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Clustering a sample of major and emerging economies regarding their economic policy uncertainty

Agrupamiento de una muestra de las principales economías y mercados emergentes con respecto de su incertidumbre de la política económica

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Abstract

Objective: this study carries out pattern identification in a sample of 16 major and emerging economies in function of their economic policy uncertainty.
Methodology: this paper applies for the groping procedure K-Means, Agglomerative Hierarchical Clustering (AHC), and Clustering and Density-Based Spatial Clustering with Noise (DBSCAN). Data: This research uses the Economic Policy Uncertainty (EPU) Index calculated monthly by the EPU Agency for several countries. In particular, it examines EPU indexes for a sample 16 countries in five crisis periods between 2008 and 2024; the sample was chosen based on data availability.
Results: global crises have created distinct country clusters transcending traditional economic groupings based on development status or geographical location. Notably, in the COVID-19 pandemic it generated an unprecedented global EPU homogeneity among countries. High-uncertainty clusters consistently emerge, often comprising large economies directly affected by crises.
Limitations: there are possible biases in news-based component of EPU indices.
Originality: to the best of the authors' knowledge, multiple clustering techniques for various crisis periods have not been implemented before.
Conclusion: global crises can equalize policy uncertainty, challenging conventional notions of economic resilience. The empirical findings emphasize the importance of considering EPU in a global context for those responsible for improving the design of economic policy.

Keywords: economic policy uncertainty, cluster analysis, K-means, DBSCAN, agglomerative hierarchical clustering
JEL Classification: C38, D80, F01, G01.

Resumen

Objetivo: este estudio lleva a cabo la identificación de patrones en una muestra de 16 economías desarrolladas y emergentes en función de la incertidumbre de su política económica.
Metodología: este artículo para el procedimiento de agrupación aplica K-Medias, agrupación jerárquica por aglomerados (AHC) y agrupación espacial basada en densidad con ruido (DBSCAN). Datos: esta investigación utiliza el Índice de Incertidumbre de Política Económica (EPU) calculado mensualmente por la Agencia EPU para varios países. En particular, se examinan los índices EPU para una muestra de 16 países en cinco períodos de crisis entre 2008 y 2024; la muestra se eligió en función de la disponibilidad de datos.
Resultados: las crisis globales han creado distintos grupos de países que trascienden las agrupaciones económicas tradicionales basadas en el nivel de desarrollo o en la ubicación geográfica. Cabe destacar que en la pandemia de COVID-19 se generó una homogeneidad global sin precedente de EPU entre países. De manera constante, surgen grupos de alta incertidumbre, que a menudo comprenden grandes economías directamente afectadas por las crisis.
Limitaciones: puede haber posibles sesgos en el componente de las noticias en periódicos de los índices EPU.
Originalidad: hasta donde saben los autores, no se han aplicado múltiples técnicas de agrupamiento para varios períodos de crisis anteriormente.
Conclusión: las crisis globales pueden igualar la incertidumbre política, desafiando las nociones convencionales de resiliencia económica. Los hallazgos empíricos enfatizan la importancia de considerar la EPU en un contexto global para un mejor diseño de la política económica.

Palabras clave: Incertidumbre de la política económica, análisis de agrupamiento, K-means, DBSCAN, agrupación jerárquica aglomerativa.
Clasificación JEL: C38, D80, F01, G01.

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Introduction

Economic Policy Uncertainty has recently become a crucial indicator in economic analysis, providing insights into the unpredictability of government actions and their potential -negative or positive- impacts on the economy. In this sense, Baker *et al.* (2016) introduced the Economic Policy Uncertainty (EPU) index as a versatile tool based on three main aspects: 1) the frequency of newspaper articles referencing economic uncertainty and policy-related terms, 2) the number of tax provisions at the federal level that could change and the disagreement among economic forecasters, and 3) the application of questionnaires to experts. This index, which analyzed 10 major U.S. newspapers, has since been adapted for other countries and policy categories, demonstrating its adaptability and relevance in diverse economic contexts.

The EPU index has demonstrated significant predictive power for economic outcomes. Empirical studies have shown that heightened policy uncertainty leads to substantial reductions in corporate investment (Gulen & Ion, 2016; Kang *et al.*, 2014), employment growth (Baker *et al.*, 2016), and global trade flows (Tam, 2018). For instance, Baker *et al.* (2019) found that an increase in policy uncertainty equivalent to the rise from 2005-2006 to 2011-2012 was associated with a 7% decline in investment and a 16% drop in hiring for policy-sensitive sectors. Similarly, Handley and Limão (2017) documented how policy uncertainty in international trade significantly reduced export market participation and investment in export-oriented industries. While some papers have raised concerns about potential media bias in the index construction (Shapiro *et al.*, 2020), the robust empirical relationship between EPU and economic outcomes has maintained its value for policymakers and researchers alike.

Literature has increasingly focused on the international dimensions of policy uncertainty. Klößner & Sekkel (2014) pioneered the analysis of cross-border EPU spillovers, demonstrating that international transmission accounts for approximately 25% of policy uncertainty dynamics across countries. Building on this, Liow *et al.* (2018) revealed that international spillovers explain about half of the EPU variations across significant economies, highlighting the growing interconnectedness of policy uncertainty. Marfatia *et al.* (2020) advanced this understanding through network analysis, revealing complex EPU transmission patterns across global financial markets. This research has been complemented by studies examining regional EPU dynamics and sectoral impacts (Phan *et al.*, 2021), and monetary policy transmission channels (Gabauer & Gupta, 2018). While these studies have significantly advanced our understanding of EPU transmission mechanisms, they primarily focus on bilateral or regional relationships, leaving a gap in understanding how countries naturally group together based on their EPU patterns during major global events.

Traditional approaches to analyzing EPU patterns and country groupings, such as vector autoregression models and Granger causality tests have faced several limitations. First, these methods typically focus on temporal relationships or pair-wise interactions, potentially missing broader structural patterns in global policy uncertainty. Secondly, these models often struggle to capture simultaneous, multi-country dynamics during crisis periods. Third, these approaches may not effectively identify natural groupings that emerge during specific global events. Clustering techniques address these limitations by allowing for the identification of natural groupings of countries that share similar EPU characteristics, even when these similarities are not immediately apparent through traditional econometric approaches.

This investigation advances beyond existing literature by analyzing EPU patterns and a global perspective on policy uncertainty dynamics. Our study employs three distinct clustering methodologies —K-Means, Agglomerative Hierarchical Clustering (AHC), and Density-Based Spatial Clustering of Applications with Noise (DBSCAN)—each offering unique advantages in identifying country groupings. While K-means provides efficient partitioning for large datasets, AHC offers insights into cluster hierarchy, and DBSCAN excels at handling non-spherical clusters and outlier detection. This multi-method approach enables a more robust identification of EPU patterns than traditional single-method analyses.

The study analyzes five significant crisis periods: 2008-2009 (Global economic downturn), 2011-2012 (Eurozone sovereign debt crisis), 2014-2016 (Ukraine crisis), 2019-2021 (COVID-19 pandemic), and 2022-2024 (Russian invasion of Ukraine and Israeli-Palestinian conflict). While the complete dataset spans from January 2013 to March 2024, we include an analysis of the 2008-2009 and 2011-2012 periods using historical EPU data for our sample of 16 countries, including major economies and emerging markets, letting to compare EPU patterns across different types of crises while maintaining consistency in the country sample.

This paper is organized as follows: A short literature review provides a comprehensive literature review on EPU and its applications in economic research; Methodological aspects outlines the methodological aspects, including data description and a detailed explanation of the clustering techniques employed; Clustering results presents the clustering analysis results for five significant global economic and political periods; finally, conclusions concludes the study, exposing that global economic crises tend to create distinct clusters of countries with similar EPU levels, often transcending traditional economic groupings.

A short literature review

EPU analysis has evolved significantly since its beginning, moving from country-specific analyses to global perspectives. The Global EPU (GEPU) index, introduced by Davis (2016), represents a GDP-weighted average of national EPU indices from 20 economies. This index has proven particularly effective in identifying significant global events such as the 9/11 attacks, the Iraq War, and the 2008 global financial crisis, demonstrating the value of analyzing EPU from a multi-country perspective.

Research on EPU transmission mechanisms has revealed complex international relationships. Klößner and Sekkel (2014) found that spillover effects account for nearly 25% of the dynamics of policy uncertainty across countries, while Liow *et al.* (2018) observed that international spillovers cause about half of the EPU across seven significant economies. These findings highlight the interconnected nature of policy uncertainty, suggesting the need for analytical approaches to capture simultaneous relationships among multiple countries.

While valuable, traditional methods of analyzing these relationships, such as spillover indices and network analysis, face certain limitations. Spillover indices, as used by Klößner and Sekkel (2014), primarily focus on bilateral relationships and may miss broader, simultaneous patterns across multiple countries. As employed by Marfatia *et al.* (2020), network analysis can identify connections but may not effectively group countries with similar EPU patterns during specific crisis periods.

Recent methodological innovations in EPU analysis have demonstrated the value of machine learning approaches. Kaveh-Yazdy & Zarifzadeh (2021) proposed an unsupervised text mining method using word-embedding representation to overcome the limitations of pre-defined dictionaries. Similarly, Xu *et al.* (2023) introduced a normalized GEPU index using unsupervised machine learning, combining Principal Component Analysis with Random Matrix Theory. These advances suggest the potential value of other machine learning techniques, including clustering, for understanding EPU patterns.

The effect of EPU on financial markets has been extensively documented. Li *et al.* (2015) and Brogaard & Detzel (2015) examine EPU effects on stock-bond correlations and asset pricing. In commodities markets, Wang & Sun (2017) explore relationships between EPU, crude oil prices, and economic activity. These studies demonstrate how policy uncertainty affects various market segments differently, suggesting that countries might cluster differently based on their financial structures and policy responses.

The predictive power of EPU for economic outcomes has been extensively documented across various domains. Born *et al.* (2018) and Ercolani & Natoli (2020) demonstrate EPU's significant role in forecasting US recessions, while Balcilar *et al.* (2016) extend this analysis to exchange rate dynamics, showing how EPU predicts both returns and volatility in currency markets. In the equity markets, Hoque & Zaidi (2019) provide sectoral evidence of EPU's impact on stock market returns under different regime-switching environments, further highlighting how policy uncertainty affects different economic sectors asymmetrically.

Methodological innovations in EPU measurement and analysis have emerged to address various analytical challenges. Azqueta-Gavaldon *et al.* (2020) developed an unsupervised machine-learning approach for analyzing EPU in the Eurozone, demonstrating the potential of advanced computational methods in policy uncertainty analysis. Similarly, Yono *et al.* (2020) constructed macroeconomic uncertainty indices using supervised topic modeling, offering new perspectives on capturing and analyzing policy uncertainty in financial markets. These methodological advances and studies like Berger & Uddin (2016) examine dynamic dependencies between equity markets, commodity futures, and EPU indexes underscore the need for sophisticated analytical approaches to capture complex, multi-dimensional relationships in policy uncertainty.

Recent clustering applications in economic analysis demonstrate its potential for understanding complex patterns. For instance, Martínez-García (2021) successfully applied clustering techniques to identify groups of countries with similar business cycle characteristics. Finally, Liu & Zhang (2022) reported how EPU affects CO_2 emissions in China in a regional context.

Methodological evolution in EPU analysis, from traditional econometric approaches to machine learning and artificial intelligence applications, highlights a crucial gap in the literature, namely the need for methods that can identify natural groupings of countries based on their EPU patterns, particularly during crisis periods. While there are various approaches at analyzing bilateral relationships regarding EPU grouping, they may need to simultaneously include broader patterns of similarity and difference across multiple economies. Within this context, clustering techniques have several advantages for analyzing EPU patterns that address the limitations of existing approaches:

a) Simultaneous pattern recognition: unlike bilateral spillover analyses, clustering can identify groups of countries exhibiting similar EPU patterns simultaneously during crisis periods.

b) Crisis-specific groupings: while network analysis shows general relationships, clustering can reveal how country groupings change across different crises.

c) Non-linear relationships: traditional correlation-based analyses assume linear relationships, whereas clustering techniques can capture non-linear similarities in EPU patterns.

d) Dynamic group formation: clustering allows for identifying how country groupings evolve across different crisis periods, providing insights into the changing nature of policy uncertainty transmission.

This evolution in EPU analysis, from superficial bilateral relationships to complex network structures, points to the need for methods to capture multifaceted patterns across countries during different crises. Clustering techniques, by identifying natural groupings based on EPU similarities, offer a promising approach to understanding these complex relationships while overcoming the limitations of traditional methodological approaches.

Methodological aspects

The connection between EPU and clustering is relevant to global economic integration. As policy decisions in one country increasingly affect others through various transmission channels (trade, financial markets and supply chains), understanding how countries cluster in terms of their policy uncertainty becomes crucial for several reasons:

a) Identifying clusters of countries with similar EPU patterns helps policymakers understand which economies benefit from coordinated policy responses.

b) Understanding how countries cluster regarding of policy uncertainty can improve risk management strategies and portfolio allocation decisions for international investors and financial institutions.

c) Clustering techniques can reveal whether EPU patterns follow traditional economic groupings or if they create new, crisis-specific alignments.

This methodological approach is valuable given the increasing complexity of global economic relationships and the need to understand how policy uncertainty propagates across different countries. By employing multiple clustering techniques, this investigation provides an understanding of how countries group regarding their EPU patterns, which is difficult to obtain through traditional analytical methods.

Data description and EPU evolution across countries

The analysis utilizes EPU data from 16 countries, with comprehensive monthly data available from January 2013 to March 2024. However, to analyze the 2008-2009 global financial crisis and 2011-2012 Eurozone crisis periods, historical EPU data is incorporated for the same countries, ensuring consistency in our sample across all analyzed periods. This allows us to examine EPU patterns across different types of crises while maintaining a constant country set for comparability.

The selection of the 16 countries (**Table 1**) represents a balanced mix of developed and emerging economies, chosen based on data availability and economic significance. The sample includes major economies (USA, China, Japan), European nations significantly affected by various crises (Germany, France, UK), and emerging markets (Brazil, Mexico, Russia), providing a diverse perspective on global EPU patterns.

Figure 1 illustrates the EPU performance for each country. The graph compares EPU indices across the sample of countries from 2003 to early 2024. The visualization delineates five significant global economic and political periods.

a) 2008-2009: Global economic downturn.
b) 2011-2012: Eurozone sovereign debt crisis.
c) 2014-2016: Ukraine crisis.
d) 2019-2021: COVID-19 pandemic.
e) 2022-2024: Russian invasion of Ukraine and the Israeli-Palestinian conflict.

In general, there has been a noticeable increase in EPU levels across most countries over time, with more frequent and intense spikes in recent years. **Figure 1** shows significant synchronization of EPU spikes across countries during major global events, particularly during the 2008 financial crisis and the 2020 COVID-19 pandemic.

Among the highest EPU levels, China consistently ranks at the top, with significant spikes during the COVID-19 pandemic and the recent Ukraine invasion. Similarly, the UK experiences high volatility, with notable peaks during the Brexit period (2016-2019) and the COVID-19 pandemic. Germany also shows increasing EPU levels over time, with significant spikes during the European debt crisis and recent global events.

In contrast, Japan has the lowest EPU levels, with fewer fluctuations than other major economies. Australia also maintains relatively stable and lower EPU levels, with exceptions during global crises, while Sweden experiences low EPU levels with minor increases during international shocks. South Korea shows moderate EPU levels, with notable spikes during global crises, reflecting its sensitivity to international economic conditions.

In a period-specific analysis, during the global financial crisis (2008-2009), EPU sharply increased in most countries, with pronounced spikes in the US, UK, and Germany. Canada and Australia also had notable increases, emphasizing the global nature of the crisis. During the European debt crisis (2011-2012), European countries, particularly Spain, Italy, and France, exhibited elevated EPU levels, while non-European countries such as South Korea and Mexico showed less dramatic increases, underscoring the regional focus of this crisis.

In the Ukraine crisis (2014-2016), Russia's EPU index displayed considerable volatility. European countries, particularly Germany and Sweden, also experienced heightened uncertainty. Brazil showed significant EPU fluctuations in Latin America, with spikes occurring between 2015 and 2016, coinciding with political instability and economic recession. Finally, concerns about trade relations with the US under the Trump administration in 2016-2017 also contributed to increased uncertainty.

During the COVID-19 pandemic (2019-2021), all countries experienced a dramatic and synchronized spike in early 2020. China rose earlier, reflecting its role as the pandemic initial epicenter. The US, UK, South Korea, and several European countries maintained high EPU levels. In Mexico, the pandemic caused a significant but short-lived EPU spike; in contrast Brazil experienced historically high uncertainty levels.

In the Russian invasion of Ukraine (2022-2024), there was a marked increase in EPU for most countries, with Russia exhibiting extreme volatility. European countries, including Germany and Sweden, saw elevated uncertainty, while the US displayed a more moderate rise. Latin American economies generally maintain higher baseline uncertainty levels than Japan and South Korea. However, Brazil and Chile have experienced more pronounced EPU fluctuations in recent years than Mexico. During major global crises, such as the 2008 financial crisis or the COVID-19 pandemic, the gap in uncertainty levels between Latin American and developed economies narrows.

EPU clustering

The clustering analysis of EPU patterns requires specific methodological considerations that address the unique characteristics of policy uncertainty data. The approach presented employs three complementary clustering techniques, each chosen to capture different aspects of EPU relationships: K-means, Agglomerative Hierarchical Clustering (AHC), and Density-Based Spatial Clustering of Applications with Noise (DBSCAN).

MacQueen (1967) introduces K-means as a partitioning algorithm that divides observations into k clusters. The K-means algorithm partitions countries into k clusters based on their EPU patterns. In this analysis, the objective function J focuses on minimizing the sum of squared distances between each country's EPU values and its cluster's average EPU pattern:

$$J = \sum_j \sum_i \| EPU_{ij} - u_i \|^2 \qquad (1)$$

where EPU_{ij} represents the $j-th$ country within the $i-th$ cluster, u_i denotes the average EPU pattern of the $i-th$ cluster and $\| \cdot \|$ is the Euclidean norm. The silhouette score (Rousseeuw, 1987) determines the optimal number of clusters, which measures how similar an object is to its cluster compared to other clusters. K-means is useful for identifying groups of countries with similar overall EPU levels during crisis periods. It is possible to resume K-means in four steps:

1. Random selection of K initial centroids.
2. Allocation of each data point to the closest centroid.
3. Recalculation of centroids based on new assignments.
4. Iteration until convergence.

In contrast, AHC constructs a hierarchy of clusters from the bottom up. For EPU analysis, the dissimilarity between clusters A and B is measured using Ward (1963) minimum variance criterion:

$$d(A,B) = \left(\frac{n_A * n_B}{n_A + n_B}\right) * \| EPU_A - EPU_B \|^2 \quad (2)$$

where n_A and n_B are the number of points in clusters A and B, and EPU_A and EPU_B are their respective centroids (average EPU values). AHC helps to understand how countries' EPU patterns merge into larger groups during crisis periods. The AHC process can be labelled as:

a) Initialization with individual clusters.
b) Iterative merging of the most similar clusters.
c) Continuation until a single cluster remains.

DBSCAN, proposed by Ester *et al.* (1996) identifies clusters based on the density of EPU patterns. The algorithm defines a neighborhood $N_\varepsilon(p)$ for a point p:

$$N_\varepsilon(p) = \{q \in D\ Countries \mid d(EPU_p, EPU_q) \le \varepsilon\} \quad (3)$$

where $d(EPU_p, EPU_q)$ represents the Euclidean distance between the EPU patterns of countries p and q. DBSCAN is useful for identifying countries with consistently similar EPU responses during crisis periods, while also detecting outliers that may represent unique policy uncertainty patterns. In this sense, the key concepts of DBSCAN are:

- Core points: Points that have at least $\min_p$ neighbors within a distance ε which defines the neighborhood boundary between two samples.
- Border points: Data points that lie within the ε distance of a core point b but lack enough neighbors to qualify as core points themselves.
- Noise points: Data points that do not qualify as either core points or border points.

The algorithm initiates with an arbitrary point and identifies all points reachable from that point given the ε and $\min_p$ parameters. If the point is a core point, it forms a cluster. If it is a border point, the algorithm moves to the next point. Points that are not part of any cluster are classified as noise. Each technique provides distinct advantages for EPU data analysis:

- K-means: Efficient for large datasets (Hartigan & Wong, 1979).
- AHC: Offers insights into cluster hierarchy (Murtagh & Contreras, 2012).
- DBSCAN: Effective for non-spherical clusters and outlier detection (Schubert *et al.*, 2017).

For each crisis period analyzed (2008-2009, 2011-2012, 2014-2016, 2019-2021, and 2022-2024), there are implemented the following analytical steps:

1. Data preparation: monthly EPU values are standardized to ensure comparability across countries with different baseline

uncertainty levels.

2. Optimal cluster determination: for K-means, we use the silhouette score to determine the optimal number of clusters, testing k values from 2 to 5.
3. Robustness checks: results from all three clustering methods are compared to ensure the identified patterns are robust to methodological choices.
4. Crisis-specific analysis: each clustering technique is applied separately to each crisis period to identify how country groupings evolve across different types of economic and political shocks.

This methodological framework allows capturing both the static grouping of countries based on their *EPU* patterns and the dynamic evolution of these groups across different crisis periods. The use of multiple clustering techniques provides complementary perspectives on how countries group together during periods of elevated policy uncertainty.

Clustering results

EPU and the 2008-2009 global economic downturn

The analysis of *EPU* across countries during the period 2008-2009, utilizing three distinct clustering methodologies: K-Means, AHC and DBSCAN yielded consistent results across all approaches. This uniformity in outcomes suggests a robust underlying structure in the data, which persists regardless of the clustering algorithm employed. The clustering analysis consistently identified two primary clusters; see, **Figure 2**.

The first cluster, designated as Cluster 0 in K-Means and AHC, and similarly in DBSCAN, encompasses a diverse group of nations including the United States, Australia, Brazil, Canada, China, Germany, and others. This cluster exhibited a mean EPU value of 140.738944, indicating a relatively high level of economic policy uncertainty among these countries during the analyzed period as can be seen in **Table 2**.

The second cluster, labeled Cluster 1 across all methodologies, comprises Chile, Italy, Spain, Russia, Mexico, and Sweden. This group demonstrated a lower mean *EPU* value of 90.65, suggesting these nations experienced comparatively less economic policy uncertainty during the same period.

The consistency in cluster composition and mean EPU values across the three distinct clustering techniques reinforces the validity of this grouping. It implies an apparent dichotomy in economic policy uncertainty levels between these two sets of countries during the 2008-2009 period, which coincides with the global economic downturn.

Finally, the higher EPU values in Cluster 0 may be attributed to the fact that it includes several major global economies (e.g., USA, China, Germany) at the epicenter of the financial crisis or significantly impacted by it. Conversely, the countries in Cluster 1, while not immune to global economic turbulence, appear to have experienced less policy uncertainty during this period.

EPU 2011-2012 Eurozone sovereign debt crisis

The analysis of *EPU* for 2011-2012, encompassing the Eurozone sovereign debt crisis, reveals a more complex clustering pattern than the previous period. The K-Means and AHC methods produced identical results, identifying six distinct clusters, while DBSCAN yielded a different perspective with only two clusters. This divergence in results across methodologies suggests a more nuanced and heterogeneous landscape of economic policy uncertainty during this period as shown in **Figure 3**.

In this case, K-Means and AHC show that Cluster 0 (Chile, Sweden) exhibited the second-lowest mean *EPU* of 100.161, indicating relatively low policy uncertainty. For instance, cluster 1 (Canada, China) demonstrated a high mean *EPU* of 218.23, suggesting significant policy uncertainty in these diverse economies. Cluster 2 (Brazil, Italy, Spain, Russia, Japan) showed a moderate mean *EPU* of 136.31, representing a mix of emerging and developed economies affected by the crisis, as it can be seen in **Table 3**.

Cluster 3 (UK and France) displayed the highest mean EPU of 265.577, reflecting the severe impact of the Eurozone crisis on these significant European economies. Cluster 4 (USA, Australia, Germany, and South Korea) exhibited a relatively high mean EPU of 172.44, indicating substantial policy uncertainty in these developed economies. Finally, cluster 5 (Mexico) showed the lowest mean EPU of 60.29, suggesting comparatively low policy uncertainty.

Notice that DBSCAN entails that cluster 0 is encompassed by most countries with a mean *EPU* of 154.47, suggesting a more homogeneous view of policy uncertainty across diverse economies. Cluster 1 (UK and France) isolated these two countries with the highest mean *EPU* of 265.577, consistent with the K-Means and Agglomerative results. The disparities in clustering outcomes between DBSCAN and the other methods highlight the complexity of economic policy uncertainty during this period. The Eurozone sovereign debt crisis appears to have had varying impacts across different economies, resulting in a more fragmented clustering pattern.

The high *EPU* values for the UK and France, consistently grouped across all methods, underscore the significant policy challenges that these major European economies faced during the crisis. Conversely, Mexico's low *EPU* suggests it may have been relatively insulated from the Eurozone turmoil. The moderate to high *EPU* values for most other countries, particularly in the larger DBSCAN cluster, indicate widespread policy uncertainty, likely reflecting the global repercussions of the Eurozone crisis and ongoing recovery efforts from the earlier global financial crisis.

EPU 2014-2016 Ukraine crisis

The period encompassing the Ukraine crisis (2014-2016) reveals intriguing patterns across the three clustering methodologies employed. This period shows a shift in global economic policy uncertainty, likely influenced by geopolitical tensions and their financial repercussions.

In K-means, cluster 0 compresses Brazil, Canada, China, the UK, France and Russia, exhibiting a high mean of *EPU* of 234.82. The inclusion of Russia and significant Western economies in this high-uncertainty group likely reflects the direct and indirect impacts of the Ukraine crisis on these nations. Cluster 1 includes US, Australia, Chile, Germany, Italy, Spain, Mexico, Japan, Sweden, and South Korea. This larger cluster shows a considerably lower mean *EPU* of 115.71, suggesting that these countries experienced relatively less policy uncertainty during this period despite the global nature of the crisis, as it can be seen in **Figure 4**.

For AHC, cluster 0, like the K-means cluster 0, adds Germany. This group showed a high mean *EPU* of 225.73. Germany's inclusion in this cluster might indicate its closer economic ties and policy alignment with other major European economies during the crisis. Cluster 1 compresses the remaining countries. This cluster demonstrated a lower mean *EPU* of 109.54, consistent with the K-means results but excluding Germany; see **Table 4**. It is noted that DBSCAN produced a single cluster encompassing all countries except the UK and Mexico, with a mean *EPU* of 158.57. This unified cluster suggests a more homogeneous view of global political uncertainty during the Ukraine crisis, potentially indicating widespread but varied impacts across different economies.

The K-means and AHC methods both identify an apparent dichotomy between high-uncertainty and low-uncertainty groups, with the high-uncertainty cluster consistently including major powers directly involved in or significantly affected by the Ukraine crisis (Russia, UK, France, and China). The emergence of Brazil and Canada in the high-uncertainty clusters across both K-means and AHC methods is noteworthy, possibly reflecting these countries' economic ties to the involved nations or their roles in global commodity markets affected by the crisis.

On the other hand, the DBSCAN results, shows a single cluster suggesting that while there were variations in *EPU* levels, the Ukraine crisis had a broadly pervasive effect on global economic policy uncertainty, creating a more interconnected landscape across diverse economies. The consistent grouping of Russia with Western powers in high-uncertainty clusters underscores the complex economic interdependencies and policy challenges arising from the crisis despite geopolitical tensions. Finally, the lower EPU values for countries like the USA, Japan, and several European nations in the K-means and AHC results might indicate a degree of economic resilience or policy stability in these economies during the crisis period.

EPU 2019-2021 COVID-19 pandemic

The COVID-19 pandemic period 2019-2021 reveals a striking pattern across all methodologies. This period is characterized by an unprecedented global health crisis with profound economic implications, reflected in the clustering results. For K-means and AHC, Cluster 0 (China), both methods isolate China in only one cluster, with an exceptionally high mean *EPU* of 682.9. This extreme value underscores the unique economic policy challenges faced by China, the initial epicenter of the pandemic. Cluster 1 (All other countries) comprising all other analyzed countries, including major economies like the USA, UK, Germany, and Japan, as well as emerging markets. This cluster shows a significantly lower, though still elevated, mean *EPU* of 210.2. DBSCAN produces a cluster that includes all countries except China, with the same mean *EPU* of 210.2 as observed in the other methods, as shown in **Figure 5**.

The extreme *EPU* value for China (682.9) across all methods highlights the country's intense economic policy uncertainty. This could be attributed to its role as the initial outbreak location, stringent lockdown measures, and the global scrutiny it faced. For all other countries, global homogeneity, regardless of their economic development status or geographical location, is remarkable, suggesting unprecedented shared economic policy uncertainty across diverse economies during the pandemic, as can be seen in **Table 5**.

While significantly lower than China's *EPU*, the mean *EPU* of 210.2 for the rest of the world is still considerably high, reflecting the global nature of the crisis and its pervasive impact on economic policymaking worldwide. The near-identical results across K-means and AHC, with DBSCAN showing similar patterns, highlight the robustness of this clustering, suggesting an unambiguous division in *EPU* levels between China and the rest of the world.

Unlike previous periods in which regional or economic status-based clusters were observed, the COVID-19 period shows a striking lack of such distinctions, highlighting the pandemic role as a great equalizer regarding economic policy challenges. The high global *EPU* likely reflects shared challenges such as managing lockdowns, implementing fiscal stimulus measures, adapting monetary policies, and addressing supply chain disruptions. China's extreme *EPU* might additionally encompass factors like international trade tensions and domestic policy responses to the initial outbreak.

EPU 2022-2024 Russian invasion of Ukraine and the Israeli-Palestinian conflict

The analysis of *EPU* for 2022-2024, marked by the Russian invasion of Ukraine and, subsequently, the Israeli-Palestinian conflict, reveals a complex and polarized global economic landscape. K-means and ACH reveal that Cluster 0 (China, Germany and Russia) has an exceptionally high mean EPU of 591.94. This clustering is particularly noteworthy given the diverse geopolitical positions of these nations about the conflict. Meanwhile, Cluster 1 (all other countries) is compressed by the remaining 13 countries, including major economies like the USA, UK, Japan, and various European and Asian nations; this cluster exhibits a significantly lower mean *EPU* of 182.58, as noted in **Figure 6**.

For the DBSCAN clustering results, cluster 0 is identical to cluster 1 in K-means and AHC methods, with the same mean *EPU* of 182.58. Cluster 1 (China and Germany), in this case, DBSCAN groups only China and Germany together, with an even higher mean *EPU* of 648.98. Notably, Russia is not included in this cluster; see, **Table 6**.

There is a high-uncertainty triad since the grouping of China, Germany and Russia in K-means and AHC exhibit an extremely high EPU (591.94), which is striking, indicating these countries faced unprecedented levels of economic policy uncertainty, albeit for potentially different reasons:

a) Russia: Direct involvement in the conflict and facing international sanctions.

b) China: Potential global economic repercussions and its complex geopolitical position.

c) Germany: High dependence on Russian energy and its central role in EU policymaking.

Likewise, there is a DBSCAN divergence since the separation of Russia from China and Germany is intriguing. The even higher *EPU* for China and Germany (648.98) in this method suggests these two countries may have faced unique policy challenges distinct from Russia's direct involvement in the conflict. The consistent clustering of most countries with a mean *EPU* of 182.58 across all methods indicates a significant but more moderate level of policy uncertainty for most of the world, recalling the global nature of the crisis's economic impact, albeit to a lesser degree than for the directly involved or highly affected nations.

The difference between DBSCAN and the other methods in handling Russia's position highlights the complexity of the situation. It suggests that while Russia's policy uncertainty was high, its pattern might have been distinct from that of China and Germany. Finally, notice that Germany's high *EPU*, grouped with China and Russia, points out the interdependencies in the global economy, particularly in energy markets and supply chains. Finally, it seems that the Palestinian-Israeli conflict did not contribute significantly in 2024 to increasing the *EPU* in the majority of the countries in the sample studied. Without a doubt, for Asian countries, particularly in the Middle East, *EPU* had significant increases in countries in the region for which there is unfortunately no data.

Conclusions

This study aimed to provide a global perspective on *EPU* indices by using clustering techniques to find patterns and groups of countries based on their *EPU* levels during significant global events. Using K-Means, AHC and DBSCAN, the main findings revealed that global economic crises tend to create distinct clusters of countries with similar *EPU* levels, often transcending traditional economic groupings based on development status or geographical location. This pattern was particularly evident during the COVID-19 pandemic (2019-2021), where an unprecedented global uniformity in *EPU* levels was observed across diverse economies, with China as a notable outlier. This finding suggests that global crises can equalize policy uncertainty on a global scale, challenging conventional notions of economic resilience and interconnectedness.

One important finding was consistently identifying high-uncertainty clusters during each period, often involving economies directly or significantly affected by the crisis. For example, during the 2022-2024 period, marked by the Russian invasion, China, Germany, and Russia formed a high-uncertainty triad across multiple clustering methods, recalling the complex interplay of geopolitical tensions and economic interdependencies.

This research stands out from previous studies by using multiple clustering techniques to analyze global *EPU* across different crisis periods. Unlike studies focusing on bilateral relationships or regional analyses, this approach provides an international perspective, highlighting similarities and differences in policy uncertainty across diverse economies. However, it is essential to note that this study has limitations. The analysis is limited by the availability of *EPU* data for only 16 countries, which may not capture the full spectrum of global economic policy uncertainty. Additionally, relying on news-based *EPU* indices may introduce potential biases related to media coverage and reporting practices across different countries.

Our findings align with and extend previous research on global *EPU* patterns. Identifying distinct country clusters during crises supports the work of Antonakakis *et al.* (2018) on time-varying spillover effects between major economies. Furthermore, the observed global homogeneity in EPU levels during the COVID-19 pandemic corroborates the findings of Caggiano *et al.* (2020) on the pervasive nature of uncertainty spillovers during extreme events. However, our study goes beyond existing literature by systematically classifying countries based on their *EPU* behavior across multiple crises, offering new insights into the evolving nature of global economic policy uncertainty.

In future research, it would be beneficial to expand on this work by including a wider range of countries, particularly emerging economies and Asian countries, to obtain a more comprehensive global perspective. Additionally, investigating the factors that contribute to the cluster formation, such as trade relationships, financial market integration, or political alliances, could offer valuable insights for policymakers and researchers.

Finally, this investigation adds to the increasing literature on economic policy uncertainty by offering a worldwide view of *EPU* trends during significant financial crises. The results underscore the significance of considering policy uncertainty on a global scale and emphasize the potential for global crises to redefine traditional economic dynamics and policy issues. As the world grapples with intricate, interconnected economic difficulties, comprehending these patterns of policy uncertainty will be essential for producing effective policies.

p. 61

Table 1
Countries used in the sample

1	Australia	9	Japan
2	Brazil	10	Mexico
3	Canada	11	Russia
4	Chile	12	South Korea
5	China	13	Spain
6	France	14	Sweden
7	Germany	15	UK
8	Italy	16	USA

Source: authors' elaboration.

p. 62

Table 2
EPU 2008-2009 country grouping results

Cluster type	Cluster ID	Countries	Mean EPU
K-Means Clusters	0	USA, Australia, Brazil, Canada, China, Germany, UK, France, Japan, South Korea	140.74
	1	Chile, Italy, Spain, Russia, Mexico, Sweden	90.65
AHC Clusters	0	USA, Australia, Brazil, Canada, China, Germany, UK, France, Japan, South Korea	140.74
	1	Chile, Italy, Spain, Russia, Mexico, Sweden	90.65
DBSCAN Clusters	0	USA, Australia, Brazil, Canada, China, Germany, UK, France, Japan, South Korea	140.74
	1	Chile, Italy, Spain, Russia, Mexico, Sweden	90.65

Source: authors' elaboration.

p. 65

Table 3

EPU 2011-2012 country grouping results

Cluster	Cluster ID	Countries	Mean EPU
K-means Clusters	0	Chile, Sweden	100.16
	1	Canada, China	218.23
	2	Brazil, Italy, Spain, Russia, Japan	136.31
	3	UK, France	265.58
	4	USA, Australia, Germany, South Korea	172.44
	5	Mexico	60.29
Agglomerative Clusters	0	Canada, China	218.23
	1	USA, Australia, Germany, South Korea	172.44
	2	Chile, Sweden	100.16
	3	Brazil, Italy, Spain, Russia, Japan	136.31
	4	UK, France	265.58
	5	Mexico	60.29
DBSCAN Clusters	0	USA, Australia, Brazil, Canada, Chile, China, Germany, Italy, Spain, Russia, Japan, Sweden, South Korea	154.47
	1	UK, France	265.58

Source: authors' elaboration.

p. 65

Table 4

EPU 2014-2016 country grouping results

Cluster type	Cluster ID	Countries	Mean EPU
K-means Clusters	0	Brazil, Canada, China, UK, France, Russia	234.82
	1	USA, Australia, Chile, Germany, Italy, Spain, Mexico, Japan, Sweden, South Korea	115.71
Agglomerative Clusters	0	Brazil, Canada, China, Germany, UK, France, Russia	225.73
	1	USA, Australia, Chile, Italy, Spain, Mexico, Japan, Sweden, South Korea	109.54
DBSCAN Clusters	0	USA, Australia, Brazil, Canada, Chile, China, Germany, Italy, France, Spain, Russia, Japan, Sweden, South Korea	158.57

Source: authors' elaboration.

Table 5

EPU 2014-2016 country grouping results

p. 66

Cluster type	Cluster ID	Countries	Mean EPU
K-Means Clusters	0	China	682.9
	1	USA, Australia, Brazil, Canada, Chile, Germany, Italy, UK, France, Spain, Russia, Mexico, Japan, Sweden, South Korea	210.2
AHC Clusters	0	USA, Australia, Brazil, Canada, Chile, Germany, Italy, UK, France, Spain, Russia, Mexico, Japan, Sweden, South Korea	210.2
	1	China	682.9
DBSCAN Clusters	0	USA, Australia, Brazil, Canada, Chile, Germany, Italy, UK, France, Spain, Russia, Mexico, Japan, Sweden, South Korea	210.2

Source: authors' elaboration.

Table 6

EPU 2022-2024 country grouping results

p. 67

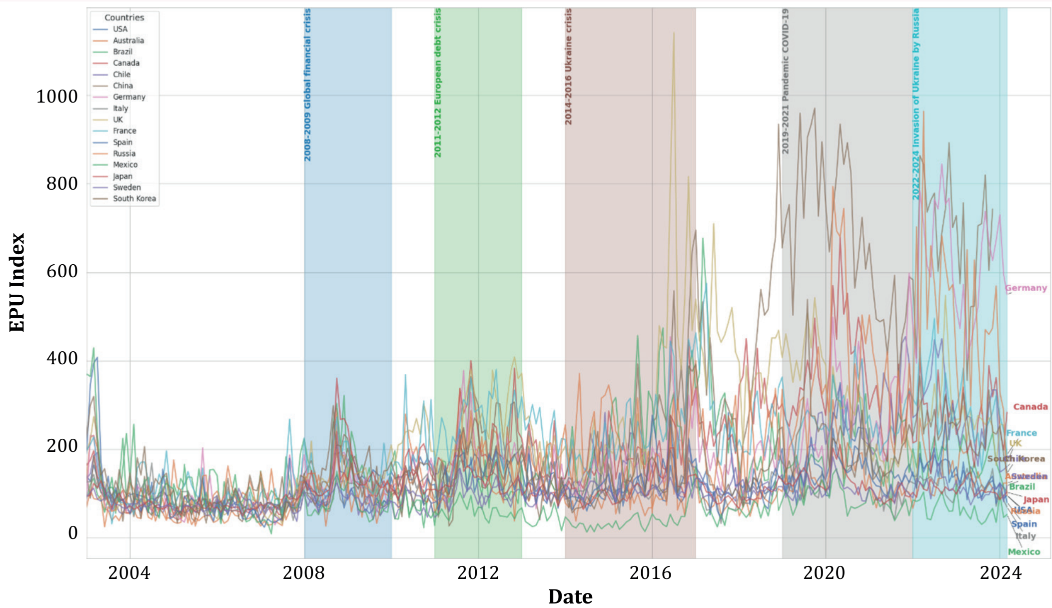
Cluster type	Cluster ID	Countries	Mean EPU
K-Means Clusters	0	China, Germany, Russia	591.94
	1	USA, Australia, Brazil, Canada, Chile, Italy, UK, France, Spain, Mexico, Japan, Sweden, South Korea	182.58
AHC Clusters	0	USA, Australia, Brazil, Canada, Chile, Italy, UK, France, Spain, Mexico, Japan, Sweden, South Korea	182.58
	1	China, Germany, Russia	591.94
DBSCAN Clusters	0	USA, Australia, Brazil, Canada, Chile, Italy, UK, France, Spain, Mexico, Japan, Sweden, South Korea	182.58
	1	China, Germany	648.98

Source: authors' elaboration.

p. 61

Figure 1

EPU dynamics

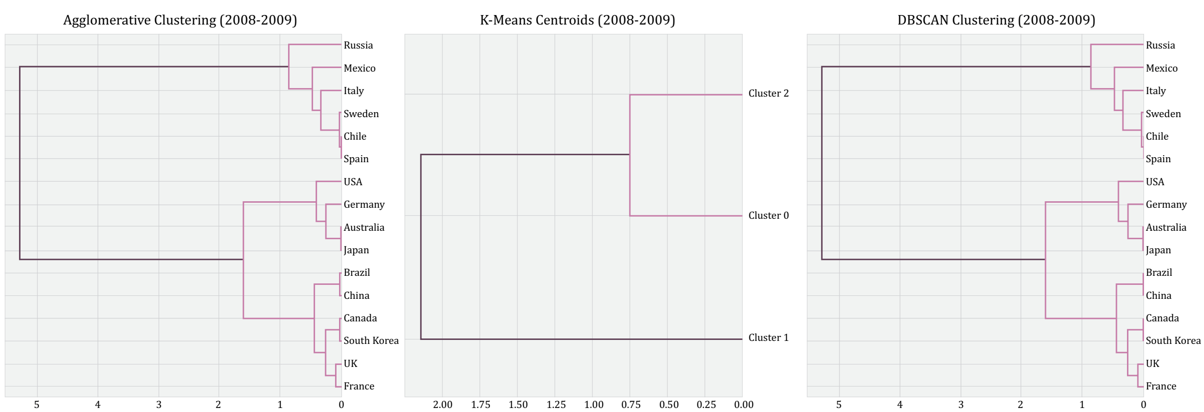


Source: author's elaboration.

p. 64

Figure 2

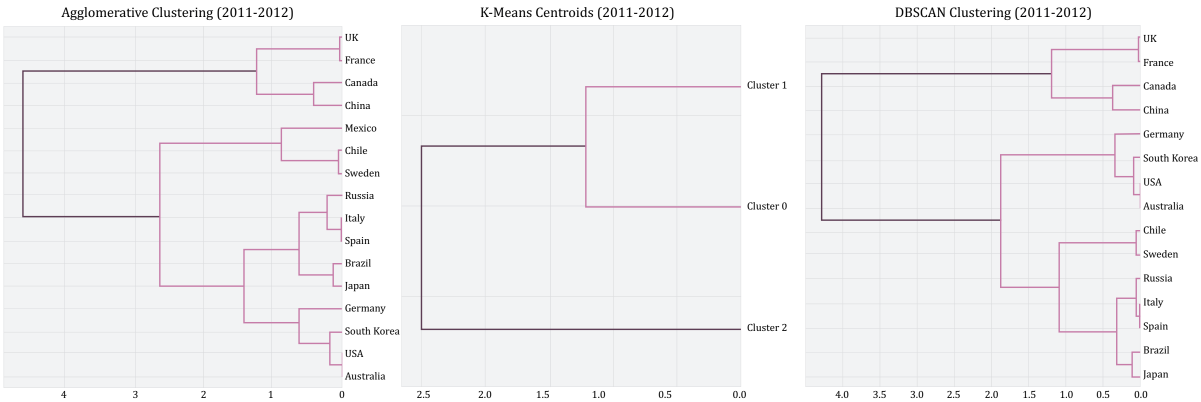
EPU 2008-2009 clustering



Source: author's elaboration.

p. 64

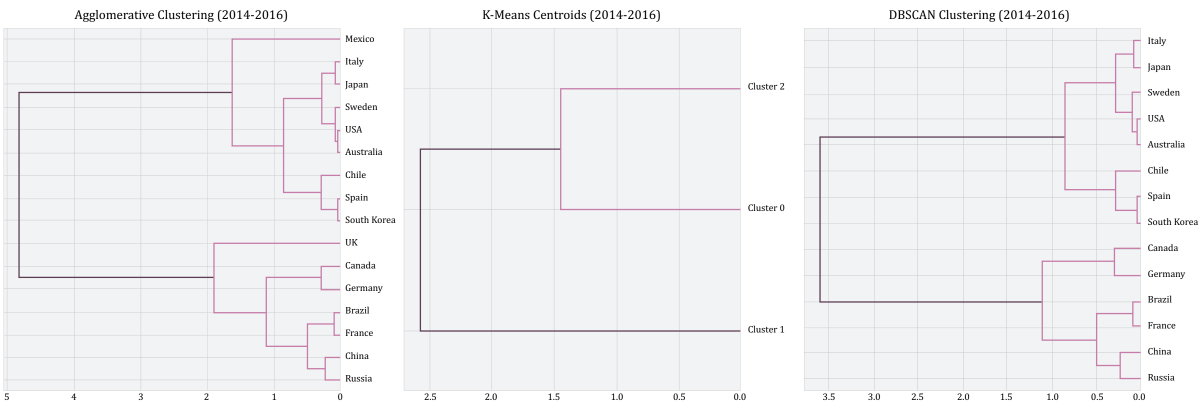
Figure 3
EPU 2011-2012 clustering



Source: author's elaboration.

p. 65

Figure 4
EPU 2014-2016 clustering

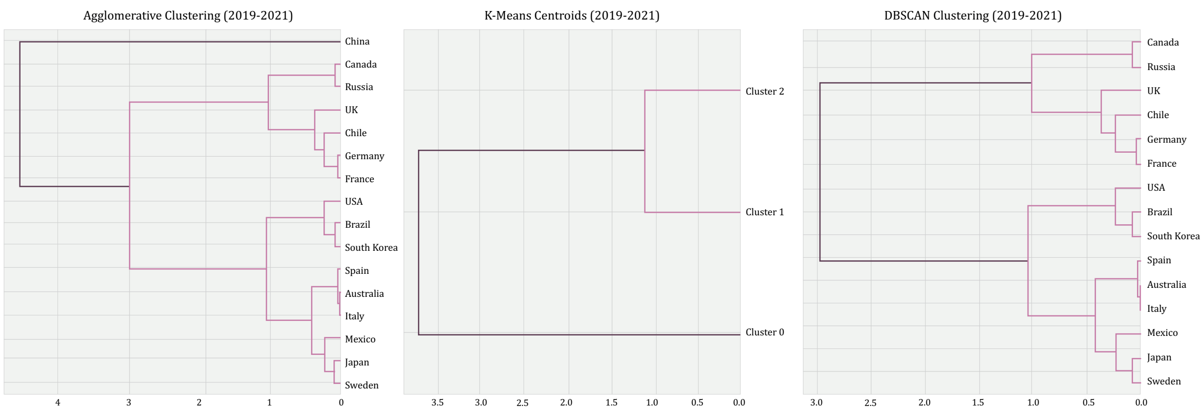


Source: author's elaboration.

p. 66

Figure 5

EPU 2019-2021 clustering

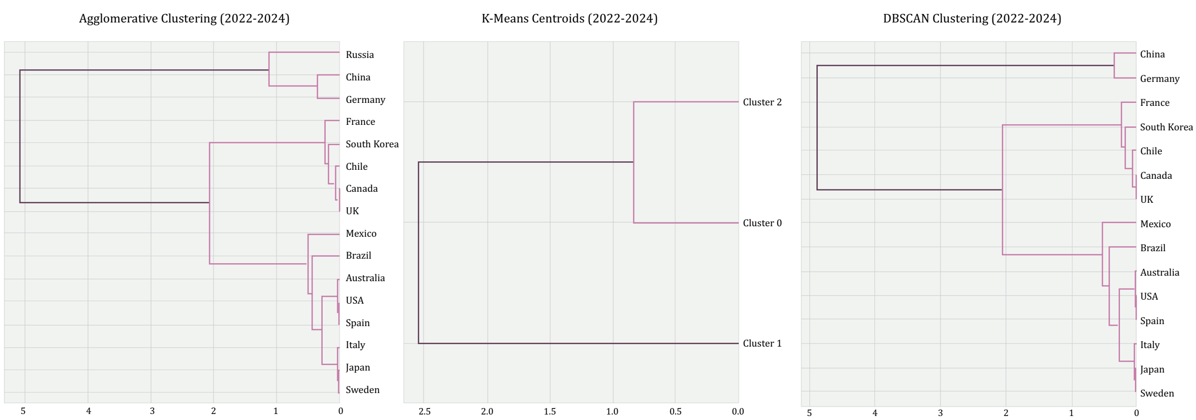


Source: author's elaboration.

p. 67

Figure 6

EPU 2022-2024 clustering



Source: author's elaboration.

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