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Mapping geopolitical fragmentation: a bilateral index for economic analysis

We present a new index that can be used for analyzing the economic impact of shifts in political relations between countries. We combine three freely available and regularly updated global indicators into a bilateral index that reflects geopolitical fragmentation across 193 countries from 2002 to 2022. In addition, we analyze political bloc building, finding that over recent years, next to a US and a China bloc, a third bloc emerged, consisting mainly of South American and Southern African countries.

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A new bloc of emerging and growth-leading economies

We show that next to the two long-standing political blocs – the US-European and the Chinese-Russian blocs – a third bloc has emerged. This bloc consists of emerging and growth-leading economies in South America and Southern Africa. India stands out as having alternated between the Chinese and the third bloc.

A theory-based index for policymaking

Our theory-based index helps derive information on the economic impact of ongoing shifts in geopolitical relations. Such information is of utmost importance to policymakers and central banks, in particular as recent political shocks and tensions have significantly altered global financial and trade flows.

Machine learning to identify geopolitical blocs

On the technical side, we use the Louvain clustering algorithm to detect geopolitical blocs. The method is a network-based machine learning approach that identifies communities inside a network structure. To the best of our knowledge, we are the first to apply the technique on geopolitical networks.

Abstract[1]

We propose a bilateral and time-variant compound indicator measuring shifts in political relations for 193 countries that covers the period from 2002 to 2022. It draws on freely available and regularly updated sources: ideal point distances of UN General Assembly votes, the Voice and Accountability Index of the World Bank and the level of representation index. We combine these indices into a politically-driven variable for geopolitical fragmentation, which can be used in economic analysis. Furthermore, we use a machine-learning method for network clustering to determine geopolitical blocs of countries that are consistent with recent observations of political shifts and events. For our last observation in 2022, the data-driven method produces three blocs: a US bloc, a Chinese bloc and a third bloc that includes mainly South American and Southern African countries. In a global environment characterized by new prioritizations and strategic shifts, our index or the information about geopolitical bloc building can serve as a valuable tool for analyzing the impact of fragmentation on trade, capital flows and migration.

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Since the onset of Russia's invasion of Ukraine, the complexity of navigating geopolitics has markedly increased. The growing influence of China as a strategic counterweight to the USA has intensified debates about the potential restructuring of the global order. Eichengreen (2024) emphasizes that while globalization persists, it is increasingly shaped by the loosening of financial ties among major economies. Recent developments, including the US-Chinese trade war, have further amplified geopolitical tensions and accelerated the shift toward a more fragmented international system. Moreover, the fact that major economies, especially autocratic countries, are increasingly following diverging geopolitical trajectories adds another layer of complexity and risk. Amid this uncertainty, measuring the shifts in geopolitical (de)alignment is important, especially considering the dependencies between China, the USA and the euro area. The data derived can be used to help policymakers make informed decision. This is also of great importance to central banks, as recent political shocks and tensions have significantly altered global financial and trade flows, often with unknown or uncertain consequences for price levels and inflation. A thorough understanding of geopolitical relationships enables a more precise quantification of risk and provides a systematic framework for uncovering political interdependencies.

However, economists usually struggle when it comes to including political developments into their econometric and theoretical models, as the concept of political relations is hard to measure, especially in the context of international politics and globalization. Recent publications have examined the influence of fragmentation on global flows. In this context, the key challenge is choosing a proper measure of geoeconomic or geopolitical fragmentation. Often, oversimplified measures are used, neglecting important connections, developments and regularities that are part of the different theoretical approaches to analyze bilateral relations.

[1] Niklas Kirsamer and Katharina Riha wrote this paper during their internship at the Oesterreichische Nationalbank (OeNB), International Economics Section.

The dominant measure of the political dimension of fragmentation used in the literature is the ideal point distance (IPD), developed by Bailey et al. (2017), which calculates political distances based on the voting behavior of countries in the UN General Assembly. The IPD is a convenient measure for several reasons: its annual, dyadic and time-variant nature is useful for panel data analyses like gravity estimations; it is argued to be exogenous to trade, capital and migration flows; and the baseline data are observable and regularly updated and reflect geopolitical policy preferences (see box 1 for further information). However, its variation is limited. It shifts significantly only after major geopolitical events which change the foreign policy preferences of a country (such as the Islamic Revolution in Iran in 1979 or the dissolution of the Soviet Union in 1991). Since the IPD relies solely on voting behavior in the UN General Assembly, structural or institutional differences and short-term, single topic conflicts may be underrepresented; this implies that determinants identified as crucial by foundational international relations theories are neglected. A more detailed discussion of alternative fragmentation indices and their limitations is provided in box 1.

Against this backdrop, we have created an index that combines the IPD with the Voice and Accountability Index (Kaufmann and Kraay, 2024) and the level of representation Index (Moyer et al., 2024) to achieve a more comprehensive view of global relations. Our index is a bilateral, time-variant measure of (geo)political proximity covering 193 countries from 2002 to 2022, providing a suitable tool to analyze the impact of geopolitics on trade, capital and migration flows. It reflects meaningful between-variation, as different country pairs exhibit plausible levels of proximity, for instance, high proximity between the USA and Israel and low proximity between the USA and Iran or Israel and Syria. Additionally, the index captures within-country pair variation over time quite well, such as the declining proximity between Ukraine and Russia and the increasing proximity between Ukraine and Western European countries.

We apply the Louvain clustering algorithm as an unsupervised machine-learning method to identify blocs of countries that are consistent with short- and long-term trends in geopolitical alignment. This approach yields more plausible results than solely using the IPD. For 2002, the first year in our sample, the Louvain clustering method identifies two blocs that essentially correspond to a US–European and a Russian–Chinese bloc. For the last available year, 2022, the index produces essentially three blocs: a US bloc, a Chinese bloc and a bloc that includes further emerging and growth-leading economies of the Global South.

The remainder of the paper is structured as follows: Section 1 discusses relevant literature on fragmentation indices. In section 2, data and methods are presented. Section 3 shows the results of both, index construction and clustering. Section 4 presents how the index can be applied in practice, along with a discussion of its limitations. Additional robustness checks are provided in the annex for further review of the results. Finally, section 6 concludes.

1 Theoretical foundation of bilateral international relations

To construct our index, we leverage the IPD's bilateral structure to capture political alignment between countries, embedding it into a broader framework of geopolitical relations and fragmentation. We choose three subindices based on the theory of bilateral international relations: The ideal point distance (IPD; Bailey et al., 2017), the Voice and Accountability Index (Kaufmann and Kraay, 2024) and the level of representation Index (Moyer et al., 2024). International relations literature, like economic theory, revolves around explaining why certain patterns of relations emerge, often summarized as rationalist theories (Smith, 2024, pp. 4). The major theories include realism (classical and structural realism) and liberalism (liberalism and neoliberalism); the current international world order is still largely described as liberal (Noelke et al., 2015). For brevity, we focus on these two overarching theories.

Realism is concerned with the balance of power in a global system of anarchy. States are the main actors, their primary motivation is the survival of national interest. Interests are formed based on the fundamental role of the state: Transferring questions of knowledge, belief and morality into laws and norms that are persistent – sometimes needing decades to change – but vary largely across states. This persistence leads to a world shaped by conflicts that sometimes erupt into hegemonial wars between emerging and existing superpowers. (Williams, 2024; Mearsheimer, 2024; Rosenboim, 2022). Hence, realism sees the survival of the state and national interests as key drivers of international relations.

The IPD reflects the assumptions imposed by realism. The UN General Assembly represents a forum of international debate and conflict where states are the main actors and revealed policy preferences are assumed to coincide with national interests. Each state has one vote, and revealed preferences are implicitly measured relative to the USA, reflecting the tendency toward superpowers. The IPD does not vary a lot over time; in fact, it reflects persistent policy preferences over time, which aligns with realism. At the same time, realism tends to neglect the UN's institutional role (Williams, 2024), which is why we turn to the theory of liberalism to incorporate further drivers of international relations.

Liberalism emphasizes three overarching themes as drivers of international relations: The divide between democratic and non-democratic states, (international) institutions and interdependence. In contrast to realism, liberalism considers states to be flexible, to be rational actors capable of progress, democracy and interdependence. Theorists value diplomacy, economic ties and human rights, assuming that democracies, authoritarian regimes and theocratic states behave differently in the international context. Further, liberalism sees international institutions like the UN, NATO or the EU as means contribute to a more orderly international order. Lastly, it emphasizes that interdependence between both states and transnational actors increases the costs of conflict, reducing the incentive to engage in it (Jørgensen, 2024; Sterling-Folker, 2024; Dunne, 2022).

While the IPD also reflects multilateralism (by representing voting in the UN), it is limited with respect to democracy and interdependence. Therefore, for our own index, we extend the IPD by two measures: the level of representation Index and the Voice and Accountability Index. The former measures varying degrees of bilateral diplomatic relationships based on the number of embassies, consulates and missions, capturing interdependence. The underlying idea is that the higher the level of diplomatic representation between two countries correlates with the degrees of interdependence. The Voice and Accountability Index describes the capability of citizens to select, monitor and replace governments in their country. In the context of liberalism, it is a measure of perceived (liberal) democracy, incorporating differences between states and developments over time with respect to democratic institutions into the index.

2 Data and method

In this section, we will first describe our data sources and the technical requirements that have to be met, before explaining the construction of our index and the bloc-building analysis.

2.1 Data

To construct a bilateral, time-varying index, the underlying data must be either inherently dyadic or suited for being reasonably transformed into a bilateral format. Additionally, to ensure temporal comparability, the data must be available on an annual basis. Another design principle is to use exclusively freely accessible and regularly updated data sources, thereby maximizing transparency and ensuring replicability. For our index, we selected three datasets: the World Bank Voice and Accountability Index, the IPD of voting in the UN General Assembly and the level of representation Index from the Frederick S. Pardee Center for International Futures, which captures diplomatic representation.

2.1.1 Level of representation

The level of representation Index (Moyer et al., 2024) spans from 1960 to 2022 and provides bilateral information on diplomatic representation for 199 countries. The data are derived from the *European World Yearbook*, which reports hosted embassies and diplomatic missions. The index ranges from 0 to 1 depending on whether a country maintains an embassy, consulate, mission or lower-level representation such as chargés d'affaires or interest sections. While it changes only gradually over time, capturing long-term trends, abrupt shifts in one country's engagement may lead to significant effects. Since larger economies tend to have more embassies across more countries, we use the bilateral average to mitigate size effects and remain exogenous to economic factors. We avoid scaling indicators with economic weights to reduce the extent of endogeneity issues (reversed causality), a common concern in political indicators.

2.1.2 Ideal point distances

The IPD measurement of votes in the UN General Assembly (Bailey et al., 2017) is a widely accepted proxy for political closeness, available for 193 countries from 1946 to 2022. It is based on an item response theory (IRT) model in which each country has a latent ideal point representing its foreign policy position. A Bayesian framework links each period's estimate to the prior, yielding a more stable and nuanced measure than simple vote similarity scores. The IPD thus captures both gradual evolution and sudden shifts, such as those triggered by regime change.

2.1.3 Voice and Accountability Index

Finally, the World Bank's Voice and Accountability Index, one of six Worldwide Governance Indicators, covers 214 countries from 1996 to 2023. It is based on perceptions drawn from surveys and expert assessments, acknowledging that perceptions influence the behavior of firms and households. The index measures citizens' ability to participate in government selection and assesses freedoms of expression, association and media independence. Unlike many democracy indices focused solely on formal institutions or expert judgments, it incorporates citizen perceptions into governance assessment, bridging the gap between *de jure* rules and *de facto* realities (Kaufmann and Kraay, 2024). It also captures short-term events such as protests and movements that have not yet been translated into political institutions. Unlike the IPD, it does not serve as a direct proxy for foreign policy preferences but rather reflects an inward-facing dimension of governance. As mentioned above, we build on the assumption that politically similar countries tend to engage more intensively in bilateral trade and coordinate external policies. This has recently been demonstrated by Cevik (2024), supporting our assumption that political similarity influences trade, capital and migration flows1

There are several other variables that could potentially measure geopolitical distance in terms of fragmentation; however, we do not use them because of issues related to data availability, bilateralization and exogeneity to economic variables. Table A1 in the annex presents an overview of additional variables considered in other studies and provides reasons for their exclusion from our composite index.

Table 1

Variables included in the index

Variable	Source	Availability	Countries	Advantage	Limitation
Level of Representation index (LOR)	Meyer et al. (2023)	Annually, 1960–2022	199.0	Reflects intensity of bilateral diplomatic ties via embassies and missions; measurement of foreign interests.	Changes slowly; possible bias linked to economic size.
UN General Assembly votes (IPD)	Bailey et al. (2017)	Annually, 1946–2022	193.0	Measures voting similarity in the UNGA as a proxy for foreign policy alignment.	Sensitive to large events; limited recent effectiveness as alignment measure.
Voice and Accountability index (VA)	World Bank (2024)	Annually, 1996–2023	214.0	Also covers domestic governance aspects linked to political similarity; sensitive to protests.	Based on perceptions, which may introduce biases; does not directly measure foreign policy preferences.

Source: OeNB.

2.2 Method

2.2.1 Index construction

This section summarizes the construction of our final index, which captures the political similarity or distance between pairs of countries over time. We follow the OECD's "Handbook on Constructing Composite Indicators – Methodology and user guide" (2008), a widely used guideline for index development (e.g., Figge and Martens, 2014; Mazziotta and Pareto, 2016; Suárez et al., 2024). It provides a step-by-step approach, allowing us to tailor the index to our needs in accordance with common practice in constructing composite indicators. For the Voice and Accountability Index, which is not inherently dyadic, we construct bilateral values by taking differences between countries, interpreting high values as longer distance and low values as proximity. The scale is then inverted to measure proximity directly. First, the components are standardized to allow a comparison across different scales, ensuring that each one contributes equally to the final index and avoiding disproportionate influence of any single component. We apply year-wise min-max standardization, rescaling each variable to a 0–1 range to produce an easily interpretable index.

$$Y_{Min-Max-Std} = \frac{X - \min{(X)}}{\max(X) - \min{(X)}} \qquad [1]$$

In this framework, a value of 0 indicates the greatest distance (least similarity) between two countries, while 1 represents the closest political alignment. This method ensures strictly positive values, which is essential when constructing larger networks, such as those analyzed using the Louvain approach, that require strictly positive values. Year-wise scaling allows a comparison of relative distances between countries within each year and tracking how these relative positions change over time. However, it does not preserve the absolute scale of the underlying measures, so temporal changes reflect shifts in relative standings rather than absolute changes in distance.

Finally, the bilateral fragmentation index is constructed as an additive index. After standardization, the components – IPD, Voice and Accountability and the diplomatic score – are combined with equal weights to reflect their equal importance in capturing political fragmentation. Furthermore, it ensures easy accessibility for reproducing the index in future updates and replications. The question of how different weights may influence the data is further discussed in the section on robustness in the annex.

The final index is interpreted as a measure of political similarity. However, due to the additive nature with equal weights, it can be transformed into a measure of political distance:

$$Index_{dissim} = 1 - Index_{sim} \qquad [2]$$

In instances where data are missing, we make reasonable substitutions based on political intuition. For 2022, we imputed values for Türkiye and Venezuela due to missing IPD data, using the corresponding 2021 values. Similarly, for 2021, we replaced the missing values for the Democratic Republic of Congo and the Republic of Congo with the available 2022 values.

2.2.2 Louvain network analysis

The Louvain network analysis is a widely used unsupervised machine-learning approach to identify communities within a network (e.g. Barteshgi et al., 2020; Setayesh et al., 2022; Farné and Vouldis, 2021). Political connections between countries can be viewed as such a complex network of relations with densely connected nodes. The goal of a bloc-building analysis is to identify groups in which countries are more closely connected to each other than to countries outside the group.

An important feature of this approach is that it relies on endogenous partitioning, as the number and size of blocs cannot be determined a priori. Furthermore, the bilateral index cannot be clustered using traditional partitioning or horizontal clustering methods such as the k-means algorithm or Ward's method, since those require vector-based data structures. Instead, the bilateral index must be transformed into a network representation where each country is a node and the edges between them are weighted by the index values. To detect communities within this network, we use the Louvain algorithm by Blondel et al. (2008), which is as an unsupervised machine-learning method well-suited for discovering hierarchical community structures in large, weighted networks.

We begin by constructing a weighted undirected graph from the bilateral index where countries are nodes and the bilateral index values determine the edge weights between them. The Louvain algorithm starts with each node in its own community. Then, in an iterative process, it evaluates for each node whether moving it to the community of one of its neighbors increases the overall modularity of the network. Modularity can be understood as a quality metric for network partitioning. It measures how well a network is divided into communities by comparing the actual density of edges within groups to the expected density if edges were randomly distributed. A high modularity value indicates that more connections exist within communities than between them, which suggests a meaningful grouping. In more formal terms, the modularity score Q, which ranges between -1 and 1, is calculated by comparing the actual edge weight A_{ij} (weight of the nodes between country *i* and *j*, zero if no edge exists) to the expected weight of an edge between those nodes in a random network with the same distribution of node strengths k_i (i.e., the sum of connection weights for each node) as in the original network. Here, m denotes the total weight of all edges in the graph. This difference is summed over all pairs of nodes that belong to the same community and normalized by $2m$. Finally, $\delta(c_i c_j)$ is an indicator function that equals 1 if countries (*c*) *i* and *j* are assigned to the same community, and 0 otherwise.

$$Q = \frac{1}{2m}\sum_{i,j}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta(c_i c_j) \qquad [3]$$

The algorithm then removes country *i* from its current community and considers moving it to every other community. In the end, the community that maximizes the modularity for this country is chosen. If no increase in modularity is achieved, the country remains in its original community. This process is repeated iteratively and sequentially for each country until a local maximum of modularity is reached. Although this algorithm is rather intuitive and fast, a known limitation of the algorithm is that the order in which countries are selected for this optimization process can influence the outcome. This issue is further discussed in the section on robustness in the annex.

3 Results

3.1 Descriptive statistics

The statistical properties of the constructed bilateral political fragmentation index show that, on average, country pairs have become politically closer over time. A short inspection of the distribution indicates a shift toward higher alignment between 2002 and 2022, with some country pairs forming tighter political clusters, while most of the countries maintain weak to moderate political ties. This divergence suggests a form of bloc formation arising from the growing relative distance between this group. A more detailed discussion of distributional changes, including trends in mean, median, variance and modality is provided in the annex.

To analyze country-level dynamics, we compared index values between 2002 and 2022. Most country pairs show little or no change, but in the top quartile of absolute changes – those with the most pronounced shifts – we identify three distinct groups of country pairs:

- A group that drifted slightly apart, with index differences smaller than -0.05. Most pairs include Venezuela, Nicaragua and Syria. Notably, there is also a decline in political proximity between Hungary and several European countries such as Denmark, Austria and Spain.
- A group that became moderately closer, with differences ranging from approximately 0.05 to 0.20. This group includes mainly smaller Pacific or African countries that politically opened up in the reviewed period. The USA appears frequently in this category, showing a relative convergence particularly with African and Pacific states.
- A third group that experienced substantial convergence, with differences between 0.25 and 0.40. Here, the most prominent countries are Quatar, Serbia and the United Arab Emirates. Substantial increases in political alignment across all regions signal a major shift in foreign policy. Rising economies like India and Brazil demonstrate broad, multiregional convergence in political alignment, with especially large proportional gains where relationships were initially distant. Their closer alignment with African countries hints at parallel foreign policy trajectories, potentially reflecting similar positioning in Global South diplomacy.

We proceed by focusing on the top quartile of changes, highlighting cases where political realignment is most pronounced and reducing noise from minor fluctuations. From this group, we identified the 15 countries that appear most frequently within the top quartile of index changes. For each, we generated heatmaps displaying the geographic distribution of index differences, providing a clearer view of where and with whom political shifts have occurred. These heatmaps are presented in the annex, together with table A3, which summarizes the major political developments in these countries. Positive differences indicate increased political alignment, whereas negative differences suggest growing divergence, often reflecting broader shifts in strategic alliances or orientations.

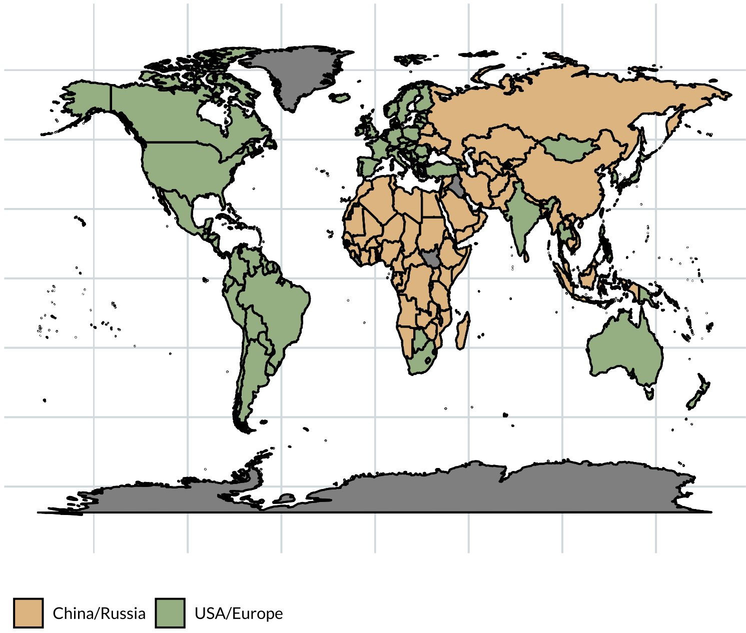
3.2 Results: network analysis and bloc building

This section presents the Louvain clustering results, demonstrating the index's validity by capturing shifts in politically aligned blocs in response to major geopolitical events. To illustrate these developments, we focus on two benchmark years: 2003 (figure 1) and 2022 (figure 2).

Focusing first on 2003, we can find two blocs: A US–European bloc and a Chinese-Russian bloc. The "Western" bloc contains almost all North and South American countries (except Cuba), nearly all of Europe (except Ukraine and Belarus) as well as Japan, South Korea, Israel, India, Thailand, the Philippines, New Guinea, South Africa, Botswana and Lesotho. The only notable outlier is Mongolia, a landlocked country with historical ties to China and Russia. The “Eastern” bloc includes most of Africa and Asia. This division broadly reflects the traditional East–West dichotomy in world politics, where political alignment correlated strongly with geography; this assumption underpinned earlier fragmentation indices, which exogenously set the poles as USA–Europe versus China–Russia.

Figure 1

Political blocs in 2003 identified by the fragmentation index
Result of the Louvain network clustering



Source: OeNB.

Figure 2 depicts political blocs in 2022, where a third bloc emerges alongside the US–European and Chinese–Russian blocs. Several cases illustrate the index’s sensitivity to geopolitical shifts. Ukraine, historically aligned with Russia, moved to the Western bloc after the 2004–05 Orange Revolution – a wave of protests against electoral manipulation that brought opposition candidate Viktor Yushchenko to power. The shift was then reinforced by the Russian annexation of Crimea (2014) and the 2022 Russian invasion of Ukraine.

Conversely, Türkiye shifted from the western to the eastern bloc, reflecting deteriorating democratic institutions captured by the Voice and Accountability Index. In Southeast Asia and the Pacific, many countries gravitated toward the Chinese–Russian bloc, consistent with China’s growing regional influence and participation in the Belt and Road Initiative (BRI).

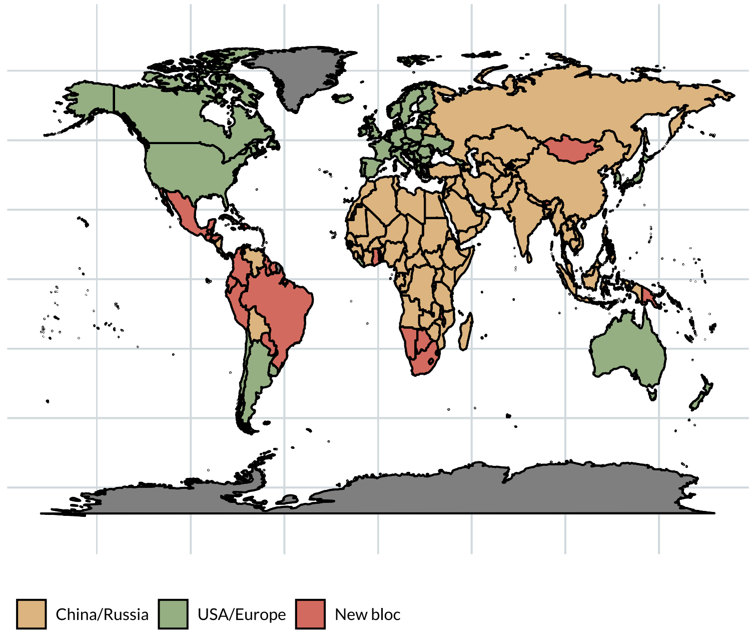
The third bloc identified through the clustering comprises several key countries in Latin America and Africa, including Mexico, Brazil and South Africa. India presents an interesting case as a swing state, having shifted between different blocs over time. Originally aligned with the European bloc, India has alternated between the China-led and the emerging third bloc. For instance, for 2021, the algorithm clearly identifies India as part of the new bloc.

This composition supports the theory that the liberal world order has increasingly been reshaped by the rise of large economies in the Global South. While China has played a significant role, this alone has not been sufficient to overturn the existing order (Chong, 2013). Countries such as Brazil, Mexico, India and South Africa share similar developmental trajectories, characterized by significant growth in export sectors and the adoption of a "state-permeated market economy." Importantly, this clustering also aligns with known cooperation frameworks, particularly the BRICS grouping, as well as with classifications such as the EAGLEs (emerging and growth-leading economies). This model stands in contrast to the liberal free market economies typical of the Global North, potentially leading to an institutional divergence from the prevailing liberal world order (Noelke et al., 2015). Our index and the Louvain clustering method appear to capture these dynamics effectively, aligning well with theoretical expectations.

As regards Brazil, one of the most prominent economies in this third bloc, liberalization reforms since 2016 have facilitated a gradual rapprochement with Europe and the USA. Grounded in liberal theory, the index effectively captures this trajectory. The close correspondence between the index's outputs and Brazil's observed liberalization processes provides robust empirical support for its theoretical foundations. Brazil's high scores reflect its integration into trade and financial systems and regional interconnectedness within South America. Yet domestically, its economy remains shaped by a "financial bourgeoisie" (De Mello Filho and Santos, 2022), which underscores the tension between external liberalization and internal structures.

Figure 2

Political blocs in 2022 identified by the Fragmentation Index
Result of the Louvain network clustering

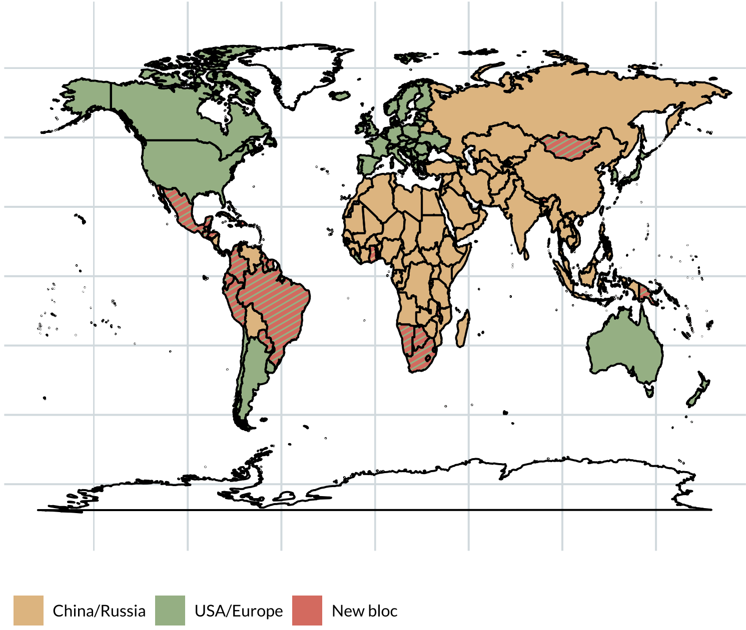


Source: OeNB.

A limitation of the method is that the Louvain clustering method is sensitive to initiation, meaning the results change depending on the initial ordering of the countries. To account for that, figure 3 displays the results we obtain after 1,000 iterations of the clustering. For the countries displayed with hatched lines, the main color presents the bloc they have mostly been assigned to, while the color of the lines represents the bloc they have been assigned to second most frequently. The map gives a clearer picture and provides two important insights. First, there is a new bloc emerging, which, however, has less strong ties compared to the classic Eastern and Western bloc. Second, there are countries, such as Chile and Argentina, but also South Africa, Malawi and Namibia, which are potentially shifting countries. These countries mainly belong to the Western/Eastern blocs, but for some iterations also to the new emerging bloc. An important feature to note is that almost all the countries displayed with hatched lines belong to the Global South, indicating that the new bloc possibly does not comply with the classic notion of a world divided along the dimension of West and East, based on the index of political proximity that considers interdependencies, geopolitical interests and institutional differences. It is important to note that for 2003, we never find a third bloc emerging, even after repeating the clustering process 1,000 times, indicating that the bloc has formed over time.

Figure 3

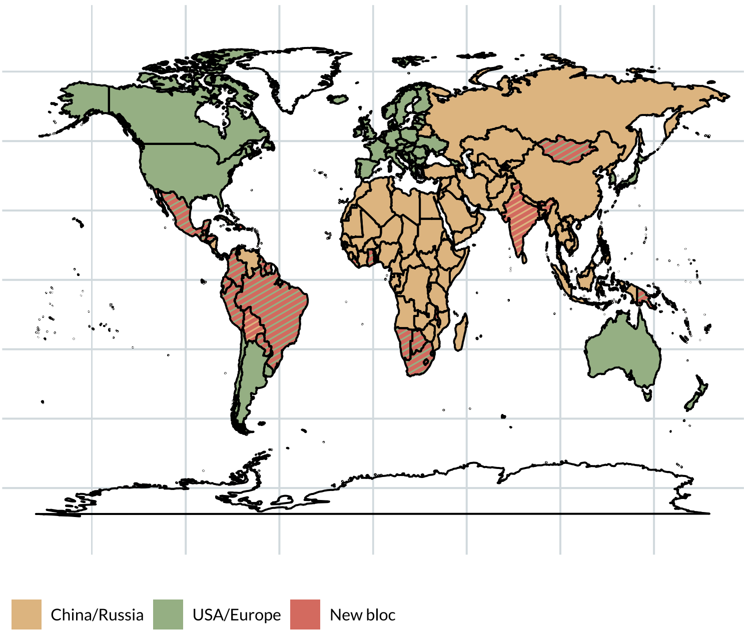
Political blocs in 2022 identified by the fragmentation index
Result of the Louvain network clustering with 1000 repetitions



Source: OeNB.

Figure 4

Political blocs in 2021 identified by the fragmentation index
Result of the Louvain network clustering with 1000 repetitions



Source: OeNB.

In summary, the network analysis delivers some evidence for the emergence of a geopolitical third bloc mainly consisting of countries considered part of the Global South and a geopolitically more fragmented world. However, it also shows that the classic Eastern and Western blocs do not disappear but still mark the main divide between countries.

4 Discussion

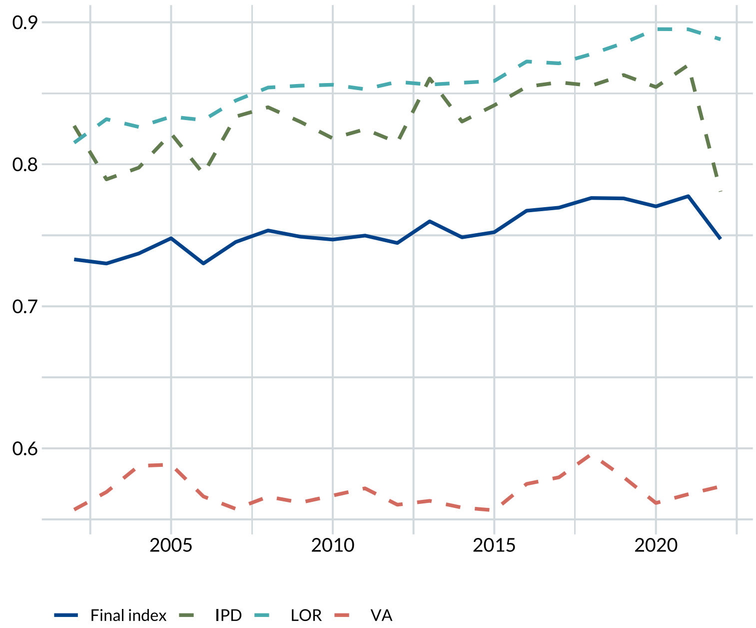
In this section, we show how the index can be applied in practice. We see two main use cases: the analysis of bloc building and geopolitics on the one hand, and the use as a complement/explanatory variable in gravity/panel estimations on the other. Further, we discuss the limitations of our framework.

4.1 Case study: China's geopolitical relations

This section illustrates the suitability of the index to analyze bilateral relations, using China as an example. Over the last three decades, China's remarkable economic growth has positioned it as the main counterpart to the USA. Chart 1 shows a steady rise in China's average political proximity to other countries, driven by an increased average level of diplomatic representation and proximity to other countries (IPD) in terms of geopolitical interest. This suggests that more countries aligned their position with China's, reinforcing its leading role in the Eastern bloc.

Chart 1

Index and components: development over time
Chinese relations: average



Source: OeNB.

From 2021 to 2022, however, average political proximity declined, mainly due to a fall in the IPD. This reflects China's decision – together with 35 other states – not to condemn Russia's invasion of Ukraine. Figure 5 confirms that China's relations worsened especially with Western countries.

Figure 5

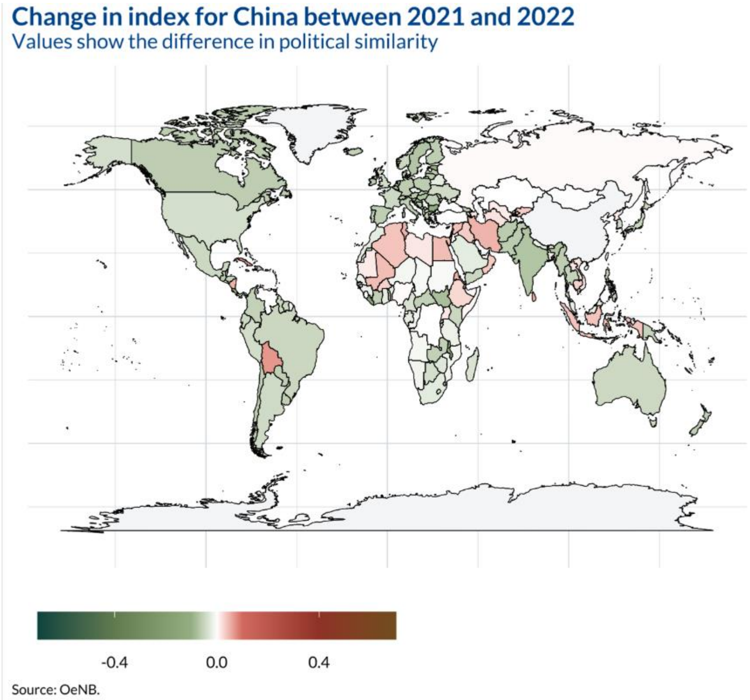
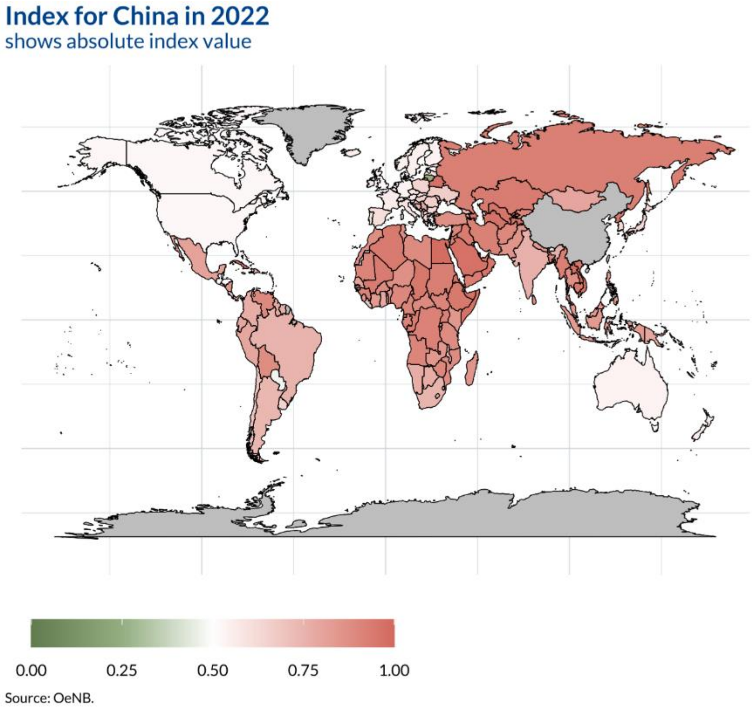


Figure 6 displays China's absolute political proximities in 2022. China shows high political proximity to countries of the former Soviet Union, the African continent and the ASEAN states. The index points to three explanations: (1) similarities in the perceived quality of political institutions, especially regarding democratic values (e.g. with Saudi Arabia); (2) aligned or converging national interests; and (3) strong mutual diplomatic ties. For a country of China's size, diplomatic relations are broadly established, which explains why values even remain around 0.5 when it comes to proximity to many Western countries.

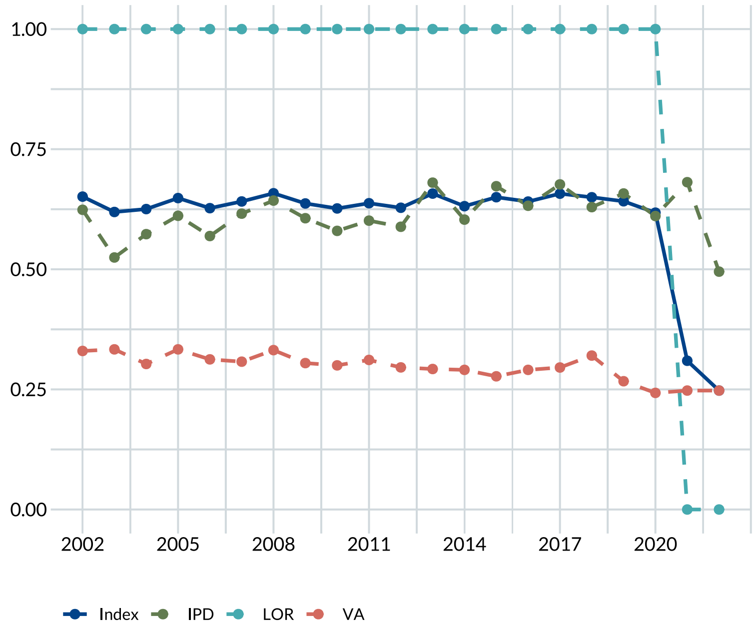
Figure 6



China’s relation to Lithuania is an interesting case, where variation in the level of representation plays a role in the index formation. As shown in chart 2, the relationship has the lowest score. In 2021, Taiwan opened a representative office under the name “Taiwanese” in Vilnius. This led to a diplomatic dispute between China and Lithuania, causing a drop in bilateral representation as official ambassadors where recalled. Chart 2, which displays the bilateral index as well as the components over time, also highlights that in the aftermath of this dispute, geopolitical interests between the countries diverged, leading to a sharp drop in the overall index.

Chart 2

Index and components: development over time
Relations between China and Lithuania



Source: OeNB.

4.2 Limitations

In this section, we cover theoretical and methodological limitations of our proposed index and discuss how to address them in related and future work. A main critique of the index is the European-American institutional bias that comes with the adoption of liberalism and realism as the underlying theory. Both views have been developed by European and American researchers and are heavily influenced by the respective region's history. Similarly, the index neglects the influence of colonial, cultural and historical ties, instead privileging Eurocentric conceptions of institutions and political systems. Although cultural and historical affinity is partially proxied through the Voice and Accountability scores and UN General Assembly voting alignments, these metrics potentially understate deep cultural differences – religious networks, diasporic links or non-Western diplomatic traditions – thereby risking understating enduring hierarchies and non-western relationships that drive fragmentation. In this context, it is crucial to include additional explanatory variables, such as dummies for a shared colonial past, official language, or historical border configurations, in empirical model estimations to better capture the persistence of structural and institutional legacies.

Beyond these conceptual limitations, our index also has methodological constraints. One notable issue arises from the inclusion of the *level of representation (LOR)*, a categorical variable with only six discrete levels. Unlike the two fully continuous measures, LOR's limited range can cause modest diplomatic shifts to yield disproportionately large normalized effects, thereby overstating volatility and distorting comparisons. While LOR remains indispensable for capturing short-term diplomatic realignments that continuous measures miss, future research might consider ordinal normalization, monotonic transformations or hybrid scaling techniques to retain its policy-relevant discontinuities while improving comparability. Given space and scope constraints, we do not implement these alternatives here, but we explicitly highlight them as avenues for robustness checks in subsequent work. A further methodological concern relates to the choice of normalization scheme. The current index relies on year-wise min–max scaling, where values in each year are rescaled between 0 and 1. This method has the advantage of improving cross-sectional comparability within a given year, ensuring that differences between dyads in a particular period are clearly visible even if the global dispersion of values changes over time. It also stabilizes the interpretation of the index for short-term, year-specific analysis. However, it comes with notable disadvantages: it obscures long-term variation, since each year is forced to appear equally dispersed, and it makes the index highly sensitive to extreme outliers within a given year. This limits its usefulness when the research focus is on long-run dynamics or when the distribution of political relations itself is shifting systematically over time. An alternative would be to normalize across the entire time period, applying min-max scaling to the full panel of observations. This approach preserves temporal comparability and highlights structural shifts across decades but comes at the cost of potentially compressing variation in years with little dispersion, making short-run changes less visible. Both approaches thus involve a trade-off between comparability across time and sensitivity within time. Future applications of the index may therefore benefit from experimenting with both normalization strategies, depending on whether the research question emphasizes within-year cross-sectional comparisons or long-run temporal trends.

We note, however, that some of these methodological concerns have already been systematically addressed in the robustness checks provided in the annex. There, we assess the stability of the index under alternative specifications, including leave-one-out exercises (testing the impact of dropping individual components), random weight assignments across more than 1,000 iterations, and extensive bootstrapping. These tests demonstrate that the core structure of the index and the resulting bloc formations remain stable across a wide range of assumptions. We also show that individual components on their own, or with others omitted, produce less differentiated and less theoretically consistent clustering results, reinforcing the added value of the composite index. Together, these exercises provide reassurance that our results are not artifacts of specific modeling choices but reflect robust features of the underlying data.

Finally, the index could be further enriched by integrating additional dimensions of interstate cooperation. Metrics such as joint membership in international organizations or cross-border engagement through civil society could provide a more nuanced account of cooperation intensity. These indicators would serve as valuable proxies for shared normative commitments, transnational institutional embeddedness or informal diplomatic channels. Given the index's modular structure, we encourage users to tailor and expand it according to the specific objectives and data availability in their analyses. Table A1 in the annex presents a selection of relevant databases considered for inclusion, along with their respective advantages and the rationale behind their exclusion from the final model.

5 Concluding remarks

In this article, we present a simple approach for building a bilateral, time-variant composition index for 193 countries to measure international relations over 20 years, taking into account ideal point distances (IPD), the level of representation index and the Voice and Accountability Index. We incorporate common theories of international bilateral relations into our index through the choice of indicators and maintain practical features conducive to regression analyses, including open source datasets, timely data availability and consistent bilateral data structure. The resulting index values align with geopolitical developments and capture short-term events. In a unique approach, we then combine state-of-the-art network machine-learning models with the index to endogenously determine geopolitical blocs of countries, providing new insights into the latent structure and dynamics of international relations.

Overall, we present a theory-based index framework for analyzing the geopolitical dimension of globalization and bilateral relations. It can help policymakers incorporate geopolitical shifts and movements in country-pair relations into the assessments of risks and strategic analyses and also contribute to research connected to (de-)globalization. Box 2 in the annex highlights potential areas of application, including the analysis of geopolitical developments concerning individual countries, relationships between countries and global shifts in geopolitical alignment. Further, the index's technical features allow its implementation in regression analyses, such as gravity estimations. Our main findings include the emergence of a third bloc (next to the US and Chinese blocs), which consists of emerging and growth-leading economies of the Global South (EAGLES), and a more fragmented or polarized world based on the distribution of the index. Finally, we show that this index delivers a more realistic and nuanced view of geopolitical relations than the commonly used ideal point distances alone.

The results presented are indicative, and we leave it to future research to explore further applications of our index, especially alongside other dimensions of globalization, such as capital, goods and migration flows, to investigate (de-)globalization and fragmentation. Furthermore, the index could also be tailored to specific scenarios by adding or removing components based on underlying theories and assumptions. We conclude the paper by underscoring the flexibility and the spectrum of methods that synergize with the index, hoping to encourage researchers to actively engage in the scientific and methodological discussion revolving around the topic of (de-)globalization and fragmentation.

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7 Annex

Box 1: How are indices used to measure geoeconomic fragmentation?

Geopolitical fragmentation is mainly measured to study its influence through/on? the main economic dimensions of globalization: trade, capital flows and migration. Across these dimensions, numerous studies have documented a noticeable slowdown in globalization after the 2008 great financial crisis (GFC). For instance, the updated version of the KOF Globalization Index, originally developed by Dreher (2006), reveals that while economic globalization has largely stagnated since the GFC, especially cultural dimensions of globalization have continued to grow (Gygli et al., 2019).

While such broad globalization indices provide valuable context, they do not capture the specific geopolitical rifts that drive fragmentation. To address this limitation, the literature has developed dedicated geoeconomic fragmentation indices with the ideal point distance (IPD) being the most prominent and widely applied. Aiyar and Ohnsorge (2024) analyze the risks and opportunities of geoeconomic fragmentation for trade and capital flows using a gravity approach with the IPD and other vulnerability and connectedness indices. They find that rising fragmentation has led to decreased connectedness and vulnerabilities, especially for exports and FDI, since 2016 and note the rise of connector countries that maintain diverse relationships across geopolitical blocs. Similarly, Abeliansky et al. (2024) examine the influence of geopolitical distance on cross-border investments in a gravity framework, finding that increased political dealignment is linked to declines in foreign direct and portfolio investment. They also highlight heterogeneity: For “nonfriendly” country pairs, increasing geopolitical distance is associated with a decrease in cross-border investment, while there is no such relationship for “friendly” country pairs. These studies demonstrate the usefulness of IPD but also point to its shortcomings, particularly its limited variation and inability to capture the full spectrum of political and institutional relations.

In response to these limitations, recent contributions in the economic literature have sought to build broader composite indices that integrate multiple political and economic dimensions. For example, Villaverde et al. (2024) use structural vector autoregressions and local projections measuring fragmentation via a dynamic hierarchical factor model with time-varying parameters and stochastic volatility. They identify a negative effect of fragmentation on the global economy, with emerging economies suffering more than advanced ones and effects differing across blocs. The complexity of this approach makes it difficult to disentangle drivers of fragmentation, and the broad coverage across dimensions (without dividing into economic a political drivers) may cause endogeneity issues in economic estimations.

A simpler approach is presented by Den Besten et al. (2023), who create a composite index classifying countries as leaning toward either the USA or China/Russia, based on Belt and Road Initiative membership, arms imports from the USA or China and Russia (SIPRI Global Arms Database), imposed sanctions by either the USA or China and Russia (Global Sanctions Database) and the country’s voting on the UN resolution on Russia’s invasion of Ukraine adopted on 2 March 2022 (UN General Assembly Eleventh Emergency Special Session). They use this index to examine whether geopolitics can explain recent developments in the composition of official reserve holdings. Attinasi et al. (2024) modify this approach by replacing membership in the Belt and Road Initiative with the Horn et al. (2021) debt database and extending UN General Assembly voting to match IPD coverage. Their index assigns scores below 0.25 to the US bloc, above 0.75 to China, and scores in between as neutral. While both indices offer a simple and intuitive approach, they are time-invariant due to aggregated averages, relative only to the USA and China, and restrict the number of blocs to three, which may oversimplify international relations and limit their application in global flow estimations.

Box 2: How to use our index in econometric analyses

In this box we highlight possible applications of our index in regression analyses that are commonly used in political evaluation and explain key econometric considerations.

The most straightforward approach is to implement the index directly as an explanatory variable for an outcome of interest. Our index shows considerable within and between variation, capturing both cross-sectional differences in bilateral political relations (see chart A5) and temporal dynamics (see Ukraine-Russia in chart A6). An example would be the use in a gravity estimation as a measure to quantify the trade costs of political distance. In this context, depending on the explained and the other independent variables, we note that the issue of endogeneity needs to be addressed meticulously to identify causal effects. Like the IPD and other political indices, our measure may be subject to reverse causality issues when explaining geoeconomic flows like trade, capital and migration. Therefore, we strongly advise that the causal chain be carefully specified, and that countermeasures such as fixed effects, instrumental variables or lagging the index are considered.

The blocs identified by the clustering method can also serve as explanatory variables, particularly when the focus is on a country's position in global relations, rather than on bilateral ties. Assignment to blocs can be implemented either through binary variables, indicating the bloc a country is most frequently assigned to in the cluster analysis, or as a probabilistic measurement. By increasing the iterations of the algorithm to 5,000 or higher, the proportion of assignments to each bloc can be interpreted as the probability of bloc membership. These probabilities, in turn, can be used as regressors to capture the strength of a country's alignment with different blocs.

When the index or the derived blocs are used as dependent variables, researchers must account for several important considerations. Especially reverse causality issues need to be addressed, as the index components represent a specific view on bilateral relations that are often connected to economic processes.

Users should note that the current index relies on year-wise normalization, which facilitates within-year comparisons but limits the comparability of trends across time. Depending on the research question, alternative scaling choices (e.g. min–max across the full period) may be more appropriate. We also emphasize that the index itself reflects assumptions about the drivers of geopolitical relations: The choice of components and their weighting implicitly define how bilateral international relations are measured. While this increases the internal consistency of the index, it also implies that certain external variables may be highly correlated with it. Consider, for example the Freedom in the World Index by Freedomhouse, which captures a similar concept as the Voice and Accountability Index. Including such a variable into a regression would likely yield significant coefficients, not due to new explanatory power, but through overlapping constructs of political fragmentation. This should highlight the methodological challenge of identifying explanatory variables that are truly external to the index's construction. Again, causal chains need to be examined cautiously.

Overall, the index and the bloc measures can be applied in a wide range of empirical settings – from gravity models to policy evaluation exercises – but careful econometric design is essential to avoid spurious inference. Further theoretical and structural limitations arising from the construction which are relevant for econometric analysis are discussed in the section on limitations

8 Annex B: descriptive statistics

8.1 Characteristics of the index

The statistical properties of the constructed bilateral political fragmentation index show that both the mean and the median have increased over time, indicating that, on average, country pairs have become politically closer. Examining the distribution (chart A1), which depicts the density of each observation and thus represents the political distance between a country pair, a bimodal pattern emerges, implying that while many country pairs maintain intermediate levels of political distance of around 0.5, others exhibit high political proximity. Between 2002 and 2022, the distribution shifted: in 2002, a larger share of country pairs displayed intermediate political distances, whereas by 2022, an increasing proportion clustered at higher levels of alignment. The second peak indicates that some country pairs have formed tight political clusters, whereas the much larger first peak shows that most countries still maintain low to moderate political ties. This divergence – with one group becoming more closely aligned while the majority remains less connected – points to bloc formation driven by the growing relative distance between groups. Especially in the period following the global financial crisis and again since 2019, the index became more dispersed with slightly higher variance and decreasing values for mean, median and modus in the last three years (see table A2). This suggests that while some clusters tightened, fragmentation across the broader system has increased.

Although descriptive, these findings should be interpreted cautiously. Geopolitical developments such as regional integration, shifting alliances or strategic realignments may partly explain the observed clustering. Future robustness checks could employ formal tests for multimodality or explore subgroup dynamics to refine these interpretations.

Chart A1

Comparison of index distribution 2002 vs. 2022

Source: OeNB.

Table A1

Excluded variables and justifications

Variable	Source	Advantage	Reason for exclusion
Geopolitical risk index	Caldara and Iacoviello (2022)	Captures tensions, war threats and geopolitical volatility.	Country-level coverage is limited (44 countries).
Energy uncertainty	Dang et al. (2023)	Reflects exposure to energy-related political instability.	Closely tied to trade and prices; hard to isolate political alignment.
Number of conflicts	Uppsala Conflict Data Program	Direct proxy for instability and violent tensions.	Skewed toward few countries/events; limited time variation.
Number of sanctions	Felbermayr et al. (2020)	Strong proxy for political distance and formal disapproval.	Often driven by economic motives; potential endogeneity to flows.
Arms Transfer Database	SIPRI	Captures alliances and strategic dependencies.	Tied to defense trade; possible overlap with economic ties.
UN peacekeeping missions	UN Department of Peace Operations	Signals cooperation in international security.	UN mandates drive decisions; not suited for symmetric bilateralization.
International NGOs	Yearbook of International Organizations	Indicates civil society linkage and shared values.	Data poorly structured for bilateral use; limited availability.
International organizations	CIA World Factbook	Reflects institutional alignment and multilateral ties.	Hard to bilateralize; inconsistent data updates.
Democracy Index	The Economist	Measures types of regime; relevant to liberal theory.	Covered by VA Index, which contains several dimensions of freedom.
Rule of Law index	World Bank	Captures institutional quality; linked to liberal cooperation.	Lacks relevance for assessing power dynamics or external alignment.
Political Stability and Absence of Terrorism	World Bank	Reflects internal coherence affecting foreign policy.	Bilateral use is misleading; two unstable states could seem "close."
Regulatory Quality	World Bank	Proxy for openness and rule-based governance.	Includes trade and financial freedom; risks endogeneity with economic flows.
Government Effectiveness	World Bank	Supports capacity for coherent foreign policy.	Reflects domestic performance, not geopolitical positioning.

Source: OeNB.

Table A2

Descriptive statistics per year

	Mean	Median	Mode	Variance
2002	0.6	0.5	0.7	0.0
2003	0.6	0.5	0.6	0.0
2004	0.6	0.5	0.6	0.0
2005	0.6	0.6	0.6	0.0
2006	0.6	0.5	0.6	0.0
2007	0.6	0.5	0.6	0.0
2008	0.6	0.6	0.7	0.0
2009	0.6	0.5	0.6	0.0
2010	0.6	0.6	0.6	0.0
2011	0.6	0.6	0.7	0.0
2012	0.6	0.6	0.7	0.0
2013	0.6	0.6	0.7	0.0
2014	0.6	0.6	0.7	0.0
2015	0.6	0.6	0.6	0.0
2016	0.6	0.6	0.6	0.0
2017	0.6	0.6	0.6	0.0
2018	0.6	0.6	0.6	0.0
2019	0.6	0.6	0.7	0.0
2020	0.6	0.6	0.6	0.0
2021	0.6	0.6	0.9	0.0
2022	0.6	0.6	0.8	0.0

Source: OeNB.

Table A3

Biggest shifts in bilateral political alignment - top 15 countries

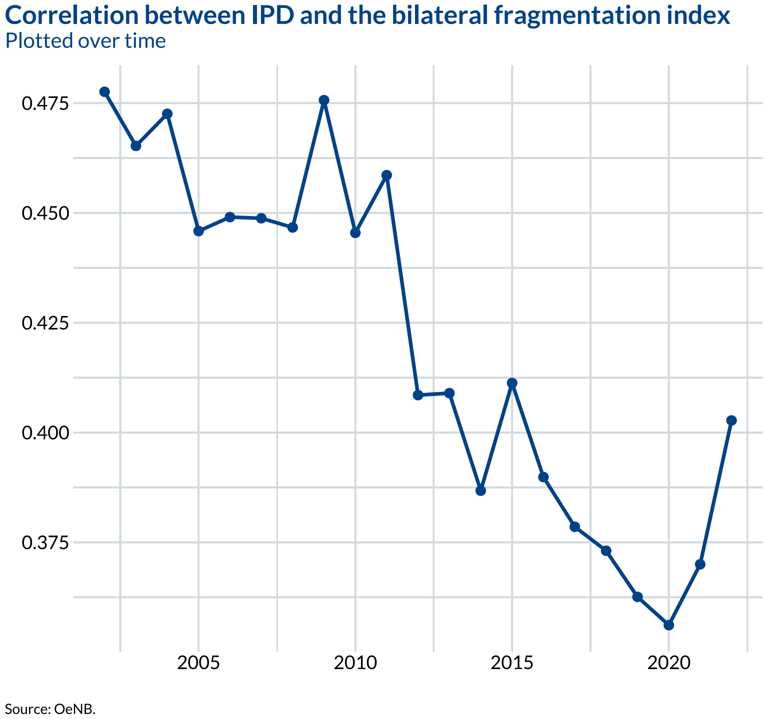
Country	Explanation
Palau	Opened up politically; more alignment with Southeast Asia and Australia.
Venezuela	Drifted apart, especially from Colombia and other South American countries; authoritarian shift toward autocratic states.
Nicaragua	Stronger alignment with China, Iran and other authoritarian states; politically closed.
Mali	Opened up politically; closer to other African countries, Central Asia, India, Brazil and Venezuela.
Syria	Moved closer to Europe, the USA and Australia, reflecting a major geopolitical shift.
Bhutan	Closer to neighbors and Central Asia; larger differences to USA and Europe.
Côte d'Ivoire	Increasing divergence from North and South America; closer to China and Iran.
Libya	Sharp increase in differences to the USA, Mexico, Australia, South America and African countries overall.
Hungary	Greater similarity with Western Europe and North America; decreasing similarity with African and Southeast Asian countries.
Qatar	Larger political differences to Europe, North and South America.
Serbia	Political differences increased across the board.
Tunisia	Closer to Venezuela and Iran; greater divergence from Europe, the Americas and especially Australia.
USA	Increasing differences to Africa, Southeast Asia and parts of South America.
United Arab Emirates	Larger divergence from Central Africa, Central Asia, Europe and Mexico.
Thailand	Moved politically closer to Western democracies; more distance to autocratic states.

Source: OeNB.

8.2 Comparison with the IPD

We observe that the correlation between the IPD and our index was approximately 47% at the beginning of the observation period. However, this correlation has decreased significantly by around 10 percentage points in recent years as chart A2 shows. This suggests that our index has begun to capture additional trends that are not reflected in the IPD, which further justifies the extension.

Chart A2

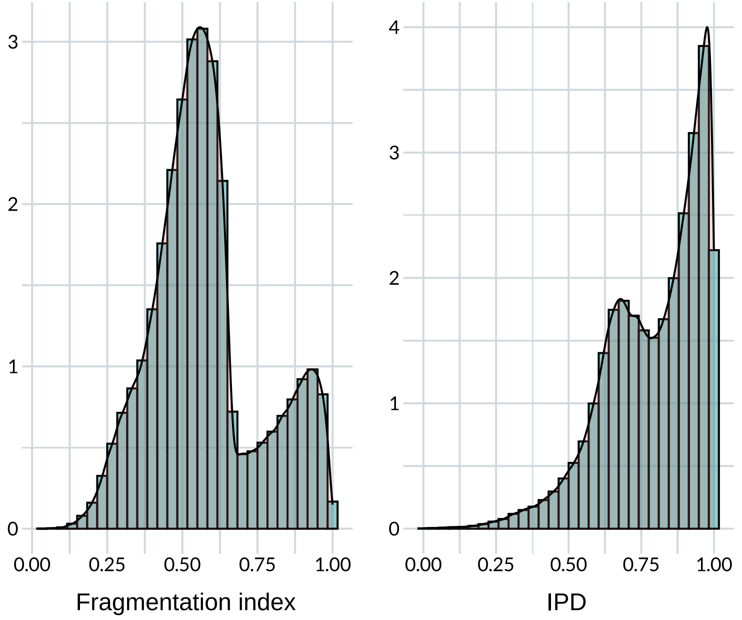


Upon closer examination of the changes over the years, we observe significant differences in the distribution of normalized values. As shown in chart A3, the IPD categorizes a larger number of countries as "quite close," with many values clustered around zero. In contrast, our index clearly distinguishes a group of countries with medium similarity, as well as a larger number of countries with similarity scores below 0.5. This divergence is likely driven by the inclusion of the Voice and Accountability Index, which assigns greater weight to differences in political systems.

When examining the distributions with respect to individual countries, the indices vary substantially. We focus on China as a special case in chart A4, given the growing importance of bilateral relations with China. In the 2022 distribution, the IPD reveals two clusters: one consisting of countries relatively close to China, and another reflecting medium dissimilarity. Our index, by contrast, highlights a third cluster of countries that are highly dissimilar to China. This suggests the possible emergence – or increasing relevance – of a third geopolitical bloc, a trend that is not currently captured by the IPD.

Chart A3

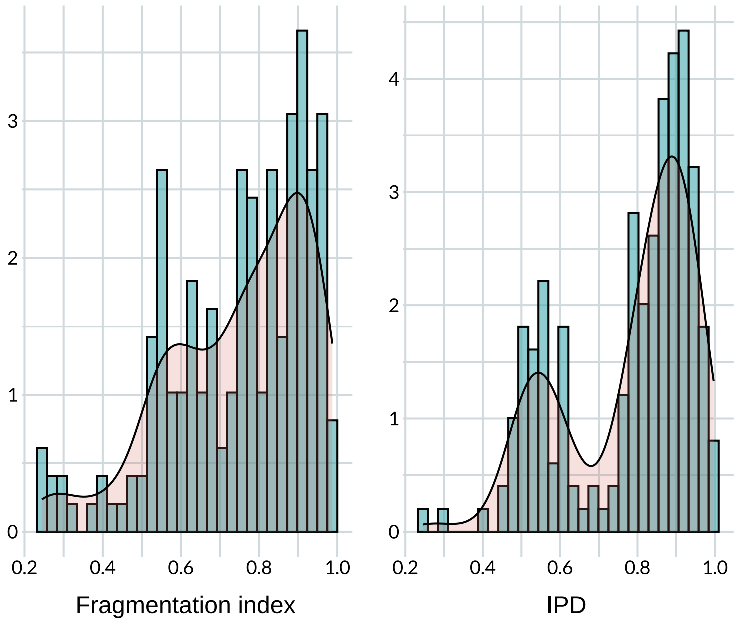
Comparison of distribution: bilateral fragmentation index vs. IPD
Observations from 2002 to 2022



Source: OeNB.

Chart A4

Comparison of Distribution: bilateral fragmentation index vs. IPD
Observations for 2022 for China

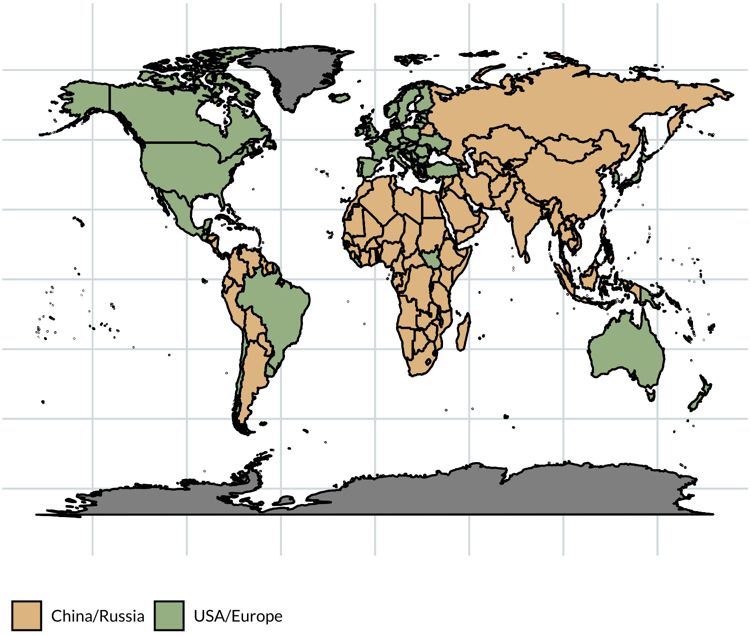


Source: OeNB.

As anticipated, the IPD alone fails to detect a third geopolitical bloc according to the Louvain clustering method over the past decade, as it only incorporates national interests as a driver of bilateral relations, while the proposed extended index includes differences in perceived democratic institutions and interdependence. Therefore, in 2022, only two blocs are identified: the first one comprising 127 countries and the second one 66. Moreover, some of the clustering results appear questionable – for instance, South Sudan, Malawi and Liberia are grouped together with European and US allies, as shown in figure A1, which raises concerns about the robustness of the IPD's classification. Overall, the IPD seems to reflect a rather static division, largely separating traditional advanced economies from the rest, without adequately capturing the geopolitical shifts observed in recent years. In contrast, our index demonstrates a clear advantage in detecting a third emerging bloc, offering a more dynamic and nuanced picture of global alignments.

Figure A1

Political blocs in 2022 identified by the IPD
Result of the Louvain network clustering



Source: OeNB.

9 Annex C: robustness

In this section, we conduct robustness checks, which include variation in the index components, the assignment of random weights and bootstrapping. We conducted a network analysis for the variations of the index and argue that the result shows the need of the individual variables to give reasonable results.

9.1 Leaving out variables

We apply the Louvain clustering procedure not only to the full composite index but also to each of its three underlying components and to variations where one component was omitted. This approach allows us to test whether the observed clustering patterns are stable and not solely driven by any dimension of the index. The results indicate that the composite index provides significantly greater explanatory power, yielding more logically consistent and detailed patterns. Omitting individual components leads to less nuanced clustering results. Specifically, excluding the IPD results in only two major blocs emerging, while removing VA reduces the distinction of the South American bloc and diminishes the diversity among African countries. Similarly, omitting LOR results in just two blocs substantially alters patterns in South America.

When clustering based on individual components alone, the results become even less differentiated. For example, using only IPD yields a simpler structure, as previously demonstrated. Using LOR alone detects four blocs which are primarily based on continental divisions, with Central Asia being grouped with Europe. This pattern fails to adequately explain international bloc-building dynamics. Clustering with the VA index alone results in only two major blocs, roughly corresponding to a division between advanced economies and emerging ones. This structure reflects more of a democracy-versus-non-democracy pattern, in line with the VA index's focus on political freedoms and rights within countries.

Overall, these variations – where one variable was omitted – tend to explain geographic similarities or represent a dichotomy between advanced and emerging economies. In contrast, the full composite index reveals a more sophisticated structure, shedding light on a rising "third bloc" that comprises countries from different continents with diverse political structures. This finding aligns more closely with the theoretical literature on emerging global realignments, further validating the robustness of the composite index.

9.2 Weighting

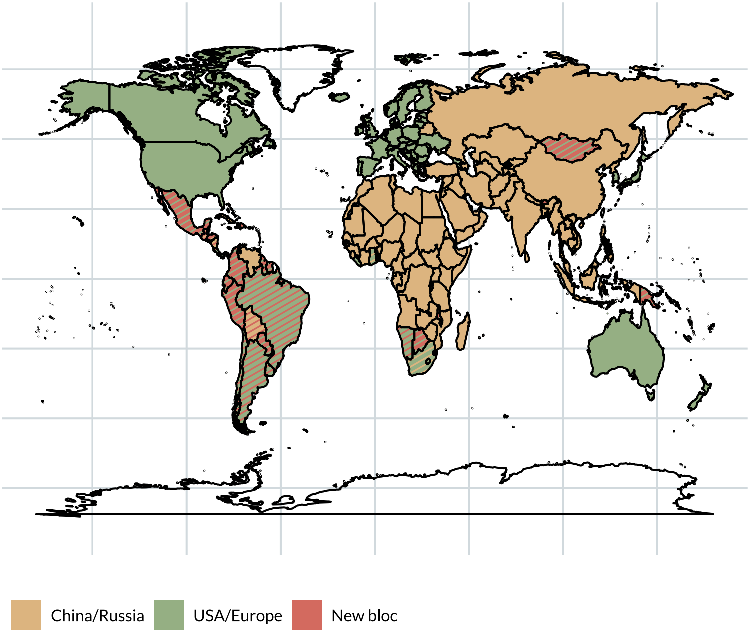
We conducted a sensitivity analysis by introducing random variation into the composite weights. Specifically, we generated 1,000 random weight combinations, restricting the values to a range between 0.2 and 0.6. This range was chosen to maintain a meaningful differentiation between the three components of the index; weights below 0.2 or above 0.6 would disproportionately emphasize or underemphasize individual dimensions.

For each of the 1,000 randomly generated weight sets, we recalculated the bilateral fragmentation values and performed corresponding network analyses. We then visualized the resulting community structures by assigning each country a color based on the group into which it was most frequently classified across all simulations. If a country exhibited ties to two groups, a secondary pattern was used to represent the second most common group affiliation as can be seen in figure A2.

The analysis revealed a high degree of stability, i.e. countries consistently grouped into the same communities across the majority of repetitions. Notably, countries already identified as core members of established blocs in the baseline network analysis remained consistently clustered. Variations were observed primarily among countries associated with the emerging "third bloc," where some instability in group membership occurred. This procedure adds value by demonstrating that the identified patterns are not artifacts of specific weight choices but persist across a broad range of plausible parameterizations. Overall, these findings support the robustness of the index construction and the main clustering results.

Figure A2

Political blocs in 2022 after the application of random weights
Results of 1,000 repetitions



Source: OeNB.

9.3 Bootstrapping

To further validate the robustness of our bilateral fragmentation index, we conducted a bootstrapping procedure for each year in our dataset. Bootstrapping does not make strong assumptions about the underlying distribution of the data, providing a flexible and reliable method for inference in our case.

For each year, we resampled the data with replacement, drawing *n* observations from the original *n* country-pair values available for that year. This procedure was repeated across 5,000 iterations to generate bootstrap distributions for key statistical properties: the mean, the mode and the standard deviation of the index.

From these bootstrap distributions, we constructed confidence intervals for each statistic and compared them with the actual observed values derived from the full sample. Across all years and all three statistical measures, the observed values consistently fell within the respective bootstrap confidence intervals, which can be seen in table A4. This result indicates that the statistical properties of the index are not driven by random variation or sample-specific anomalies but are instead robust features of the underlying data structure. This result strongly supports the stability and reliability of our index over time. It confirms that the index's descriptive patterns are not artifacts of random noise, but reflect substantive, consistent geopolitical developments.

Table A4

Annual index values with bootstrap confidence intervals

Mean, mode and standad deviation (SD) by year

	Bootstrap confidence intervals (2.5% - 97.5%)			Observed values		
	Mean	Mode	SD	Mean	Mode	SD
2003	0.558 – 0.563	0.526 – 0.568	0.178 – 0.182	0.560	0.557	0.180
2004	0.558 – 0.563	0.543 – 0.561	0.178 – 0.182	0.560	0.553	0.180
2005	0.565 – 0.57	0.557 – 0.584	0.177 – 0.18	0.568	0.575	0.179
2006	0.562 – 0.567	0.553 – 0.579	0.177 – 0.181	0.565	0.571	0.179
2007	0.564 – 0.57	0.552 – 0.57	0.179 – 0.182	0.567	0.562	0.181
2008	0.569 – 0.574	0.554 – 0.574	0.179 – 0.182	0.572	0.564	0.181
2009	0.564 – 0.57	0.552 – 0.572	0.182 – 0.185	0.567	0.560	0.183
2010	0.57 – 0.576	0.551 – 0.574	0.18 – 0.184	0.573	0.562	0.182
2011	0.569 – 0.574	0.554 – 0.573	0.181 – 0.185	0.572	0.564	0.183
2012	0.572 – 0.578	0.544 – 0.564	0.178 – 0.182	0.575	0.554	0.180
2013	0.577 – 0.582	0.548 – 0.579	0.179 – 0.182	0.580	0.566	0.180
2014	0.577 – 0.582	0.545 – 0.571	0.177 – 0.181	0.579	0.556	0.179
2015	0.572 – 0.578	0.53 – 0.579	0.179 – 0.183	0.575	0.568	0.181
2016	0.577 – 0.582	0.529 – 0.582	0.178 – 0.182	0.579	0.539	0.180
2017	0.58 – 0.585	0.53 – 0.549	0.178 – 0.181	0.583	0.536	0.180
2018	0.583 – 0.588	0.555 – 0.572	0.177 – 0.18	0.586	0.564	0.179
2019	0.587 – 0.592	0.543 – 0.581	0.177 – 0.181	0.589	0.559	0.179
2020	0.588 – 0.593	0.538 – 0.583	0.178 – 0.181	0.591	0.571	0.180
2021	0.589 – 0.594	0.543 – 0.567	0.178 – 0.182	0.592	0.554	0.180
2022	0.585 – 0.59	0.541 – 0.591	0.181 – 0.184	0.587	0.561	0.183

Source: OeNB.

9.4 Correlation analysis

The correlation matrix in table A5 shows that LOR behaves almost orthogonally to both the IPD and VA index – its pairwise correlations hover around −0.02 and −0.08 across the full dataset. In other words, embassy-level ties (LOR) offer a structural perspective quite distinct from political distance (IPD) or political value alignment (VA). Because LOR changes only gradually over time as shifts in foreign mission or embassy opening/closures are rare, its low correlation is not a cause for concern; rather, it confirms that LOR injects orthogonal, long-run diplomatic context into the index, anchoring it in the fixed network of state representation. In section 8.1 we have already seen how the exclusion of LOR leads to less reliable results. Thus, including it ensures that differences in diplomatic footprint as a proxy for long-term political engagement remain visible.

Meanwhile, IPD and VA capture more dynamic dimensions of domestic- and foreign-policy alignment; their intercorrelation of about 0.42 is well within the acceptable 0.3–0.8 range for composite indicators. In fact, the IPD shows the lowest item-total correlation with the final index at 0.42, while LOR reaches up to 0.72. All these item-index correlations fall into the recommended 40%–80% bracket, satisfying best practice: no variable is so weakly related as to be irrelevant, nor so highly correlated as to be redundant.

Finally, remember that a high item–index correlation simply indicates shared direction of movement, not an overweighting effect. Since we normalize and average each component equally, LOR's strong co-movement with the composite index does not amplify its influence; it confirms that its stable, structural signal lines up with short-term political shifts captured by IPD and VA.

Table A5

Pairwise correlations: variables and constructed index

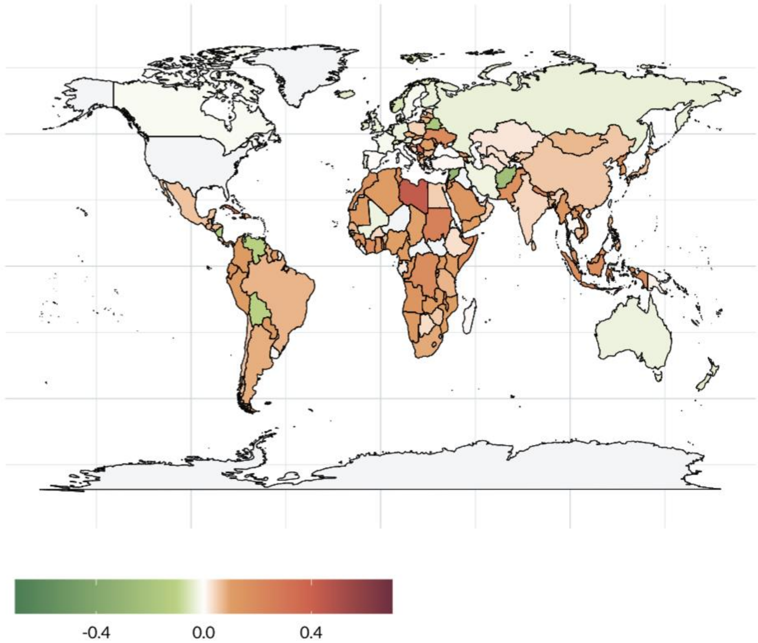
	Voice and Accountability	Level of Representation	UN votes IPD	Constructed index
Voice and Accountability	1.00			
Level of Representation	-0.02	1.00		
UN votes IPD	0.42	-0.08	1.00	
Constructed index	0.55	0.78	0.42	1.00

Source: OeNB.

Figure A3

Change in Index for USA between 2002 and 2022

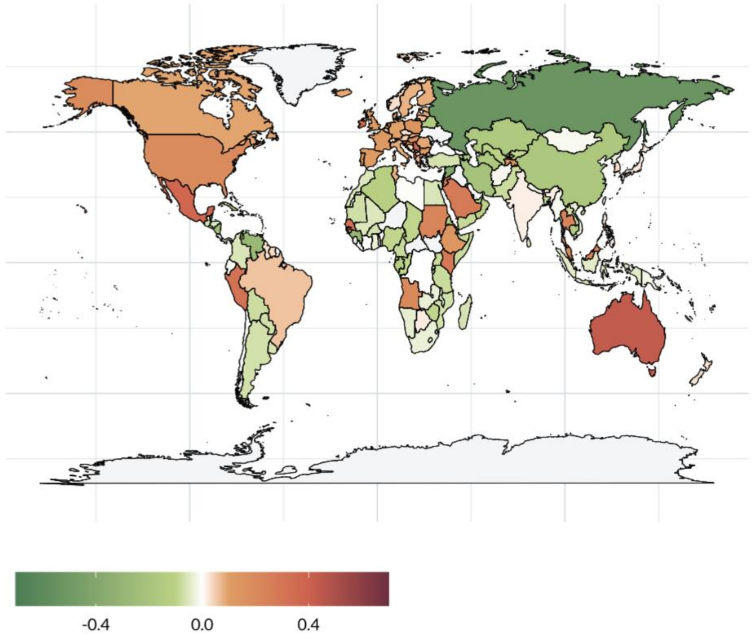
Values show the difference in political similarity



Source: OeNB

Figure A4

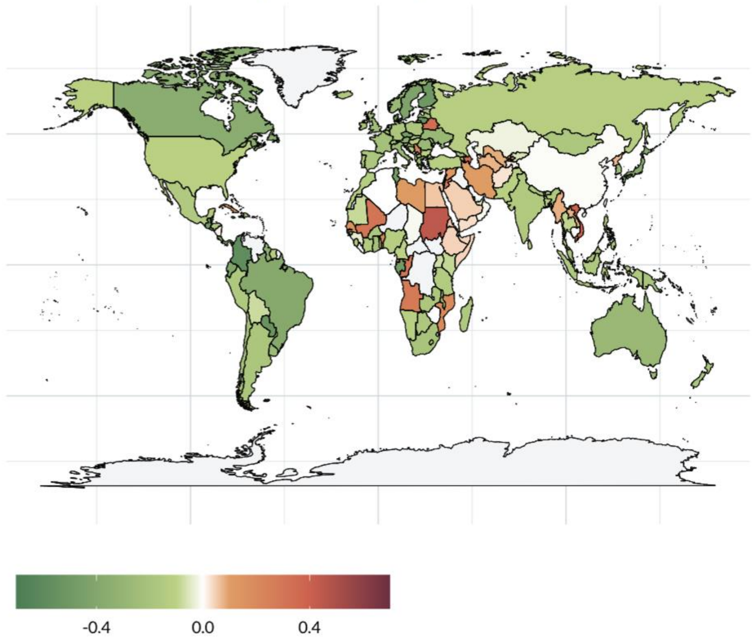
Change in Index for Ukraine between 2002 and 2022
Values show the difference in political similarity



Source: OeNB

Figure A5

Change in Index for Venezuela between 2002 and 2022
Values show the difference in political similarity



Source: OeNB

Chart A5

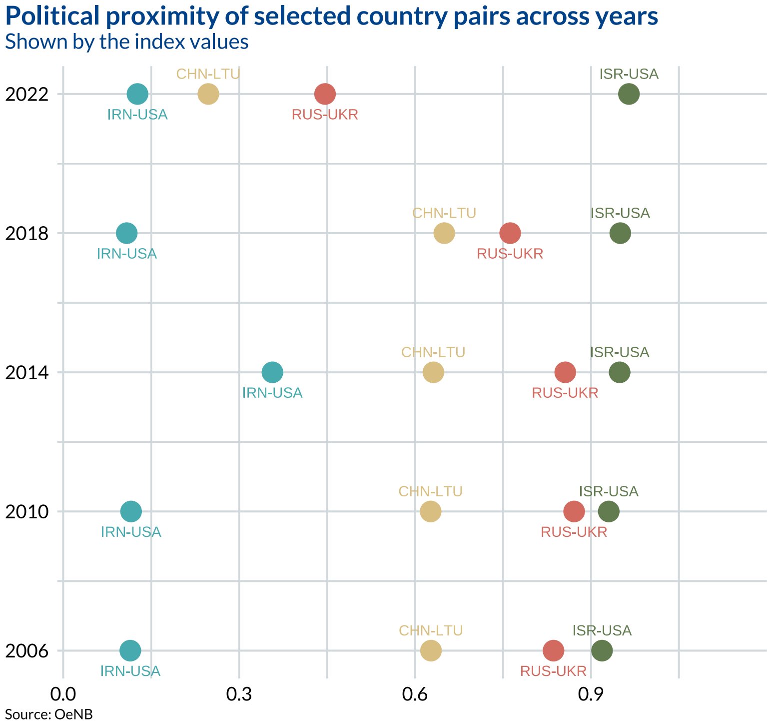


Chart A6

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