economic Development	Expenditure on university type education (quality)
TEA	Total Entrepreneurial Activity	Entrepreneurial Activity	Start up and Early-Stage Entrepreneurship Activity
External variables			
CGTExppc_1	Exports.of.cultural.goods/GDP (current US$)	Exporting	Importance to your economy
CGTExppc_2	Exports.of.cultural.goods/Exports of all goods	Exporting	Importance to your exports
CGTImppc_1	Imports.of.cultural.goods/GDP (current US$)	Importing	Importance to your economy
CGTImppc_2	Imports.of.cultural.goods/Exports of all goods	Importing	Importance to your imports
Profiling variables			
YTHprcnt	[Population aged 14 years or younger (thousands) + Population aged 15–24 years (thousands)] / Total population (thousands)	Age Profile	Level of youthfulness
PVTYprcnt	Poverty headcount ratio at $3.20 a day (PPP) (% of population)	Poverty Profile	Inherent Poverty (indirectly brings in spread of wealth)

Table 2
Breakdown of frequencies of inclusion of countries (in country-year observations terms).

Spain - 10	Uruguay - 7	USA – 5	Cyprus - 3	France - 1
Sweden - 10	Croatia - 6	Austria - 4	Iran - 3	Georgia - 1
Ireland - 9	Estonia - 6	Brazil - 4	Kazakhstan - 3	Guatemala - 1
Slovakia - 9	Norway - 6	Chile – 4	Bulgaria - 2	Japan - 1
Argentina - 8	Portugal - 6	Ecuador - 4	Czechia - 2	Malaysia - 1
Italy - 8	Romania - 6	Germany - 4	Denmark - 2	Panama - 1
Latvia - 8	Belgium - 5	Lithuania - 4	South Africa - 2	Slovenia - 1
Poland - 8	Canada - 5	Greece - 4	Thailand - 2	France - 1
Finland - 7	Colombia - 5	Mexico - 4	Tunisia – 2	Georgia - 1
Hungary - 7	Luxembourg - 5	Russia - 4	Australia - 1	Guatemala - 1
UK - 7	Netherlands - 5	Costa Rica - 3	El Salvador – 1	

represented by a horizontal line).

It is of benefit to compare the two versions of each external variable considered, each for export (CGTExppc_1 and CGTExppc_2) and import (CGTImppc_1 and CGTImppc_2) of cultural trade, see Fig. 5.

In Fig. 5, in each plot, each point gives a (CGTExppc_1, CGTExppc_2) coordinate (in 4a) and (CGTImppc_1, CGTImppc_2) coordinate (in 4b). In each plot there is noticeable 'heavy' grouping of points around the 0.00 to 0.003 values, with then sparser points beyond these intervals for a few country-year observations, regression lines, and associated 95 % confidence intervals also included.

4. Method: cluster analysis

This study undertakes a configurational (clustering) approach in its analysis, to investigate the relationship between entrepreneurship and country characteristics towards cultural export and import trade activity. Ketchen and Shook (1996), in a critique of clustering, observed such analysis can provide very rich descriptions of configurations (here country-year observations) without over specifying the model. Crum et al. (2022) also note that such an approach could benefit entrepreneurship research. To explain in further detail, in simple terms, clustering considers a set of objects in such a way that objects in the same cluster are more similar to each other than to those in other clusters. Following Crum et al. (2022), it is important to remind the reader that a cluster approach is a useful tool in such early-stage research, as this study should be seen.

Here, a fuzzy clustering approach is adopted, named fuzzy c-means (FCM - Bezdek, 1981; Bezdek et al., 1984; Saxena et al., 2017), the results generated using R software and the fclust package (with specific coding). In contrast to more traditional 'crisp' clustering like the Ward's method and k-means, where with continuous clustering variables describing the cases, they are assumed to be only associated with a single cluster, FCM understandably works on the premise that each case may have grades of membership to different clusters. Here, a recent development on FCM is also included, namely using a polynomial fuzzifier (see Klawonn and Höppner, 2003; Winkler et al., 2011). This development means the fuzzifier functions are a linear combination of both fuzzy c-means and crisp k-means algorithms, meaning cluster membership is not only over the values of the open interval (0, 1), but allows membership values of [0, 1], including 0 and 1 (see Ferraro and Giordani, 2015).

An important feature of this (FCM) non-hierarchical approach to clustering is 'what' number of clusters to establish (see Ketchen and Shook, 1996; Saxena et al., 2017). There exist several nascent measures to help on this 'number of clusters' issue, see Xu et al. (2016). Following Ketchen and Shook (1996) and McDermott et al. (2013), theoretical meaningfulness (deductive approach) was also an important consideration. It follows, here, four clusters were considered appropriate number to consider, also noting 227 number of cases being considered (so potential for meaningful numbers of cases associated with each cluster).

5. Clustering results

An initial exposition of the established four-cluster solution (C1, C2, C3 and C4) of the culture-entrepreneurship data set is given in Fig. 6.

In Fig. 6a, the five variables used for clustering, GDPprcap, RPOPprcnt, GERDprcnt, GETDprccnt and TEA, are described by boxplots, each describing the spread of values for that clustering variable over all considered cases. We note, following Hair et al. (2010), standardised variable forms of the clustering variables were used in the clustering process using FCM are used (with zero mean and unit standard deviation as noted in y-axis scale), for each clustering variable to

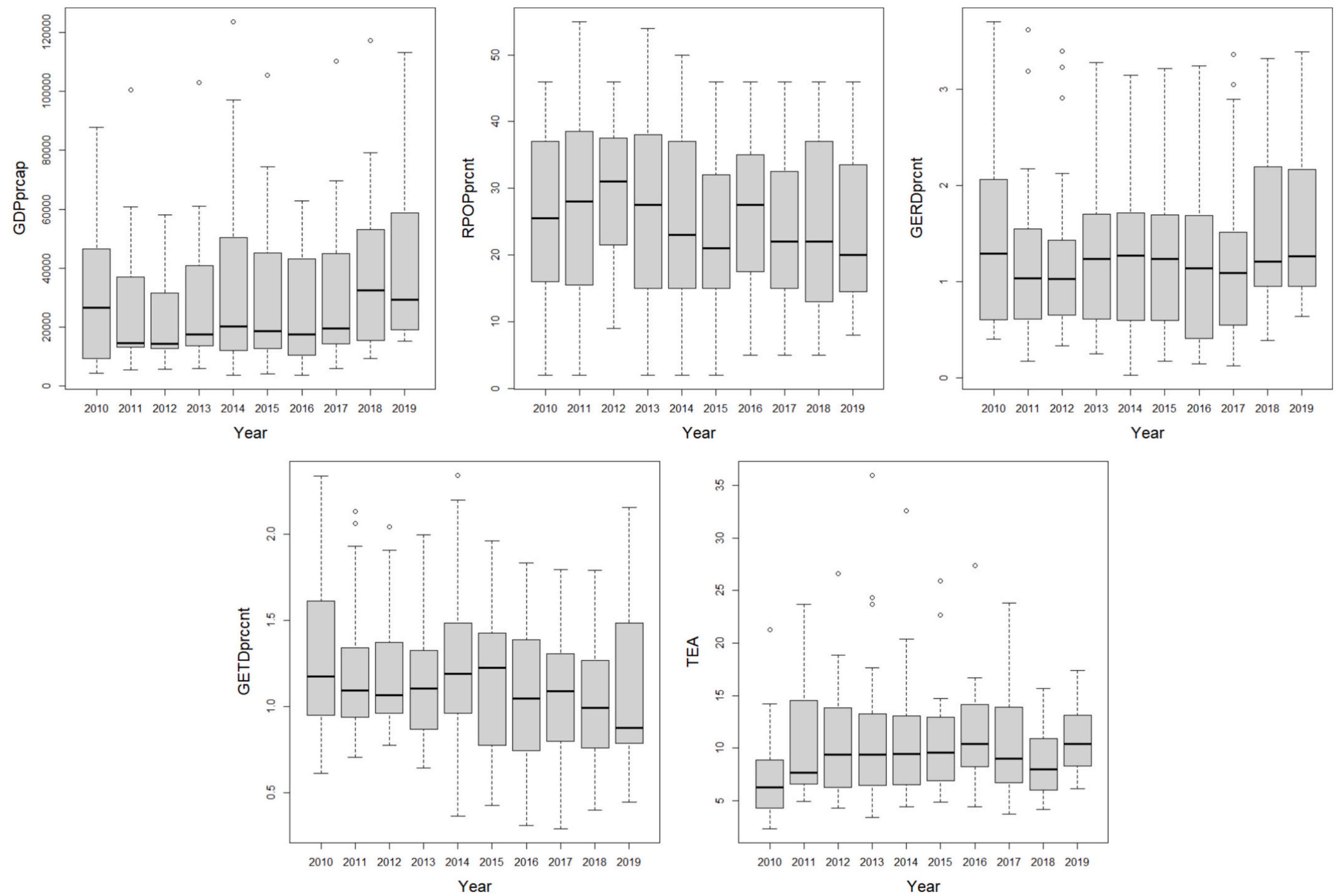

Fig. 2. Boxplots of clustering variables' values across the considered years 2010 to 2019.

limit impact of variation in original interval scaled data.

Across the set of boxplots, a series of point-lines are drawn, showing the respective individual cluster details associated with the clustering variables. Moreover, each point represents the mean value of that variable associated with the cases in a specific cluster, with the lines joining up the respective variable mean values of the variables for a single cluster. On the right end of each point-line is an initial cluster label (C?), with the number shown the number of cases associated with that cluster in majority association terms.[3]

In Fig. 6b, a further graphical interpretation of the variable based clustering of the country-year observations is given. Moreover, for each cluster, the set of five boxplots explicitly shows the spread of the clustering variable values for the cases majority associated with that cluster.[4] ANOVA tests can again be employed to test the level of difference between the sets of case values associated with each cluster on each clustering variable. The ANOVA results are, GDPprcap ($F(1, 225) = 13.9$, $p = 0.00024$***), RPOPprcnt ($F(1, 225) = 42.8$, $p = 4e{-}10$***), GERDprcnt ($F(1, 225) = 74.3$, $p = 1.2e{-}15$***), GETDprccnt ($F(1, 225) = 224$, $p \leq 2e{-}16$***) and TEA ($F(1, 225) = 10.1$, $p = 0.0017$**). The tests show there is statistically significant difference in the sets of cluster case values across all the clustering variables. These results then allow more specific Bonferroni 'post hocs' to be undertaken on each clustering variable (see Hair et al., 2010; McDermott et al., 2013) to examine between cluster variations. The post-hoc results are shown in Fig. 6a, where dark shaded ovals are shown around groups of clusters case mean points where there is no post-hoc statistical difference between them.

Following the graphical and statistical evidence-based elucidation of the four clusters, given in Fig. 6, an attempt is next made to summarise, most obviously by using the relative strengths of the clustering variables to define each cluster as follows.

C1 (55) - High GDP, Low RPOP, High GERD, High GETD and Low TEA so defined - Rich, Urban, Innovative, Educated, non-entrepreneurial.
C2 (37) - Low GDP, Low RPOP, Low GERD, Mid GETD and High TEA so defined - Poor, Urban, Non-innovation, Basic Education, Start-Up reliant.
C3 (82) - Low GDP, High RPOP, Low GERD, Low GETD and Mid TEA so defined - Poor, Rural, Non-innovation, Non-education, Start-up friendly.
C4 (53) - High GDP, Mid RPOP, Mid GERD, Low GETD and Low TEA so defined - Rich, Urban-Rural balanced, Basic innovation, Non-education, non-entrepreneurial.

These defined clusters of country-year observations are then considered in terms of their relationship with international trade in cultural goods. The established clusters of country-year observations, based on clustering variables, GDP (GDPprcap), rurality (RPOPprcnt), education (GERDprcnt), research (GETDprccnt) and entrepreneurship (TEA), are considered in terms of the cluster variations in the associated levels of trade in cultural goods. In technical terms, this consideration of 'external' variables against established clusters is also a form of validation of the undertaken clustering

[3] With using FCM, a case has a grade of membership to each cluster, majority association means a case will be singly associated with a single cluster for which they have the largest grade of membership towards.

[4] We note briefly that Fig. 5b also offers a mechanism for the initial ordering of the clusters (C1, C2, C3 and C4). That is, they are shown in Fig. 5b in the order based on overall mean of all clusters variables values of cases in a cluster (largest mean C1 and smallest mean C).

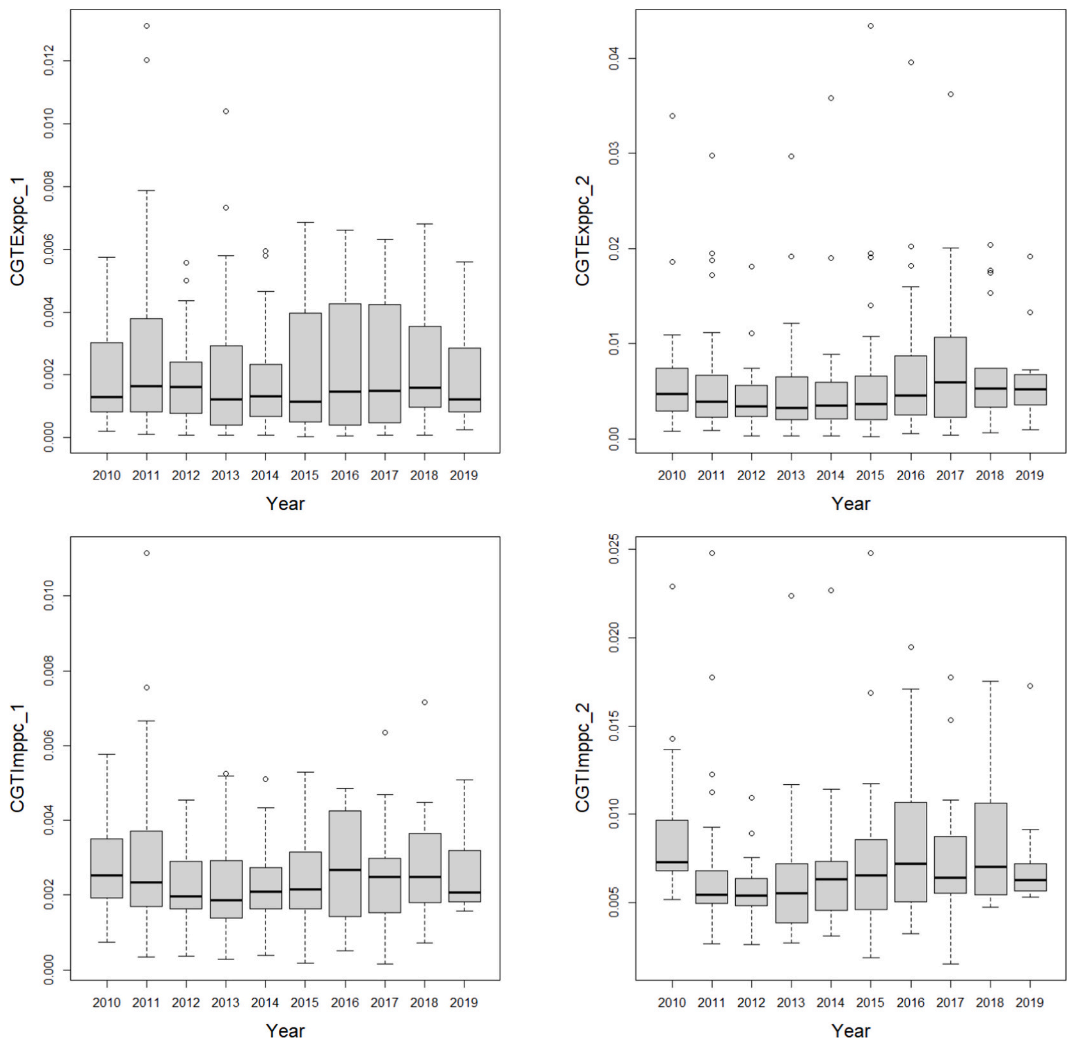

Fig. 3. Boxplots of external variables' values across the considered years 2010 to 2019.

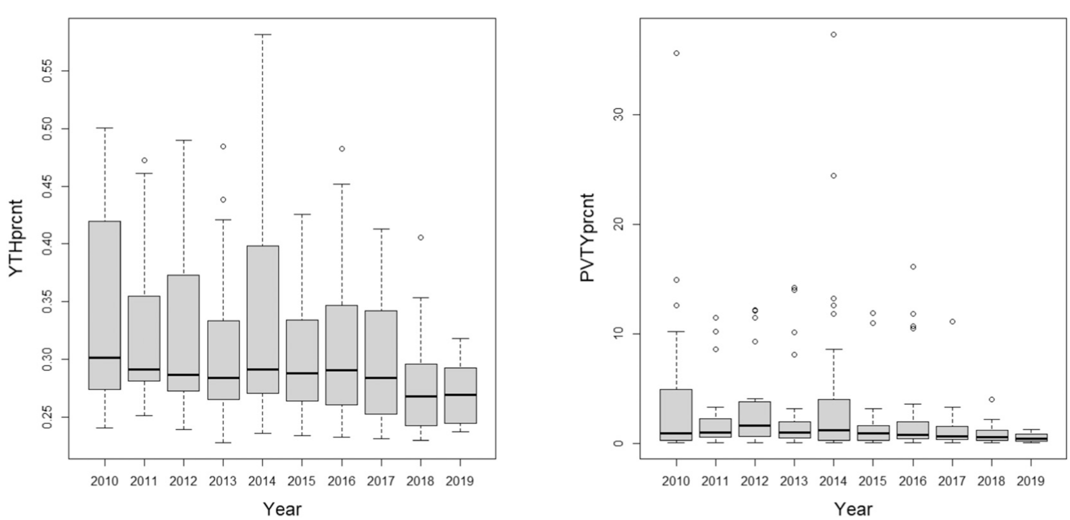

Fig. 4. Boxplots of profile variables' values across the considered years 2010 to 2019.

process (Ketchen and Shook, 1996; Crum et al., 2022).

Here, as described in Table 1, four external variables are considered, which each describe a facet of cultural trade in the considered country-year observations making up the culture-entrepreneurship data set. Moreover, two versions each of the export (CGTExppc_1 and CGTExppc_2) and import (CGTImppc_1 and CGTImppc_2) of cultural goods are considered (see Table 1 for their descriptors).

Two graphs are again presented describing the cluster relationships

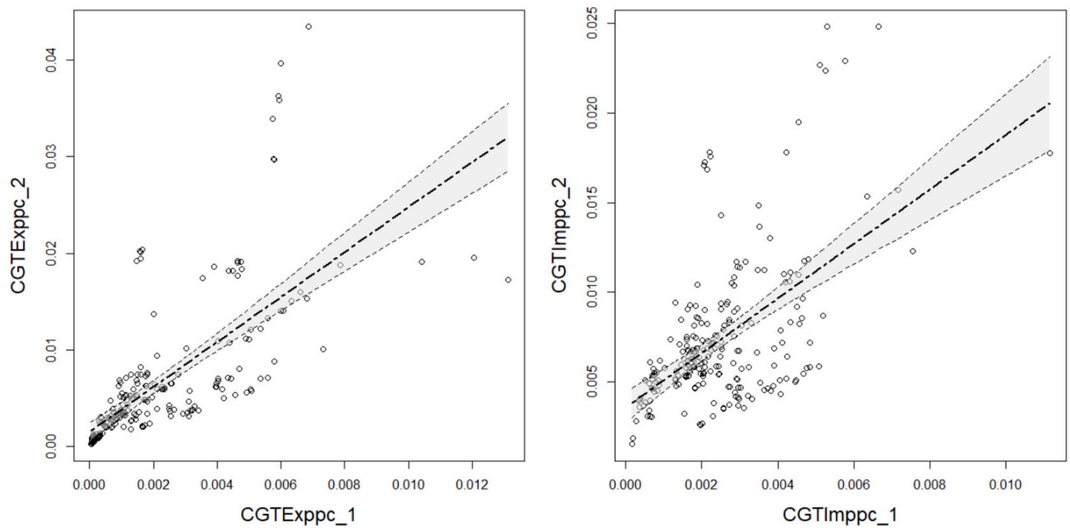

Fig. 5. Scatterplots of pairs of export and import dimensions of cultural trade.

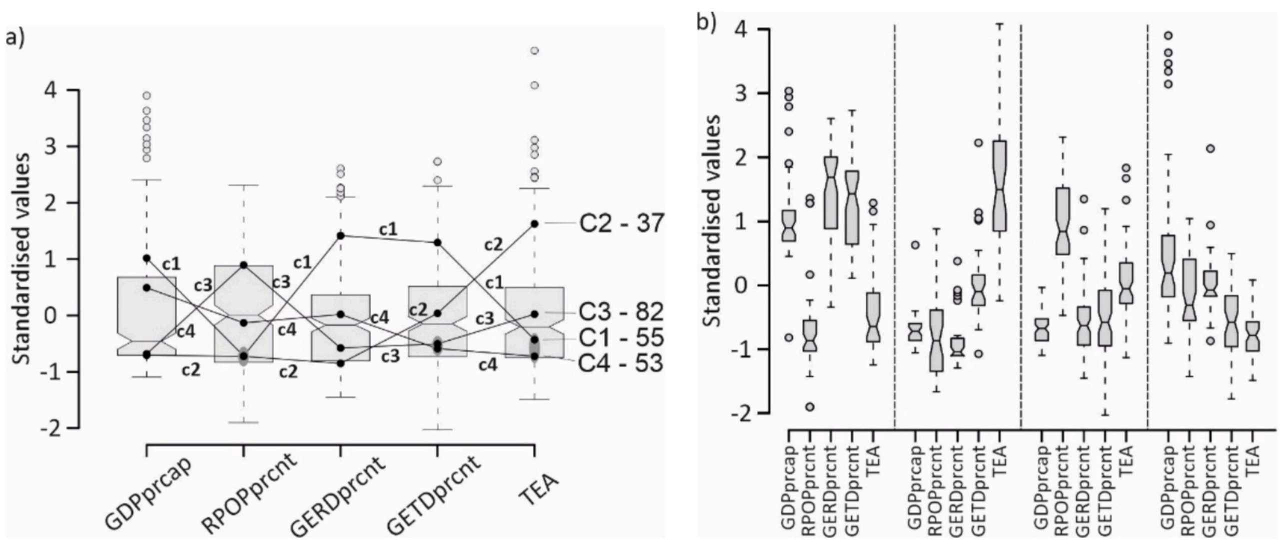

Fig. 6. Elucidation of cluster variable contribution to established clusters (C1, C2, C3 and C4).

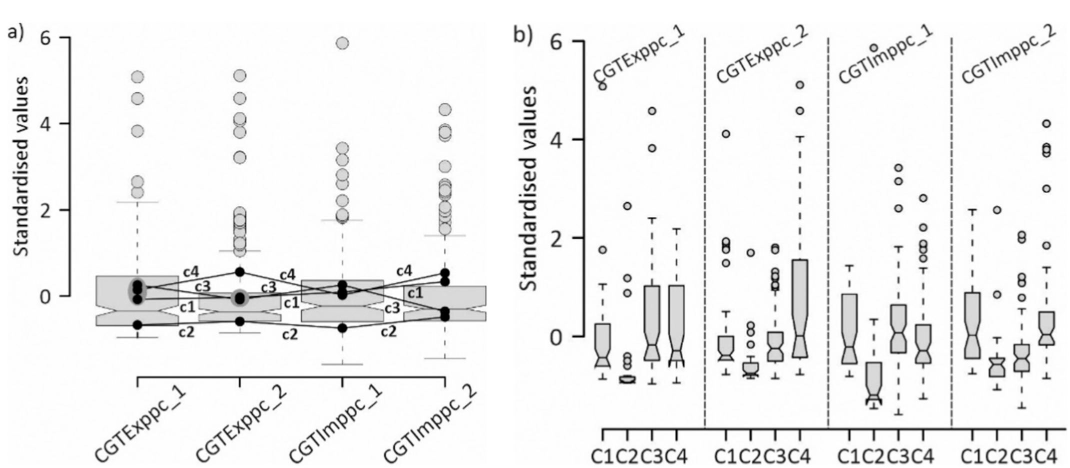

Fig. 7. Comparison of clusters to external variables.

to each of the four cultural trade external variables considered, namely, CGTExppc_1, CGTExppc_2, CGTImppc_1 and CGTImppc_2, see Fig. 7 (for ease of representation the original cluster labels C1, C2 C3 and C4 are used in the plots given).

In Fig. 7a, the four cultural trade external variables are descried by boxplots, with respective cluster means of the external variables represented by point-lines (as in Fig. 5a). In Fig. 7b, the respective external variable cluster boxplots are shown for each of the four clusters (as in

Fig. 5b). In terms of the ordering of the clusters, using their cluster means values, are CGTExppc_1 - C2 < C1 < C4 < C3; CGTExppc_2 - C2 < C3 < C1 < C4; CGTImppc_1 - C2 < C4 < C1 < C3; CGTImppc_2 – C2 < C3 < C1 < C4.

An immediate consideration is then on the statistical difference in the cluster external variable values. Here ANOVA tests are undertaken, CGTExppc_1 (F(1, 225) = 6.22, p = 0.013*), CGTExppc_2 (F(1, 225) = 11.4, p = 0.00085***), CGTImppc_1 (F(1, 225) = 1.28, p = 0.26) and CGTImppc_2 (F(1, 225) = 0.33, p = 0.57). It follows, there appears to be statistically significant differences in the levels of export cultural trade across the established clusters for both CGTExppc_1 and CGTExppc_2, but not statistically significant differences with respect to the import cultural trade, CGTImppc_1 and CGTImppc_2. It follows, post-hoc details are only presented for the export cultural trade external variables, CGTExppc_1 and CGTExppc_2 (since only those show ANOVA based statistical significance), as shown with the use of dark grey oval notation across the sets of clusters mean points in Fig. 6a, only for these two external variables.

An attempt is also made here to offer a level of profiling of the established clusters. As described in Table 1 two specific profiling variables are considered (available in UIS data set), namely, YTHprcnt and PVRTYprcnt. We include one further variable here, namely the year of each case (country-year observation), to them consider a possible year effect form of profiling. As employed previously, a visualisation of the profiling of the clusters, using, Year, YTHprcnt and PVTYprcnt, is first given, see Fig. 8.

In Fig. 8a and b results are presented showing the variations in the cluster associated case profiling variable values as employed previously, see Figs. 6 and 7. In terms of mean-based ordering; Years – C2 < C3 < C1 < C4; YTHprcnt – C4 < C1 < C3 < C2 and PVTYprcnt – C1 < C4 < C3 < C2. The associated ANOVA tests are next given, Year (F(1, 225) = 0.17, p = 0.68), YTHprcnt (F(1, 225) = 8.05, p = 0.005**); and PVTYprcnt (F (1, 225) = 0.43, p = 0.51). These tests show only YTHprcnt is statistically different across the four established clusters. Hence again, dark grey oval notation is applied to the points on the YTHprcnt profiling variable to denote where there is no 'post-hoc' statistically significant difference between pairs of clusters (points). One further set of results are given, at the most granular level, namely individual country level, see Fig. 9.

In Fig. 9, the two sets of matrix-cell based plots are presented, in relation to CGTExppc_1 (left) and CGTExppc_2 (right). Each row in a plot represents a country, and the cells present in a row correspond to that country's associated country-year observations in the culture-entrepreneurship data set. The main columns denote the individual years, left to right, 2010 through to 2019. In each plot, the ordering of the countries is rank ordering based on the highest (top) to lowest (bottom) of the respective mean external variable values over their set of country-year observations. Final description is the cells are labelled with the cluster that country-year observation is majority associated with (the shading light grey to dark grey allows further seeing of patterns – and are ordered based on the C1 to C4 – see footnote 4).

In Fig. 9a, in regard to CGTExppc_1, the countries are ranked (on overall mean CGTExppc_1 Values) from top (Malaysia – 0.013) to bottom (Iran – 0.000) [noting a number of near 0]. We see the scattering of cells shown in the matrix (acknowledging not all countries had all years included). Looking at the rows, and the labelling in cells does suggest there is limited evidence of a country changing cluster majority associations over the available years (exceptions being looking bottom to top, Canada, Costa Rica, and Estonia). In Fig. 9b, in regard to CGTExppc_2, the countries are ranked (on overall mean CGTExppc_2 Values) from top (UK – 0.036) to bottom (Ecuador – 0.000). This allows us to add geographical but also socio-economic information to the naming of the clusters, adding further clarity, as is shown below.

C1 (55) - High GDP, Low RPOP, High GERD, High GETD and Low TEA so defined - Rich, Urban, Innovative, Educated, non-entrepreneurial (Example Countries: Austria, Belgium, Finland, Germany, Norway, Sweden, USA, Netherlands, Canada) Northern European and America.
C2 (37) - Low GDP, Low RPOP, Low GERD, Mid GETD and High TEA so defined - Poor, Urban, Non-innovation, Basic Education, Start-Up reliant (Example Countries: Argentina, Brazil, Chile, Colombia, Ecuador Uruguay): South American.
C3 (82) - Low GDP, High RPOP, Low GERD, Low GETD and Mid TEA so defined - Poor, Rural, Non-innovation, Non-education, Start-up friendly (Example Countries: Cyprus, Croatia, Hungary, Latvia, Lithuania, Poland, Portugal, Romania, Slovakia, Kazakhstan, Iran): Economically peripheral.
C4 (53) - High GDP, Mid RPOP, Mid GERD, Low GETD and Low TEA so defined - Rich, Urban-Rural balanced, Basic innovation, Non-education, Non-entrepreneurial (Example Countries, Greece, Italy, Ireland, Luxembourg, Russia, Spain, UK): Culturally Marketed.

Fig. 9 also indicates, very broadly, that for to CGTExppc_1 (8a), clusters C3 and C4 are much more strongly represented in the higher values of exports of cultural goods as a proportion of overall GDP, whilst C1 and C2 are more strongly represented in the lower values. For CGTExppc_2 (8b) cluster C4 seems more strongly represented in the higher values for Exports of cultural goods as a proportion of exports of all goods. This seems to show that generally (though not for C4 countries such as Russia and Ireland), culturally marketed countries are more reliant on cultural exports to their overall exports. To bring together the results presented so far, a series of hierarchical regressions are undertaken, a series for each of the two export oriented international trade

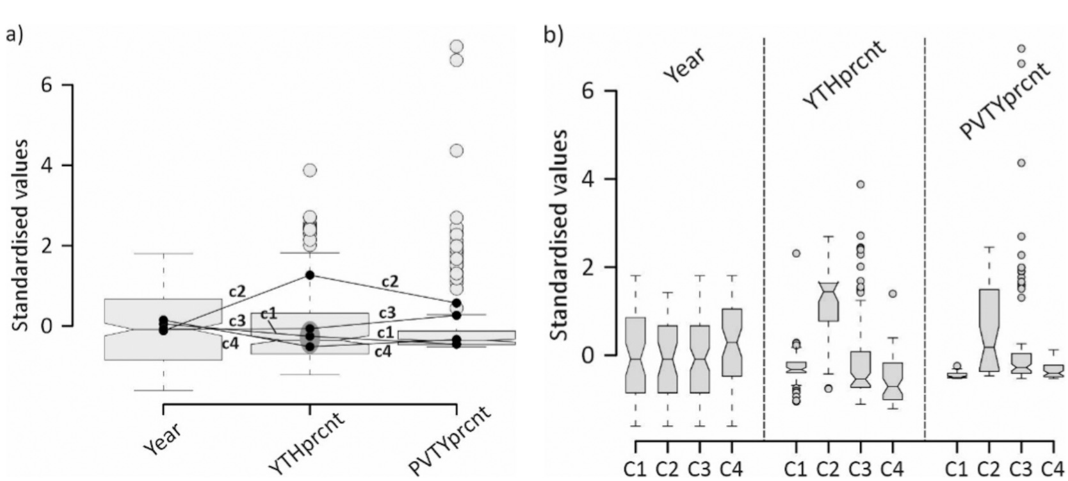

Fig. 8. Comparing clusters to profiling variables.

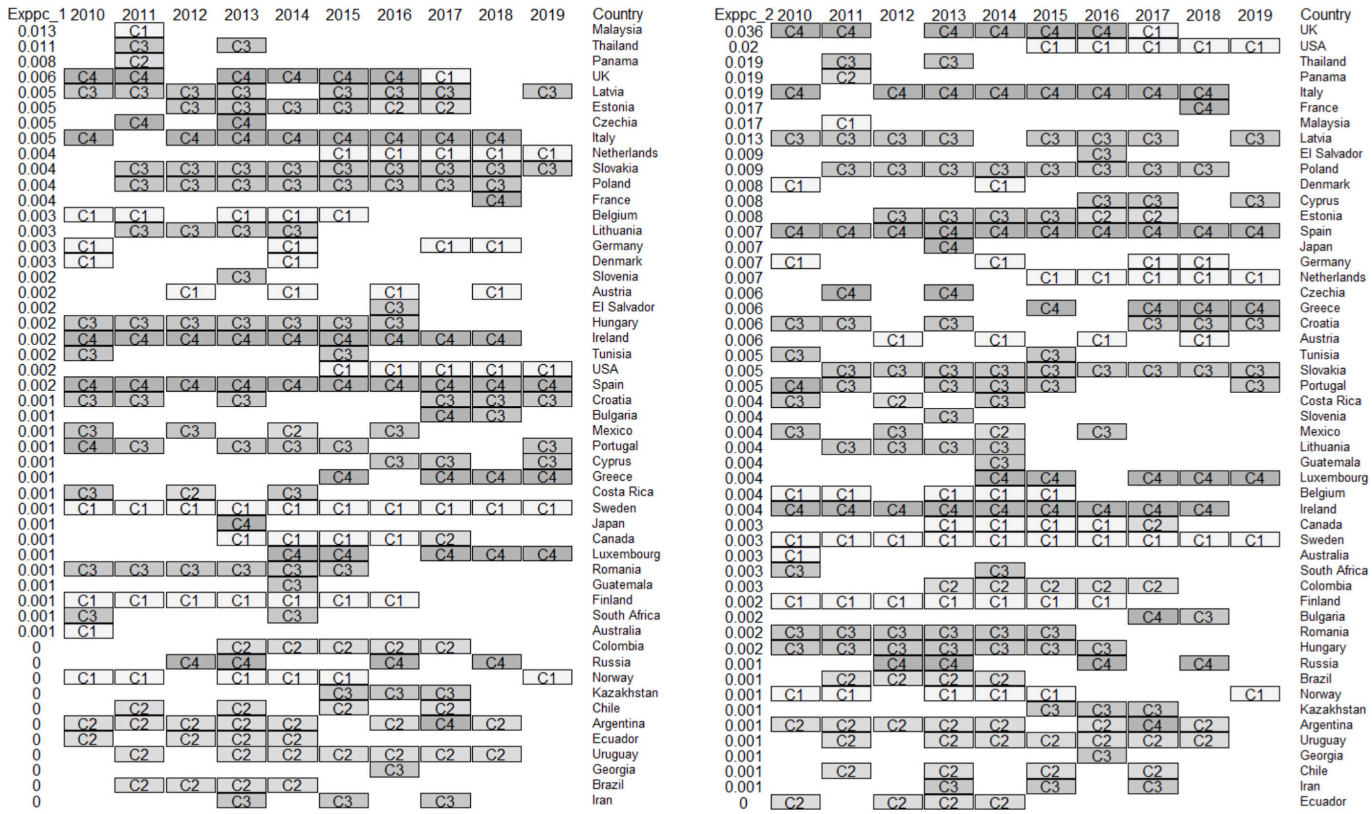

Fig. 9. Matrix cell-based elucidation of country-year observations to CGTExppc_1 (8a) and CGTExppc_2 (8b).

external variables. As discussed in Andrews and Beynon (2017), hierarchical regression analysis involves transforming the clusters into dummy variables, generating four separate regression equations, a different cluster used as a reference category for each model. This then allows us to compare the strength of the three (dummy scored) clusters in relation to cultural goods exports with the cluster that serves as the reference category in each case. The findings of each of the sets of hierarchical regressions are next separately discussed, see Tables 3 (for CGTExppc_1) and 4 (for CGTExppc_2). (See Table 4.)

For CGTExppc_1 (Exports.of.cultural.goods/GDP (current US$)), which measures the importance of the export of cultural goods to the economy as a whole, the results show positive and significant relationships in a number of the equations for C3 (Poor, Rural, Non-innovation, Non-education, Start-up friendly) and C4 (Rich, Urban-Rural balanced, Basic innovation, Non-education, Non-entrepreneurial). Interestingly, C3 can also be seen to have stronger values. Conversely, C1 (Rich, Urban, Innovative, Educated, non-entrepreneurial) and C2 (Poor, Urban, Non-innovation, Basic Education, Start-Up reliant) show negative and significant relationships in a number of the equations. Again, interestingly, C2 (start-up reliant) is more strongly negative than C1.

Table 3
CGTExppc_1 hierarchical regression results.

	–C1	–C2	–C3	–C4
Intercept	51.397	50.995	51.992	51.803
C1	–	0.403	−0.595**	−0.406*
C2	−0.403	–	−0.998**	−0.809**
C3	0.595***	0.998***	–	0.189
C4	0.406*	0.809**	−0.189	–
Year	−0.025	−0.025	−0.025	−0.025
YTHprcnt	−0.564	−0.564	−0.564	−0.564
PVTYprcnt	−0.037*	−0.037*	−0.037*	−0.037*
Adj. R2	0.157	0.157	0.157	0.157
F (6, 220)	8.03***	8.03***	8.03***	8.03***

Signif. codes: '***' [0, 0.001]; '**' (0.001, 0.01]; '*' (0.01, 0.05]; '^' (0.05, 0.1]; ' ' (0.1, 1].

Table 4
CGTExppc_2 hierarchical regression results.

	–C1	–C2	–C3	–C4
Intercept	−17.956	−18.538	−17.966	−17.265
C1	–	0.581*	0.010	−0.691**
C2	−0.581*	–	−0.572*	−1.273**
C3	−0.010*	0.572*	–	−0.701**
C4	0.691***	1.273***	0.701***	–
Year	0.009	0.009	0.009	0.009
YTHprcnt	0.212	0.212	0.212	0.212
PVTYprcnt	−0.011	−0.011	−0.011	−0.011
Adj. R2	0.154	0.154	0.154	0.154
F (6, 220)	6.67***	6.67***	6.67***	6.67***

Signif. codes: '***' [0, 0.001]; '**' (0.001, 0.01]; '*' (0.01, 0.05]; '^' (0.05, 0.1]; ' ' (0.1, 1].

For CGTExppc_2 (Exports of cultural goods/Exports of all goods), which measures the importance of the export of cultural goods to exports as a whole, the results show positive and significant relationships for C4 (Rich, Urban-Rural balanced, Basic innovation, Non-education, non-entrepreneurial). Conversely, C2 (Poor, Urban, Non-innovation, Basic Education, Start-Up reliant) highlight negative and significant relationships in several of the eqs. C1 and C3, are positive in some equations and negative in others. In terms of the control variables, the results suggest that only poverty has a significant (negative) effect on cultural goods exports and only in terms of relative importance to the economy as a whole, this not preventing C3 countries from deriving greater importance for their cultural goods exports as a proportion of their overall economy.

6. Discussion

In this section, the research questions are considered and discussed. Previous research in the area of cultural goods trade has focused on exports only (Maghssudipour et al., 2023; Park, 2014; Salim and Mahmood, 2015); individual countries (Zukauskaite, 2012; Park, 2014;

Salim and Mahmood, 2015), sectors (Demetry, 2019), and analysed the impact of variables individually (Marvasti, 1994; Park, 2014; Salim and Mahmood, 2015). The results of this study, however, extend the work of Crum et al., (2022) by both including the role of entrepreneurship and through analysis which clusters economic development and entrepreneurship variables together. This also supports Salim and Mahmood's (2015) contention, that existing economic development-related frameworks (in their case the gravity model of trade) model can have added relevance when also considered in the context of other, environmental factors (in their case cultural ties and commonalities, in our case entrepreneurship). The results allow a view of the interactions of drivers of cultural industries in terms of geography and industry, allowing broader development of theory and policy as a result.

RQ1. Are there distinct groups of countries defined by different combinations (clusters) of cultural sector relevant, trade and entrepreneurship related, variables most likely to drive imports and exports of cultural goods?

In answering this question, the results show that the four clusters established demonstrate (statistical) variation across the considered clustering as well as distinct geographical and/or socio-economic differences, which were realised by the hierarchical regression analysis undertaken for the export focused external variables. The fact that the import focused variables did not show such statistical variation across the clusters, however, also identifies that the sets of drivers of imports and exports are not identical.

RQ2. Do these clusters have significantly different impacts on imports and exports of cultural goods?

In responding to this RQ, unsurprisingly, the results show that whilst for the more broadly economically based Northern American and European economies of C1 the results are inconsistent, for C4, containing the countries most strongly culturally marketed, there is the most consistent positive relationship with cultural exports being important to both the economy AND to exports as a whole. For the South American focused cluster C2, a high reliance on new firms, in an environment of low GDP, an urban environment and with only basic education is not conducive to exports being important either to the economy as a whole or exports as a whole. For the economically peripheral countries of C3, however, where the environment is start-up friendly (but not reliant), having a poor rural and non-innovation-education environment is still compatible with cultural goods exports being important to the economy as a whole, but inconclusive for cultural goods exports within total exports.

The role of language in the clusters extracted, which may help distinguish between the more global strongly cultural countries in C4 and the more economically peripheral ones in C3. C4 countries for example (or at least some of them) may have a relative advantage in the export of cultural goods, because of linguistic-related factors (including those related to diaspora and colonial ties) (Maghssudipour et al., 2023), over both other countries sharing the same language- if its other conditions are better, but also over countries with similar conditions but which do not have the same linguistic conditions, even where these countries are geographically proximate. This may help to explain, therefore the results for C4 countries, particularly the UK, Ireland, Spain, Italy, and Russia. The results for C4 would also tend to support, but only for exports, Salim and Mahmood's (2015) contention, that an existing economic development model has added impetus in the context of cultural goods because of the connected importance of cultural ties and commonalities.

7. Conclusions

This study has investigated the relationship between a number of country-based economic and entrepreneurship variables and certain cultural trade descriptors. By considering a novel cluster approach, emphasis was placed on the case-based understanding of configurations of the clustering variables, GDPprcap, RPOPprcnt, GERDprcnt, GETDprccnt and TEA, through which distinctly different types of cultural goods clusters were identified. These results offer initial insights into this phenomenon that can act as a baseline for further study. However, it is apparent that further ongoing research is required exploring different types of cultural trade in greater depth- and how they can be supported through the development of focused ecosystems to enable further growth.

The implications for policy and practice are, firstly, that there are clear clusters of often geographically designated countries sharing similar combinations of conditions that drive or hinder trade in cultural goods, which policy makers can potentially employ to support the sustainable development of their own cultural industries. Thus, the development of similar economic policy and support ecosystems within these countries to enable the same trading clusters. Second, whilst more traditional strong cultural exporters, such as the UK, unsurprisingly find the cultural industries of great importance both to their economy and exports, the results also demonstrate that cultural industries can also be important to the economies of more economically peripheral countries, where such entrepreneurial activity is also important.

The specific implications for practice include the specific need for entrepreneurship-promotion in these economically peripheral countries to help develop trade in cultural goods, whilst for more traditionally strong cultural exporters, the role of innovation may be of greater relevance, and therefore in need of greater policy support to further develop the cultural industries. Cultural trade in all its forms offers a significant national opportunity to encourage entrepreneurial growth profiting on the existing competencies and strengths of individuals and regions.

CRediT authorship contribution statement

Malcolm Beynon: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **David Pickernell:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Paul Jones:** Writing – review & editing, Conceptualization.

Declaration of competing interest

None.

Appendix A

In this appendix, a series of boxplots are given, showing the spread of respective variables' values of the considered country-year observations, and broken down by country (noting countries have different frequency of inclusion in the data set – see Table 2).

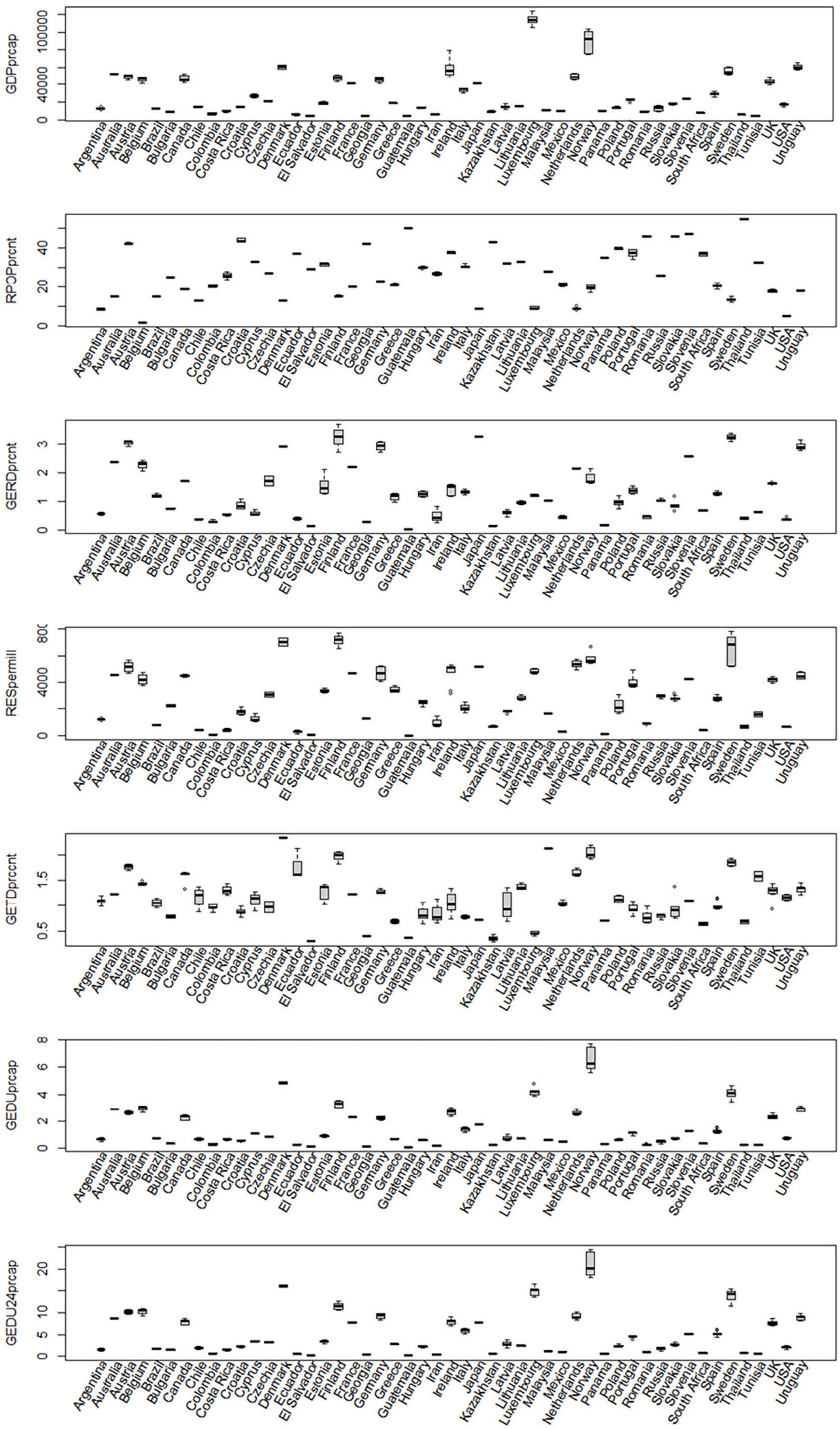

Fig. A1. Series of box plot of clustering variables by country.

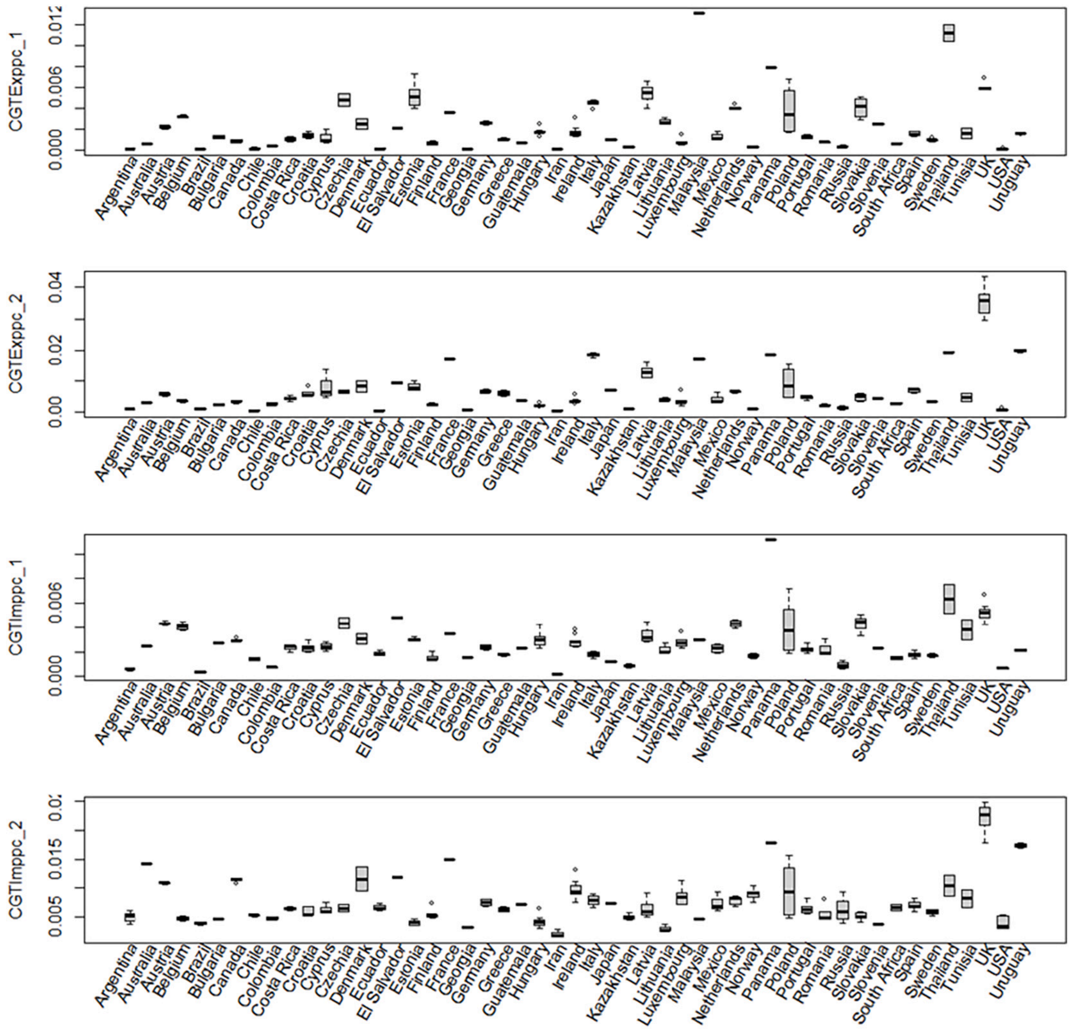

Fig. A2. Series of box plot of external variables by country.

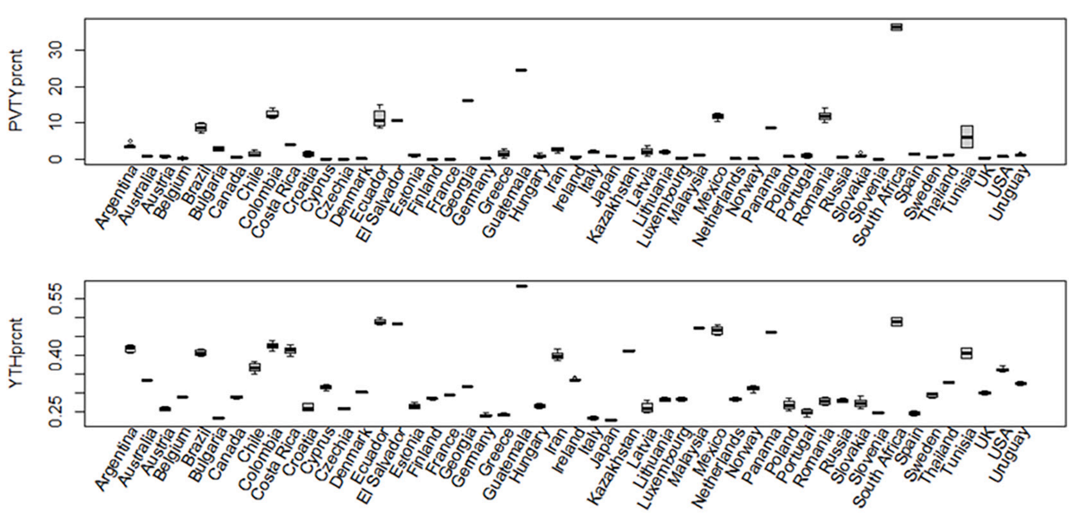

Fig. A3. Series of box plot of profiling variables by country.

Data availability

The data are publicly available.

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