Assessing the Relationship Between Air Quality, Wealth, and the First Wave of COVID-19 Diffusion and Mortality

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1 Introduction

The COVID-19 disease, which spread out at the end of 2019, was declared, on the 11th of March 2020, as a pandemic by the World Health Organization. By April 21, 178 countries had confirmed cases of COVID-19 infection.[1] The total count of reported cases and casualties is still rising at the time of writing this chapter.

The pandemic is having a huge social and economic impact. Social distancing and lockdowns measures that have been adopted to limit its diffusion have severely limited industrial, commercial, and transportation activities. On the other hand, lockdown measures have had positive effects on the environment in general, such as better air and water quality, less pollution, and a lower anthropic pressure on several animal species (EEA, 2020). The relationship between the environment and the COVID-19 pandemic has also attracted attention because it was notable that the areas being hit the most by the virus were also among the most polluted of the planet. Wuhan and the province of Hubei, where the outbreak began, Lombardy in Italy, and the Madrid area in Spain, which have all heavily suffered from the viral infection, are regions with a very poor air quality.

[1] Data obtained from the World Health Organization website: https://www.who.int.

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There is a twofold rationale behind the link identified between air pollution and the COVID-19 pandemic. First, it has been argued that poor air quality correlates with a greater diffusion of COVID-19 because atmospheric conditions favoring the permanence of airborne pollutants, such as particulate matter (PM), would also facilitate the spread of the virus conveyed by the droplets of human saliva floating in the air, which seems to be one of the main sources of contagion. PM could serve as a carrier of COVID-19 virus. Second, there may be a relationship between air quality and mortality due to COVID-19 infection because chronic exposure to environmental pollution in general and poor air quality in particular have a debilitating effect on the body, increasing its exposure to other respiratory diseases, and reducing the immune system's response to infections. All these effects can increase the mortality risk associated with COVID-19.

Research into these aspects is ongoing. By estimating an ecological regression model on the data of 35 US counties, Wu et al. (2020) provide evidence of the link between mortality rates and long period exposure to air pollutants (PM 2.5 in particular). Other published studies seem to confirm the above-mentioned links between air quality and coronavirus diffusion. Wu et al. (2020) estimated an 8% increase in the COVID-19 death rate associated with a rise of 1 mg/m^3 in PM 2.5 levels in some US regions. Ogen (2020) found a positive correlation between NO_x exposure and COVID-19-related mortality in 66 administrative regions in Italy, Spain, France, and Germany. Setti et al. (2020) found evidence of COVID-19 on outdoor PM in samples tested in the province of Bergamo (Lombardy, Italy), which experienced the highest diffusion and mortality rates in Italy (and among the highest worldwide). Fiasca et al. (2020) have estimated that an increase in PM 2.5 concentration by one unit corresponded to an increase of COVID-19 incidence rates of 1.56×10^4 people infection due to exposure. Other studies that have found a significant relationship between PM (2.5. or 10) and COVID-19 cases in Italy are Fattorini and Regoli (2020) and Bontempi (2020a). However, the evidence gained to date is not conclusive about the link between air quality and the diffusion of COVID-19 and the associated mortality (Bontempi, 2020b; Copat et al., 2020), in particular when taking into account countries' specificities.

Inspired by the evidence of the uneven diffusion of COVID-19 worldwide, and supported by recent results, such as in Sarmadi et al. (2020), who find an association between GDP, meteorological factors, and COVID-19 related variables, we check whether the macroeconomic structure of countries, as well as more direct factors like air pollution, plays a role in explaining the first wave of COVID-19 infection and death rates.

The rationales supporting our conjecture are the following. First, countries' different levels of wealth can be associated with more or less developed health care systems, in terms of facilities, personnel, and organization. Wealthier countries probably had a better chance of taking care of infected people and testing larger proportions of the population for contagion. This last aspect might also be a factor introducing a significant measurement bias in the way COVID-19-related hospitalizations and deaths have been counted.

At the same time, economic wealth interacts with air pollution levels. We know that a combination of less efficient production and transport systems, particularly in less developed countries, and a lower quality of energy consumption coincide with high environmental externalities (Sovacol, 2012). The cross-country data we use here confirm as much, showing a negative relationship between real per capita GDP and air pollution, as measured from the concentrations of small particulate (PM 2.5).

The role of agriculture needs to be considered as well, not just for its contribution to GDP, but also because of how it relates to air pollution. At a first glance, countries based largely on agriculture might be expected to be less exposed to air pollution, but high-tech and intensive animal breeding is associated with the extensive use of manure for fertilization, which is in turn associated with large particulate formation. Our analysis on the COVID-19 pandemic included both economic and environmental factors, so their interactions were tested too.

The contagion and death percentages observed around the world have been very different as well as those across the regions inside each country. Much of these differences is due to idiosyncratic factors, such as the early occurrence/isolation of a zero patient, the over-/under-evaluation of contagion risks on the side of local public health authorities, and so on (see, for example, Russo et al. (2020), and Villaverde and Jones (2020)). Therefore, to assess the relevance of macro socio-economic factors, whose influence is general and indirect, it is necessary to use cross section analysis, which smooths out idiosyncratic noise.

To develop our analysis, we merge data on worldwide country-level COVID-19 infections and deaths provided by the European Centre for Disease Prevention and Control (ECDC) and macro-economic data provided by the World Development Indicators of the World Bank group. Using a final sample of 142 countries, we first run a cross-sectional regression using, as the dependent variables, both COVID-19 infections and deaths, and, as main regressors, air pollution, wealth, and countries' total resident population. Then, we cluster countries according to their "economic similarity" and test the impact of air pollution on COVID-19 infections and mortality within each group.

This chapter is organized as follows: Section 2 presents the data and the preliminary analysis; Section 3 presents the cluster analysis and the results of the related estimates. Section 4 concludes.

2 Data and Preliminary Analysis

To build the dataset, we merge information from two sources. Data on COVID-19 infections (variable: INFECTIONS) and deaths (variable: DEATHS) are used to compute the dependent variables. They are drawn from the ECDC, an EU agency for the protection of European citizens against infectious diseases and pandemics. The data on the distribution of COVID-19 worldwide are updated on a daily basis by the ECDC's Epidemic Intelligence team, based on reports provided by national health authorities.[2]

Data for these two variables were collected for 5 days of the first wave of COVID-19 diffusion: March 24, March 31, April 7, April 14, and April 21, 2020. The COVID-19 outbreak did not develop everywhere at once, and national authorities have adopted different strategies and policies to deal with the pandemic. The first diffusion of COVID-19 has taken a certain amount of time. Countries have reacted to it with lockdown and other measures that have been implemented differently across time and countries. All these have affected the measurement of the effects of stock variables, and that is why we measure the effect of wealth and pollution on the diffusion and mortality of COVID-19 in different periods, from the start of the outbreak until the moment when the strictest lockdown measurers started to be lifted in the European countries have been hit earliest and most severely (Italy and Spain). At the beginning of our observation period, the relationship might have been influenced by the different pace at which COVID-19 was spreading around the globe. By the end of April 2020, lockdown measures were having an effect on the phenomenon. We nonetheless show stable, significant results across the dates selected, which means that our findings are robust to the timing of the virus diffusion and to the heterogeneity of the policies adopted. COVID-19 variables are merged with the data from the World Bank on:

- PM 2.5: mean annual exposure to PM 2.5 (micrograms per cubic meter).
- GDPPC: real per capita GDP (in 2010 US$ at PPP).
- POPULATION: total resident population.

Table 1 presents the summary statistics of these variables.

Table 2 shows the pairwise correlations of the total number of COVID-19 infections, and the total number of COVID-19-related deaths, with PM 2.5 exposure and real per capita GDP on 5 different days between March and April 2020.

Table 1 Summary statistics

Variable	Mean	Std. dev.	Min	Max
INFECTIONS 24/03	2648.04	10,336.8	1	81,553
INFECTIONS 21/04	17,028.93	72,148.47	6	787,752
DEATHS 24/03	114.98	625.48	0	6077
DEATHS 21/04	1196.82	4956.5	0	42,539
PM 2.5	28.43	20.32	5.861	99.73
GDPPC	15,661.6	20,679.9	370.74	10,9453
POPULATION (mln)	50.554	165.51	0.072	1386.4

[2]For more information, see: https://www.ecdc.europa.eu/en/covid-19/data-collection.

Table 2 Correlations of COVID-19 infections and related deaths with PM 2.5 and GDPPC

	Infections				
	24/03	31/03	07/04	14/04	21/04
PM 2.5	−0.059	−0.132	−0.145*	−0.143*	−0.139*
GDPPC	0.200**	0.275***	0.276***	0.269***	0.261***
	Deaths				
	24/03	31/03	07/04	14/04	21/04
PM 2.5	−0.032	−0.100	−0.148*	−0.168**	−0.170**
GDPPC	0.107	0.177**	0.243***	0.274***	0.280***

***Significant at 1% level; **significant at 5% level; *significant at 10% level

Unlike the literature on air pollution and coronavirus diffusion, we find a negative correlation between the two, whereas the correlation between coronavirus (both infections and deaths) and wealth is positive.[3] For the number of deaths, we also note that all correlations become stronger and more significant toward the end of April.

We test the hypothesis that COVID-19 outcomes (both infections and deaths) have a significant relation with both PM 2.5 and real per capita GDP (while controlling for population) by means of a negative binomial regression. The analysis is replicated for each week from the 24 of March up to the 21 of April; for deaths, the first week is not considered to take into account the lag between the contagion and its consequences. Results are reported in Table 3.

We see that the estimated coefficient for PM 2.5 is not statistically significant when GDPPC is included as a regressor. This indicates that the relationship between pollution and COVID-19 might be spurious. However, we suspect that the socio-economic characteristics of each country might play a crucial role in explaining the link between pollution and COVID-19. To evaluate this, data are integrated with macro-economic information provided by the World Development Indicators of the World Bank on:

- IMPORT/GDP: import intensity (i.e., import value as a share of domestic GDP).
- AGRVA/GDP: agriculture value added as a share of GDP.
- MANVA/GDP: manufacturing value added as a share of GDP.[4]
- CO_2: CO_2 emissions (metric tons per capita).
- TEMP: average temperature in March (in °C).

[3]We should stress that the correlation between PM 2.5 and COVID-19 infections or deaths is at country level, or *between* countries. It may be that, *within* countries, there is a higher level of contagion or mortality in regions where air quality is lower.

[4]We have omitted the share of services as a proportion of GDP (SERV/GDP) as an explanatory variable because it is collinear with AGRVA/GDP and MANVA/GDP.

Table 3 Infections and deaths: relationship with pollution and wealth

	Infections				Deaths		
NEG BIN	(1)	(2)	(3)	(4)	(2)	(3)	(4)
PM 2.5	−0.014	−0.013	−0.012	−0.012	−0.019	−0.020	−0.019
	(0.013)	(0.009)	(0.008)	(0.008)	(0.018)	(0.014)	(0.012)
GDPPC	0.00008***	0.0001***	0.0001***	0.00006***	0.00009***	0.00008***	0.00008***
	(0.00002)	(0.00002)	(0.00001)	(0.00001)	(0.00003)	(0.00002)	(0.00002)
POPULATION	0.016	0.013	0.012	0.012	0.020	0.018	0.017
	(0.016)	(0.011)	(0.010)	(0.008)	(0.020)	(0.017)	(0.014)
N	142	142	142	142	142	142	142
Pseudo R^2	0.050	0.043	0.040	0.038	0.053	0.053	0.053
Wald χ^2	23.37***	31.12***	34.63***	36.71***	30.39***	36.40***	41.92***
Alpha	2.753***	2.455***	2.394***	2.350***	3.862***	3.699***	3.585***
AIC	2013.67	2431.55	2553.44	2648.95	1437.10	1567.13	1662.30

(1) = March 24; (2) = April 7; (3) = April 14; (4) = April 21. Robust standard errors in brackets. Each estimate includes a constant term. ***Significant at 1% level; **significant at 5% level; *significant at 10% level

Table 4 Summary statistics

Variable	Mean	Std. dev.	Min	Max
IMPORT/GDP	0.458	0.250	0.116	1.825
AGRVA/GDP	0.099	0.098	0.0003	0.486
MANVA/GDP	0.128	0.063	0.010	0.374
CO_2 per capita	4.954	6.168	0.053	43.86
TEMPERATURE (March, °C)	14.83	11.47	−18.72	30.63

The import intensity measures the degree of (inward) trade openness of the economy; the agricultural and manufacturing value added considers the different GDP composition of the economy; The CO_2 emissions measure the relative efficiency in using energy as primary energy sources, accounting for both availability of hydrocarbon primary energy sources and technological development of the energy sector. Finally, temperature strongly relates with the geographical coordinates of countries and is suspected to play a crucial role in pandemic diffusions.

Since the World Bank provides information on PM 2.5 exposure up until 2017, we measure all the explanatory variables in the same year. The CO_2 variable has been included as a measure of the intensity and efficiency with which primary energy sources are used in a country to generate the aggregate output. Table 4 reports the summary statistics of these variables.

3 Cluster Analysis

The negative sign of the relationship between the impact of PM 2.5 on infections and deaths and the possible spurious correlation between COVID-19 and PM 2.5. deserves further examination. In this section, we check whether the association between air quality and COVID-19 outcomes changes across different areas of the world with respect to the economic structure and to climate-related variables. The 142 countries are grouped using Ward's method, a well-known hierarchical approach to grouping observations (see Blashfield, 1980, for example). We identify seven clusters based on all the variables listed in Table 4. The composition of each cluster is represented in Fig. 1.

Table 6 reports the list of countries. Table 7 shows the eigenvectors of the correlation matrix, while the corresponding eigenvalues are shown in Table 8. Table 9 shows the mean values of each item in the clusters.

Cluster 1 is the group that explains the largest amount of the total variance. It includes many European countries and the USA: these countries share a high-income level, a large share of services as a proportion of their GDP, a high exposure to CO_2 emissions per capita, a small share of agriculture, and a low temperature in

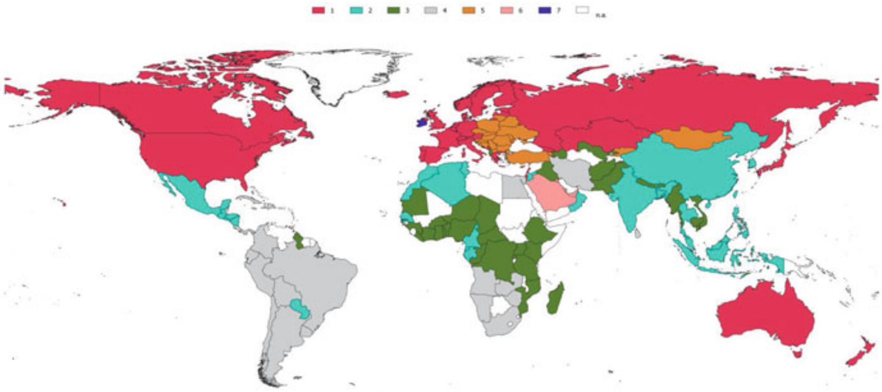

Fig. 1 Clusters of countries

March. Cluster 2 mainly comprises Eastern Asian and Northern African countries, which share a low weight of manufacturing as a proportion of domestic GDP and a moderately high import propensity. Cluster 3 is essentially made up of West Asian and Sub-Saharan countries, sharing a high openness to imports. Cluster 4 is a mix of countries sharing high CO_2 emissions and a high average temperature in March, e.g., countries below the Equator. Cluster 5 includes service economies sharing a low temperature in March. Cluster 6 contains high-income countries specializing in natural resource extraction. Cluster 7 pools four small open economies (three islands) with a large share of services and agriculture, and a moderately high level of CO_2 emissions.

We interpret the clusters using a linear discriminant analysis. We thus obtain linear combinations of the variables (the so-called canonical discriminant axes) that maximize the separation between the different classes/clusters. These axes are calculated to respect reciprocal orthogonality, so they can be used to plot individual data on a Cartesian space, to enable a visual inspection of the bivariate distribution of the clusters. Figure 2 shows the distribution of the 142 countries, grouped into the 7 clusters (using a different color for each cluster). Four clusters tend to stand out quite clearly. Clusters 7 and 1, on the right, denote high GDP levels. The countries they contain exhibit a high share of services as a proportion of GDP, and high levels of CO_2 emissions per capita, a low share of agriculture, and a low temperature in March. Cluster 7 is also characterized by high import levels. On the left, we see cluster 3, which is characterized by a high share of agriculture. In the middle, and lower down, we find cluster 4, with the lowest average import propensity. The remaining clusters 2, 5, and 6 are not neatly separable on Fig. 2, but Table 9 shows the average values of each cluster for the variables used in the cluster analysis.

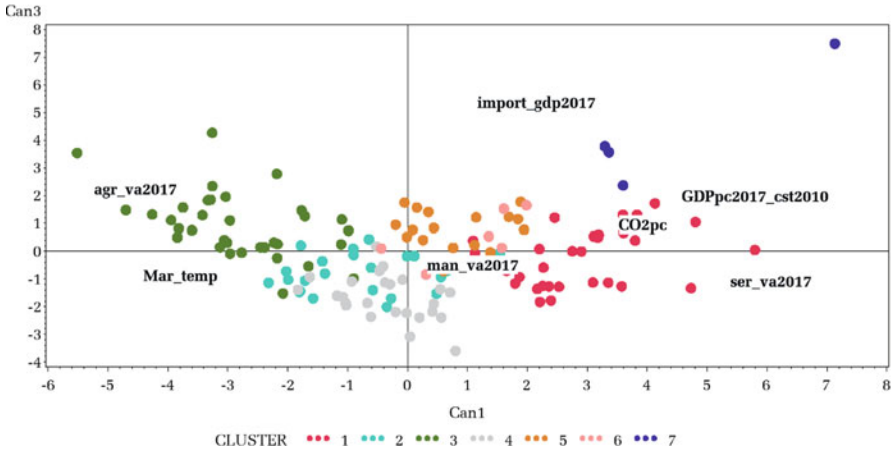

Fig. 2 Distribution of countries and clusters on the first two canonical axes

For each cluster, we adopt seven dummies, which take the value of 1 when a country belongs to the corresponding cluster. Then, we split our air pollution variable into seven new variables multiplying PM 2.5 levels by each cluster dummy (PM2.5$_i$*cluster *j*). As a final step, we estimate the following equation, one for COVID-19 infections and one for related deaths (both as on April 21, 2020), using a negative binomial regression model:

$$Y_{iT} = \gamma_0 + \sum_{j=1}^{7} \gamma_j \text{PM2.5}_i^* \text{ cluster (i)}_j + \beta_2 \text{POP}_i + u_{iT},$$

where T refers to the 21st, 14th, and 7th of April, respectively, and cluster (i)$_j$ =1 if country i belongs to cluster j and 0 otherwise.

Table 5 shows the results. In one case, namely cluster 1 (the wealthiest economies in the world), higher PM 2.5 concentrations (strongly) correlate with higher rates of infection and death (at each date). We also find evidence of a (weak) positive correlation between PM 2.5 and COVID-19 infections in cluster 5. In cluster 3, the association between PM 2.5 and COVID-19 outcomes is negative and strongly significant: these low-income countries are mainly in Africa and East Asia. Such a negative and significant estimated coefficient is nevertheless roughly ten times smaller than the positive coefficient of PM*cluster1. The same order of magnitude holds for the marginal effects at the mean: on April 21, a rise of 10 μg in PM 2.5 levels per cubic meter corresponds, on average, to 9850 more infections and 608 more deaths in cluster 1 countries and to 1430 less infections and 64 fewer deaths in cluster 3 countries.

Table 5 Correlation between pollution, wealth, and COVID-19 infections and deaths, by cluster

	Deaths			Infections		
NEG BIN	April 21	April 14	April 7	April 21	April 14	April 7
PM2.5*cluster1	0.304***	0.313***	0.333***	0.211***	0.223***	0.234***
	(0.053)	(0.056)	(0.058)	(0.045)	(0.046)	(0.048)
PM2.5*cluster2	−0.013	−0.011	−0.006	−0.020**	−0.020*	−0.016
	(0.013)	(0.018)	(0.019)	(0.010)	(0.010)	(0.012)
PM2.5*cluster3	−0.032***	−0.031***	−0.025***	−0.031***	−0.030***	−0.032***
	(0.009)	(0.009)	(0.010)	(0.007)	(0.007)	(0.008)
PM2.5*cluster4	0.038	0.043	0.053*	0.028	0.029	0.030
	(0.025)	(0.026)	(0.027)	(0.022)	(0.023)	(0.025)
PM2.5*cluster5	0.033*	0.031	0.031	0.039**	0.036**	0.031*
	(0.019)	(0.020)	(0.020)	(0.017)	(0.018)	(0.018)
PM2.5*cluster6	−0.010	−0.011	−0.010	0.013**	0.009	0.005
	(0.008)	(0.008)	(0.009)	(0.005)	(0.006)	(0.006)
PM2.5*cluster7	0.085	0.064	0.056	0.097*	0.082	0.067
	(0.117)	(0.107)	(0.102)	(0.055)	(0.064)	(0.061)
POPULATION	0.011**	0.010**	0.009*	0.010***	0.010**	0.010***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
N	142	142	142	142	142	142
Pseudo R^2	0.068	0.072	0.078	0.047	0.049	0.051
Wald χ^2	128.1***	114.4***	95.96***	146.1***	127.8***	123.1***
Alpha	3.121***	3.138***	3.157***	2.081***	2.151***	2.151***

Robust standard errors in brackets. Each estimate includes a constant term. ***Significant at 1% level; **significant at 5% level; *significant at 10% level. Clusters are identified using the following variables: GDPPC, IMPORT/GDP, AGRVA/GDP, MANVA/GDP, SERVVA/GDP (services value added on GDP), CO_2 per capita and TEMP

At the same time, there is a limited negative relationship between air pollution and COVID-19 infections and related deaths for countries in cluster 3, which are mostly in Sub-Saharan regions (the poorest economies, largely based on agriculture) for which we cannot advance a plausible explanation. This puzzle might relate to data quality issues, especially with organizational difficulties and the costs of testing for the infection on large samples of the population.

4 Conclusions

In this chapter, we have analyzed the relationship between pollution, measured by concentration of PM 2.5, wealth, and COVID-19 worldwide during the first wave of the pandemic, taking into account the socio-economic characteristics of the countries. We have shown that air quality negatively affects both COVID-19 infections and deaths, but this is true only for the richest cluster of countries that are mostly located in the northern hemisphere. For the other countries, once they are grouped in different clusters according to their level and composition of GDP, trade openness, energy efficiency, and climate features, such a relationship does not hold anymore. This put evidence in favor of the possible linkage between COVID-19 diffusion and pollution through the socio-economic features of the most advanced countries.

There are several factors to consider regarding the quality of available data on COVID-19 that can influence our results. The first aspect concerns the homogeneity of the data collection process. Apart from costs and organizational problems, different policies have been adopted around the world concerning the use of testing for the infection and mitigation measures. There has been a generalized scarcity of test kits, which has influenced how the phenomenon has been measured. Overall, it is safe to assume that the official COVID counts fall abundantly short of the real number of infections around the world.

This may be true of the real number of deaths as well. There are non-trivial problems with certifying a death as being due to COVID-19. It preliminarily demands doing a test. Many of the elderly people infected with COVID-19 have been treated outside hospitals and died in nursing homes, adding to the difficulty of applying the test and establishing the cause of death.[5] Besides, a large proportion of the people dying with the infection are elderly and have underlying medical conditions, including cardiocirculatory and respiratory problems. In such cases, definitively establishing the ultimate cause of death is not always easy and can be costly and time-consuming.

Nevertheless, our analysis gives an account of the impact of air pollution and economic and environmental variables on the COVID-19 pandemic around the world. The study of this phenomenon is growing, and we welcome future analyses that include local and global factors to help explain the relationship between air pollution and COVID-19 pandemic, as done in this work.

[5] In Italy, for instance, the classification protocol states that only people who die after officially testing positive in hospitals can be classified as COVID-19 victims. Some reports (e.g., Gabanelli & Ravizza, 2020) show that in several EU countries (e.g., the Netherlands, Belgium, among others), the mortality rate due to coronavirus remains particularly low, but in the first 4 months of 2020, these countries have had more than double the mortality rates of the same period in 2019. It is not clear why different countries count COVID-19-related deaths differently.

Appendix

Table 6 Clusters of countries

Cluster	Countries
1	Australia, Austria, Belgium, Canada, Cyprus, Denmark, Spain, Estonia, Finland, France, Germany, Georgia, Greece, Iceland, Israel, Italy, Japan, Kazakhstan, Lebanon, Latvia, Montenegro, The Netherlands, Norway, New Zealand, Portugal, Russian Federation, Sweden, Switzerland, The United Kingdom, The United States
2	Bangladesh, China, Cameroon, Algeria, Gabon, Equatorial Guinea, Guatemala, Honduras, Indonesia, India, Jordan, Korea, Rep., Morocco, Mexico, Malaysia, Nicaragua, Oman, Philippines, Paraguay, Senegal, El Salvador, Thailand, Tunisia
3	Afghanistan, Albania, Azerbaijan, Benin, Burkina Faso, Bhutan, Central African Republic, Cote d'Ivoire, Congo, Dem. Rep., Congo, Rep., Ethiopia, Ghana, Guinea, Gambia, Guyana, Iraq, Kenya, Cambodia, Liberia, Madagascar, Myanmar, Mozambique, Mauritania, Niger, Nigeria, Nepal, Pakistan, Rwanda, Chad, Togo, Timor-Leste, Tanzania, Uganda, Uzbekistan, Vietnam
4	Angola, Argentina, Belize, Bolivia, Brazil, Chile, Colombia, Cabo Verde, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, Egypt, Grenada, Iran, Jamaica, Sri Lanka, Namibia, Panama, Peru, Uruguay, South Africa, Zambia, Zimbabwe
5	Armenia, Bulgaria, Bosnia and Herzegovina, Belarus, Czech Republic, Croatia, Hungary, Kyrgyz Republic, Lithuania, Moldova, North Macedonia, Mongolia, Poland, Romania, Serbia, Slovak Republic, Slovenia, Turkey, Ukraine
6	United Arab Emirates, Bahrain, Brunei Darussalam, Kuwait, Qatar, Saudi Arabia
7	Ireland, Luxembourg, Malta, Singapore

Table 7 Eigenvectors of the correlation matrix

Cluster	Eigenvalue	Difference	Proportion	Cumulative
1	3.0519	1.9871	0.4360	0.4360
2	1.0648	0.1769	0.1521	0.5881
3	0.8879	0.1044	0.1268	0.7150
4	0.7835	0.1295	0.1119	0.8269
5	0.6540	0.2849	0.0934	0.9203
6	0.3692	0.1806	0.0527	0.9731
7	0.1886	–	0.0269	1

Table 8 Eigenvalues of the correlation matrix

Cluster →	1	2	3	4	5	6	7
GDPPC	0.480	0.147	−0.014	0.228	−0.045	0.747	−0.370
AGRVA/GDP	−0.484	0.199	0.125	0.091	−0.297	0.520	0.587
MANVA/GDP	0.124	−0.835	0.443	−0.120	0.078	0.213	0.161
SERVA/GDP	0.436	0.147	−0.291	−0.373	0.476	0.111	0.572
IMPORT/GDP	0.206	0.463	0.836	−0.076	0.108	−0.158	0.040
CO_2	0.390	−0.079	−0.033	0.757	−0.174	−0.280	0.399
TEMP	−0.368	−0.004	0.056	0.456	0.797	0.109	−0.078

Table 9 Average values of clusters

Cluster	Freq.	GDPPC	AGRVA/GDP	MANVA/GDP	SERVA/GDP	CO_2	IMPORT/GDP	TEMP
1	30	39,074	0.03	0.12	0.66	7.9	0.42	2.8
2	23	6217	0.09	0.20	0.53	3.5	0.39	21.1
3	35	1615	0.23	0.09	0.43	0.8	0.43	22.1
4	25	6758	0.07	0.10	0.58	2.6	0.33	22.1
5	19	10,809	0.06	0.16	0.54	5.0	0.61	2.0
6	6	35,377	0.01	0.12	0.52	26.3	0.49	21.8
7	4	66,405	0.01	0.16	0.70	10.1	1.39	10.6

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