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Measuring Soft Power: A New Global Index

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Measuring Soft Power: A New Global Index

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ABSTRACT: Soft power is difficult to measure directly, and existing indicators—mostly subjective and not always transparent—fail to take into account the multidimensional nature of soft power. In this paper, we introduce a new comprehensive Global Soft Power Index (GSPI) composed of six dimensions for a broad sample of countries over a long span of time. The proposed framework allows for comparisons not only at the "headline" level of the GSPI, but also at the level of the sub-indices, which in turn helps identify and study how countries differ at a granular level of soft power. In a final step of the analysis, we present a possible macro-financial application to investigate the relationship between soft power and exchange rates. The results indicate that some dimensions of the GSPI play an important role in explaining exchange rate volatility. Overall, the composite GSPI presented in this paper provides a systematic approach to measure soft power along its multiple dimensions. By capturing the matrix of soft power characteristics, the GSPI offers significant advantages in comparative analysis of soft power across countries and over time.

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WORKING PAPERS

Measuring Soft Power

A New Global Index

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Contents

Executive Summary

The recent emergence of geopolitical tensions across the world has renewed greater interest in power politics and transitions. In broad terms, power is the ability to affect others to get the outcomes one prefers, and that can be accomplished by coercion, payment, or attraction and persuasion. Soft power, on the other hand, is the ability to obtain preferred outcomes by attraction rather than coercion or payment. As an analytic concept in international relations, soft power captures intangible resources beyond material considerations. With digitalization accelerating the diffusion of power within and across countries, soft power has increasingly become more and more important to the shaping of global outcomes in an interconnected world.

In this paper, we present a new comprehensive Global Soft Power Index (GSPI) based on 29 indicators along six dimensions for a broad set of countries over the period 1990–2021. We use a standard three-step approach to reduce multidimensional data into a single composite index: (i) normalization of variables; (ii) aggregation of normalized variables into the sub-indices representing a particular dimension; and (iii) aggregation of the sub-indices into the final index. Being a systematic framework, the approach we use to calculate the GSPI captures the matrix of soft power characteristics and offers significant advantages in comparing the level of soft power across countries and over time. A key characteristic of the GSPI is that it is an aggregation of different sub-indices, each representing a particular functional dimension of soft power, which helps identify and study how countries differ at a granular level of soft power.

We demonstrate the macro-financial relevance of the composite GSPI by testing the impact of soft power on exchange rates. According to our analysis, low soft-power countries present a dynamic between soft power and the volatility of real exchange rates that is significantly different from that for medium and high soft-power countries. Although the “headline” GSPI does not appear to be statistically significant in explaining exchange rate volatility, the culture and global reach dimensions of soft power are clearly relevant at almost all levels of statistical significance. The fact that global reach is the most significant sub-index of soft power is an interesting result because this is precisely the dimension that is responsible for most of the differentiation between medium and high soft-power countries.

There is substantial variation in the level of soft power across countries. For example, as of 2021, the GSPI ranges from a minimum of -0.59 in Dominican Republic to a maximum of 1.68 in South Korea. Although advanced economies tend to have a higher level of soft power compared to developing countries, this is not categorically the case, especially when we consider the evolution of soft power over time. To give an idea of how the GSPI progresses in each country over time, we compare the GSPI scores for China and the United Kingdom. The United Kingdom used to have a significantly higher level of soft power than China. However, China’s soft power increased significantly from 0.70 in 2004 to 1.17 in 2021, while the United Kingdom’s soft power declined from 1.32 to 0.85 over the same period.

Overall, our GSPI and its sub-indices present a systematic approach to measure soft power along multiple dimensions, which capture the matrix of soft power characteristics and offer significant advantages in comparing the level of soft power across countries and over time. The macro-financial application presented in this paper is only one of the many possible use cases of the GSPI. In our view, the proposed framework for measuring and evaluating soft power contributes to the growing literature on the study of this important dimension of power and provides a new avenue for econometric exploration its influence on economic and political and developments.

I. Introduction

The recent emergence of geopolitical tensions across the world has renewed greater interest in power politics and transitions. In broad terms, power is defined as the ability to affect others to get the outcomes one prefers, and that can be accomplished by coercion, payment, or attraction and persuasion. Soft power, on the other hand, is the ability to obtain preferred outcomes by attraction rather than coercion or payment. As an analytic concept in international relations, soft power is popularized by Nye (1990) to capture intangible resources beyond material considerations. With digitalization accelerating the diffusion of power within and across countries, soft power has increasingly become more important to the shaping of global outcomes in an interconnected world.

Composite indicators are popular tools for monitoring and assessing the performance of countries on a wide spectrum of issues ranging from human development, environmental sustainability, corruption, innovation, competitiveness, or other complex phenomena that are not directly measurable and not uniquely defined.[1] There have been several attempts to measure soft power and analyze its influence on political and macroeconomic developments. Treverton and Jones (2005), for example, discuss measuring soft power in terms of how effective non-state actors like corporations and humanitarian organizations are in international affairs. McClory (2015) and McClory and Harvey (2016), on the other hand, operationalize the conceptual framework put forward by Nye (1990) and build the Soft Power 30 index that compares the relative strength of countries' soft power resources by combining objective and subjective data. While these efforts provide insight into soft power, data sources are not always transparent, or easily and consistently replicate over time beyond a small set of countries. Consequently, it is not possible to use these indicators in a systemic empirical analysis of how soft power affects economic and financial outcomes.

To close this important gap in the literature, we construct a new analytical Global Soft Power Index (GSPI) based on 29 indicators along six dimensions for a broad set of countries over the period 1990–2021. To capture the multidimensional nature of soft power in a single composite index, we build the composite GSPI using a standard three-step approach: (i) normalization of variables; (ii) aggregation of normalized variables into the sub-indices representing a particular functional dimension; and (iii) aggregation of the sub-indices into the final index. As a systematic framework, the approach we use to calculate the GSPI captures the matrix of soft power characteristics and offers significant advantages in comparing the level of soft power across countries and over time. A key characteristic of the GSPI is that it is an aggregation of different sub-indices, each representing a particular functional dimension of soft power. The GSPI is composed of six of these dimensions (or sub-indices): commercial, culture, digital, education, global reach, and institutions. This approach allows for comparisons not only at the "headline" level of the GSPI, but also at the level of the sub-indices which in turn helps identify and study how countries differ at a granular level of soft power.

Our analysis shows substantial variation in the level of soft power across countries. For example, as of 2021, the GSPI ranges from a minimum of -0.59 in Dominican Republic to a maximum of 1.68 in South Korea. Although advanced economies tend to have a higher level of soft power compared to developing countries, this is not categorically the case, especially when we consider the evolution of soft power over time. To give an idea of how the GSPI progresses in each country over time, we compare the GSPI scores for China and the United

[1] Examples include the Human Development Index (UNDP, 1990), the Sustainable Society Index (Van de Kerk and Manuel, 2008), and the Environmental Performance Index (Hsu and Zomer, 2014).

Kingdom. The United Kingdom used to have a significantly higher level of soft power than China. However, China's soft power increased significantly from 0.70 in 2004 to 1.17 in 2021, while the United Kingdom's soft power declined from 1.32 to 0.85 over the same period.

We demonstrate the macro-financial relevance of the GSPI by testing the impact of soft power on exchange rate volatility, as discussed in Cevik, Harris, and Yilmaz (2017). According to our analysis, low soft-power countries present a dynamic between soft power and REER volatility that is significantly different from that for medium and high soft-power countries. Although the GSPI does not appear to be statistically significant in explaining REER volatility, the culture and global reach dimensions of soft power are clearly relevant at almost all levels of statistical significance. The fact that global reach is the most significant sub-index of soft power is an interesting result because this is precisely the dimension that is responsible for most of the differentiation between medium and high soft-power countries. The macro-financial application presented in this paper is only one of the many possible use cases of the GSPI. In our view, the proposed framework for measuring and evaluating soft power contributes to the growing literature on the study of this important dimension of power and provides a new avenue for econometric exploration its influence on economic and political and developments.

The remainder of this paper is structured as follows. Section II provides an overview of the data used in the construction of the composite GSPI. Section III describes the index methodology. Section IV presents the GSPI. Section V demonstrates the macro-financial effects of soft power. Finally, Section VI provides concluding remarks.

II. Data Overview

In determining the soft power characteristics of countries, rather than relying on an arbitrary choice of a small set of variables, we take an agnostic view on its taxonomy and start with a wide range of demographic, institutional, political, and social indicators for the broadest possible sample of countries during the period from 1990 to 2021. Data availability, however, constraints the set of countries, and we can construct the most comprehensive version of the GSPI for a balanced panel of 66 countries over the period 2007–2021. The list of countries included in our sample is presented in Table A1 in the appendix.

Our main proposed objective is to develop the GSPI as a comprehensive composite index of soft power across the world. Nevertheless, soft power is a broad concept that encompasses many dimensions. In order to incorporate these dimensions, following the approach of the Technology Achievement Index (UNDP, 2001; Sen *et al*., 2003), the Global Innovation Index (Dutta, 2012), and many other composite indices in the empirical literature, we construct the GSPI based on six sub-indices. This gives clarity to what we are defining as the main components of our soft power index and facilitates an intermediate link between measurable variables and the fairly broad concept of soft power. Moreover, this framework also allows us to measure each of the dimensions of soft power individually and to study them separately as well as jointly.

We measure soft power in six dimensions: (i) Commercial, (ii) Culture, (iii) Digital, (iv) Education, (v) Global Reach, and (vi) Institutions. Table A2 in the appendix reports the dimensions and indicators as well as detailed information on data sources. In total, we consider 29 variables to construct our index. For most variables, the series are already available in annual frequency. For series that are released less often than on a yearly basis, as, for example, the number of Olympic medals, we use the latest information available as the yearly realization.

Descriptive statistics for each of the variables included in our study are presented in Table A3 in the appendix. The 29 variables used in the construction of the GSPI have not only very different means and extreme values, but also differ significantly with respect to their standard deviations. Therefore, this requires the application of a normalization procedure before aggregation. This step needs to take into account the properties of the data with respect to the measurement units in which the indicators are expressed and their robustness against possible outliers in the data (Ebert and Welsch, 2004). Accordingly, we opt for following the *z*-score standardization procedure recommended by the OECD Handbook on Constructing Composite Indicators of the Joint Research Centre of the European Commission (OECD, 2008). For each individual indicator $x_{i,t}$ representing the value of the indicator for country i at time t, we calculate the average across countries $x_{i=\bar{\imath},t}$ and the standard deviation across countries $\sigma_{i=\bar{\imath},t}$ and then normalize each observation according to the following *z*-score transformation:

$$z_{i,t} = \frac{x_{i,t} - x_{i=\bar{\imath},t}}{\sigma_{i=\bar{\imath},t}}$$

This approach converts indicators into a common scale with an average of 0 and standard deviation of 1. The average of 0 avoids introducing aggregation distortions stemming from differences in the mean value of each indicator. The formula to calculate the *z*-score is the value of an indicator minus the average of the indicator across countries, divided by the standard deviation. So that all $z_{i,t}$ have similar dispersion across countries. With this standardized set of variables in hand, we can proceed to the construction of the GSPI.

There is a trade-off between creating a comprehensive measure of soft power and data availability. More data is available for a larger sample of countries in the past two decades rather than earlier in the sample. The extent of missing data varies considerably across indicators. For example, data coverage is strong for commercial and education variables, but weak for culture variables. In some cases, such as cultural exports, data were not being collected before 2007 on a comprehensive basis. Where data are not yet available for the latest year (e.g., 2021), the values are set equal to the latest available observations (e.g., 2020). Regarding data availability in the early sample, we opt for only constructing the indices from the date that information is available for all variables of interest, which yield a balanced dataset.

III. Index Methodology

The construction of the GSPI follows a standard three-step approach found in the literature on reducing multidimensional data into one summary index: (i) normalization of variables; (ii) aggregation of normalized variables into the sub-indices representing a particular functional dimension; and (iii) aggregation of the sub-indices into the final index.

Our objective is to construct not only a “headline” soft power index, but also to have measures for each of the six dimensions that we use to construct the GSPI: Commercial, Culture, Digital, Education, Global Reach, and Institutions. We hence begin by constructing a sub-index for each of these dimensions of soft power. The variables included in the construction of each of the sub-indices can be found in the table with the information regarding the data sources (Table A2 in the appendix).

A crucial part of any index construction is the methodology used for the weighting of the variables considered to form the index. Since there is inevitably a high degree of collinearity among some of the variables we take into account, we consider a variable weighting and aggregation technique that systematically eliminates those variables in the original set that are best explained by the remaining variables. When used in a benchmarking framework, weights can have a significant effect on the overall composite indicator and country rankings. Some weighting techniques are derived from statistical models, such as the factor analysis, others from participatory methods, like an analytical hierarchy process. However, regardless of which method is used, weights are essentially value judgments. While some analysts might choose weights based only on statistical methods, others might reward components that are deemed more influential, depending on expert opinion, to better reflect policy priorities or theoretical factors. In constructing the GSPI, we follow the weighting methodology based on principal component analysis (PCA) recommended by OECD (2008).

The PCA method—first proposed by Pearson (1901)—is one of the most successful multivariate approaches to the problem of creating low dimensional data representation. The literature on principal components and classical factor models is large and well known.[2] The PCA (or factor analysis) groups together individual indicators that are collinear to form a composite indicator with most relevant information from individual indicators. Each factor, estimated using the PCA methodology, reveals the set of highest possible variation and latent structures in the data.

More formally, these factors are constructed using the eigenvectors with the largest eigenvalues of the empirical covariance matrix of the data for which we want to extract the factors (Murphy, 2012). The factor (eigenvector) associated with the highest eigenvalue will be the one explaining most of the variation in the data, the factor (eigenvector) associated with the second highest eigenvalue will be the one explaining most of the variation in the data that is orthogonal to the first factor, and so on. The eigenvalues of the empirical covariance matrix hence tell us about the variation explained by each factor while the associated eigenvectors tell us about the weights of each variable in this factor.

The idea of using the PCA approach as a weighting mechanism is to account for the highest possible variation in the indicator set using the smallest possible number of factors. The choice of the number of factors is a crucial one when conducting the PCA. Regarding this choice, we follow the approach of the Handbook on Constructing Composite Indicators (OECD, 2008) for selecting weights and choose all factors that contribute individually to at least ten percent of the overall variance.

For clarification, let’s consider the PCA methodology for selecting index weights from OECD (2008) for a specific sub-index constructed in our study. Consider the example of the sub-index for the Education dimension. To measure this dimension of soft power, we use the following variables: Education expenditure (as a share of GDP), the number of journal articles, the OECD Program for International Student Assessment (PISA) scores in mathematics, science and reading, primary education completion rate, the share of population with tertiary education, and years of schooling.

We begin by estimating all possible factors of these series based on the PCA approach described above. The information about all possible factors that can be extracted from the Education variables in our dataset is displayed below in Table A4 in the appendix. Following the methodology described above, we use all factors that explain at least 10 percent of the variation in the data to construct the weights. In the case of the Education sub-index, for example, this means using Factor 1 and Factor 2 to calculate the weights, as these are the only factors that explain more than ten percent of the total variance.

[2] Kim and Mueller (1978) and Karamizadeh *et al*. (2013) provide a detailed review of the PCA literature.

After selecting which factors will be taken to account, the next step is to use the weights from these factors to calculate the weights for each variable in the sub-index. In accordance to the guidance of OECD (2008) and following Nicoletti *et al*. (1999), we begin by setting all weights which are less than 0.10 in the selected factors to 0.00. After eliminating these small weights, the final weightings for the sub-index are calculated as a weighted sum of the factor weights where the explained variances are used as weights.

Using the Education sub-index as an example for the approach of Nicoletti *et al*. (1999), Table A5 in the appendix provides an illustration of the steps to obtain the aforementioned subindex weights. We begin by calculating the “Weighted Total” which is just the sum of all weights for a factor times the variance explained by that factor. The sub-index weights for each variable can then be calculated as the weighted sum of the factor weights for that variable—using the variance explained by each factor as weights—divided by the sum of the weighted totals. To clarify, consider the case of the PISA: Maths variable. The sub-index weight can be calculated as:

$$w_{PISA:\,Maths} = \frac{(0.20*0.71)+(0.13*0.12)}{0.62+0.11} = 0.22$$

Accordingly, we get the following final weights for the Education sub-index: 0.02 for Education Expenditure, 0.33 for Journal Articles, 0.22 for PISA: Maths, 0.19 for PISA: Reading, 0.21 for PISA: Science, and 0.02 for Tertiary Education. The variables Primary Completion and Years of Schooling are not included in the index as their factor weights in the most relevant factors are lower than 0.10.

We follow the same methodology described above for each of the sub-indices. The complete set of weights for the commercial, culture, digital, education, global reach, and institutions sub-indices can be found in Table A6 in the appendix. Once we have obtained the weights for each of the sub-indices using the methodology described above, we use them to calculate these sub-indices and aggregate them into the overall GSPI. To perform this aggregation, we follow the additive aggregation method recommended by Fagerberg (2002) and (OECD, 2008) and calculate the “headline” GSPI as the average value of our sub-indices. For each country *i* at year *t*, we aggregate:

$$GSPI_{i,t} = \frac{\sum_s Sub\text{-}Index_{i,t,s}}{n_s}$$

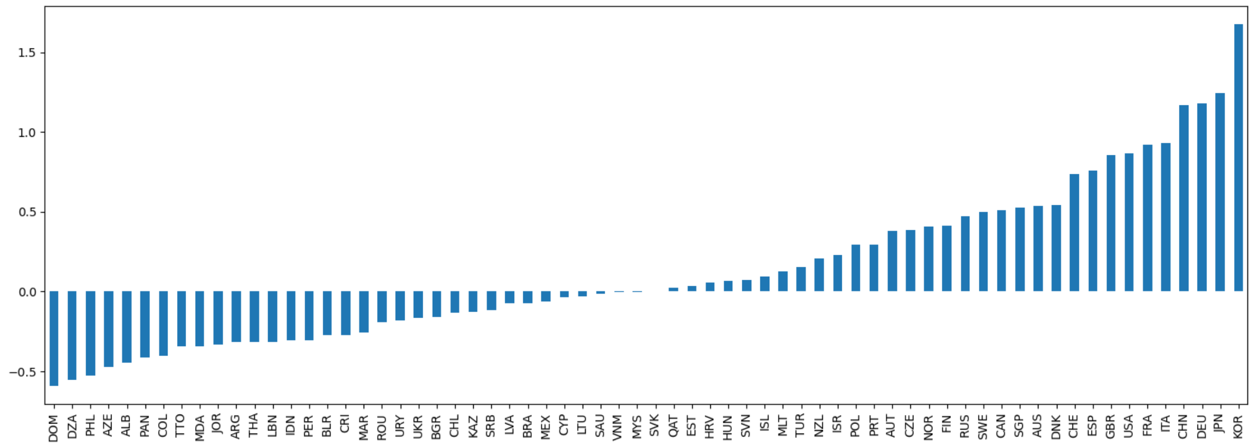
where s = {commercial, culture, digital, education, global reach, and institutions} represents all sub-indices averaged to construct the final composite GSPI.

All variables are normalized to become standard *z*-scores and we only apply linear combinations of these variables when constructing the sub-indices. Accordingly, the sub-indices are also standardized, allowing us to take a simple average to aggregate them since they are all represented as cross-sectional *z*-scores (Greene, 2003). As a last step, we subtract the median score from the “headline” GSPI in that to facilitate interpretation of the results and guarantee that the overall index has 0 as its median score.

IV. Index Results

With the sub-indices and the “headline” GSPI in hand, we can now classify countries and discuss how countries differ with respect to the GSPI score as well as at a granular level of sub-indices. We are able to construct sub-indices and the GSPI for a broad sample of 66 countries on a yearly basis from 2007 to 2021, which the latest year for which we have observations for most variables used to construct the composite GSPI.

Figure 1. Soft Power Across the World, 2021



Source: Authors' estimations.

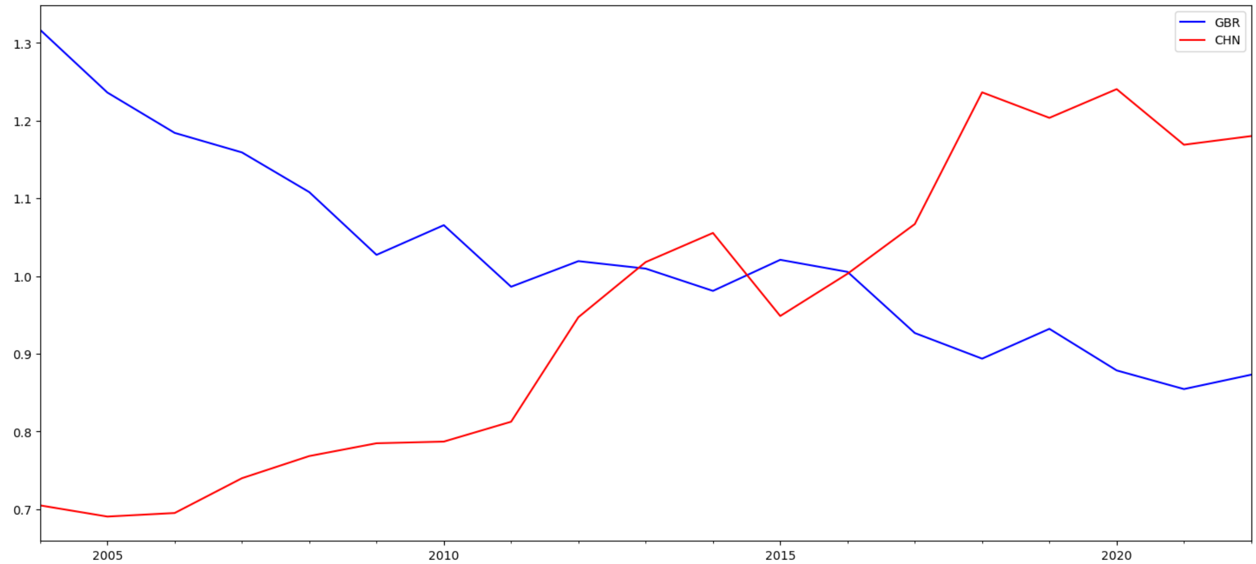
First, there is a significant variation in the level of soft power across countries. An interesting analysis is to focus on the cross-sectional differences in the "headline" GSPI score as of 2021 as presented in Figure 1 for all countries in our sample. The GSPI ranges from a minimum of -0.59 to a maximum of 1.68, with a median value of 0 and a standard deviation of 0.49. The country with highest level of soft power is South Korea with a score of 1.68, followed by Japan (1.25), Germany (1.18) and China (1.17), which remain significantly above the 1.00 threshold. The country with the lowest level of soft power is Dominican Republic with a score of -0.59, followed closely by Algeria (-0.55), the Philippines (-0.53) and Azerbaijan (-0.47). Overall, advanced economies tend to have a higher level of soft power compared to developing countries, but this is not categorically the case, especially when we consider the evolution of soft power over time.

Second, to give an idea of how the GSPI progresses in each country over time, let's take a look into the GSPI scores for China (CHN) and the United Kingdom (GBR) from 2004 to 2021. The values for both of these countries are plotted in Figure 2. We can observe that the United Kingdom used to have a significantly higher level of soft power than China. However, China's soft power increased significantly from 0.70 in 2004 to 1.17 in 2021, while the United Kingdom's soft power declined from 1.32 to 0.85 over the same period. As a result, in 2021, the "headline" GSPI score shows China as having a higher level of soft power than the United Kingdom.

What is perhaps a bit surprising the extremely high level of soft power for Japan and South Korea—the two countries with the highest GSPI scores in our sample. In order to understand not only this but also what drives the overall differences in the GSPI across countries, we now turn to the analysis of the sub-indices used to construct the "headline" GSPI. A better way to understand these results is to visualize the values of the different sub-indices in a scatter-plot graph. However, before plotting the different sub-indices for each country, we use the information from the sub-indices themselves to group the countries in an agnostic manner. We follow the approach of Likas *et al*. (2003) and group the countries in our sample according to the 2021 values for the sub-indices using K-Means clustering. The K-Means algorithm is a popular data-clustering methodology. The term was first used by MacQueen *et al*. (1967), though the algorithm was first proposed by Stuart Lloyd in 1957 as a technique for pulse code modulation.[3]

[3] Only published in 1982 as Lloyd (1982).

Figure 2. Soft Power: China vs. United Kingdom



Source: Authors' estimations.

The idea is to group the observations into clusters based on the observation feature values. Given the desired number of clusters, the algorithm will start with a random allocation of each observation into these clusters and iterate until it achieves the classification that results in the least squared Euclidian distance between the observations classified in each cluster and the cluster centroids. A detailed description of the algorithm can be found in Likas *et al*. (2003) and Na *et al*. (2010).

In our framework, the objective is to group 66 countries into clusters according to the sub-index values for each country. We follow the approach of Pham *et al*. (2005) to select the number of clusters according to the improvement in the sum of square distances between the cluster centroids and the feature observations and group the countries into four groups. The groups chosen by the K-Means Clustering algorithm are the following:

- Group 1: ALB, ARG, AZE, BGR, BLR, BRA, CHL, COL, CRI, DOM, DZA, IDN, JOR, KAZ, LBN, MAR, MDA, MEX, MYS, PAN, PER, PHL, QAT, ROU, SAU, SRB, THA, TTO, TUR, UKR, URY, VNM.
- Group 2: AUS, AUT, CAN, CHE, CYP, CZE, DNK, EST, FIN, HRV, HUN, ISL, ISR, LTU, LVA, MLT, NOR, NZL, POL, PRT, SGP, SVK, SVN, SWE.
- Group 3: CHN, DEU, ESP, FRA, GBR, ITA, RUS, USA.
- Group 4: JPN, KOR.

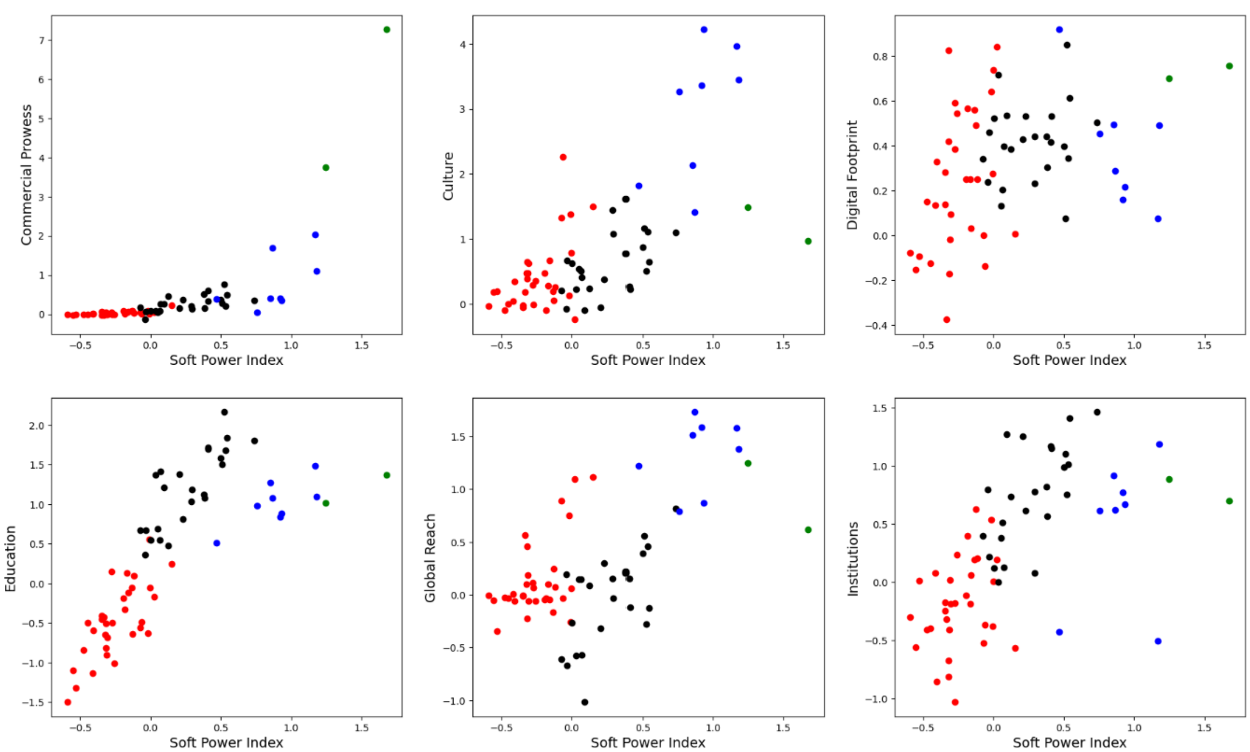
From the list of countries in each of the groups above we can already start to guess which characteristics are responsible for driving the classification. In order to see how the sub-indices differ for these groups, we plot each of the sub-indices against the GSPI. These plots, presented in Figure 3, help us to understand where the differences between the four groups of countries identified by the K-Means clustering algorithm originate from.

Group 1 is the set of countries with low soft power. These countries have, on average, lower levels for each of the sub-indices but are considerably behind others in the Education and Institutions dimensions. Group 2 represents the countries with medium level of soft power. These are mostly developed nations that present high levels of Education and Institutions, but do not have much of an impact on other countries via the dimensions measured by the Culture and Global Reach sub-indices. Finally, Groups 3 and 4 are the countries with high levels of soft power. By looking at Figure 3, we can see that the only reason why these are considered as different groups is because Japan and South Korea (the only countries in Group 4) have significantly higher Commercial Prowess and perform meaningfully worse in the Culture dimension in comparison to other high soft power countries.

Taking into account both the set of countries in each of the groups and the information displayed in Figure 3, a superficial description of the identified groups would be that Group 1 (green) represents the set of developing countries with overall low soft power, Group 2 (blue) represents the developed countries with overall medium soft power, and finally, Groups 3 (red) and 4 (black) represent the countries with high soft power (mostly advanced economies but also with "soft-powerful" developing nations such as China and Russia).

The information presented here regarding both the values of the sub-indices and the GSPI confirm what one would expect regarding the level of soft power for these 66 countries in our most comprehensive sample. However, the merit of the proposed GSPI is that we have arrived at the information presented in this section in a purely systematic manner. In doing so, we propose a measure of soft power and its dimensions that can be used to formally evaluate different countries and study the relationship between soft power and its dimensions and many variables of interest. In the next section, we consider one of such possible applications of the GSPI and its composing sub-indices to study the relationship between soft power and real exchange rate volatility.

Figure 3. Soft Power Index and Its Components



Note: Green denotes Groups 1; blue denotes Group 2; red denotes Group 3; and black denotes Group 4.
Source: Authors' estimations.

V. An Application: Soft Power and Exchange Rates

We demonstrate the macro-financial relevance of the GSPI by testing the impact of soft power on exchange rate volatility. Since the breakdown of the Bretton Woods system, major shifts in the global economy and financial markets have exacerbated the magnitude of exchange rate fluctuations. While Friedman (1953) famously argued that exchange rate volatility is a manifestation of macroeconomic volatility, empirical studies have uncovered a range of anomalies and puzzles that contradict the theoretical models of exchange rates. Meese and Rogoff (1983), for example, showed that there is no stable relationship between exchange rate fluctuations and fundamental factors, conflicting with the theoretical models predicting that exchange rate volatility can only increase when the variability of the underlying fundamentals increases.

Exchange rate volatility is still of great interest to academics, policymakers, and market practitioners because of the potential linkages between the behavior of exchange rates and other economic and financial variables. The general consensus in the literature is that exchange rate volatility reflects a variety of global and country-specific factors, such as income growth, inflation, fiscal and current account balances, foreign exchange reserves, financial and trade openness, and the size and type of capital flows.[4]

Although there is no theoretical model linking exchange rate volatility to soft power, this empirical approach is consistent with the institutions-growth nexus—a widespread consensus in the literature—as a useful illustration of the linkages we have in mind between soft power and exchange rate fluctuations. In a recent research, Cevik, Harris, and Yilmaz (2017) find evidence of a possible link between soft power variables—that encapsulate a country's demographic, institutional, political, and social underpinnings that are generally ignored in the literature—and the volatility of REER when considering a panel of developed and emerging market economies. In this exercise, we assess whether our proposed GSPI and its sub-indices to have a noticeable effect on exchange rate volatility.

Using the REER series from the IMF's International Financial Statistics (IFS) database and following the methodology used in Cevik, Harris, and Yilmaz (2017), we calculate the annual REER volatility as the realized volatility of the log returns of the REER sampled at monthly frequencies.[5] That is, we estimate each country's annual REER volatility as:

$$VOL_{i,t} = \sum_{m=1}^{12} r_{i,m-t}^2$$

where $r_{i,m-t} = log(REER_{i,m-t}) - log(REER_{i,(m-1)-t})$ represents the monthly log returns of the real effective exchange rate for country *i* on month *m* of year *t*.

Focusing only on countries with flexible exchange rate regimes, we plot the GSPI against REER volatility in Figure 4 separately for low, medium and high levels of soft power. Although this is just simple a scatter-plot representation of REER volatility against our GSPI, one can observe the negative relationship between the two variables. This point is further emphasized by checking the means and medians for each variable in each group. Altogether, there appears to be relationship between the two variables, which shows variation with the

[4] Contributions include Edwards (1987), Cote (1994), Hausmann and Gavin (1996), McKenzie (1999), Hau (2000), Hau (2002), Clark *et al*. (2004), Hausmann *et al*. (2006), and Morales-Zumaquero and Sosvilla-Rivero (2010).

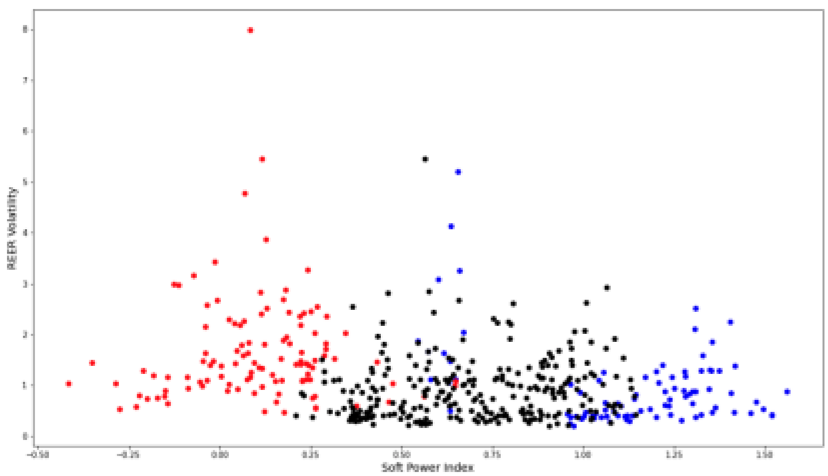
[5] Realized volatility, also known as historical volatility, is the sum of sample variances over a given period. A detailed explanation can be found in Andersen and Bollerslev (1998).

level of soft power. Of course, this may just be due to the fact that low soft power countries are mostly developing economies whereas medium and high soft power countries are mostly advanced economies.

In order to control for other possible covariates that might influence real exchange rate volatility, we follow Cevik, Harris, and Yilmaz (2017) and study the relationship between our proposed indices and real exchange rate volatility in a panel framework. The authors argue that soft power variables are more likely to have an impact on exchange rate volatility in the cross-section rather than in the time series and thus a panel regression should be used in an attempt to uncover this relationship.

In order to capture the fundamental macroeconomic drivers of exchange rate volatility, we include the same nine control variables from Cevik, Harris, and Yilmaz (2017) drawn from the literature on exchange rate modeling. The control variables are, in alphabetical order, credit, current account, export concentration, inflation, stock market capitalization, trade openness, volatility of government consumption, volatility of labor productivity growth, and volatility of terms of trade.

Figure 4. Headline GSPI and Exchange Rate Volatility



Source: Authors' estimations.

Moreover, exchange rate volatilities present an auto-regressive behavior (Rapach and Strauss, 2008). In order to control for this, we also include the lags of $VOL_{i,t}$ in our panel framework. In their study, Cevik *et al*. (2017) consider a standard entity fixed effects panel model in order to allow for country specific heterogeneity. However, because the time horizon of our analysis (from 2007 to 2021 on a yearly basis) is significantly shorter than the one considered in Cevik, Harris, and Yilmaz (2017), we allow for time specific heterogeneity by including yearly time dummies. That is, we consider a model with both time and country fixed effects. Common shocks are a key determinant of real exchange rate volatility (Campos-Martins and Padilha, 2021) and such a framework allows to account for this feature.

We begin by analyzing the relationship between real exchange rate volatility and the overall GSPI. Following the framework described in the previous paragraphs, we consider the following specification:

$$VOL_{i,t} = \mu_i + \gamma_t + \sum_{k=1}^{2} \alpha_k VOL_{i,t-k} + \delta' Z_{i,t} + \beta GSPI_{i,t} + \epsilon_{i,t}$$

where $VOL_{i,t}$ is the volatility of REER as described above, $\boldsymbol{Z}_{i,t}$ is the 9X1 vector with the control variables, and $GSPI_{i,t}$ is the GSPI for country *i* at year *t*. The lag length K is selected via Bayesian Information Criterion (BIC). We also consider the expanded specification in which, rather than using just the composite GSPI, we include the sub-indices of the GSPI. This expanded model takes the following form:

$$VOL_{i,t} = \mu_i + \gamma_t + \sum_{k=1}^{2} \alpha_k VOL_{i,t-k} + \delta' Z_{i,t} + \beta' X_{i,t} + \epsilon_{i,t}$$

where we have replaced the $GSPI_{i,t}$ scalar from Model (5) by the 6X1 vector $\boldsymbol{X}_{i,t}$ representing each of the sub-indices that compose the $GSPI_{i,t}$ and the scalar parameter β by the 6X1 vector of coefficients β. These models are then estimated using the fixed effects estimator with the lag length (K) equal to 2 according to the BIC.

Many insights can be derived by analyzing the results presented in Table 1. First, focusing on the results from the first model, we can see that the most meaningful variables in explaining real exchange rate volatility are inflation, the volatility of labor productivity growth, and the volatility of the terms of trade index. Trade openness is also relevant to a lesser extent. However, the main result for our analysis is that the overall GSPI does not seem to be significant in explaining real exchange rate volatility. Although the coefficient is in the direction one would expect, with higher index levels leading to lower real exchange rate volatility, its *p*-value is fairly high (0.22), indicating that GSPI is not significant at any relevant significance level.

Table 1. Soft Power and Exchange Rate Volatility

	Model GSPI	Model Sub-indices
β	-0.3918	
(GSPI)	(0.22)	
β_1		0.0153
(Commercial)		(0.86)
β_2		-0.5116
(Culture)		(0.04)**
β_3		0.0276
(Digital)		(0.82)
β_4		-0.0884
(Education)		(0.72)
β_5		-0.9937
(Global Reach)		(0.01)**
β_6		-0.1093
(Institutions)		(0.33)

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: Authors' estimations.

In the second model, we incorporate information about the sub-indices rather than using the composite GSPI index and obtain parameters with significance levels that are very similar to those of the first model. The main difference is that now, by considering each dimension of soft power as a separate variable, some of them are shown to be significant. The results presented in Table 4 suggest that both the Culture and the Global Reach dimensions of soft power are significant in explaining real exchange rate volatility even when we control for fundamental macroeconomic drivers. As expected, both coefficients are negative indicating that the higher the level of these sub-indices the lower the level of real exchange rate volatility. Furthermore, Global Reach, the "purest" measure international soft power reach, seems to be the most significant of the two sub-indices.

On the whole, these results are in line with the findings from Cevik, Harris, and Yilmaz (2017) where some soft power variables are shown to meaningfully explain real exchange rate volatility. We consider both a model with our headline GSPI and a model with each individual soft power sub-index. Although the composite GSPI does not seem to be significant in explaining real exchange rate volatility, the culture and global reach dimensions of soft power are shown to be relevant at almost all significance levels. Moreover, the results also suggest that global reach is the dimension of soft power with the most impact on real exchange rate volatilities.

VI. Concluding Remarks

Soft power has grown in importance in an increasingly interconnected world. In this paper, we develop a new composite index of soft power based on 29 indicators along six dimensions for a broad sample of countries across the world over the period 1990-2021. The GSPI is constructed using a three-step approach to reduce multidimensional data into a single composite index: (i) normalization of variables; (ii) aggregation of normalized variables into the sub-indices representing a particular functional dimension; and (iii) aggregation of the sub-indices into the final index.

Additionally to presenting the index methodology, we discuss how countries differ with respect to their latest sub-indices and “headline” GSPI reading. By using the latest information about the sub-indices, we are able to identify four group of countries. The first one is the group of low soft power countries with mostly developing nations that are considerably behind others in the education and institutions dimensions. The second group is the group of medium soft power countries. These are mostly developed nations that present high levels of education and institutions, but do not have much of an impact on other countries via the dimensions measured by the culture and global reach subindices. The third group is the group of high soft power countries, excluding Japan and South Korea which appear to form a separate group. Although Japan and South Korea are similar to other high soft power countries, they have significantly higher commercial prowess and perform meaningfully worse in the culture dimension.

To assess the GSPI’s macro-financial application, we look at the effect of soft power on REER volatility as discussed in Cevik, Harris, and Yilmaz (2017). According to our analysis, low soft-power countries present a dynamic between these two variables that is significantly different from that for medium and high soft-power countries. In order to control for other possible covariates that might influence the behavior of REERs, we study the relationship between our proposed indices and exchange rate volatility in a panel framework that also includes conventional macroeconomic factors drawn from the literature on exchange rate modeling. Our results presented in this paper are in line with the findings from Cevik, Harris, and Yilmaz (2017). Although the “headline” GSPI does not appear to be statistically significant in explaining REER volatility, the culture and global reach dimensions of soft power are clearly relevant at almost all levels of statistical significance. The fact that global reach is the most significant sub-index of soft power is an interesting result because this is precisely the dimension that is responsible for most of the differentiation between medium and high soft-power countries.

On the whole, our composite GSPI and its sub-indices present a systematic approach to measure soft power along multiple dimensions. Capturing the matrix of soft power characteristics, the GSPI offers significant advantages as it allows us to compare the level of soft power across countries and over time. The macro-financial application presented in this paper is only one of the many possible use cases of the GSPI. In our view, the proposed framework for measuring and evaluating soft power contributes to the growing literature on the study of this important dimension of power and provides a new avenue for econometric exploration its influence on economic and political and developments.

Appendix

Appendix Table A1. List of Countries

ALB	KAZ
ARG	KOR
AUS	LBN
AUT	LTU
AZE	LVA
BGR	MAR
BLR	MDA
BRA	MEX
CAN	MLT
CHE	MYS
CHL	NOR
CHN	NZL
COL	PAN
CRI	PER
CYP	PHL
CZE	POL
DEU	PRT
DNK	QAT
DOM	ROU
DZA	RUS
ESP	SAU
EST	SGP
FIN	SRB
FRA	SVK
GBR	SVN
HRV	SWE
HUN	THA
IDN	TTO
ISL	TUR
ISR	UKR
ITA	URY
JOR	USA
JPN	VNM

Appendix Table A2. List of Variables and Data Sources

Variable Name	Dimension	Source	Definition
Outward Foreign Investment	Commercial Prowess	UNCTAD	Outward Foreign Investment
Patents	Commercial Prowess	World Bank	Number of international
Trademarks	Commercial Prowess	World Bank	Number of trademarks
Cultural Exports	Culture	UNCTAD	Exports of cultural goods
International Tourists	Culture	World Bank	Number of international
Olympic Medals	Culture	Olympic Committee	Total number of medals in
World Heritage Sites	Culture	UNESCO	Number of UNESCO World
Internet Access	Digital Footprint	World Bank	Number of internet users
Mobile Phones Access	Digital Footprint	World Bank	Number of mobile phones
Education Expenditure	Education	World Bank	Government expenditure on
Journal Articles	Education	World Bank	Number of journal articles
PISA: Maths	Education	World Bank	Mean performance on the
PISA: Reading	Education	World Bank	Mean performance on the
PISA: Science	Education	World Bank	Mean performance on the
Primary Completion	Education	World Bank	Primary completion rate
Tertiary Education	Education	World Bank	Gross tertiary educational
Years of Schooling	Education	World Bank	Barro-Lee: Average years of
Aid and Assistance	Global Reach	World Bank	Official development
Diplomatic Events	Global Reach	GDELT	Share of diplomatic cooperation
Embassies	Global Reach	Lowy Institute	Lowy Institute number of
Migrants	Global Reach	World Bank	Number of migrants
Refugees	Global Reach	World Bank	Number of refugees
Bureaucratic Effectiveness	Institutions	ICRG	The PRS Group International Country
Corruption	Institutions	ICRG	The PRS Group International Country
Democratic Accountability	Institutions	ICRG	The PRS Group International Country
Government Stability	Institutions	ICRG	The PRS Group International Country
Rule of Law	Institutions	ICRG	The PRS Group International Country

Appendix Table A3. Descriptive Statistics

Variable Name	Start Date	Mean	Standard Deviation	5th Percentile	95th Percentile
Outward Foreign Investment	1/1/1970	2.28	25.87	-0.25	5.27
Patents	1/1/1980	0.01	0.03	0	0.04
Trademarks	1/1/1980	0.29	1.4	0	0.53
Cultural Exports	1/1/2007	0.17	0.38	0	0.63
International Tourists	1/1/1995	123.6	337.74	0.53	644.25
Olympic Medals	1/1/1960	9.45	22.6	0.19	33.24
World Heritage Sites	1/1/1978	3.78	6.64	0	16
Internet Access	1/1/1990	28.03	29.87	0.03	86.53
Mobile Phones Access	1/1/1980	57.29	54.1	0.03	146.92
Education Expenditure	1/1/1970	4.34	2.68	1.54	7.38
Journal Articles	1/1/2000	0.03	0.05	0	0.15
PISA: Maths	1/1/2000	461.39	59.83	361.53	543.8
PISA: Reading	1/1/2000	458.29	55.26	358.31	526.89
PISA: Science	1/1/2000	464.82	54.74	375.37	539.47
Primary Completion	1/1/1970	78.41	24.78	28.31	105.67
Tertiary Education	1/1/1970	22.16	23.21	0.68	72.45
Years of Schooling	1/1/1970	6.18	3.29	1.09	11.53
Aid and Assistance	1/1/1960	6.35	10.96	0.01	24.69
Diplomatic Events	1/1/1979	9.51	7.1	3.97	18.18
Embassies	1/1/2006	78.57	40.54	24	152
Migrants	1/1/1960	11.13	15.87	0.26	50.33
Refugees	1/1/1960	1.24	5.16	0	4.51
Bureaucratic Effectiveness	1/1/1984	2.17	1.15	0	4
Corruption	1/1/1984	2.92	1.32	1	5.5
Democratic Accountability	1/1/1984	3.81	1.65	1	6
Government Stability	1/1/1984	7.45	2.11	4	11
Rule of Law	1/1/1984	3.65	1.42	1	6

Appendix Table A4. PCA: Education Sub-Component

	Variance Explained	Education Expenditure	PISA: Maths	PISA: Reading	PISA: Science	Primary Completion	Journal Articles	Years of Schooling	Tertiary Education
Factor 1	**71%**	1%	20%	20%	19%	0%	29%	5%	6%
Factor 2	**12%**	11%	13%	10%	15%	0%	33%	3%	14%
Factor 3	**7%**	0%	0%	0%	0%	1%	25%	1%	72%
Factor 4	**4%**	30%	0%	2%	1%	1%	0%	65%	2%
Factor 5	**3%**	53%	0%	0%	1%	10%	11%	19%	6%
Factor 6	**2%**	4%	0%	0%	0%	87%	1%	7%	0%
Factor 7	**1%**	0%	36%	60%	2%	0%	0%	1%	1%
Factor 8	**0%**	0%	30%	8%	61%	0%	0%	0%	0%

Appendix Table A5. Steps for Obtaining Weights (Education Sub-Component)

	Variance Explained	Education Expenditure	PISA: Maths	PISA: Reading	PISA: Science	Primary Completion	Journal Articles	Years of Schooling	Tertiary Education
Factor 1	71%	1%	20%	20%	19%	0%	29%	5%	6%
Factor 2	12%	11%	13%	10%	15%	0%	33%	3%	14%
Weights		**2%**	**22%**	**19%**	**21%**	**0%**	**33%**	**0%**	**2%**

Appendix Table A6. Weights for GSPI Sub-Components

Sub-Index	Variable Name	Weight
Commercial Prowess	Outward Foreign Investment	28%
Commercial Prowess	Patents	68%
Commercial Prowess	Trademarks	4%
Culture	Cultural Exports	26%
Culture	International Tourists	0%
Culture	Olympic Medals	0%
Culture	World Heritage Sites	74%
Digital Footprint	Internet Access	49%
Digital Footprint	Mobile Phones Access	51%
Education	Education Expenditure	2%
Education	PISA: Maths	22%
Education	PISA: Reading	19%
Education	PISA: Science	21%
Education	Primary Completion	0%
Education	Journal Articles	33%
Education	Years of Schooling	0%
Education	Tertiary Education	2%
Global Reach	Aid and Assistance	0%
Global Reach	Embassies	74%
Global Reach	Migrants	26%
Global Reach	Refugees	0%
Global Reach	Diplomatic Events	0%
Institutions	Bureaucratic Effectiveness	18%
Institutions	Corruption	18%
Institutions	Democratic Accountability	23%
Institutions	Government Stability	22%
Institutions	Rule of Law	19%

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