Is Geoeconomic Fragmentation that Bad? Measuring its Impacts on Bilateral Trade

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Abstract

This paper develops a multidimensional index of geoeconomic fragmentation (geofragmentation) and studies its effects on international trade. Using sixteen indicators spanning trade, financial, mobility, and political dimensions for up to 98 countries over 2000–2024, we estimate a bloc-restricted dynamic factor model that extracts a global fragmentation factor and four dimension-specific factors without imposing arbitrary weights. We then embed the index in a gravity model estimated via Poisson pseudo-maximum likelihood on annual bilateral trade flows from 2000 to 2023, classifying countries into U.S.-aligned, China-aligned, and non-aligned blocs based on UN General Assembly voting patterns. We find that geofragmentation has risen steadily since the global financial crisis and now approaches its post-September 11 peak, and that it significantly reduces bilateral trade, with inter-bloc flows contracting more than intra-bloc flows. Non-aligned countries, however, increase trade with both blocs during high-fragmentation episodes, acting as connectors that partially offset decoupling. These results suggest that fragmentation is reconfiguring, rather than reversing, global economic integration.

Keywords: Geoeconomic fragmentation, dynamic factor model, gravity model, geopolitical blocks.

JEL Classification: F02, F51, F60, C33, F14.

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1. Introduction

For decades after the Cold War, globalization marked an unprecedented period of economic integration, characterized by trade liberalization, technological diffusion, and increased labor mobility. This era promoted strong cross-border economic relationships driven by efficiency and comparative advantage. However, recent geopolitical tensions are challenging this trajectory, raising the possibility of a new phase marked by geoeconomic fragmentation (geofragmentation). The escalating U.S.–China trade disputes, the U.K.'s exit (Brexit) from the European Union, the fallout from Russia's invasion of Ukraine, and the conflict in the Middle East have all catalyzed a shift in international economic dynamics, highlighting the rising importance of strategic competition among major powers.

Despite the persistent stability in trade metrics (such as the share of global trade in GDP), these developments suggest that the global economic landscape is undergoing profound changes. Rather than a simple decline in globalization, we may be witnessing a reorganization of economic interactions, with trade and investment increasingly directed toward politically aligned partners. Understanding and quantifying this complex geofragmentation poses significant challenges, demanding a multidimensional approach to capture shifts in trade policies, financial flows, and geopolitical tensions.

Despite recent advances in understanding geofragmentation, significant gaps persist in the empirical literature. Most studies tend to focus on a limited range of indicators, primarily examining trade or geopolitical risk, without accounting for the broader spectrum of economic domains that fragmentation may simultaneously impact. Furthermore, there is a lack of empirical research quantifying the macroeconomic effects of fragmentation shocks across various countries and geopolitical blocs within a cohesive framework. This paper addresses these issues by introducing a multidimensional geofragmentation index that aggregates indicators across trade, finance, mobility, and political dimensions of fragmentation. Using a dynamic factor model, we estimate the index without imposing arbitrary weights, allowing the data to reveal the relative significance of each indicator while capturing the shared dynamics of fragmentation. We then use the index to estimate its effect on global trade patterns using a gravity model.

We recognize that some indicators capture policy drivers of fragmentation (e.g., sanctions, trade restrictions, geopolitical risk), while others reflect economic manifestations of the process (e.g., trade, investment, and mobility outcomes). Our objective is not to identify a single causal mechanism but to characterize geofragmentation as a broad latent phenomenon encompassing both policy actions and observable economic reconfigurations.

Our analysis consists of two main steps. First, we construct a geofragmentation index using sixteen indicators that reflect various aspects of global geoeconomic fragmentation, categorized into trade, financial, mobility, and political dimensions. A dynamic factor model isolates both a global fragmentation factor and specific dimension factors to track changes over time. Second, we investigate shifts in international trade patterns using a gravity-model framework, examining how trade flows align with geopolitical blocs defined by countries' political alignments in the UN General Assembly, categorizing nations into U.S.-aligned, China-aligned, and non-aligned groups to elucidate the influence of geopolitical dynamics on trade relationships.

Our results reveal a sustained rise in geofragmentation since the global financial crisis, as captured by our multidimensional index. Gravity model analysis indicates that trade flows are curtailed by geofragmentation, with inter-bloc trade (between geopolitically distant groups) declining relative to intra-bloc trade, fostering more segmented global networks. We also find that non-aligned countries play a pivotal role as trade connectors amid fragmentation, channeling flows between rival blocs and mitigating direct decoupling. These patterns suggest supply chains are rerouted through neutral partners during heightened tensions. Taken together, these findings contribute to the growing empirical evidence that geopolitical tensions are reshaping the global economy.

More broadly, our findings suggest that geofragmentation should not be interpreted as the end of globalization but rather as a reconfiguration of global economic networks, characterized by stronger intra-bloc linkages and an increasing role for non-aligned economies as trade connectors.

A growing literature examines the economic consequences of geofragmentation and the increasing role of geopolitical tensions in shaping global economic integration. Recent contributions document that geopolitical alignment is increasingly associated with patterns of trade, investment, and financial flows, suggesting economic linkages are reorganizing along geopolitical lines (Blanga-Gubbay and Rubínová, 2023; Campos et al., 2023; Hakobyan et al., 2023; Gopinath et al., 2025; Parente and Moreau, 2024). These studies emphasize that fragmentation may undermine the efficiency gains from global integration and yield heterogeneous effects across countries, depending on their economic structures and geopolitical positions.

Methodologically, the literature on geofragmentation and trade policy can be organized into three complementary strands: structural trade models that quantify welfare costs, firm and trade-level studies that document reallocation patterns, and macroeconomic approaches that trace broader transmission mechanisms.

A first strand assesses the costs of fragmentation using structural trade models and general equilibrium frameworks. These papers simulate scenarios in which trade barriers, investment costs, or other cross-border frictions rise between geopolitical blocs, typically finding substantial welfare losses, reduced international trade, lower productivity from diminished openness, weaker technology diffusion, and eroded economies of scale (Campos et al., 2023; Hakobyan et al., 2023; Parente & Moreau, 2024; Baur et al., 2025). While providing key theoretical insights into disrupted global value chains and reduced specialization, these calibrated exercises often leave open questions about empirical trends in observed economic data.

A second strand offers empirical evidence from detailed trade and firm-level data, focusing on events like U.S.–China trade tensions, Brexit, and other shocks. These works document trade diversion, supply-chain reorganization, and shifts in investment patterns, with firms reallocating sourcing to third countries acting as intermediaries or "connector economies" that link production networks across blocs. Rather than uniform trade declines, tensions prompt reallocation toward politically aligned partners (Blanga-Gubbay and Rubínová, 2023; Fajgelbaum et al., 2020; Freund et al., 2024; Bloom et al., 2019; Utar et al., 2023).

A third strand investigates macroeconomic consequences using vector autoregressions, panel VARs, and local projections. These studies show geopolitical shocks propagate fluctuations in output, inflation, and financial conditions via heightened uncertainty, volatility, and disruptions to trade and investment. Beyond bilateral flows, fragmentation affects economies through broader transmission mechanisms (Ginn and Saadaoui, 2025; Fernandez-Villaverde et al., 2024; Iacoviello et al., 2024, Cerdeiro et al., 2022).

Finally, our study relates to work measuring fragmentation as a multidimensional phenomenon, such as Fernández-Villaverde et al. (2024). However, our research differs in methodology, the sample of countries, the time period, and the specific indicators used to construct the geofragmentation index. Related work explores international linkages through broader measures of globalization (LaBelle et al., 2023) and compares current fragmentation dynamics with historical events such as the Cold War (Gokmen, 2017; Gopinath et al., 2025). Our study adds to the empirical evidence on how geopolitical tensions influence international trade patterns and shows the emergence of non-aligned economies as connector countries that partially offset the effects of geopolitical fragmentation.

The remainder of the paper proceeds as follows. Section 2 presents the data and sixteen indicators across trade, financial, mobility, and political dimensions used to construct the geofragmentation index. Section 3 details the methodology, including the dynamic factor model, and gravity models. Section 4 reports the results on fragmentation evolution and impacts. Section 5 concludes.

2. Data

We rely on 16 indicators to capture the process of geofragmentation at the global level, with country coverage reaching up to 98 economies depending on the indicator. We list those indicators in the Table 1. This comprehensive approach aims to develop a robust measure, as no single metric adequately captures the multifaceted nature of geofragmentation (Fernández-Villaverde et al., 2024).

We divide the 16 variables into four dimensions of geofragmentation. The first five variables correspond to the trade fragmentation dimension, while variables 6–9 capture financial fragmentation. Variables 10–12 relate to mobility fragmentation, reflecting restrictions on the cross-border movement of factors. Finally, variables 13–16 measure political fragmentation. This disaggregation enables a nuanced analysis of how different facets of geofragmentation, both independently and collectively, influence international trade and macroeconomic performance[4].

In Table 1, we present the summary statistics of our data sample. The dataset includes 16 variables mentioned previously. These statistics cover the period between January 2000 and December 2024. This extensive temporal coverage allows for a robust analysis of fragmentation trends and their evolving impacts over nearly a quarter-century.

Building on these variables, we now turn to the four dimensions of our geofragmentation measure. Most of the literature studies fragmentation primarily through the lens of trade. Indeed, the underlying idea is that, as geopolitical tensions intensify, countries increasingly take geopolitical considerations into account when forming trade relationships, rather than relying solely on economic efficiency. This dynamic has been particularly evident during major geopolitical shocks, including the U.S.–China trade war, Brexit, and, more recently, the war in Ukraine[5]. However, such geopolitical realignments demand a multifaceted approach to measurement, extending beyond traditional trade metrics to encompass financial flows, migration, and patent transfers, as these factors collectively delineate the contours of evolving geoeconomic blocs (Airaudo et al., 2025).

4 We provide a detailed description of the construction of each variable in the Appendix. The dimensional classification follows Fernández-Villaverde et al. (2024), although our selection of specific variables differs.

5 See Alfaro and Chor (2023); Dang et al. (2023); Freund et al. (2024); Kahn et al. (2024); Bloom et al. (2019); and Gopinath et al. (2025), among others.

Table 1. Summary statistics of the Indicators in the DFM

Category	Indicator	Frequency	Sample	Mean	Standard Deviation
	Trade Openness	Quarterly	2000Q1-2024Q4	0.52	0.05
	Non Tariff Measures - GTA	Quarterly	2010Q1-2024Q4	29.55	18.42
Trade Fragmentation	*Tariff Measures - GTA*	Quarterly	2010Q1-2024Q4	2.41	1.58
	Temporary Trade Barriers	Quarterly	2010Q1-2024Q4	59.34	18.03
	Tarif	Annual	2000-2024	4.1	0.39
	FDI Ratio	Quarterly	2000Q1-2024Q4	0.02	0.01
Financial Fragmentation	*FFB Ratio*	Quarterly	2000Q1-2024Q4	0.03	0.02
	Capital Control Measures	Annual	2000-2019	0.28	0.06
	FDI and Capital Measures - GTA	Quarterly	2010Q1-2024Q4	0.92	0.93
	Migration Flow	Annual	2000-2023	-0.53	0.22
Mobility Fragmentation	*Patent Flows**	Annual	2000-2019	17.6	51.11
	Migration Measures - GTA	Quarterly	2010Q1-2024Q4	0.57	0.51
	Geopolitical Risk	Quarterly	2000Q1-2024Q4	105	32.73
Geopolitical Fragmentation	*Geoeconomic Connectedness*	Annual	2000-2024	0.58	0.05
	Geoeconomic Vulnerability	Annual	2000-2024	1.25	0.06
	Number of Sanctions	Annual	2000-2023	37.88	31.55

Note: We report the mean and standard variation of the series used in the estimation of the DFM model. Patent flows is on thousands.

The trade dimension is constructed to identify manifestations of global trade disintegration. It incorporates five variables delineating diverse facets of international trade interconnectedness. Foremost, the trade-to-GDP ratio gauges overall global economic openness as a proxy for globalization. Next, we draw on indicators from the Global Trade Alert (GTA) database tracking tariff and non-tariff barriers. This bifurcation reflects emerging evidence that policymakers favor non-tariff instruments to reorient trade streams and safeguard domestic sectors. Tariffs, however, remain critical impediments to cross-border trade. Thus, we encompass both tariff and non-tariff measures from Global Trade Alert, as well as the World Trade Organization's aggregate tariff metric.

A parallel strand of the literature examines the role of cross-border investment flows in geofragmentation. The premise is that geopolitical affinities now steer allocations of foreign direct investment and portfolio capital. Governments and firms thereby pivot investments toward aligned partners, diminishing engagements with rivals. This dimension employs FDI and capital-control variables from the GTA database. Although overlapping with trade effects, such as FDI and financial curbs, are deliberately leveraged to reconfigure capital and financial geographies.

The mobility dimension captures geofragmentation via shifts in production-factor mobility. Migration restrictions curtail international labor flows, while knowledge-diffusion barriers constrain the transfer of technological capabilities. Migration flows herein proxy labor mobility, signaling openness to cross-border workforce movement. International patent flows, meanwhile, approximate the dissemination of technological knowledge. These are supplemented by GTA migration policy indicators, which document state interventions that influence human mobility and trade.

Finally, a growing literature highlights the macroeconomic consequences of geopolitical risk and political tensions for the global economy, whereby shocks fracture trade-finance ties, amplify uncertainty, and undermine cooperative integration[6]. We augment this political dimension with geoeconomic connectedness and vulnerability metrics, quantifying trade with politically congruent partners. We further incorporate cross-country sanctions counts, embodying economic levers in geopolitical contention. Together, these indicators allow us to account for the political drivers of fragmentation and their potential impact on global economic integration. This comprehensive framework for measuring geofragmentation enables granular analysis of its effects on global trade and macroeconomic aggregates.

3. Methodology

Our methodology consists of two parts. First, we use a dynamic factor model (DFM) and the 16 indicators about geoeconomic fragmentation to create global factors summarizing the aggregate dynamic of the different dimensions of geofragmentation. This framework allows us to represent geofragmentation as a multidimensional and unobserved process whose evolution is inferred from the joint behavior of a large set of indicators. Next, examine how fragmentation reshapes international trade patterns using a gravity model framework. This comprehensive approach, leveraging dynamic factor models, and gravity models, provides a robust quantitative assessment of geofragmentation's intricate effects on bilateral trade flows.

[6] See for example Mulabdic and Yotov, (2025); Iacoviello et al. (2025); Ginn and Saadaoui (2025); Mignon and Saadaoui, (2024); Yilmazkuday, (2026).

3.1. A Dynamic Factor Model for Geofragmentation

Geofragmentation is not directly observable and therefore cannot be measured using a single empirical indicator. Existing definitions remain conceptually broad. Following Fernández-Villaverde et al. (2024), we treat geofragmentation as a latent process inferred from observable economic and political indicators. Specifically, we model geofragmentation as a set of latent factors capturing different dimensions of the phenomenon, together with a global factor summarizing its aggregate dynamics. This framework allows us to represent geofragmentation as a multidimensional and unobserved process whose evolution is inferred from the joint behavior of a large set of indicators. The factor should be interpreted as a reduced-form measure of fragmentation rather than a structural measure of geopolitical shocks.

More specifically, we estimate a bloc-restricted Dynamic Factor Model (DFM), following the empirical strategy of Centorrino et al. (2025) and building upon the methodological contributions of Bańbura and Modugno (2014) and Bork (2009). The model encompasses four categories of variables (trade fragmentation, financial fragmentation, mobility fragmentation, and political fragmentation) alongside a global fragmentation factor, all estimated jointly. Each category is driven by a category-specific latent factor, augmented by a global factor that loads on all variables. This specification facilitates the identification of common dynamics underlying geofragmentation, while accommodating idiosyncratic fluctuations within each dimension.

Dynamic factor models have been extensively employed in macroeconomic analysis since the seminal contributions of Sargent and Sims (1977) and Gweker (1977). They play a prominent role in nowcasting, forecasting, and policy analysis by efficiently handling large datasets, reducing dimensionality, and extracting underlying signals from noisy indicators. In the present application, we utilize 16 observable variables that furnish informative signals of geofragmentation. The dynamic factor model explicitly accommodates trending behavior and structural co-movements across the series.

Following Centorrino et al. (2025), we seasonally adjust all variables and define $y_t = [x_t^T, x_t^F, x_t^M, x_t^P]'$, in which x_t^T is the vector where we collect the trade variables, x_t^F the financial variables, x_t^M the mobility variables and x_t^P the political variables.

The model takes the form:

$$y_t = \phi(t) + \Lambda f_t + \varepsilon_t \tag{1}$$

Where $\phi(t) = [\phi^T(t), \phi^F(t), \phi^M(t), \phi^P(t)]'$ is a vector of deterministic nonlinear time trends, $f_t \in \mathbb{R}^r$ represents the r factors, Λ the matrix of factor loadings, and ε_t a stationary vector of disturbances, uncorrelated with f_t and $\phi(t)$.

We assume the factors follow a stationary VAR(1) process:

$$f_t = Af_{t-1} + Qu_t \tag{2}$$

Where $u_t \sim N(0, I_r)$.

Because we assume the factors are stationary, they do not exhibit deterministic or stochastic trends in the baseline specification. However, following Centorrino et al. (2025), we also consider a specification with trended factors. We begin by assuming:

$$f_t = \phi_F(t) + f_t^* \tag{3}$$

Where $\phi(t)$ is a factor-specific trend, and,

$$y_t = \Lambda\phi_F(t) + \Lambda f_t^* + \varepsilon_t \tag{4}$$

Which implies $\Lambda\phi_F(t) = \phi(t)$. Thus, we can estimate a de-trended version of the model as:

$$y_t^* = \Lambda f_t^* + R\varepsilon_t \tag{5}$$

$$f_t^* = Af_{t-1}^* + Qu_t \tag{6}$$

Where we assume R and Q are diagonal and collect the variances of the measurement equation and of the factor's equation.

The estimation follows these steps. First, we de-trend the observable variables, and we fit a local quadratic regression in which the least-squares objective function is weighted by the inverse of the distance between points. We assume a longer-term trend, noting that the estimated trend reverses around 1.5 years. Then, we estimate the model in (5) and (6) using the expectation-maximization (EM) algorithm as described in Bańbura and Modugno (2014). This algorithm is consistent with observations with missing data, allowing us to use data at different frequencies and start on different dates. Following Bork (2009), we impose a block restriction on Λ as follow:

$$\Lambda = \begin{bmatrix} \lambda_{g,T} & \lambda_T & 0 & 0 & 0 \\ \lambda_{g,F} & 0 & \lambda_F & 0 & 0 \\ \lambda_{g,M} & 0 & 0 & \lambda_M & 0 \\ \lambda_{g,P} & 0 & 0 & 0 & \lambda_P \end{bmatrix} \tag{7}$$

This specification ensures that global factor loadings are applied across all observable variables, effectively capturing the common dynamics underlying geofragmentation. In contrast, local factors are exclusively associated with their respective subsets of variables, thereby isolating group-specific co-movements and mitigating the risk of cross-group contamination. This block structure not only enhances the economic interpretation of the factors but also refines identification by constraining the loading matrix.

The joint likelihood of y^* and f^* is written as

$$l(y^*, f^* | \Lambda, \mathrm{A}, \mathrm{R}, \mathrm{Q}) = \Pi_{t=1}^{T} f_{\varepsilon|R}(y_t^* - \Lambda \mathrm{f}_t^*) f_{u|Q}(f_t - Af_{t-1}) \tag{8}$$

Which, following Bork et al. (2008), can be written as:

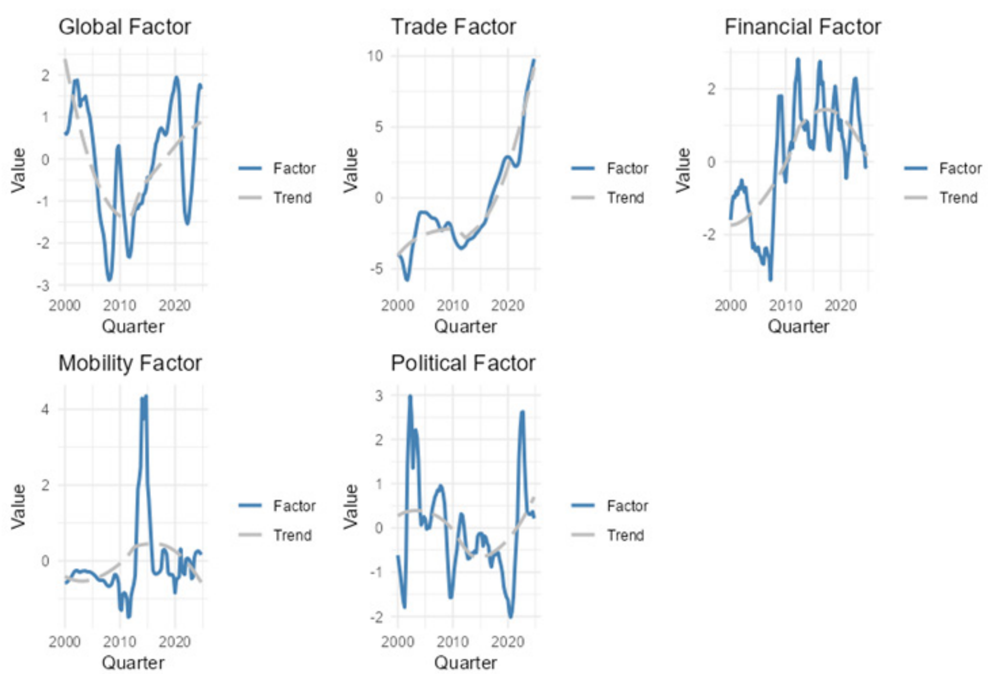
$$\begin{aligned} -2lnl(y^*, f^* | \Lambda, \mathrm{A}, \mathrm{R}, \mathrm{Q}) \\ = Tln(R) + \sum_{t=1}^{T} (y_t^* - \Lambda \mathrm{f}_t^*) R^{-1} (y_t^* - \Lambda \mathrm{f}_t^*)' + Tln(Q) \\ + \sum_{t=1}^{T} (f_t^* - Af_{t-1}^*) Q^{-1} (f_t^* - Af_{t-1}^*)' \end{aligned} \tag{9}$$

The expectation-maximization (EM) algorithm works as follows. We begin by initializing the factors f_t^* using principal components. Then, we estimate the parameters $\Lambda, \mathrm{A}, \mathrm{R}$ and Q by maximizing the log-likelihood in (9), adding the restriction on the factor loadings Λ. With this estimation, we run a Kalman filter and obtain new estimates for the factor f_t^*. We run this iteration until the log-likelihood converges.

We recover the trended factor f_t by first calculating its associated trend component. Specifically, given the estimated loading matrix Λ and the vector of observable trends $\phi(t)$, obtained from the local quadratic regression, we can recover the factor trend as $\phi_F(t) = (\Lambda'\Lambda)^{-1}(\Lambda'\phi(t))$, and the final trended factors as $f_t = \phi_F(t) + f_t^*$.

Figure 1 presents the estimates of the five latent factors. The global geofragmentation factor, which loads on all observed variables, constitutes the central object of interest in our analysis. The remaining four factors capture trade, financial, mobility, and political fragmentation, respectively. Although these dimension-specific factors provide meaningful information about the evolution of particular channels, their relative strength depends on the covariance structure of the underlying indicators. Consequently, we interpret them primarily as controls that isolate the common global component from domain-specific fluctuations. This comprehensive index provides a more nuanced understanding of geofragmentation by integrating diverse indicators, thereby mitigating biases inherent in univariate measures and aligning with methodologies that account for the multifaceted nature of global economic integration (Fernández-Villaverde et al., 2024).

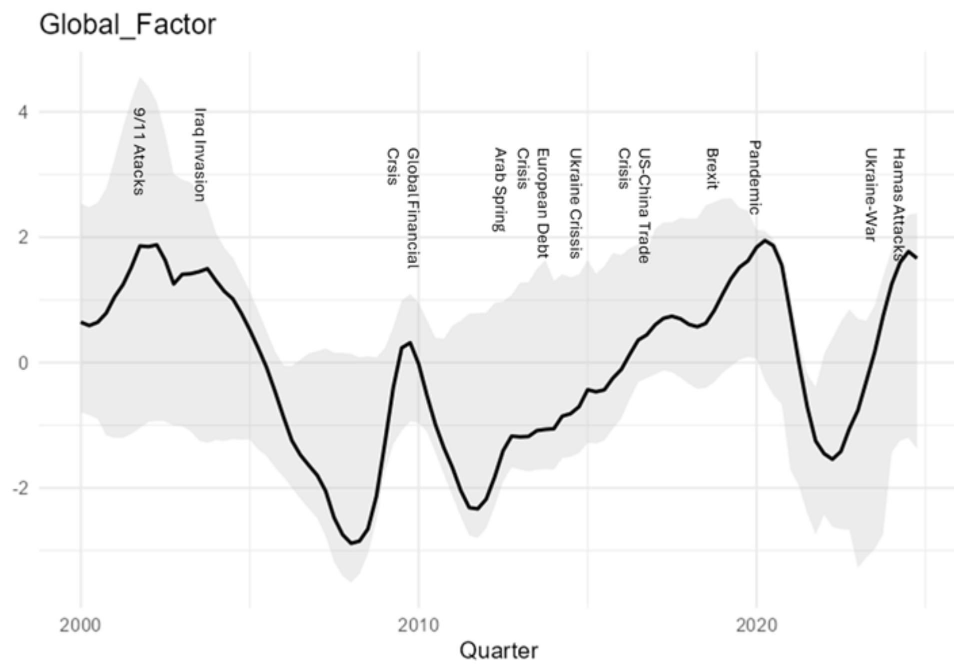
Figure 1. Estimated geofragmentation factors



Note: Factors estimates with their estimated trends.

Figure 2 presents the global geofragmentation factor alongside a narrative overlay of major geopolitical events over the past two decades. The co-movement between the estimated factor and key geopolitical episodes is economically intuitive. While geofragmentation rises following the outbreak of the war in Ukraine, the factor reaches its historical peak around the September 11, 2001, events, rather than in the most recent period. In the early 2000s, when globalization forces remained relatively strong, the factor followed a downward trajectory. This pattern reversed around the 2008–2009 global financial crisis, which triggered a pronounced spike. Over the 2011–2019 period, often characterized by gradual de-globalization and rising geopolitical tensions, the factor exhibited a sustained upward trend. The global geofragmentation factor, therefore, offers a granular perspective on the fluctuating landscape of international economic integration, reflecting the cumulative impact of various geopolitical stressors and policy shifts.

Figure 2. Estimated global geofragmentation factor



Note: The chart displays the global geofragmentation factor alongside major geopolitical events, and its 90% confidence interval. The confidence interval is constructed using a bootstrap procedure. Specifically, we bootstrap the cyclical components in equation (6), recover the corresponding coefficients, and reconstruct the bootstrapped trend and cyclical components of the factors. The estimates are based on 1,000 bootstrap replications.

Although recent developments have reinforced the perception that the global economy is entering a markedly fragmented phase, our estimates indicate that current geofragmentation levels remain comparable to, and not substantially above, those observed in the immediate aftermath of September 11. Whether the index surpasses its historical maximum will depend on the persistence and escalation of ongoing geopolitical tensions. However, the escalating frequency and intensity of geopolitical events in recent years suggest a growing trend towards heightened instability, as evidenced by notable peaks during conflicts such as those in Ukraine and the Middle East (Zhyvko, 2024). This underscores the critical need for a robust and adaptable framework to quantify geopolitical fragmentation, particularly one that can differentiate between transient shocks and sustained shifts in the global economic architecture (Fernández-Villaverde et al., 2024).

3.2. Gravity Model

We also examine the effects of geofragmentation on trade networks using standard gravity models. These assess whether fragmentation alters the structure of bilateral trade flows through four alternative specifications estimated on annual data. The models incorporate traditional determinants of bilateral trade, such as economic size and geographic distance, alongside variables capturing the intensity of geofragmentation between trading partners. In particular, we have the following specifications:

$$Y_{sdt} = \beta_1 geofrag_t + \beta X_{sdt} + \varepsilon_{sdt} \tag{10}$$

$$Y_{sdt} = \beta_1 highgeofrag_t + \beta X_{sdt} + \varepsilon_{sdt} \tag{11}$$

$$\begin{aligned} Y_{sdt} = {} & \beta_1 highgeofrag_t \times betweenbloc_{sdt} + \beta_2 highgeofrag_t \times non\_aligned_{sdt} \\ & + \beta X_t + \varepsilon_{sdt} \end{aligned} \tag{12}$$

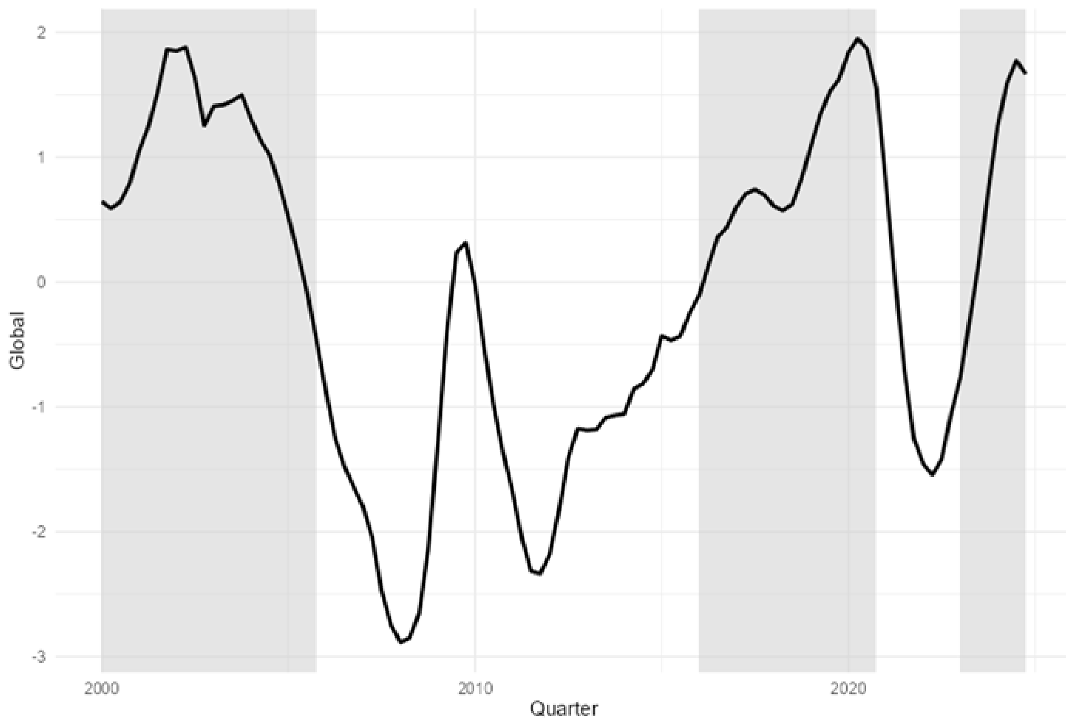
$$\begin{aligned} Y_{sdt} = {} & \beta_1 highgeofrag_t \times geodist_{sdt} + \beta_2 highgeofrag_t \times non\_aligned_{sdt} + \beta X_{sdt} \\ & + \varepsilon_{sdt} \end{aligned} \tag{13}$$

where Y_{sdt} denotes the exports from origin country s, to destination country d in period t; geofrag represents the global geofragmentation index, while $highgeofrag_t$ is a dummy variable identifying periods of high geofragmentation (see Figure 3). The variable $betweenbloc_{sdt}$ indicates if the trade flow occurs between countries that are in the same bloc and $non\_aligned_{sdt}$ indicates whether the trade flow occurred with a non-aligned country . The variable $geodist_{sdt}$ is the geopolitical distance between the country-pair s and d in year t , we calculate it as the absolute distance between their ideal points estimation, following Bailey et al. (2017). We also examine how high geofragmentation affects trade by analyzing its interaction with the inter-bloc and non-aligned dummies. Specifically, we assess whether inter-bloc trade contracts increase and how trade with non-aligned countries is impacted during high geofragmentation episodes. Additionally, we investigate the influence of geopolitical distance on trade between geopolitically distant countries in these periods. The vector (X) includes standard gravity controls such as distance between capitals, country contiguity, common colonial history, shared languages, and participation in regional trade agreements. Some specifications also include fixed effects for origin, destination, and year.

[7] We construct this indicator by standardizing the geofragmentation index and assigning a value of one when the standardized index exceeds one.

[8] See Annex B for details about blocs' classification.

Figure 3. Global geofragmentation factor and high-geofragmentation periods



Note: High-geofragmentation periods are defined by first standardizing the quarterly global geofragmentation factor and then constructing an annual indicator as the simple average of the four quarters. Years in which the index exceeds one are classified as high-geofragmentation perods. Shaded area corresponds to high-geofragmentation periods.

We employ the gravity model estimated via Poisson pseudo-maximum likelihood (PPML), as proposed by Silva and Tenreyro (2006), using annual data from 2000 to 2023. To study heterogeneity across country groups, we further disaggregate the model into distinct subsamples: advanced economies, emerging economies (EMEs), EMEs excluding China, the U.S.-led bloc, the China-led bloc, and the non-aligned bloc . This granular analysis facilitates a more nuanced understanding of how disparate levels of economic development and geopolitical alignment affect the vulnerability of trade relationships to fragmentation shocks.

[9] See Appendix B for the bloc definitions.

4. Gravity Results

To dissect the mechanisms through which geofragmentation impacts trade flows, we employ a gravity model framework. As we mentioned in the methodology, we use different measures of geofragmentation and their interaction in the gravity model framework to identify changes in trade patterns worldwide. This allows for a granular assessment of how various dimensions of fragmentation, such as those related to geopolitical alignment or trade policy uncertainty, differentially influence bilateral trade flows and trade elasticity. Specifically, we integrate our constructed measures of geo-economic fragmentation into an augmented gravity equation to quantify their impact on trade volumes, controlling for standard gravitational determinants.

This approach enables the isolation of specific fragmentation effects from other trade determinants, thereby enhancing the precision of impact assessments on trade resilience and diversification strategies. Table 2 (first two regressions) presents the results of our geofragmentation measures, without controls, from the standard gravity model, to identify their impact on bilateral trade flows before estimating the amplified gravity model. Results show that geofragmentation, as proxied by the global geofragmentation index, negatively impacts trade flows across the full sample and different country subsamples. In this sense, geofragmentation is bad news for trade.

We also examine whether episodes of high geofragmentation are associated with changes in trade flows. An increasing body of evidence indicates that direct trade relationships between the United States and China are gradually being replaced by indirect connections through third countries. Notably, countries that have gained the most in their share of U.S. imports have also seen significant increases in their exports to China (Alfaro and Chor, 2023; Dang et al., 2023; Freund et al., 2024; Utar et al., 2023; Kahn et al., 2024).

As mentioned in Section 3, we categorize countries into three geopolitical groups: a U.S.-aligned bloc, a China-aligned bloc, and a non-aligned group. The non-aligned group is not closely associated with either major power and may serve as intermediaries during periods of heightened fragmentation, potentially connecting the two rival blocs.

To check this possibility, we enhance the baseline specifications with two additional interaction terms. The first term interacts the high-geofragmentation dummy with an indicator for trade occurring between countries from different blocs. The second term interacts the high-geofragmentation dummy with an indicator for trade involving at least one non-aligned country (third regression Table 2). This empirical approach is similar to the methodology used by Gopinath et al. (2025), though their analysis interacts these variables with a post-conflict dummy rather than a fragmentation indicator. The findings indicate that bilateral trade between opposing geopolitical blocs declines substantially during episodes of heightened geofragmentation. In contrast, trade involving non-aligned countries reveals a more nuanced dynamic, occasionally fulfilling a mitigating function, which aligns with their role as "connector" economies. This pattern indicates that, although geopolitical frictions may foster partial decoupling, non-aligned countries can leverage their neutral positioning to mediate trade exchanges between rival blocs, thereby serving as intermediaries in the global supply chain.

We also evaluate another specification that includes the interaction between the high geofragmentation dummy and the geopolitical distance between importer and exporter countries. Findings show that increased geopolitical distance significantly amplifies the negative impact of fragmentation on bilateral trade flows, substantiating the hypothesis of a geoeconomic division (fourth regression Table 2).

Table 2. Gravity results: effect of geofragmentation on bilateral trade (no controls)

	(1) All Countries	**(2) Advanced**	**(3) EMEs**	**(4) EMEs no China**	**(5) Bloc 1**	**(6) Bloc 2**	**(7) Bloc 3**
Variable							
geofrag	*-0.0358****	-0.0343***	-0.0426***	-0.0522***	-0.0319***	-0.0428***	-0.0432***
	(0.0028)	(0.0026)	(0.0062)	(0.0047)	(0.0021)	(0.0078)	(0.0055)
Fixed Effects							
Origin FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes
Observations	*543544*	263764	279780	272386	198989	148266	176264

	(1) All Countries	**(2) Advanced**	**(3) EMEs**	**(4) EMEs no China**	**(5) Bloc 1**	**(6) Bloc 2**	**(7) Bloc 3**
Variable							
high_dummy	*-0.2549****	-0.2385***	-0.3295***	-0.3833***	-0.2171***	-0.3237***	-0.3194***
	(0.0204)	(0.0193)	(0.0360)	(0.0292)	(0.0169)	(0.0427)	(0.0459)
Fixed Effects							
Origin FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes
Observations	*543544*	263764	279780	272386	198989	148266	176264

	(1) All Countries	(2) Advanced	(3) EMEs	(4) EMEs no China	(5) Bloc 1	(6) Bloc 2	(7) Bloc 3
Variable							
diffbloc_high	*-0.6463****	-0.1322***	-0.0834	-0.0178	-0.1132***	-0.0790	0.1371***
	(0.1237)	(0.0430)	(0.1322)	(0.1476)	(0.0368)	(0.0980)	(0.0489)
non_aligned_high	*0.2778****	0.0626	-0.0333	-0.0413***	0.0374**	-0.0118	-0.4353***
	(0.0738)	(0.0541)	(0.0802)	(0.0097)	(0.0183)	(0.0553)	(0.0366)
Fixed Effects							
Origin FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	*Yes*	Yes	Yes	Yes	Yes	Yes	
Observations	*546770*	262826	283944	276743	199887	170290	176593

	(1) All Countries	(2) Advanced	(3) EMEs	(4) EMEs no China	(5) Bloc 1	(6) Bloc 2	(7) Bloc 3
Variable							
dist_high_dummy	*-0.4489****	-0.4037**	-0.6225***	-0.7858***	-0.4221**	-0.5070***	-0.7748***
	(0.0503)	(0.1626)	(0.0772)	(0.1186)	(0.1650)	(0.1074)	(0.2910)
Fixed Effects							
Origin x Year FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes
Destination x Year FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes
Observations	*546770*	262825	283942	276741	199887	170280	176585

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

We now estimate the extended gravity model that includes our geofragmentation measures, along with a comprehensive set of standard controls. Tables 3 and 4 present these results, which confirm a statistically significant and economically meaningful negative effect of geofragmentation on bilateral trade volumes. This effect remains evident even after accounting for these controls. Subsample analysis indicates that the impact of geofragmentation is more detrimental to emerging countries than to advanced ones. These findings highlight the widespread and disruptive impact of geofragmentation on global trade dynamics. They demonstrate how this global phenomenon systematically alters trade patterns by increasing effective trade costs, particularly between geopolitically distant partners. This amplified impact is consistent with research demonstrating that increased geopolitical polarization and sensitivity of trade costs to geopolitics lead to lower trade volumes and reduced incomes, particularly for emerging markets and developing economies, (Hakobyan et al., 2023).

Table 3. Gravity results: effect of geofragmentation on bilateral trade (with controls)

	(1) All Countries	***(2) Advanced***	***(3) EMEs***	***(4) EMEs no China***	***(5) Bloc 1***	***(6) Bloc 2***	***(7) Bloc 3***
Variable							
Geofrag	*-0.0353****	-0.0358***	-0.0325***	-0.0528***	-0.0332***	-0.0423***	-0.0402***
	(0.0034)	(0.0032)	(0.0096)	(0.0047)	(0.0026)	(0.0119)	(0.0063)
Distcap	*-0.0001****	-0.0001***	-0.0001***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Contig	*0.8641****	0.9990***	0.6143***	0.8238***	0.9109***	0.5974***	1.172***
	(0.0911)	(0.1437)	(0.1384)	(0.1462)	(0.1250)	(0.2219)	(0.3294)
Comcol	*0.7460****	0.7754**	0.6974***	0.4849***	0.5730	0.7496***	0.8135***
	(0.1304)	(0.3275)	(0.1378)	(0.1246)	(0.5193)	(0.1227)	(0.2194)
fta_wto	*0.7419****	0.7888***	1.004***	0.6161***	0.7681***	0.8623***	0.6365***
	(0.0766)	(0.0828)	(0.1465)	(0.1204)	(0.0915)	(0.1312)	(0.1875)
comlang_off	*0.1572***	0.1646	0.0534	0.0691	0.1960*	0.2224	0.2936***
	(0.0619)	(0.1076)	(0.1209)	(0.1886)	(0.1160)	(0.1405)	(0.0898)
Observations	*543544*	263764	279780	272386	198989	148266	176264
Fixed Effects							
Origin FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Gravity results: effect of high-fragmentation periods on bilateral trade (with controls)

	(1) All Countries	(2) Advanced	(3) EMEs	(4) EMEs no China	(5) Bloc 1	(6) Bloc 2	(7) Bloc 3
Variable							
high_dummy	-0.2463***	-0.2431***	-0.2497***	-0.3718***	-0.2215***	-0.3187***	-0.2817***
	(0.0225)	(0.0248)	(0.0572)	(0.0297)	(0.0215)	(0.0544)	(0.0466)
Distcap	-0.0001***	-0.0001***	-0.0001***	-0.0002***	-0.0002***	-7.99e-05**	-8.97e-05***
	(1.87e-05)	(1.55e-05)	(3.54e-05)	(2.32e-05)	(1.20e-05)	(4.03e-05)	(2.99e-05)
Contig	0.8650***	0.9999***	0.6148***	0.8285***	0.9118***	0.5979***	1.173***
	(0.0912)	(0.1437)	(0.1385)	(0.1460)	(0.1250)	(0.2221)	(0.3296)
Comcol	0.7444***	0.7733**	0.6965***	0.4850***	0.5710	0.7487***	0.8131***
	(0.1305)	(0.3272)	(0.1376)	(0.1247)	(0.5194)	(0.1237)	(0.2195)
fta_wto	0.7386***	0.7822***	1.003***	0.6038***	0.7613***	0.8624***	0.6314***
	(0.0780)	(0.0842)	(0.1469)	(0.1211)	(0.0933)	(0.1325)	(0.1896)
comlang_off	0.1583**	0.1654	0.0551	0.0723	0.1967*	0.2232	0.2955***
	(0.0619)	(0.1076)	(0.1205)	(0.1879)	(0.1160)	(0.1414)	(0.0896)
Observations	543544	263764	279780	272386	198989	148266	176264
Fixed Effects							
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 presents estimates from the extended gravity model, which examines interactions between the high-geofragmentation dummy and trade between countries from different blocs, as well as between the high-geofragmentation dummy and trade with non-aligned countries. The coefficients for advanced economies indicate that periods of heightened fragmentation are associated with a more intra-trade structure, leading to reduced trade flows toward geopolitically distant blocs. A similar pattern is observed for countries within the U.S.-aligned and China-aligned blocs. The estimation for bloc-3 reveals that non-aligned countries tend to increase trade across blocs and reduce trade among themselves during periods of high fragmentation. This suggests that they function as connector countries, as previously mentioned. This finding aligns with recent literature that posits that, while geopolitical tensions are reshaping global commerce, a complete fragmentation into isolated economic spheres has yet to occur, underscoring the growing importance of connector economies (Fan et al., 2025; Kang, 2025).

Table 5. Gravity results: inter-bloc trade and non-aligned countries in periods of high-fragmentation (with controls)

	(1) All Countries	(2) Advanced	(3) EMEs	(4) EMEs no China	(5) Bloc 1	(6) Bloc 2	(7) Bloc 3
Variable							
diffbloc_high	*-0.0453*	-0.1702***	0.0765	0.0885	-0.1473**	-0.1215	0.1387***
	(0.0476)	(0.0510)	(0.0561)	(0.0637)	(0.0616)	(0.1022)	(0.0519)
non_aligned_high	*-0.0163*	0.1193**	-0.0712	-0.0072	0.0900*	0.0211	-0.3920***
	(0.0384)	(0.0548)	(0.0704)	(0.0417)	(0.0499)	(0.0836)	(0.0398)
Distcap	*-0.0001****	-0.0001***	-0.0001***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0,00002)	(0,00002)	(0,00002)	(0,00002)	(0,00002)	(0,00002)	(0,00002)
Contig	*0.9025****	1.015***	0.5551***	0.8393***	0.9319***	0.5785**	1.163***
	(0.1022)	(0.1498)	(0.1579)	(0.1447)	(0.1270)	(0.2401)	(0.3327)
Comcol	*0.8837****	1.113***	0.8033***	0.4798***	1.560***	0.8113***	0.8111***
	(0.1034)	(0.4001)	(0.1345)	(0.1372)	(0.5035)	(0.1516)	(0.2342)
fta_wto	*0.5621****	0.5985***	0.7604***	0.4827***	0.5784***	0.5288***	0.6851***
	(0.0723)	(0.0909)	(0.1407)	(0.1591)	(0.1019)	(0.0962)	(0.2155)
comlang_off	*0.1938****	0.1988*	0.0421	0.0903	0.2018*	0.2902***	0.2518**
	(0.0561)	(0.1020)	(0.1109)	(0.1717)	(0.1079)	(0.0949)	(0.1038)
Observations	*543544*	263764	279780	272386	198989	148266	176264
Fixed Effects							
Origin FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes
Destination FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	*Yes*	Yes	Yes	Yes	Yes	Yes	No

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

In Table 6, we present the results of the interaction between the high geofragmentation dummy variable and the geopolitical distance between importers and exporters. The findings indicate that during periods of high geofragmentation, trade with geopolitically distant partners increases for non-aligned countries. We interpret this trend as further evidence that non-aligned economies can serve as connector countries during times of high geofragmentation, facilitating indirect trade relationships between nations belonging to competing geopolitical blocs. This intermediary role allows them to partially mitigate the negative impacts of trade restrictions by acting as conduits for goods and services that would otherwise face significant barriers (Gopinath et al., 2025).

However, this intermediation role carries economic consequences, including increased transaction costs and changes in supply chain configurations. Baur et al. (2025) highlight the potential advantages that non-aligned countries may experience during periods of high geopolitical risk. They suggest that these countries' manufacturing sectors could benefit as nations in rival blocs substitute direct trade with each other by redirecting flows through non-aligned economies. Consequently, longer-term gains from global trade linkages may arise, as our findings indicate that episodes of heightened geofragmentation are associated with a reorganization of trade flows.

Table 6. Gravity results using the interaction of geopolitical distance and high geofragmentation as independent variable, with controls

	(1) All Countries	*(2) Advanced*	*(3) EMEs*	*(4) EMEs no China*	*(5) Bloc 1*	*(6) Bloc 2*	*(7) Bloc 3*
Variable							
dist_high_dummy	*-0.0008*	0.0999	-0.1206***	-0.1683*	0.0235	-0.2174*	0.2441*
	(0.0354)	(0.0746)	(0.0001)	(0.0874)	(0.0903)	(0.1180)	(0.1382)
Distcap	*-0.0001****	-0.0001***	-0.0001***	-0.0002***	-0.0002***	-0.0001***	-0.0001***
	(0,00001)	(0,00001)	(0,00001)	(0,00001)	(0,00001)	(0,00001)	(0,00001)
Contig	*0.8843****	0.9882***	0.5335***	0.8352***	0.911***	0.5428***	1.190***
	(0.0659)	(0.0748)	(0,00001)	(0.1132)	(0.0710)	(0.1530)	(0.2281)
Comcol	*0.8833****	1.148***	0.7895***	0.4916***	1.581***	0.8045***	0.8166***
	(0.1434)	(0.2061)	(0,00001)	(0.1395)	(0.2459)	(0.1883)	(0.2347)
fta_wto	*0.6116****	0.6954***	0.7978***	0.4823***	0.677***	0.5575***	0.5013***
	(0.0609)	(0.0837)	(0,00001)	(0.1132)	(0.0798)	(0.1055)	(0.1513)
comlang_off	*0.1969****	0.2096***	0.0200***	0.0647	0.2068**	0.2810**	0.2940**
	(0.0613)	(0.0770)	(0,00001)	(0.1335)	(0.0817)	(0.1342)	(0.1249)
Observations	*494410*	243035	251369	244486	186437	140743	167211
Fixed Effects							
Origin x Year FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes
Destination x Year FE	*Yes*	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

In summary, our analysis demonstrates that geofragmentation exerts a substantial downward pressure on bilateral trade flows, particularly between geopolitically distant partners and rival blocs, underscoring how heightened geopolitical tensions systematically raise effective trade costs and promote partial decoupling in global trade. This reorientation of trade patterns, particularly the increased reliance on "connector" economies, suggests a complex recalibration rather than a complete cessation of global economic integration (Hardwick, 2025).

More intriguingly, geofragmentation does not merely reduce trade volumes but profoundly reshapes their patterns, elevating the role of non-aligned countries as vital "connector" economies. During periods of high fragmentation, these nations increase trade with distant blocs while reducing intra-group flows, positioning themselves as intermediaries that facilitate indirect exchanges between competing powers (Fan et al., 2025; Kang, 2025). This dynamic suggests potential long-term opportunities for neutral economies to capture gains from reorganized supply chains, mitigating some adverse effects of division and preventing full economic isolation.

Conclusions

This paper presents a new multidimensional index of geofragmentation, developed using a dynamic factor model that incorporates trade, financial, mobility, and political indicators. Our primary objective is to quantify fragmentation as a latent process and assess its impacts on international trade patterns. A series of extended gravity models shows how fragmentation affects bilateral trade flows, particularly within geopolitical blocs and with non-aligned countries.

The empirical results indicate that geofragmentation has increased in recent years. Our gravity model analyses provide compelling evidence regarding the restructuring of trade patterns. Findings indicate that high levels of fragmentation are linked to reduced trade between geopolitically distant partners and rival blocs. At the same time, there is an increase in intra-bloc trade among advanced economies aligned with the U.S. Notably, non-aligned countries emerge as "connector" economies, enhancing trade with distant blocs while reducing intra-group exchanges. This role enables them to facilitate indirect transactions that help mitigate direct barriers.

Our findings suggest that fragmentation should not be interpreted as the end of globalization but rather as a reconfiguration of global economic networks. While aligned blocs strengthen their internal ties, neutral economies gain prominence and potentially offset some losses by expanding their production and trade volumes. This dynamic aligns with emerging literature on geoeconomics, which emphasizes the incomplete decoupling of economies and the bridging function of unaligned states.

From a policy perspective, governments in rival blocs can focus on diversified trade strategies that leverage connector economies to maintain access to essential goods despite restrictions. Non-aligned countries can capitalize on their neutrality by investing in logistics, manufacturing resilience, and diplomatic hedging to enhance long-term gains. Finally, advanced research agendas should refine measurements of fragmentation and model adjustments in supply chains to inform proactive international cooperation.

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Appendix

A. Data construction for the DFM

A1. The trade openness ratio

The trade openness ratio is defined as the sum of exports and imports of goods and services divided by nominal GDP. We construct the global indicator by first computing a quarterly series of nominal GDP in current US dollars by doing a linear interpolation of the annual GDP series for the 98 countries available in the World Economic Outlook Database (WEO). For each country with available data in balance of payments (BoP) statistics from the International Financial Statistics, we compute a country trade openness ratio. We obtain the global indicator by averaging all countries' trade openness ratios, using current GDP in US dollars as weights, restricted to countries with available data.

A2. Non-tariff measures (GTA)

From the Global Trade Alert website, we retrieve a monthly time series of the count of the implemented measures classified as harmful and which are included in the following Multi-Agency Support Team (MAST) Chapters: Pre-shipment inspection and other formalities, Contingent trade-protective measures, Non-automatic licensing and quotas, Price-control measures including additional taxes and charges, Finance measures, Measures affecting competition, Trade-related investment measures, Distribution restrictions, Restrictions on post-sales services, Subsidies (excluding export subsidies), Government procurement restrictions, Intellectual property measures, and Export-related measures (including subsidies). We compute the quarterly series by summing the number of measures in each month.

A3. Tariff measures (GTA)

From the Global Trade Alert website, we retrieve a monthly time series of the count of the implemented measures classified as harmful and which are classified as Tarif Measures. We compute the quarterly series by summing the number of measures in each month.

A4. Temporary trade barriers

From the Temporary Trade Barriers Database, which follows Bown (2020) methodology, we retrieve a monthly time series of the total count of implemented trade remedy measures including antidumping, countervailing, and safeguard measures for all the 30 countries in the database. We compute the quarterly series by summing the number of measures in each month.

A5. Tariff

We retrieve tariff data from the World Trade Organization (WTO) tariff and trade data platform. For each country we consider the tariff applied to the most favored nation tariff regarding all products. We construct the global indicator by averaging by the current GDP in U.S. dollars from the WEO database. The data is on annual frequency.

A6. The FDI ratio

The FDI ratio is defined as the Foreign Direct Investment inflows divided by nominal GDP. We construct the global indicator by first computing a quarterly series of nominal GDP in current US dollars by doing a linear interpolation of the annual GDP series for the 98 countries available in the World Economic Outlook Database (WEO). For each country with available data in balance of payments (BoP) statistics from the International Financial Statistics, we compute a country FDI ratio. We obtain the global indicator by averaging all countries' FDI ratios, using current GDP in US dollars as weights, restricted to countries with available data.

A7. The FFB ratio

The FFB ratio is defined as the Portfolio Investment inflows divided by nominal GDP. We construct the global indicator by first computing a quarterly series of nominal GDP in current US dollars by doing a linear interpolation of the annual GDP series for the 98 countries available in the World Economic Outlook Database (WEO). For each country with available data in balance of payments (BoP) statistics from the International Financial Statistics, we compute a country FFB ratio. We obtain the global indicator by averaging all countries' FFB ratios, using current GDP in US dollars as weights, restricted to countries with available data.

A8. Capital Control Measures

The IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) reports the presence of rules and regulations for international transactions by asset categories for each country. Fernandez et al. (2016) use the narrative description in the AREAER to determine whether there are restrictions on international transactions, with 1 representing the presence of a restriction and 0 representing no restriction according to several rules. They construct 1 or 0 indicators in each country for inflows and outflows of 10 asset categories (equity, bonds, money market instruments, collective investment, financial credits, foreign direct investment, derivatives, commercial credits, financial guarantees, and real estate). A country indicator is calculated as the average of the 20 sub-indicators. We compute the global indicator by averaging each country with data using the current GDP in U.S. dollars from the WEO database.

A9. FDI and CCM Measures (GTA)

From the Global Trade Alert website, we retrieve a monthly time series of the count of the implemented measures classified as harmful and which are included in the following category: FDI measures and Capital Control Measures. We compute the quarterly series by summing the number of measures in each month.

A10. Migration flow ratio

We compute the migration flow ratio as the absolute number of net migration in each country. We obtain the data from the World Population Prospects 2024 (WPP) from the United Nations. We construct the global indicator by averaging each country using as weight the total population also obtained from the WPP. The frequency of the data is annual.

A11. Patent flows

Patent flow data comes from the International Patent and Citations across Sectors (INPACT-S) compiled by LaBelle et al. (2023). Cross-border patents are those filed in one country by a resident of another. The global indicator is calculated as the average of the countries in the database weighted by the current GDP in U.S. dollars from the WEO. The data is annual and is available up to 2019.

A12. Migration Measures (GTA)

From the Global Trade Alert website, we retrieve a monthly time series of the count of the implemented measures classified as harmful and which are classified as Migration Measures. We compute the quarterly series by summing the number of measures in each month.

A13. Geopolitical Risk

Geopolitical risk data comes from Caldara & Iacoviello (2022). The index counts the number of articles related to adverse geopolitical events in each newspaper each month as a share of the total number of news articles. We use the global indicator listed on their website. We construct the quarterly dataset by averaging the months in the quarter.

A14. Geoeconomic vulnerability

We compute geoeconomic vulnerability as delineated in Aiyar & Ohnsorge (2024). The idea is that countries that trade with geopolitically distant partners are more geopolitically vulnerable. We calculate this indicator by first computing the geopolitical distance of each country pair. We use the Bailey et al. (2017) dataset on ideal point estimation, which uses a dynamic ordinal spatial model to estimate each country's foreign policy position on a single dimension reflecting alignment with the US-led liberal order, based on roll-call votes in the United Nations General Assembly (UNGA) from 1946 to 2023. We define the geopolitical distance of each country pair as the absolute difference in their ideal point estimates. We compute the trade weights for each country using trade data from the IMF Direction of Trade Statistics (DOTS); for 2024, we repeat the 2023 weights. We compute the global indicator by averaging all countries indicators using the current GDP in U.S. dollars from the WEO dataset. The indicator is on annual frequency.

A15. Geoeconomic connectedness

We compute geoeconomic connectedness as delineated in Aiyar and Ohnsorge (2024). The idea is similar to the geoeconomic vulnerability indicator, but rather than capturing a first moment we compute a weighted standard deviation. Therefore, the greater the variety of geopolitical positions in a country's trade partner basket, the more geopolitically connected that country is. Rather than computing the weighted average of ideal point distances as in the vulnerability indicator, we compute their weighted standard deviation. Trade weights are constructed using the same method as for the geoeconomic vulnerability indicator. The indicator is on annual frequency.

A16. Number of Sanctions

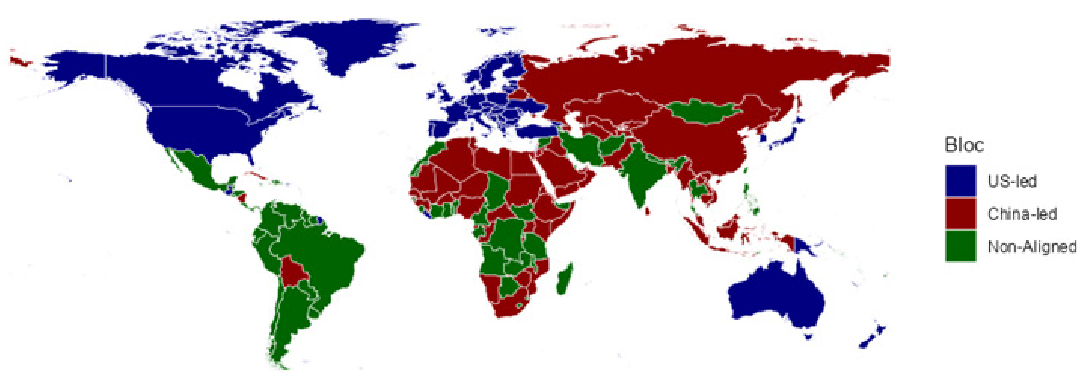
We use the number of sanctions from the Global Sanctions Database (GSDB), constructed by Felbermayr et al. (2020). The database covers sanctions effectively applied by individual nations, country groups, the United Nations (UN), and other international organizations in response to various violations of international norms. We count the total number of sanctions applied each year.

B. Dividing countries into blocs

A central feature of geofragmentation is the reorientation of cross-border economic linkages away from purely efficiency-driven considerations toward politically aligned networks of exchange. Rather than forming connections solely on the basis of comparative advantage or market complementarities, countries increasingly condition trade, financial, and technological relationships on geopolitical affinity. The most widely used empirical proxy for political alignment is the Ideal Point Estimation (IPE) developed by Bailey et al. (2017), which applies a spatial voting framework to infer countries' latent policy preferences from their voting behavior in the United Nations General Assembly.

Focusing on the period 2000–2024, we construct three geopolitical blocs: a U.S.-aligned bloc, a China-aligned bloc, and a non-aligned bloc. We classify countries based on the average distance of their estimated ideal points from those of the United States and China. Specifically, countries in the 30th percentile closest to the United States are assigned to the U.S.-led bloc, those in the 30th percentile closest to China are assigned to the China-led bloc, and the remaining countries are categorized as non-aligned.

Figure 6. Geopolitical blocs



Note: The chart displays the division of countries into three geopolitical blocs: a U.S.-led bloc, a China-led bloc, and a non-aligned bloc. The classification is based on countries' ideal point estimates from Bailey et al. (2017). Countries are assigned to blocs according to their average distance from the United States and China during the period 2000–2024.

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