ESRB
European Systemic Risk Board
European System of Financial Supervision

EUROPEAN CENTRAL BANK
EUROSYSTEM

Financial stability risks from geoeconomic fragmentation – Annex

January 2026

ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation

Contents

1 Framework and indicators

1.1 Framework

The concept of geopolitics has a long and complex history. According to Flint (2022), "[geopolitics] is about the exercise of power. It is about geography. […] It is about a multitude of connected actions and actors and the geographies they make, change, and maintain" and is the "struggle over the control of geographical entities with an international and global dimension, and the use of such geographical entities for political advantage". The term geopolitics is often associated with the concept of major powers, i.e. countries that extend their influence far beyond their own borders through military force, trade or financial means (Kennedy, 1987).

The term geoeconomics is frequently used alongside the concept of geopolitics. Mohr and Trebesch (2025) describe geoeconomics as a broad, emerging field "that examines the links between geopolitics and economics", encompassing not only economic power and economic warfare but also actual warfare, including military financing and arms production. By contrast, however, a narrower definition is proposed in Blackwill and Harris (2016), namely "the use of economic instruments to promote and defend national interests [and] advance geopolitical goals". Similarly, Clayton et al. (2023) define geoeconomics as the practice whereby dominant countries "use their financial and economic strength to extract economic and political surplus from other countries around the world" to achieve their national objectives by, for example, threating to disrupt supply chains, restrict access to goods, sever financial relationships or withhold technological cooperation, rather than through direct military conflict.

This report adopts a broad concept of geopolitics that encompasses the use by states of all available instruments to pursue their interests and expand their power and influence, including military strength. This is in line with Caldara and Iacoviello (2022), who define geopolitical risk as "the threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations", thereby also encompassing instruments of hybrid warfare, such as cyberattacks, physical sabotage and the spread of disinformation. Additionally, geopolitical objectives are often pursued through economic means, including trade policies, sanctions and currency manipulation – collectively referred to as geoeconomic instruments. By adopting a broad definition of geopolitics, this report also takes into account geoeconomic risks when referring to geopolitical risks. The primary aim of this report is to analyse the impact of geopolitical risk on financial stability. This includes examining the effects of sudden geoeconomic shocks as well as the gradual process of geoeconomic fragmentation, which Aiyar et al. (2023) define as "a policy-driven reversal of global economic integration often guided by strategic considerations". Thus, geoeconomic fragmentation can be understood as a form of strategic disintegration driven by geopolitical motives (Mohr and Trebesch, 2025).

Categorisation of geopolitical risks

The analysis in this report combines several dimensions of geopolitical risks, encompassing a wide range of events and actions that can undermine political, economic and financial stability. The different types of geopolitical risks fall into five different categories: (i) military conflict and war; (ii) infrastructure; (iii) trade; (iv) capital and finance; and (v) politics and society (**Figure 1 in report**).

Military conflicts and wars are the most extreme form of geopolitical risk. This risk includes sudden military actions, such as annexations and invasions, which result in immediate confrontation between two or more nations and entail enormous humanitarian and economic costs. Nuclear threats also fall into this category, creating widespread fear and uncertainty. Over time, ongoing military conflicts affect regional, and even global, stability, leading to significant increases in military spending.

Critical infrastructure is of strategic importance from a geopolitical risk perspective. Cyberattacks or physical sabotage of critical infrastructure, such as power plants, pipelines, communication systems and payment systems, can have significant economic costs and create uncertainty. Over time, geopolitical tensions can lead to technological decoupling in order to reduce dependencies and vulnerabilities and can therefore have a negative impact on trade relationships and productivity.

Trade disruptions have direct economic effects. Immediate trade restrictions, such as trade sanctions, embargoes and tariffs, disrupt supply chains and have a negative impact on economic and financial activities. Over time, a change in trade relationships and increasing protectionism can lead to global trade fragmentation, with potential welfare losses.

Capital and finance-related measures have a direct impact on financial markets. Immediate measures, such as capital controls, capital sanctions and currency manipulation, can change the flow of capital and distort exchange rates, affecting funding conditions and liquidity. Over time, capital market restrictions and regulatory patchworks can lead to global capital market fragmentation, resulting in lower cross-border investment, fewer diversification opportunities and higher funding costs.

Undermining the political system and social cohesion is a threat to democracy. Foreign election interferences, as well as the spread of disinformation and propaganda, are aimed at destabilising political systems and manipulating public opinion. Over time, the polarisation of societies and the destabilisation of democratic systems can erode social cohesion and political stability, leading to long-term civil unrest and weaker institutions.

1.2 Geopolitical indicators used in the analysis

This Annex documents the broader set of indicators compiled, explored and assessed during construction of the geopolitical risk and uncertainty toolkit. It complements the main text by offering more detail on the selection process, indicator properties and supporting diagnostics. The Annex consists in four parts. Section 1.2.1 presents a full inventory, including acronyms, definitions and data sources, of the indicators that underlie the various visualisations and empirical tools used throughout the report. Section 1.2.2 groups the selected indicators thematically and illustrates their evolution over time through standardised charts. The structure follows the narrative-based framework introduced in Section 2 of the main text. Section 1.2.3 outlines additional and exploratory indicators that were considered during the analysis but not retained in the baseline visualisations or empirical models. Section 1.2.4 provides supporting statistical diagnostics, including tests for frequency limitations, indicator interdependencies, dimensionality reduction and cluster structure. Together, these sections offer transparency concerning the underlying data and analytical considerations that informed the selection and use of indicators across different components of the report.

1.2.1 Overview of the geopolitical risk and uncertainty indicators used in the analysis

This section documents the full list of indicators compiled for the analysis of geopolitical, macro-financial and structural risks. Table A.1 provides, for each indicator, its mnemonic (as used in the dataset) and abbreviation (as used in this report), a short description and the original data source. The indicator set draws from a diverse range of databases and institutions, including central banks, academic sources, policy research institutions and international organisations. It includes high-frequency market-based indicators (e.g. CLIFS, CISS and GPR), lower-frequency structural or institutional metrics (e.g. capital restriction indices, military expenditure and UN voting patterns) and novel indices capturing emerging or hard-to-measure dimensions, such as cyber incidents or perceived geopolitical threats.

Understanding the source and construction methodology of each indicator is not only important for transparency, but also has empirical implications. For example, news-based indicators (such as GPR indices or EMV trackers) tend to exhibit greater persistence, given that media coverage often amplifies and prolongs the impact of an initial shock. By contrast, indicators derived from official statistics or institutional databases (e.g. trade volumes, military spending and capital controls) typically reflect slower-moving structural changes and are revised at a lower frequency. These differences affect how indicators behave in time-series models, their responsiveness to new events and their value in forecasting frameworks. This overview therefore also helps in interpreting the empirical performance of the indicators throughout the report and supports informed selection for different types of analysis.

Table A.1

List of geopolitical risk, fragmentation and domestic response indicators

Indicator	Description	Source
General		
[1] World Uncertainty Index	The World Uncertainty Index (WUI) is calculated by measuring the number of times, expressed as a percentage, that the word “uncertain” (and its variants) appears in Economist Intelligence Unit country reports and then multiplying the result by 1,000,000. A higher value indicates greater uncertainty. For instance, a value of 200 means that the word constituted 0.02 percent of all words, or about twice in a typical 10,000-word report.	Ahir, Bloom and Furceri (2018)
[2] Economic Policy Uncertainty Index	The Economic Policy Uncertainty (EPU) Index combines news coverage of economic policy uncertainty, the number of expiring US federal tax provisions and the dispersion in professional macroeconomic forecasts.	Baker, Bloom & Davis (2016)
[3] JLN Real Uncertainty Index	The JLN Real Uncertainty (RealUn) Index is a broad-based measure of three-month ahead real uncertainty, drawn from a large number of real time series.	Ludvigson, Ma and Ng (2021)
[4] JLN Macro Uncertainty Index	The JLN Macro Uncertainty (MacroUn) Index is a broad-based measure of three-month ahead macro uncertainty, drawn from a large number of macro time series.	Jurado, Ludvigson and Ng (2015)
[5] Geopolitical Fragmentation Index & country-bloc subindexes: China-Russia, US-EU, Others Bloc Fragmentation Index	The Geopolitical Fragmentation (Frag) Index is derived from various empirical indicators (measuring trade, capital flows, migration and political alignment) using a dynamic hierarchical factor model with time-varying parameters and stochastic volatility. The country-bloc indicators are derived using the baseline approach, with adjustments for bloc-level data while ensuring consistency in other aspects.	Fernández-Villaverde et al (2024)
Military		
[6] Geopolitical Risk Index	The Geopolitical Risk (GPR) Index measures the frequency of newspaper articles reporting geopolitical tensions, wars and terrorist threats, capturing changes in global geopolitical risk levels.	Caldara and Iacoviello (2022)
[7] GPR Threats Index	The Geopolitical Risk Threats (GPRT) Index tracks articles focused on threats or rising tensions that may lead to future geopolitical events.	Caldara and Iacoviello (2022)
[8] GPR Acts Index	The Geopolitical Risk Acts (GPRA) Index tracks articles specifically discussing actual geopolitical events, such as wars or terrorist attacks.	Caldara and Iacoviello (2022)
[9] Bondarenko Geopolitical Risk Perceptions Index	The Bondarenko Geopolitical Risk Perceptions (GPRP) Index measures geopolitical risk based solely on local-language newspaper coverage from a country’s own media, capturing how geopolitical tensions and events are perceived domestically rather than in international sources.	Bondarenko et al. (2024)
[10] Bilateral Indicator of Local Perception of Geopolitical Risk Indicator & by source country or country group	Bilateral Indicators of Local Perception of Geopolitical Risk (BiGPRs) are calculated using national news sources, thus capturing distinct, idiosyncratic geopolitical perspectives at national level. The indicators are then decomposed into bilateral components, thus capturing two dimensions: who is perceived to be causing the risk and who is doing the reporting.	Alonso-Álvarez et al. (2025)
[11] National Security Policy EMV Tracker	The National Security Policy Equity Market Volatility (EMVsec) Tracker is that part of the main EMV Tracker that is based on newspaper articles whose content aligns closely with the Chicago Board Options Exchange (CBOE) Volatility (VIX) Index and realised S&P 500 volatility. Of these articles, 13% mention national security issues alongside broader topics, such as the macroeconomic outlook, commodity markets and various policy areas.	Baker et al. (2019)
[12] Number of Conflict Events Indicator	The Number of Conflict Events (NoConfl) Indicator counts all recorded organised violence events worldwide, including state-based, non-state and one-sided violence, based on georeferenced event data (GED) from the Uppsala Conflict Data Program (UCDP).	UCDP/GED
[13] Number of International Armed Conflicts Indicator	The Number of International Armed Conflicts (NoArmedConfl) indicator counts all organised violence events involving at least one state government on each side (interstate and internationalised interstate conflict), based on the UCDP Peace Research Institute Oslo (PRIO) Armed Conflict Dataset.	UCDP/PRIO Armed Conflict Dataset

Indicator	Description	Source
[14] Military Expenditure Indicator	The Military Expenditure Indicator measures the share of a government's total expenditure allocated to military purposes, including armed forces, defence ministries and military aid, expressed as a percentage of general government expenditure or GDP.	World Bank Group
Infrastructure		
[15] Significant Cyber Incidents Indicator	The Significant Cyber Incidents (NoCyb) Indicator records major cyberattacks on government agencies, the defence industry, high-tech companies and critical infrastructure, including incidents of cyber-enabled theft, espionage and disruption, as identified by the Centre for Strategic and International Studies (CSIS) based on public reporting.	CSIS
[16] Energy-related Uncertainty Index	The Energy-related Uncertainty Index (EUI) is constructed by counting uncertainty terms and energy-related keywords in monthly Economist Intelligence Unit country reports (1996-2022), normalising each to a mean of 100 and then averaging the two resulting indices for each country.	Dang et al. (2023)
Trade		
[17] Trade Volume Indicator (% GDP) (trade openness)	The Trade Volume Indicator measures the sum of exports and imports of goods and services as a share of GDP, indicating the degree of a country's integration into global trade.	Eurostat, Main aggregates, national accounts (MNA)
[18] Global Supply Chain Pressure Index	The Global Supply Chain Pressure Index (GSCPI) combines global transportation cost measures and supply chain-related Purchasing Managers' Index (PMI) components from major economies to provide a summary of supply chain disruptions, normalised so that zero reflects the historical average and positive values indicate above-average pressures.	Federal Reserve Bank of New York
[19] Trade Policy Uncertainty Index	The Trade Policy Uncertainty (TPU) Index quantifies uncertainty over trade policy by measuring the share of articles in leading US newspapers discussing trade policy alongside terms related to uncertainty.	Caldara et al. (2019)
[20] World Trade Uncertainty Index	The World Trade Uncertainty Index (WTUI) measures country-level economic uncertainty by calculating the frequency of the word "uncertain" and related terms in Economist Intelligence Unit country reports, normalised to a mean of 100.	Ahir, Bloom and Furceri (2019)
[21] Trade Policy EMV Tracker	The Trade Policy Equity Market Volatility (EMVtp) Tracker is a subcomponent of the newspaper-based Equity Market Volatility Tracker that captures equity market volatility linked to news articles discussing trade policy, identified through text analysis of articles whose content correlates with the VIX and realised S&P 500 volatility.	Baker et al. (2019)
[22] Trade Fragmentation Index	The Trade Fragmentation (TFrag) Index is a subindex of the Geopolitical Fragmentation Index, capturing fragmentation in global trade patterns using a dynamic factor (DFM) model applied to multiple indicators of trade integration and flows.	Fernández-Villaverde et al (2024)
Capital & finance		
[23] Capital Restriction Index	The Capital Restriction (CC) Index measures the presence of restrictions on capital inflows and outflows across six asset categories (equities, bonds, the money market, collective investment, financial credit and foreign direct investment) for 91 countries, extending earlier datasets to 2011. It is based on codifying legal restrictions from the International Monetary Fund's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).	Fernández et al. (2015)
[24] JLN Financial Uncertainty Index	The JLN Financial Uncertainty (FinUn) Index is a broad-based measure of 3-months ahead financial uncertainty drawn from large number of financial time series.	Jurado, Ludvigson and Ng (2015)
[25] Common Volatility Index	The Common Volatility (COVOL) Index is a global risk measure capturing volatility shocks that occur simultaneously across many asset classes and estimated using a factor model applied to financial market data.	Engle and Campos-Martins (2023)
[26] Financial Fragmentation Index	The Financial Fragmentation (FinFrag) Index is subindex of the Geopolitical Fragmentation Index and captures cross-border financial market fragmentation through a DFM model applied to multiple financial integration indicators.	Fernández-Villaverde et al (2024)
[27] Foreign Direct Investment Ratio	The Foreign Direct Investment (FDI) Ratio is the sum of foreign direct investment inflows and outflows, as a percentage of GDP	ECB data portal

Indicator	Description	Source
[28] Financial Flows Ratio	The Financial Flows Ratio is the sum of portfolio and other investment inflows and outflows, as a percentage of GDP	ECB data portal
[29] Equity Market Segmentation Index	The Equity Market Segmentation Index measures the degree to which a country's equity market is segmented from global markets and is based on the proportion of stock return variance explained by global versus local factors.	Bekaert et al. (2011)
[30] Allocated Foreign Exchange Reserves Index & Composition	The Allocated Foreign Exchange Reserves (FXR) Index measures the value and currency composition of official foreign exchange reserves held by monetary authorities, including claims denominated in US dollars and other major currencies.	IMF Currency Composition of Official Foreign Exchange Reserves (COFER) Database
Politics & Societal		
[31] Global Number of Active Sanctions Index	The Global Number of Active Sanctions Index tracks the total number of active sanctions regimes worldwide each year, as documented in the Global Sanctions Database (GSDB), which records bilateral, multilateral and plurilateral sanctions cases from 1950.	GSDB, Felbermayr et al. (2020)
[32] Global Sanctions Intensity Index	The Global Sanctions Intensity (GSI) Index measures the intensity of sanctions imposed on a country by quantifying the number, scope and severity of active sanctions, based on systematically coded sanctions data from official and public sources.	Bondarenko et al. (2024)
[33] Migration Fear Index	The Migration Fear Index is constructed from automated text searches by calculating the share of major newspaper articles that contain terms related to immigration (e.g. "immigration", "migrants", "refugees"), with the index value proportional to the frequency with which two such terms are mentioned relative to the total articles.	Bloom, Davis and Baker (2015)
[34] Migration Policy Uncertainty Index	The Migration Policy Uncertainty (MigPU) Index calculates the share of newspaper articles containing both migration-related terms (e.g. "immigration", "visa", "refugee") and uncertainty terms (e.g. "uncertain", "risk", "concern"), expressed relative to the total number of articles.	Bloom, Davis and Baker (2015)
[35] Elections & Political Governance EMV Tracker	The Elections and Political Governance EMV (EMVelec) Tracker is a subcomponent of the Equity Market Volatility Tracker that captures equity market volatility linked to news articles discussing elections, political transitions and governance issues, identified through text analysis of articles whose content correlates with the VIX and realised S&P 500 volatility.	Baker et al. (2019)
[36] UN Votes Ideal Point Indicator & percentage of agreement: **- with China** **- with Russia** **- with the United States**	The UN Votes Ideal Point (UNidealP) Indicator measures a country's foreign policy alignment by estimating its "ideal point" on a latent policy spectrum, derived from roll-call voting patterns in the UN General Assembly using scaling methods, such as dynamic ordinal item response theory (IRT) models.	Bailey, Strezhnev and Voeten (2017)
[37] Mobility Fragmentation Index	The Mobility Fragmentation (MobFrag) Index is a subindex of the Geopolitical Fragmentation Index by Fernández-Villaverde et al (2024) that captures fragmentation in the international movement of people by using a dynamic factor model applied to multiple cross-border mobility indicators, such as migration flows, travel and visas.	Fernández-Villaverde et al (2024)
[38] Political Fragmentation Index	The Political Fragmentation (PolFrag) Index is a subindex of the GFI that captures divergence in countries' political positions and alliances using a DFM applied to indicators such as UN voting alignment and international treaty participation.	Fernández-Villaverde et al (2024)
Domestic Response		
[39] Common Composite Indicator	The Common Composite Indicator (CCI) aggregates information from five core indicators (change in bank credit-to-GDP ratio, growth of real total credit, change in debt service ratio, change in residential real estate price-to-income ratio and current account balance as a percentage of GDP).	Constructed by the authors; systemic risk indicator (SRI)-based
[40] Systemic Risk Indicator	The Systemic Risk Indicator (SRI) measures the financial cycle and, by extension, system-wide financial imbalances. The SRI captures risks stemming from domestic credit, real estate markets, asset prices and external imbalances.	Lang, Izzo, Fahr and Ruzicka (2019)
[41] Financial Cycle Indicator	The Financial Cycle Indicator is constructed based on common movements of indicator series related to financial sector cycles. First, the spectral approach (power cohesion) is used to obtain country-specific financial-cycle frequencies across a set of variables. Second, a unique composite financial cycle measure is obtained through time-varying aggregation of this set of variables.	Schüler, Hiebert and Peltonen (2020)

Indicator	Description	Source
[42] CBOE Volatility Index	The Chicago Board Options Exchange Volatility Index (CBOE VIX) is based on real-time prices of options on the S&P 500 Index. It is designed to reflect investors' consensus view of future (30-day) expected stock market volatility.	CBOE
[43] Equity Market Volatility Tracker	The Equity Market Volatility (EMV) Tracker is a newspaper-based (11 major US newspapers) tracker that moves with the CBOE VIX and with the realised volatility of returns on the S&P 500.	Baker, Bloom and Davis (2019)
[44] Euro Stoxx 50 Volatility Index	The Euro Stoxx 50 Volatility (VSTOXX) Index is based on EURO STOXX 50 real-time options prices and is designed to reflect market expectations of near-term-to-long-term volatility by measuring the square root of the implied variance across all options of a given time to expiration.	STOXX
[45] Country-Level Indicator of Financial Stress	The Country-Level Indicator of Financial Stress (CLIFS) includes six, mainly market-based, financial stress measures that capture three financial market segments: equity markets, bond markets and foreign exchange markets. In addition, in aggregating the sub-indices, the CLIFS Index takes the co-movement across market segments into account.	Duprey and Klaus. (2015)
[46] Composite Indicator of Systemic Stress	The Composite Indicator of Systemic Stress (CISS) is based on 15 raw, mainly market-based, financial stress measures that are divided equally into five categories, namely the financial intermediaries sector, money markets, equity markets, bond markets and foreign exchange markets.	Holló, Kremer and Lo Duca (2012)
[47] Price-based Financial Integration Indicator	The Price-based Financial Integration Indicator is a composite indicator that aggregates ten indicators for money, bond, equity and retail-banking markets. The indicator is bounded between zero (full fragmentation) and one (full integration). Increases in the indicator signal greater financial integration.	Hoffmann, Kremer and Zaharia (2019)
[48] Quantity-based Financial Integration Indicator	The Quantity-based Financial Integration Indicator is a composite indicator that aggregates five indicators for money, bond and equity markets. The indicator is bounded between zero (full fragmentation) and one (full integration). Increases in the indicator signal greater financial integration.	Hoffmann, Kremer and Zaharia (2019)

Sources: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.

1.2.2 Indicator patterns within risk groups

This section explores the time dynamics of selected indicators, grouped according to the five narrative-based risk categories defined in the Framework. Within each group, we illustrate the behaviour of a representative subset of indicators through individual charts, focusing on their sensitivity to historical events, structural trends and comparative behaviour over time. These visuals support the broader indicator screening process by highlighting how different risk signals manifest in the data — including event-driven spikes, persistent trends, and variation in data frequency and comparability. While not exhaustive, the examples offer insight into the monitoring potential and limitations of various indicators across thematic areas.

General geopolitical risks

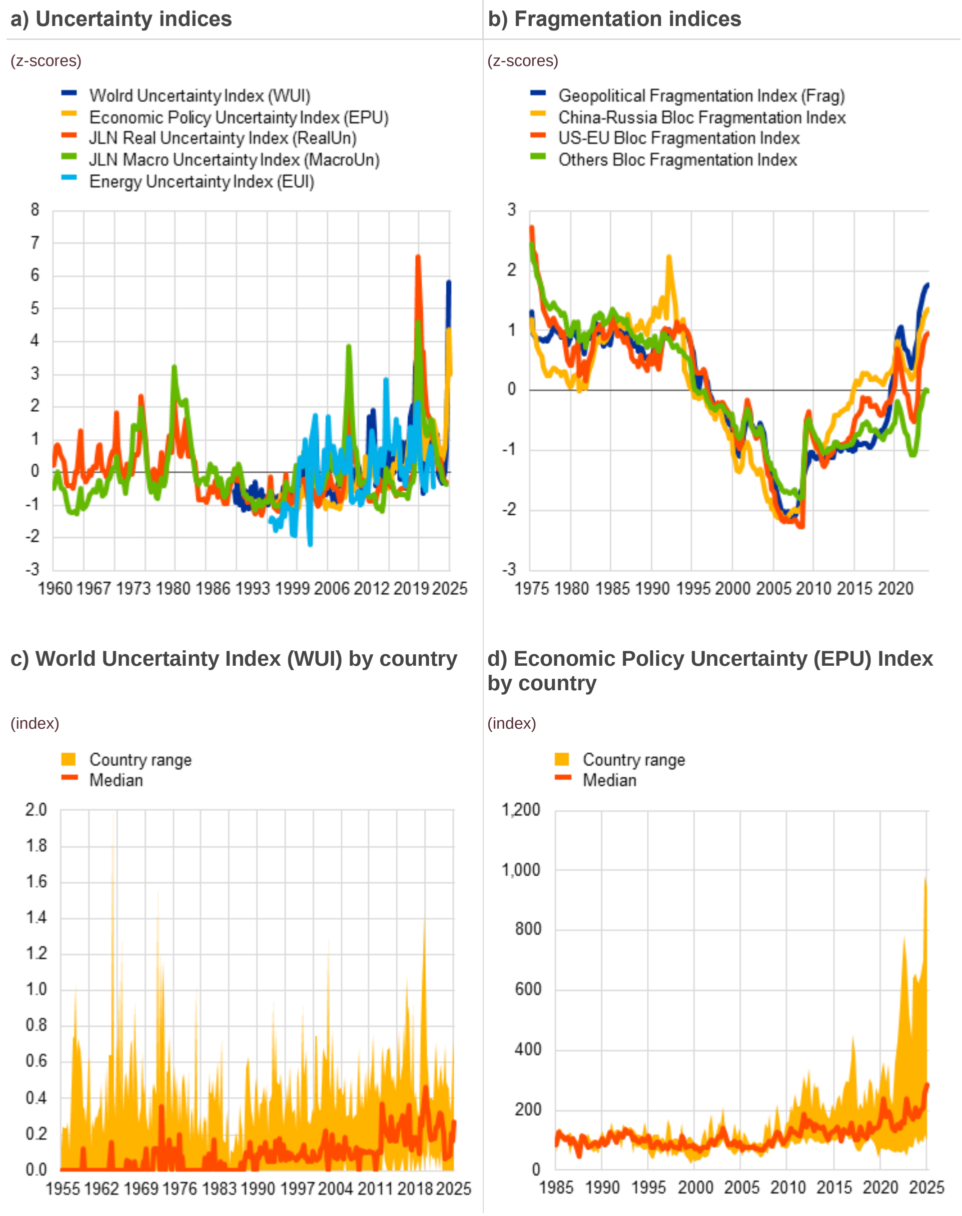
This group includes uncertainty indicators that cover broader aspects of geopolitical risks. Part of this group consists of news-based indices, such as the World Uncertainty Index (WUI), the Economic Policy Uncertainty Index (EPU) Index and the Energy-related Uncertainty Index (EUI). The remaining indicators are derived from macroeconomic and financial data.

Macroeconomic and policy uncertainty is captured by indicators such as the EPU Index and the JLN suite, , including macroeconomic and real-sector uncertainty. Although some of these indicators have limited geographical coverage, they are conceptually valuable for assessing global sentiment and regime shifts. Notable recent peaks in these indicators align with the COVID-19 pandemic, rising trade tensions, the Russian-Ukraine conflict and the post-2025 policy reorientation in the United States (**Chart A.1**).

Fragmentation is represented by the Geopolitical Fragmentation Index (GFI) and its country-bloc sub-indices which are derived from a number of indicators. The Defragmentation trends that began in most cases at the beginning of 1990s stopped abruptly during the global financial crisis of 2008, and subsequently changed course for most country blocs.

Chart A.1

General geopolitical risk indicators



Sources: See the sources corresponding to each indicator in Table A.1 of this Annex.
Notes: WUI data are available for all EU countries except Estonia, Cyprus, Luxembourg and Malta. EPU data are available for Germany, Greece, Spain, France, Ireland, Italy and Sweden.

The Energy-specific Uncertainty Indicator (EUI) was considered, but found to lag recent developments and was therefore excluded from the core modelling set.

Military conflict, war and infrastructure risks

This group includes indicators related to armed conflict, geopolitical tensions, military expenditures, and broader infrastructure-related risks. The indicators fall into three broad types: (i) news-based indices, such as the Geopolitical Risk (GPR) Index and the National Security Policy Equity Market Volatility Tracker; (ii) event-based conflict data, including the number of ongoing international or civil conflicts; and (iii) structural indicators, such as military expenditure.

The GPR indices, and their subcomponents (e.g. acts, threats), are constructed from news coverage using keyword frequency and show clear spikes around major geopolitical events, such as the Gulf Wars of 1991 and 2003, the attacks on the United States of 11 September 2001 (9/11) and the 2022 Russian invasion of Ukraine. Bilateral Indicators of Local Perception of Geopolitical Risk (BiGPRs) show the differences in risks coming from different countries and regions.

Event-based indicators, such as the number of armed conflicts, are less affected by media attention and instead reflect the duration and accumulation of conflicts over time. These provide a longer-term view of geopolitical instability, albeit at a lower frequency.

Structural indicators, including military expenditure (as a share of GDP or government budget), help track long-term trends in defence capacity and commitment. The data are sourced from official statistics and are consistent across countries, but the annual frequency of these indicators limits their use in high-frequency empirical models.

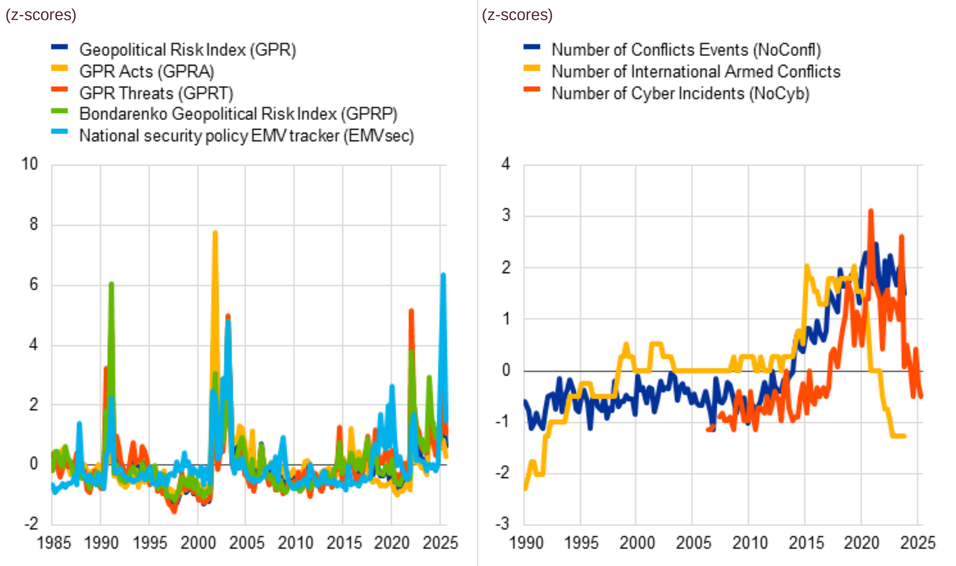
The number of cyber incidents, compiled by the Centre for Strategic and International Studies (CSIS), offers a more topical lens on modern conflict risks, but is limited by its short time series. While useful for capturing recent developments, its lack of historical depth constrains its use in empirical modelling.

To aid comparability, all the global indicators are transformed into standardised scores (z-scores). **Chart A.2** provides representative examples, distinguishing between news-based proxies and structural or event-based measures.

Chart A.2

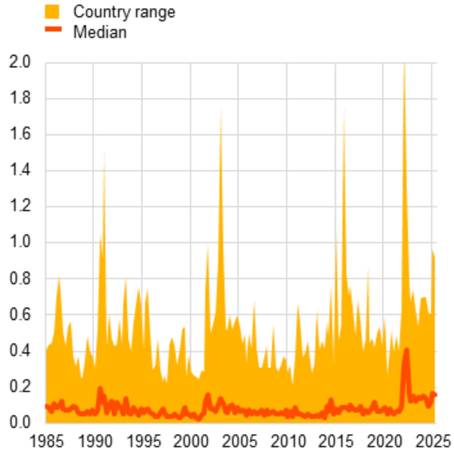
Military conflict, war and infrastructure indicators

a) Geopolitical risk-related indices | **b) Military conflict-related indicators**



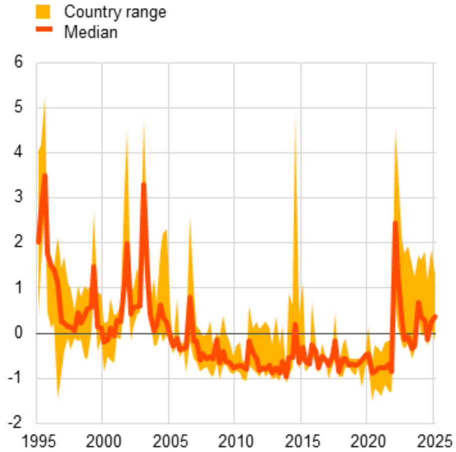
c) Geopolitical Risk Index (GPR) by country

(index)



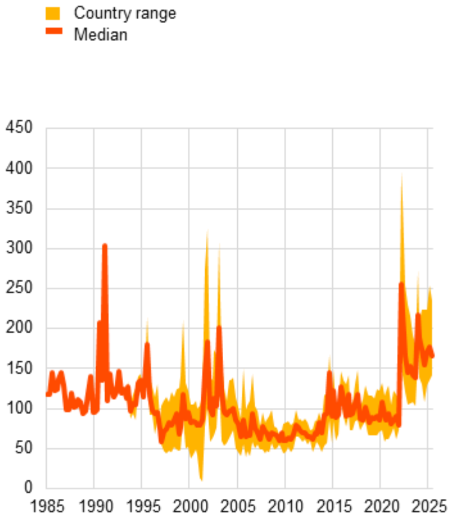
d) Bondarenko Geopolitical Risk Perceptions (BiGPR) Index by country

(z-scores)



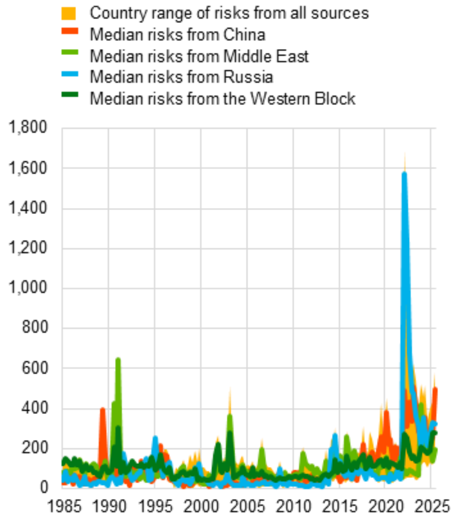
e) BiGPR by country

(index)



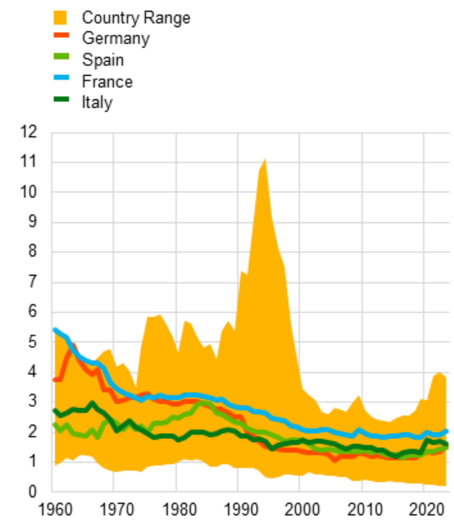
f) BiGPR by country and risk source

(index)



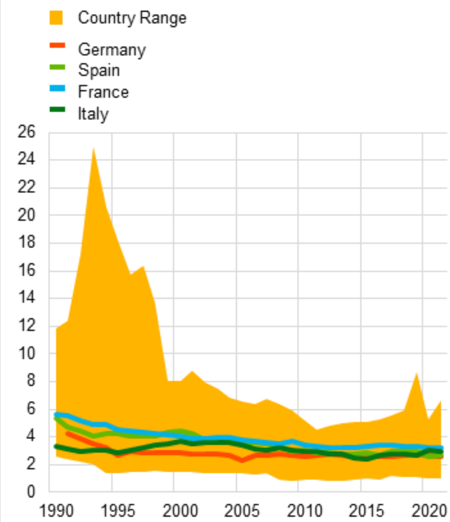
g) Government military expenditure (% of GDP)

(percent)



h) Government military expenditure (% of gov budget)

(percent)



Source: See the sources corresponding to each indicator in Table A.1 of this Annex.
Notes: Geopolitical risk (GPR) data are available for Belgium, Denmark, Germany, Spain, Finland, France, Italy, Hungary, the Netherlands, Poland, Portugal and Sweden. Bondarenko Geopolitical Risk Perceptions (GPRP) data were available for Germany, Spain, France, Italy and the Netherlands. Bilateral Indicator of Local Perception of Geopolitical Risk (BiGPR) data are available for Belgium, Germany, Ireland, Spain, France, Italy Austria, and Poland. For risk sources, data are only available for Germany, Spain, France and Italy.

Trade-related uncertainty and disruption indicators used in the analysis

This group of indicators captures risks stemming from shifts in trade policy, disruptions to global supply chains and the escalation of international sanctions. While some of these measures are event-based or media-driven, others reflect structural and institutional developments that evolve more gradually.

The Trade Policy Uncertainty (TPU) Index is consistently selected in empirical screening owing to its strong co-movement with financial stress and downturn episodes. Its high frequency and global coverage make it a key proxy for policy-driven trade tensions. Complementing this, the Global Supply Chain Pressure Index (GSCPI) provides a real economy view of supply-side bottlenecks, spiking during periods of major disruptions such as the COVID-19 pandemic and the Russian invasion of Ukraine (**Chart A.3**).

Longer-run shifts in global trade patterns are reflected in the Trade Openness (TO) Ratio (trade volume, % of GDP), which shows an increasingly upward trajectory for the EU over the past few decades. This trend points to rising exposure to external developments, which may amplify the EU's vulnerability to global shocks.

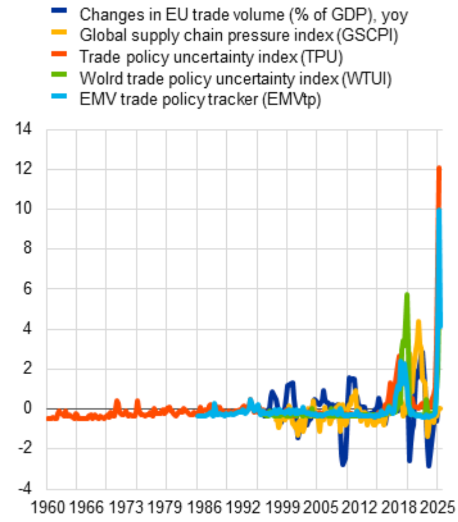
Overall, the indicators in this category combine high-frequency shocks with structural trends, making them useful for both short-term monitoring and longer-term resilience assessments.

Chart A.3

Trade-related indicators

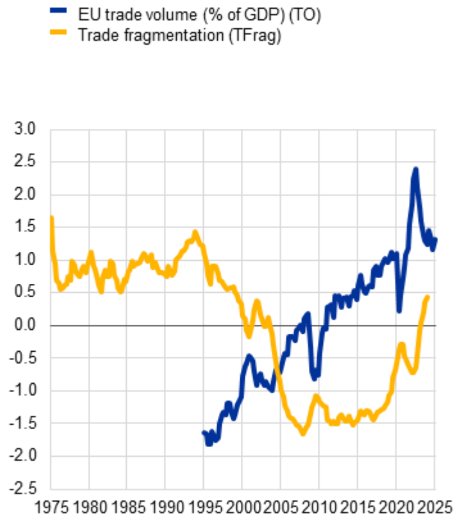
a) Shock indicators

(z-scores)



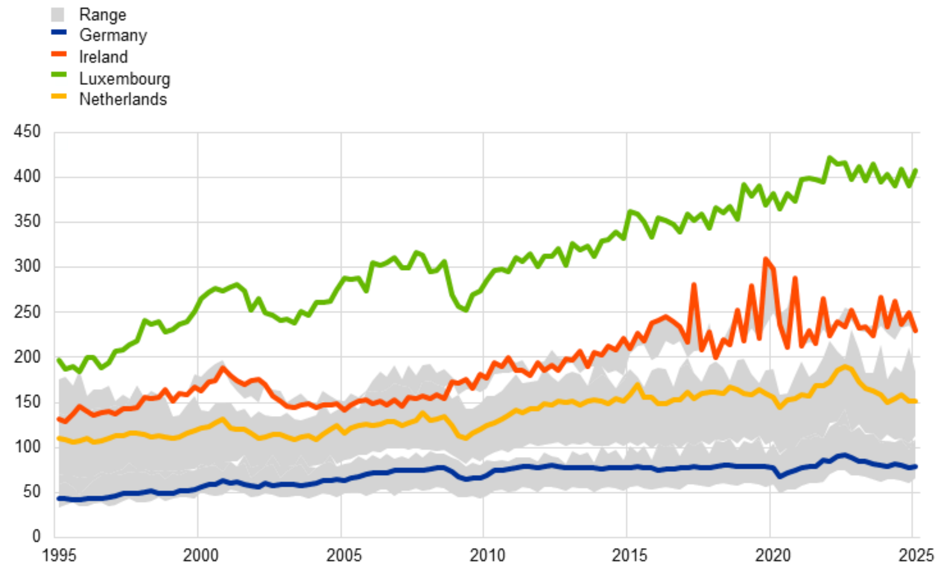
b) Trend and fragmentation indicators

(z-scores)



c) Trade openness by country

(percent)



Source: See the sources corresponding to each indicator in Table A.1 of this Annex.
Notes: Yoy stands for year on year change, TO for trade openness. Countries with relatively lower trade openness are Germany, Estonia, Greece, Spain, France, Italy, Hungary, Portugal, Poland Romania, Finland and Sweden. Countries with high trade openness are Belgium, Bulgaria, Czech Republic, Denmark, Cyprus, Latvia, Lithuania, Hungary, the Netherlands, Austria, Slovenia and Slovakia. Countries with very high trade openness are Ireland and Malta. Luxembourg stands out as the EU Member State with the highest trade openness.

Capital and financial market uncertainty indicators used in the analysis

This group comprises indicators that track uncertainty and volatility in financial markets – two dimensions that are highly relevant for GaR modelling. These indicators vary in frequency, scope and thematic focus, covering both local and global sources of risk.

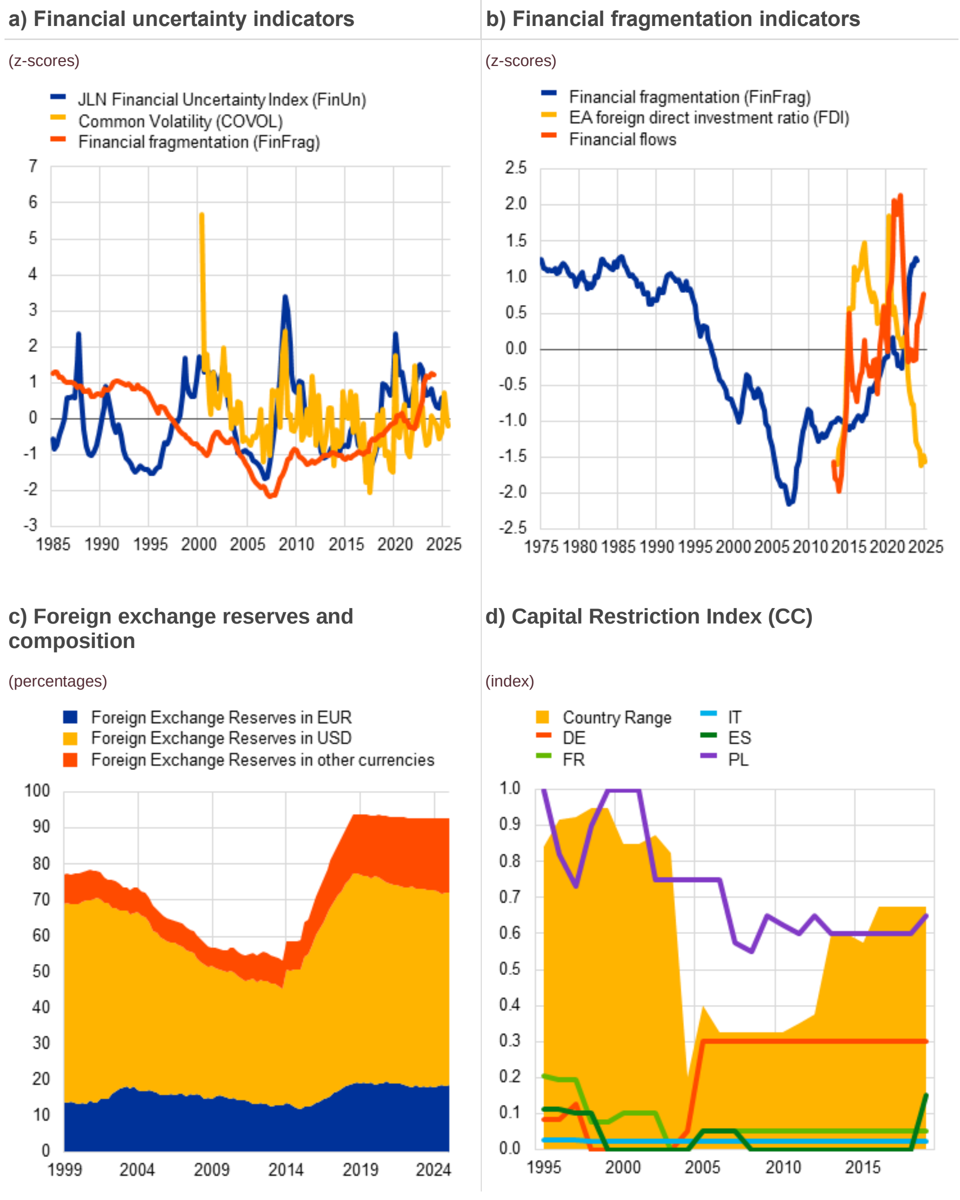
Financial uncertainty is captured through the JLN Financial Uncertainty Index. Although it has limited geographical coverage, it is conceptually valuable for assessing global sentiment and regime shifts. Notable recent peaks align with the COVID-19 pandemic, rising trade tensions and the post-2025 policy reorientation in the United States.

The COVOL Index aggregates volatility signals across financial markets and has shown robust predictive performance in LASSO-based GaR models.

Financial fragmentation, foreign direct investment, equity market segmentation and foreign exchange reserve indicators show trend developments in this risk category. A trend towards greater fragmentation can be seen since the 2008 global financial crisis (**Chart A.4**).

Chart A.4

Capital and finance indicators



Source: See the sources corresponding to each indicator in Table A.1 of this Annex.
Notes. Capital restriction index data are available for Belgium, Bulgaria, Czech Republic, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Cyprus, Latvia, Hungary, Malta, the Netherlands, Austria, Poland, Portugal, Finland, Slovenia and Sweden.

The Capital Restriction Index, compiled by the International Monetary Fund (IMF), complements this group by capturing shifts in institutional openness, although major euro area countries continue to be classified as highly open, with the exception of Germany following a regulatory shift in 2006.

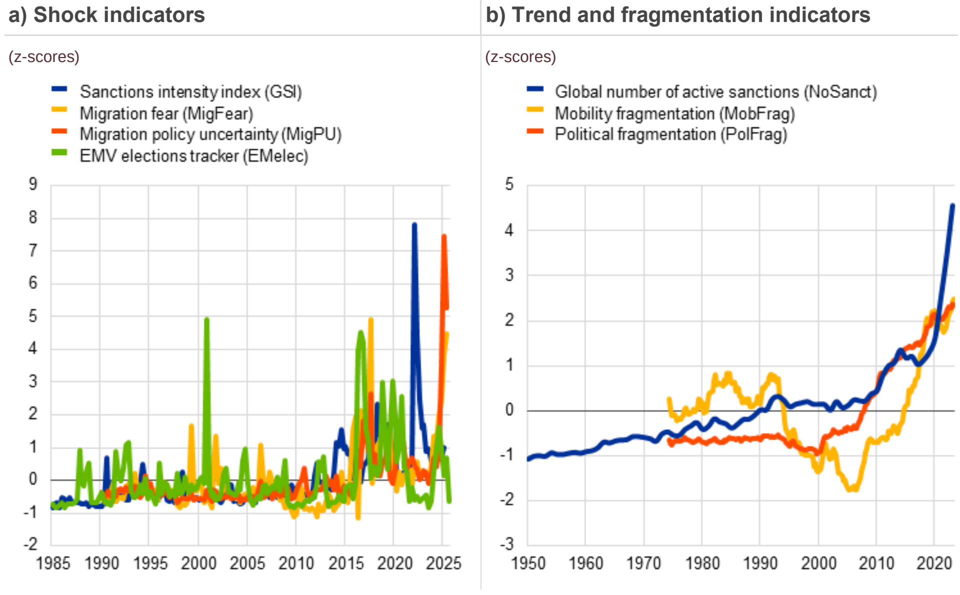
Politics and society-related indicators used in the analysis

Two related indicators from the Global Sanctions Database, the Global Sanctions Intensity (GSI) Index and the Global Number of Active Sanctions (GSDB) Index, offer distinct insights. While the GSI Index captures changes in the number of active sanctions (thus highlighting sudden events, such as the spike in 2022), the GSDB Index tracks the cumulative number of active sanctions, which has shown a steady upward trend since the 2009, particularly in recent years.

The Migration Fear (MigFear) Index exhibits pronounced peaks, especially during periods of heightened concern in Europe following the 2015 migrant crisis. The Migration Policy Uncertainty (MigPU) Index shares several of those spikes, as well as a more recent peak during the COVID-19 crisis.

Chart A.5

Politics and society-related indicators



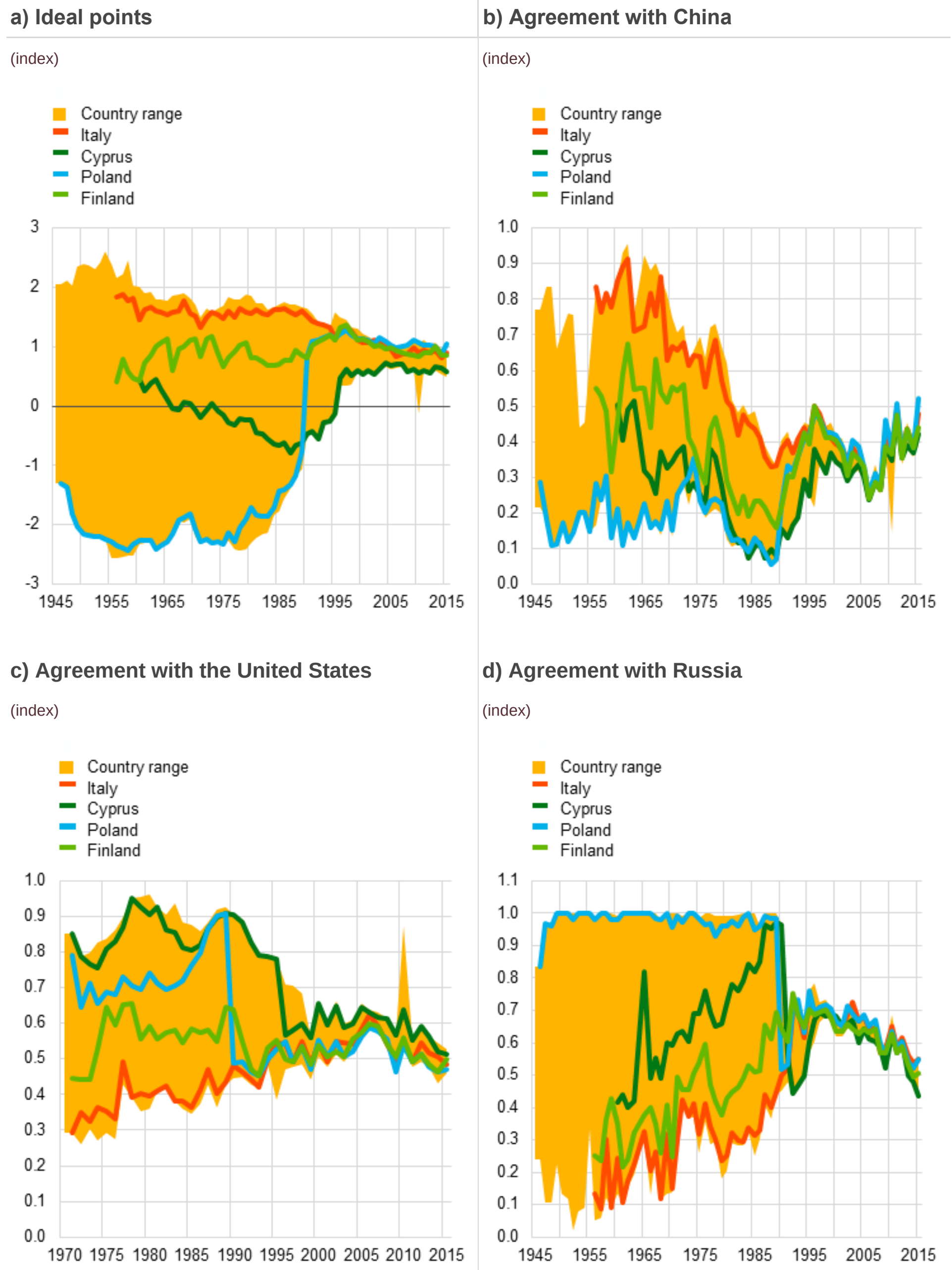
Source: See the sources corresponding to each indicator in Table A.1 of this Annex.

The UN voting alignment indicators track how countries position themselves in UN resolutions. These data series reveal both abrupt shifts, such as those seen in former Warsaw Pact countries following the collapse of the Soviet Union, and gradual realignments, such as the declining political proximity of Western European countries to the United States over the post-war period. At the same time, modest increases in alignment with China and Russia can be observed in some regions. These patterns, derived from ideal points and percentage agreement with the positions adopted by major powers (United States, China, Russia), provide a long-term perspective on evolving geopolitical orientations.

Together, these indicators help to identify periods and domains in which international cooperation weakens or breaks down, providing a structural complement to the more event-driven or uncertainty-based measures used elsewhere in the analysis.

Chart A.6

UN voting alignment: ideal points and agreement with United States, China, and Russia



Source: See the sources corresponding to each indicator in Table A.1 of this Annex.
Notes: The data track international alignment by calculating ideal points and vote agreement percentages across major UN resolutions. Shifts in alignment reflect both regime changes and broader geopolitical trends. The charts represent data on 11 countries that can be clustered in four groups: Belgium, Italy and Luxembourg (represented by Italy); Greece and Finland (represented by Finland); the Czech Republic, Estonia, Hungary, and Poland (represented by Poland) and Cyprus and Malta (represented by Cyprus).

Domestic structural vulnerability indicators used in the analysis

Domestic structural vulnerabilities shape how external shocks are transmitted, absorbed and amplified within national economies. This section focuses on slow-moving, country-specific indicators that reflect underlying macro-financial imbalances and structural resilience. In doing so, it also explores cross-country heterogeneity in these vulnerabilities, illustrating how differences in financial conditions, institutional setups and exposure profiles may influence the impact of global geopolitical and economic shocks.

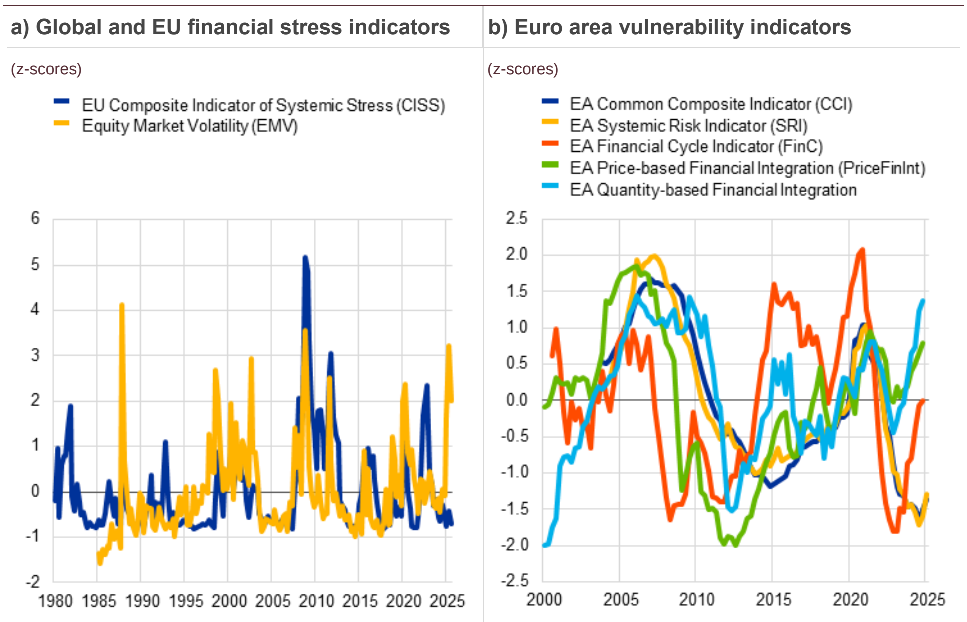
Financial market volatility is monitored using several high-frequency, market-based proxies:

- The Composite Indicator of Systemic Stress (CISS) captures systemic stress in financial markets but is limited by data availability across countries.
- The Country-Level Indicator of Financial Stress (CLIFS), with broader country coverage, serves as the main volatility proxy in the GaR baseline specification.
- Other volatility indices, such as the VIX and VSTOXX, were evaluated but excluded owing to their high correlation with CLIFS and lower relevance outside their home markets.

Two composite indicators are particularly relevant, the Common Composite Indicator (CCI) and the Systemic Risk Indicator (SRI). Both aim to summarise domestic financial-cycle conditions and are based on the same methodological framework. The CCI, however, excludes the equity price component of the SRI, making it more suitable for Member States where equity markets are relatively shallow or equity prices less informative as systemic stress signals. The CCI was retained in the GaR baseline specification owing to this refinement, as well as its broader country coverage and more stable statistical properties.

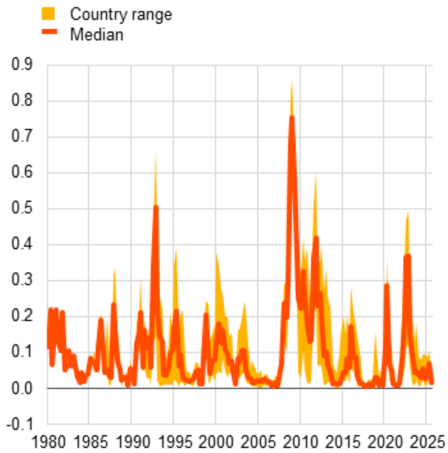
Chart A.7

Systemic stress and domestic vulnerabilities



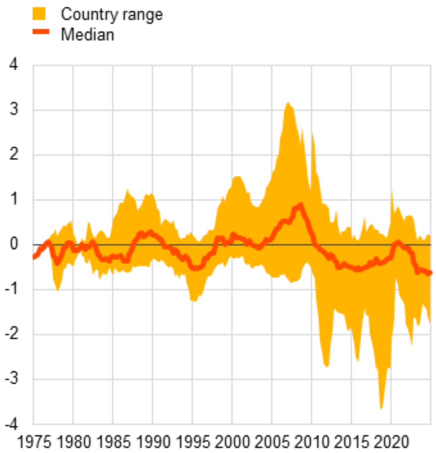
c) Composite Indicator of Systemic Stress (CISS) by EU Member State

(index)



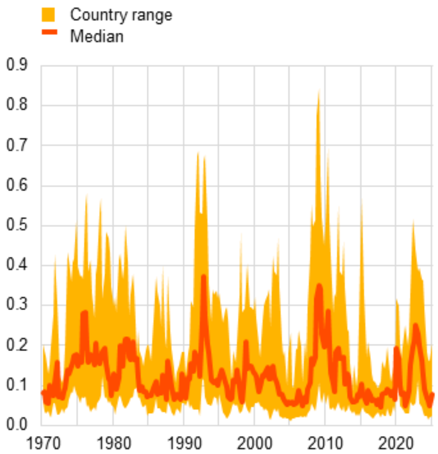
d) Common Composite Indicator (CCI) by EU Member State

(index)



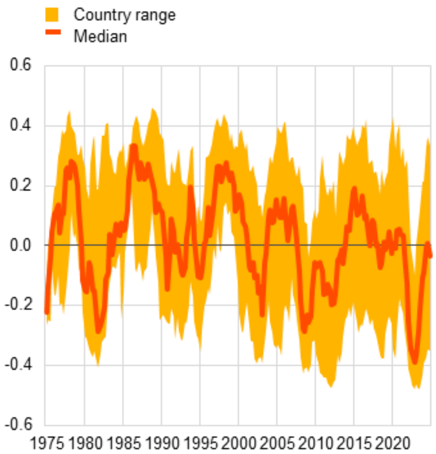
e) Country-Level Indicator of Financial Stress (CLIFS)

(index)



f) Financial Cycle Indicator (FCI) by country

(index)



Source: See the sources corresponding to each indicator in Table A.1 of this Annex.
Note. The CISS is available for Belgium, Germany, Ireland, Spain, France, Italy, the Netherlands Austria, Portugal and Finland.

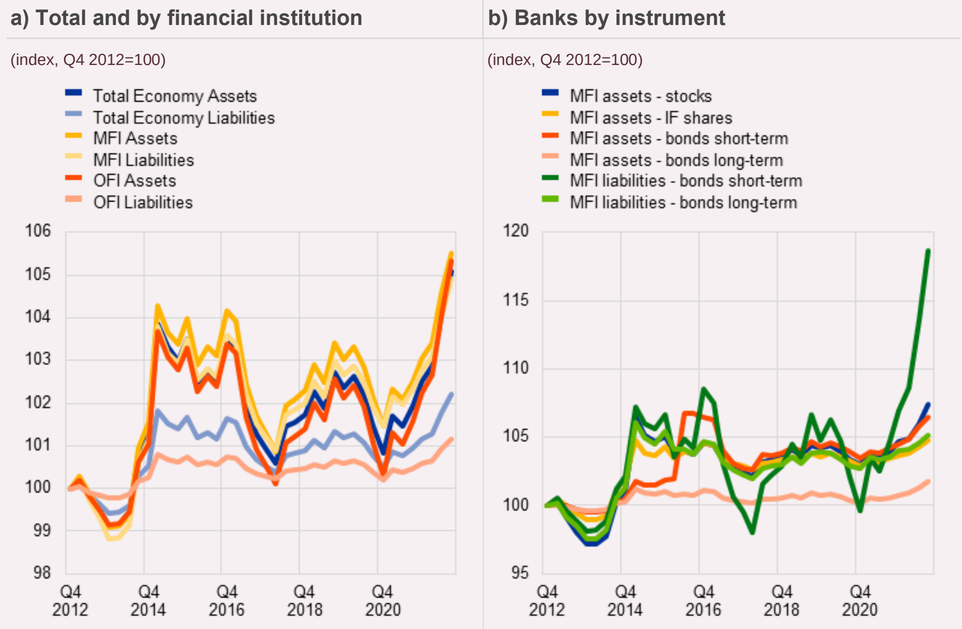
Box A.1
Geopolitical risk transmission through financial positions

Financial position-weighted effective exchange rates to assess external risks

Geopolitical shocks and geoeconomic fragmentation can directly and indirectly affect foreign exchange rates and affect financial stability risks directly and indirectly.[1] The risks may stem from heightened financial volatility or sudden, unexpected exchange rate shifts, as well as from changes in economic policies. For example, trade policies alter cross-border capital flows and the demand for currencies. The resulting changes in exchange rates and in cross-border financial positions also affect domestic financial conditions. Trade-weighted effective exchange rates fall short, however, of measuring the impact on financial institutions and on financial stability risks more broadly.

Chart A

Financial position-weighted effective exchange rates for Germany



Source: Deutsche Bundesbank External Statistics.
Notes: MFI stands for monetary financial institution, OFI for other financial intermediary, IF for investment fund and PI for portfolio Investment.

To account for the financial channel for exchange rates, bilateral exchange rates need to be weighted according to their importance in cross-border financial positions (Lane and Shambaugh, 2010). This makes it possible to measure the influence of, for example, the US dollar on the balance sheets of EU financial institutions. It also makes it possible to analyse the transmission of geopolitical risks separately for assets or liabilities and by the financial instruments held by different financial institutions. For Germany, for example, there are important

[1] See, for example e.g. IMF (2025a), IMF(2025b), Executive summary, and BIS (2025a), Chapter II.

differences in the financial weighted effective exchange rates for banks and non-banks, as well as in terms of assets and liabilities (**Chart A, panel b**).[2] Around 40% of the asset side and 20% of the liability side of Germany's international investment position (IIP) is denominated in foreign currency, with the US dollar accounting for more than half of these positions.[3] This makes the financial channel for exchange rates a relevant macro-financial transmission channel. Given that Germany is a net creditor with a relatively large share of foreign-denominated assets, an asset-based financial foreign exchange (FX) indicator is much more sensitive to exchange rate shocks than a liability-based indicator. Further inspection shows that the net creditor position of Germany in foreign currencies stems primarily from non-bank financial intermediaries (NBFIs), whereas the balance sheet for the monetary financial institutions (MFIs) sector appears to be currency matched. Broken down by financial instrument, however, the high volatility of the indicator for short-term bonds held by MFIs reveals their short-term funding needs in foreign currencies. For NBFIs, the higher variability of their asset-weighted exchange rates – due to their equity holdings – may amplify the transmission of geopolitical shocks. In combination with recent evidence of an acceleration in the hedging of such exposures by NBFIs through banks using short-term FX derivatives,[4] this would seem to support calls for MFIs to put the necessary arrangements in place to be able to access central bank cross-currency swap lines swiftly if needed.[5]

This shows that financial position-weighted effective exchange rates can provide timely signals of potential risks on the asset and liability sides for different financial sectors. Swings in exchange rates resulting from geopolitical shocks can affect the financial system and its stability through the positions held by financial institutions.

1.2.3 Additional indicators considered in the analysis

In addition to the core set of indicators presented in Sections 3 of the report, several complementary indicators were considered for analytical or exploratory purposes. These indicators are either conceptually novel or designed to capture financial transmission channels or extend existing geopolitical indicators with a regional or bilateral focus. While not part of the baseline indicator set used in the heatmaps or in the model-based forecasting, they provide useful inputs for country-level analysis, robustness checks and the design of alternative scenarios.

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2 For details of how the indicator is constructed, see Deutsche Bundesbank (2018).

3 See the statistics on the international investment position for Germany published on the Deutsche Bundesbank website.

4 E.g. in line with the trend observed globally by the Bank for International Settlements in its most recent Triennial Central Bank Survey (BIS, 2025b), German banks reported that their total foreign exchange turnover had more than doubled since the previous survey and that this had primarily taken the form of short-term foreign exchange FX swaps with other financial institutions and cross border. In this regard, see also Deutsche Bundesbank (2024).

5 See also ECB (2024), Box 4.

Trade policy shock indicator

Metiu (2021) constructs a measure of US trade policy announcement shocks using micro-level data on anti-dumping, countervailing duties and safeguards – collectively known as temporary trade barriers (TTBs) and which have been the main instruments of trade restriction by advanced economies since the early 1980s (Bown and Crowley, 2013). TTBs are frequently used by the United States, not only to address unfair trade but also as a tool for protectionism (Knetter and Prusa (2003); Bown and Crowley, 2013), making them a useful basis for identifying trade policy shocks. The shock series is constructed by counting US-imported products subject to new TTB investigations from the first quarter of 1988 to the fourth quarter of 2015. T, matching this count with product-level bilateral trade data to create a time series of the real value of US imports affected by TTB initiations. This series is then regressed on macroeconomic variables to isolate exogenous variation, with the residual representing US trade policy announcement shocks.

Composite indicator for the trade-weighted global uncertainty factor

To complement the standard set of uncertainty and volatility indicators, a composite uncertainty factor was constructed and tested in the GaR LASSO estimations. This indicator sought to account for both the global intensity of uncertainty shocks and country-specific trade exposure to such shocks. The uncertainty factor was constructed by scaling a dynamic factor model (DFM)-based global uncertainty measure (extracted from the TPU, WTUI and WUI Indices) to each country’s trade openness (i.e. the ratio of exports and imports to GDP). This approach was designed to capture how strongly global uncertainty is likely to affect individual economies, given their trade exposure. Although conceptually appealing, the indicator displayed relatively low time variation, with only one prominent spike observed during the COVID-19 crisis. It failed to react clearly to other major global uncertainty episodes, including geopolitical tensions, and therefore lacked responsiveness for short-term risk forecasting in the GaR framework.

1.2.4 Exploratory analysis of the indicators used in the analysis

This section presents the diagnostic work to assess the usability, coverage and interdependence of the full indicator set. While the results do not directly determine the final model specifications, they inform the screening and prioritisation process by flagging practical constraints and potential redundancies. The analysis first examines the availability and frequency of each series, as several conceptually relevant indicators are only available at annual frequency or have short historical coverage, limiting their suitability for high-frequency modelling. Nevertheless, these still hold value for structural assessments and robustness checks. The subsequent analysis explores statistical relationships between indicators, including correlations, principal component patterns and clustering, to highlight redundancy risks, shared dynamics and the scope for proxy selection across different geopolitical and macro-financial themes.

Empirical validation and interdependencies

A set of complementary techniques was applied to evaluate both the structure of the indicator space and its macro-financial relevance. The objective was twofold: first, to identify interdependencies and redundancies within the broader set of indicators; and second, to isolate those most promising for empirical modelling, particularly in the GaR framework. Correlation analysis and Granger causality tests were used to measure linear dependencies and predictive relationships between indicators and macro-financial outcomes, namely GDP growth, financial stress (CLIFS) and domestic financial vulnerabilities (CCI). These diagnostics helped identify potential redundancies and flag variables with forward-looking information content. PCA was applied to explore shared dynamics and detect latent thematic structures. Rather than using PCA solely for dimensionality reduction, the principal components were interpreted to group indicators with similar behaviour over time. The first few components, jointly explaining around 60% of the variance, correspond closely to clusters such as geopolitical tensions, financial market volatility and macroeconomic uncertainty. Hierarchical clustering grouped indicators by similarity in historical dynamics, revealing five clusters that align closely with the narrative typology: slow-moving structural measures of fragmentation and conflict; financial market volatility; event-driven policy uncertainty; the GPR family of geopolitical risk indices; and macroeconomic or real economy volatility. These clusters help identify representative indicators within each group, as summarised in the GEO heatmap,. LASSO-based variable selection in the GaR framework formed the core empirical filter. The LASSO-regularised quantile regression estimated the conditional distribution of future GDP growth using a baseline set of controls (lagged GDP, CLIFS, and CCI) alongside the broader set of geopolitical and uncertainty indicators as candidate regressors. LASSO identified the most informative predictors while maintaining model simplicity and robustness. Non-crossing quantile constraints followed Bondell, Reich, and Wang (2010), and adaptive LASSO regularisation drew on the approach of Szendrei and Varga (2023). Summary results are discussed in Section 2.4.6 of the Annex, with full output tables provided for each forecast horizon.

Indicator availability and frequency limitations

Differences in frequency and historical depth impose practical constraints on indicator use in modelling. While many series are updated monthly or quarterly, others are only available annually or have limited historical coverage, reducing their applicability for GaR. Annual-only indicators, such as military expenditure as a share of GDP (% of GDP), the Global Number of Active Sanctions (NoSanct) Index, the Capital Restriction Index (CC) and the UN Votes Ideal Point (UNidealP) Indicator, are best suited to trend analysis and structural alignment studies. Indicators with short or lagged histories, including Significant Cyber Incidents (NoCyb), fragmentation indices such as the Trade Fragmentation Index (TFrag) and the Political Fragmentation Index (PolFrag), as well as conflict measures, such as the Number of Conflict Events (NoConfl), face limitations for real-time monitoring or dynamic estimation. These constraints informed the decision to exclude certain indicators from the final empirical subset, while retaining them in the broader conceptual framework and the heatmap for contextual monitoring.

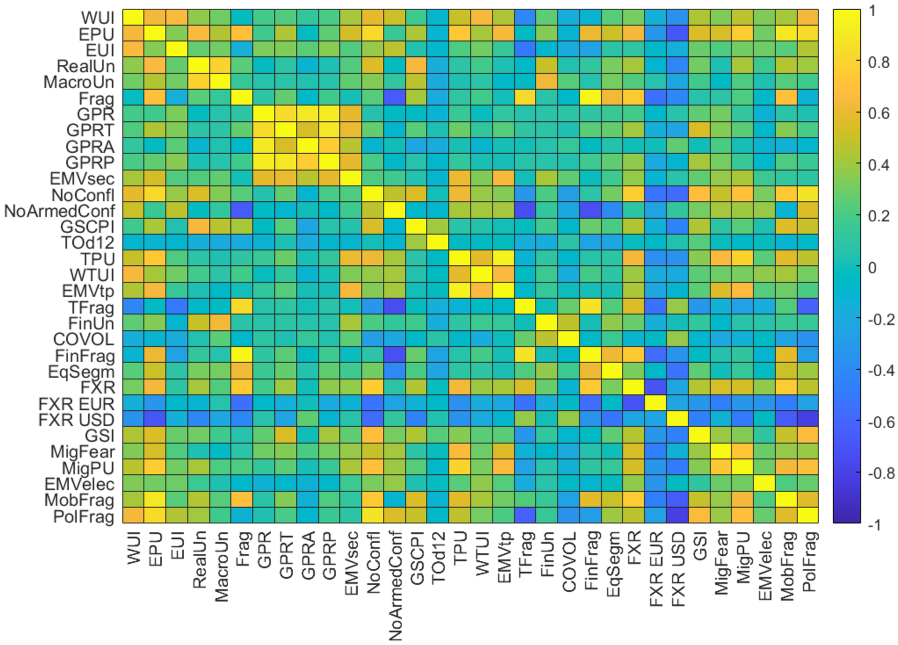
Correlation patterns and indicator interdependencies

Correlation diagnostics confirm that the thematic groupings are broadly consistent with the narrative classification. The results show (**Chart A.8**) that many indicators cluster strongly within their thematic category, while others remain largely orthogonal, suggesting complementary information content. Geopolitical risk indices display strong internal consistency, but show limited correlation with macro-financial indicators. Trade policy measures form a coherent group, though they are also linked to other policy and conflict-related indicators. Structural indicators, including trade openness and foreign exchange reserve composition, remain largely independent.

The diagnostics also highlight potential multicollinearity risks for the GaR framework **(Table A.2)**. The CLIFS, a core GaR input, is moderately to strongly correlated ($|r| > 0.5$) with macro and financial uncertainty measures, particularly the Financial Uncertainty (FinUn) Index across many countries. The Common Composite Indicator (CCI), the other baseline regressor, is highly correlated with the Macro Uncertainty (MacroUn) Index, the Financial Uncertainty (FinUn) Index, the Economic Policy Uncertainty (EPU) Index, the number of conflicts (NoConfl) indicator and all the fragmentation indicators. By contrast, almost all the Geopolitical Risk (GPR) Index variants and most of the Trade and Politics and Society-related indicators show low correlation with either of the baseline controls, supporting their inclusion as candidate regressors.

Chart A.8

Correlation matrix of selected indicators



Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Notes: WUI stands for World Uncertainty Index, EPU for Economic Policy Uncertainty Index, EUI for Energy-related Uncertainty Index, RealUN for JNL Real Economic Uncertainty Index, MacroUN for JLN Macro Uncertainty Index, Frag for Geopolitical Fragmentation Index, GPR for Geopolitical Risk Index, GPRT for Geopolitical Risk Threats Index, GPRA for Geopolitical Risk Acts Index, GPRP for the Geopolitical Risk Perceptions Index, EMVsec for National Security Policy Equity Market Volatility Tracker, NoConfl for Number of Conflict Events, NoArmedConfl for Number of International Armed Conflicts, GSCPI for Global Supply Chain Pressure Index, TOd12 for Trade openness, year-on-year difference, WTUI for World Trade Uncertainty Index, EMVtp for Trade Policy Equity Market Volatility Tracker, TFrag for Trade Fragmentation Index, FinUn for Financial Uncertainty Index, COVOL for Common Volatility Index, FinFrag for Financial Fragmentation Index, EqSegm for Equity Market Segmentation Index, FXR for Allocated Foreign Exchange Reserves Index, GSI for Global Sanctions Intensity, MigFear for Migration Fear Index, MigPU for Migration Policy Uncertainty Index, EMVelec for Elections and Political Governance Equity Market Volatility Tracker, MobFrag for Mobility Fragmentation Index and PolFrag for Political Fragmentation Index. The chart presents pairwise correlation coefficients. Samples differ by indicator pairs. The maximum sample begins with the second quarter of 2000 and ends with the second quarter of 2025. Details of the indicators concerned can be found in in Table A.1 of this Annex.

Table A.2

Number of countries where indicator correlation with CLIFS or CCI exceeds 0.5 in absolute terms

Indicator	r(CLIFS) >0.5	r(CLIFS) <-0.5	r(CCI) >0.5	r(CCI) <-0.5	Number of countries
World Uncertainty Index (WUI)	0	0	0	1	1
World Uncertainty Index (WUI), country-specific	0	0	0	0	0
Economic Policy Uncertainty Index (EPU)	1	0	2	6	9
Economic Policy Uncertainty Index (EPU), country-specific	0	0	0	1	1
JLN Real Uncertainty Index (RealUn)	1	0	3	0	4
JLN Macro Uncertainty Index (MacroUn)	9	0	8	0	14
Geopolitical fragmentation Index (Frag)	0	0	3	7	10
Geopolitical Risk Index (GPR)	0	0	0	1	1
Geopolitical Risk Index (GPR), country-specific	0	0	0	1	1
Geopolitical Risk Threats Index (GPRT)	0	0	0	0	0
Geopolitical Risk Acts Index (GPRA)	0	0	1	0	1
Bondarenko Geopolitical Risk Perceptions Index (GPRP)	0	0	0	3	3
Bondarenko Geopolitical Risk Perceptions Index (GPRP), country-specific	0	0	0	0	0
Local Perception of Geopolitical Risk (BiGPR)	0	0	0	2	2
National Security Policy Equity Market Volatility Tracker (EMVsec)	0	0	1	1	2
Number of conflict events (NoConfl)	0	0	2	9	11
Number of international armed conflicts (NoIntConfl)	0	1	1	0	2
Global Supply Chain Pressure Index (GSCPI)	0	0	3	0	3
Trade volume (% GDP) or trade openness (TO), yoy difference	0	0	0	1	1
Trade Policy Uncertainty Index (TPU)	0	0	0	2	2
World Trade Uncertainty Index (WTUI)	0	0	0	0	0
Trade Policy EMV Tracker (EMVtp)	0	0	0	1	1
Trade fragmentation Index (TradeFrag)	0	0	4	4	8
JLN Financial Uncertainty Index (FinUn)	18	0	6	0	22
Common Volatility Index (COVOL)	0	0	0	0	0
Financial Fragmentation Index (FinFrag)	0	0	2	9	11
Global Sanctions Intensity Index (GSI)	0	0	0	3	3
Migration Fear Index (MigFear)	0	0	0	1	1
Migration Policy Uncertainty (MPU)	0	0	0	1	1
Elections & Political Governance Equity Market Volatility Tracker (EMVelec)	0	0	0	0	0
Mobility Fragmentation Index (MobFrag)	0	0	3	10	13
Political Fragmentation Index (PolFrag)	1	0	2	13	16

Source: Calculations by the ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Notes: The table shows the number of EU countries for which the indicators are highly correlated with the Country-Level Indicator of Financial Stress (CLIFS) or Common Composite Indicator (CCI). The samples differ by country. The maximum sample begins with the second quarter of 2000 and ends with the first quarter of 2025.

Principal component analysis

This subsection presents the results of the PCA used to explore latent structures in the indicator dataset. The first six components, which account for 17%, 13%, 10%, 9%, 6% and 5% of the total variance respectively, are shown below (**Chart 9**). Loadings are reported for all the indicators included in the PCA sample.

These results complement the narrative classification developed in Section 3 of the report by providing a data-driven grouping of indicators with similar time dynamics.

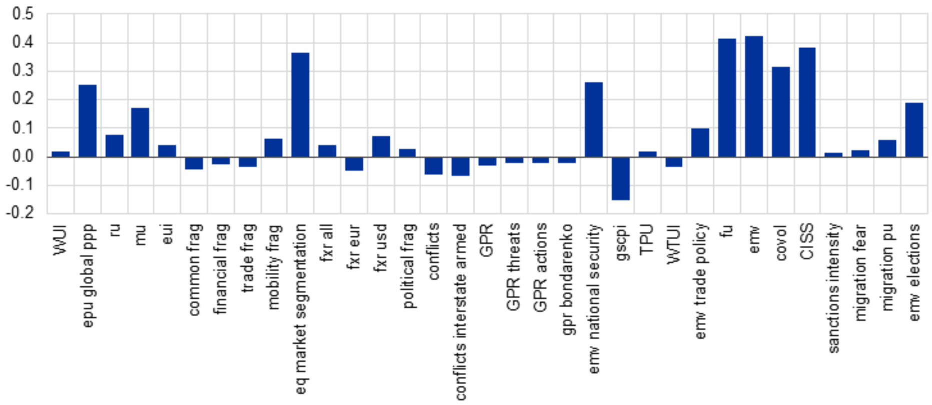
Chart A.9

Principal component analysis

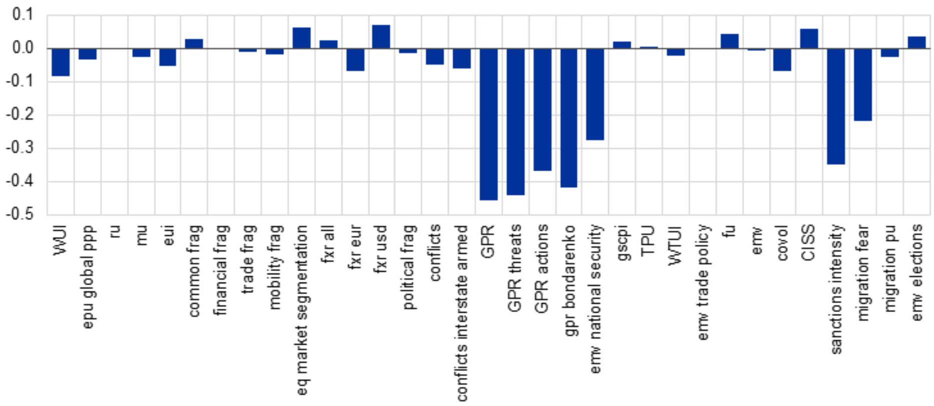
Rotated factor loading by factor – Differenced data

(factor loadings)

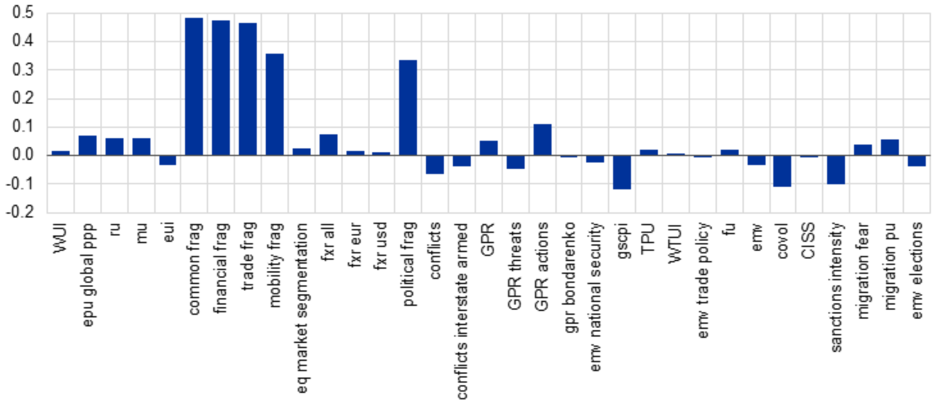
a) Factor 1



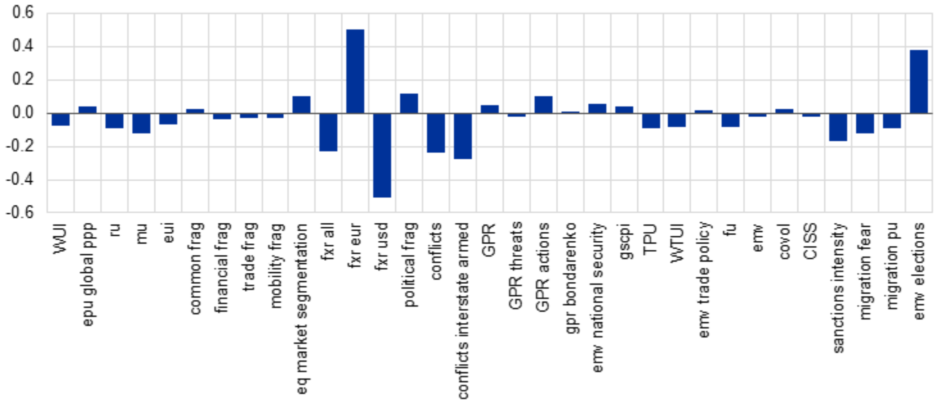
b) Factor 2



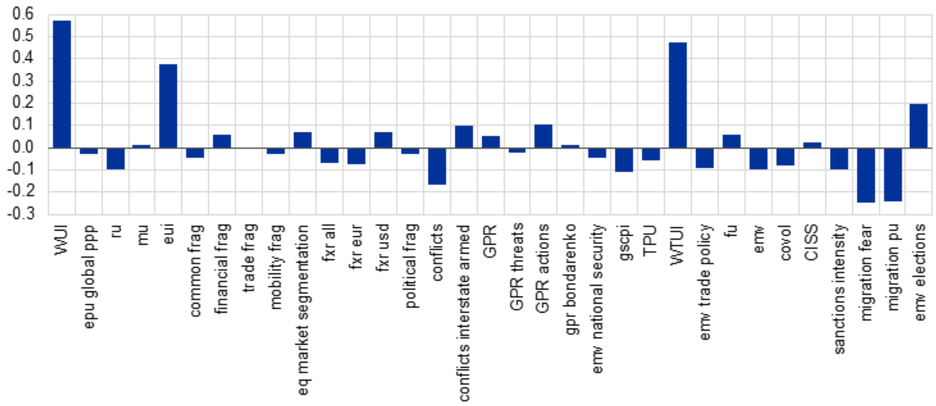
c) Factor 3



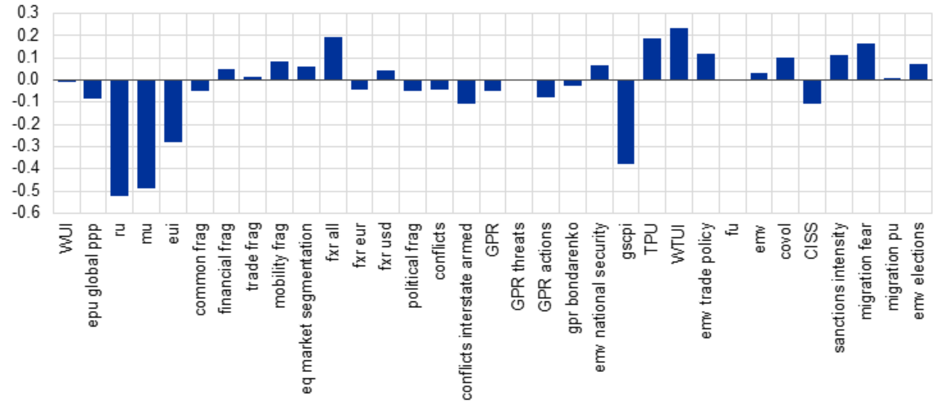
d) Factor 4



e) Factor 5



f) Factor 6



Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: The first six factors explain 17%, 13%, 10%, 9%, 6% and 5% of the variation.

Granger causality

The following table summarises the results of Granger causality tests between each indicator and key macro-financial outcomes (real GDP growth, SRI). The tests were conducted using a bivariate VAR with two lags (**Chart A.10**). The purpose is to identify indicators that offer potential early warning value for macroeconomic or financial stress dynamics, as discussed in Section 3 of the report.

Chart A.10

Summary of Granger causality test results (2-lag bivariate VARs)

	WUI	epu global ppp	ru	mu	eui	common frag	financial frag	trade frag	mobility frag	eq market segmentation	fxr all	fxr eur	fxr usd	political frag	conflicts	conflicts interstate armed	GPR	GPR threats	GPR actions	gpr bondarenko	emv national security	gscpi	TPU	WTUI	emv trade policy	fu	emv	covol	CISS	sanctions intensity	migration fear	migration pu	emv elections
WUI		0	1	1	0	1	1	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
epu global ppp	1		1	1	1	1	1	1	0	1	0	0	1	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0
ru	0	1		0	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0	1	0	1	0	0	1	0	1	0	0	0	0
mu	0	1	0		1	1	1	1	0	1	0	1	1	1	1	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0
eui	1	0	0	0		1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0
common frag	1	0	0	0	0		0	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
financial frag	1	0	0	0	0	0		1	1	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
trade frag	1	0	0	0	0	1	1		1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
mobility frag	1	1	0	0	0	1	1	1		1	0	0	0	1	0	1	0	1	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0
eq market segmentation	0	0	0	0	1	0	0	0	0		0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
fxr all	0	1	0	0	0	1	1	1	0	0		0	0	0	0	1	0	1	0	1	0	0	1	0	0	0	0	0	0	0	1	0	1
fxr eur	0	0	0	0	0	0	1	1	0	0	1		0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0
fxr usd	0	0	0	0	0	0	0	0	0	1	0	1		0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0
political frag	1	1	0	0	0	1	1	0	1	1	0	0	0		1	1	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	1	0
conflicts	1	1	0	1	1	1	1	1	1	1	0	0	0	0		1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
conflicts interstate armed	1	0	0	0	0	1	0	0	1	0	1	0	0	1	0		0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
GPR	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GPR threats	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GPR actions	0	0	0	0	0	1	0	1	0	0	0	1	1	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0
gpr bondarenko	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0		0	0	0	0	0	0	0	0	0	0	0	0	0
emv national security	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0
gscpi	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0		0	0	0	0	0	0	0	1	0	0	0
TPU	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0		1	1	1	1	0	0	0	0	1	1
WTUI	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1		1	1	1	0	0	0	0	0	0
emv trade policy	1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1		1	0	0	0	0	0	0	0
fu	0	1	1	0	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		1	1	1	0	0	1	0
emv	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1		0	0	0	0	0	0
covol	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0		1	0	0	0	1
CISS	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0
sanctions intensity	1	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0
migration fear	0	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0		0	1
migration pu	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0		0
emv elections	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Notes: WUI stands for World Uncertainty Index, EPU for Economic Policy Uncertainty Index, EUI for Energy-related Uncertainty Index, RealUN for JNL Real Economic Uncertainty Index, MacroUN for JLN Macro Uncertainty Index, Frag for Geopolitical Fragmentation Index, GPR for Geopolitical Risk Index, GPRT for Geopolitical Risk Threats Index, GPRA for Geopolitical Risk Acts Index, GPRP for the Geopolitical Risk Perceptions Index, EMVsec for National Security Policy Equity Market Volatility Tracker, NoConfl for Number of Conflict Events, NoArmedConfl for Number of International Armed Conflicts, GSCPI for Global Supply Chain Pressure Index, TOd12 for Trade openness, year-on-year difference, WTUI for World Trade Uncertainty Index, EMVtp for Trade Policy Equity Market Volatility Tracker, TFrag for Trade Fragmentation Index, FinUn for Financial Uncertainty Index, COVOL for Common Volatility Index, FinFrag for Financial Fragmentation Index, EqSegm for Equity Market Segmentation Index, FXR for Allocated Foreign Exchange Reserves Index, GSI for Global Sanctions Intensity, MigFear for Migration Fear Index, MigPU for Migration Policy Uncertainty Index, EMVelec for Elections and Political Governance Equity Market Volatility Tracker, MobFrag for Mobility Fragmentation Index and PolFrag for Political Fragmentation Index. The chart presents pairwise correlation coefficients. Samples differ by indicator pairs. The maximum sample begins with the second quarter of 2000 and ends with the second quarter of 2025. Details of the indicators concerned can be found in Table A.1 of this Annex.

Cluster analysis

The hierarchical clustering analysis identifies four broad groups of global indicators that capture different empirical dimensions of geopolitical and macro-financial risks (**Chart A.11** and **Chart A.12**). The clusters can be interpreted as follows:

Cluster 1 – Global uncertainty. This cluster includes the World Uncertainty Index (WUI), the World Trade Uncertainty Index (WTUI), the Energy-related Uncertainty Index (EUI), the Trade Policy Uncertainty (TPU) Index and the Trade Policy Equity Market Volatility (EMVtp) Tracker. It also groups risks into societal and political event risks, such as migration fear (MigFear), election-related uncertainty (EMVelec) and international armed conflicts (NoArmedConfl). Together these indicators capture broad, global and event-driven uncertainty, reflecting shifts in expectations and perceived risks before they fully materialise.

Cluster 2 – Fragmentation trends. The indicators for this cluster capture political, economic and institutional disintegration. They cover economic policy uncertainty (EPU), geopolitical fragmentation (Frag), financial fragmentation (FinFrag), conflict events (NoConfl), global sanctions intensity (GSI), migration policy uncertainty (MigPU), political fragmentation (PolFrag), and mobility fragmentation (MobFrag). This cluster highlights the overlap between fragmentation dynamics and policy-driven stresses.

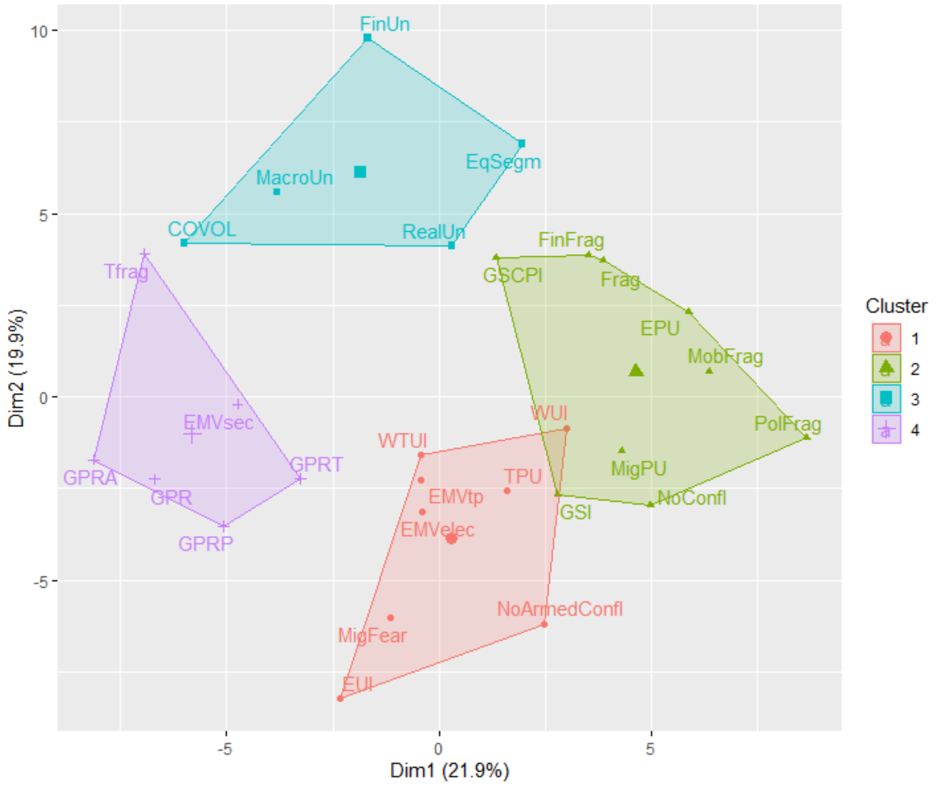
Cluster 3 – Macro-financial volatility. This cluster groups together the econometric uncertainty indices from the JLN suite (RealUn, MacroUn, FinUn), the COVOL Index and the Equity Market Segmentation (EqSegm) Index. These indicators captured macro-financial stress and short-term volatility in fundamentals, providing complementary information to market-based stress measures.

Cluster 4 – Geopolitical risk. This cluster is dominated by the Caldara-Iacoviello Geopolitical Risk (GPR) Index and its subcomponents (the Geopolitical Risk Threats (GPRT) Index and the Geopolitical Risk Acts (GPRA) Index), the Geopolitical Risk Perceptions (GPRP) Index, the National Security Policy EMV (EMVsec) Tracker and the Trade Fragmentation (TFrag) Index. These indicators capture geopolitical narratives, conflict-related risks and broader security tensions, often responding quickly to international events.

In conclusion, the clustering results align closely with the differentiated predictive horizons of the recommended indicators (**Box A**). Indicators in the Global Uncertainty Cluster (such as WUI, TPU and WTUI) and the Macro-financial Volatility Cluster (such as RealUn, FinUn and COVOL) tend to capture short to medium-term downside risks, showing stronger relevance at horizons of one to four quarters. By contrast, indicators grouped in the Fragmentation Cluster (e.g. EPU, FinFrag, sanctions intensity and migration policy uncertainty) and in the Geopolitical Risks Cluster (e.g. BiGPR, EMVsec, MigFear and GSI) capture more persistent structural dynamics and are particularly informative at longer horizons of up to eight quarters.

Chart A.11

Cluster plot of geoeconomic indicators used in the analysis

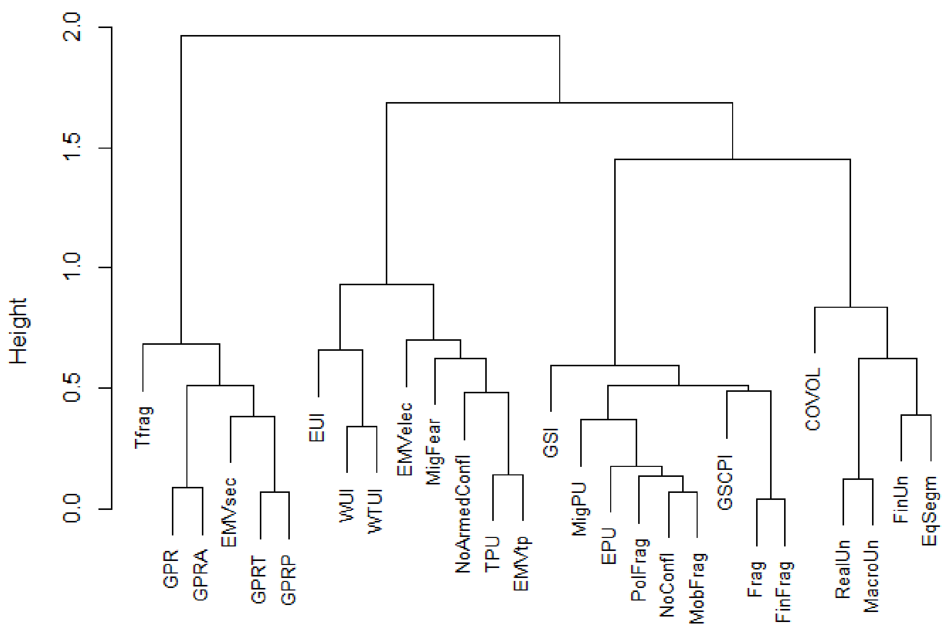


Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: EPU stands for Economic Policy Uncertainty Index, EUI for Energy-related Uncertainty Index, RealUN for JNL Real Economic Uncertainty Index, MacroUN for JLN Macro Uncertainty Index, Frag for Geopolitical Fragmentation Index, GPR for Geopolitical Risk Index, GPRT for Geopolitical Risk Threats Index, GPRA for Geopolitical Risk Acts Index, GPRP for Geopolitical Risk Perceptions Index, NoConfl for Number of Conflict Events, NoArmedConfl for Number of International Armed Conflicts, GSCPI for Global Supply Chain Pressure Index, WTUI for World Trade Uncertainty Index, EMVtp for Trade Policy Equity Market Volatility Tracker, TFrag for Trade Fragmentation Index, FinUn for Financial Uncertainty Index, COVOL for Common Volatility Index, FinFrag for Financial Fragmentation Index, GSI for Global Sanctions Intensity Index, MigFear for Migration Fear Index, MigPU for Migration Policy Uncertainty Index, EMVelec for Elections and Political Governance Equity Market Volatility Tracker, MobFrag for Mobility Fragmentation Index, EqSegm for Equity Market Segmentation and PolFrag for Political Fragmentation Index. Cluster 1 corresponds to global uncertainty, Cluster 2 to fragmentation trends, Cluster 3 to macro-financial volatility and Cluster 4 to geopolitical risk. The cluster analysis is based on a subset of global geopolitical indicators with at least quarterly frequency.

Chart A.12

Cluster dendrogram of indicators

(dissimilarity measure)



Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Notes: TFrag stands for Trade Fragmentation Index, GPR for Geopolitical Risk Index. GPRA for Geopolitical Risk Acts Index. EMVsec for National Security Policy EMV Tracker, GPRT for Geopolitical Risk Threats Index, GPRP for Geopolitical Risk Perceptions Index, EUI for Energy-related Uncertainty Index, WUI for World Uncertainty Index. WTUI for World Trade Uncertainty Index, EMVelec for Elections and Political Governance Equity Market Volatility Tracker MigFear for Migration Fear Index, NoArmedConfl for Number of International Armed Conflicts, TPU for Trade Policy Uncertainty Index, EMVtp for Trade Policy Equity Market Volatility Tracker, GSI for Global Sanctions Intensity Index, MigPU for Migration Policy Uncertainty Index, EPU for Economic Policy Uncertainty Index, PolFrag for Political Fragmentation Index, NoConfl for Number of Conflict Events, MobFrag for Mobility Fragmentation Index, GSCPI for Global Supply Chain Pressure Index, Frag for Geopolitical Fragmentation Index, FinFrag for Financial Fragmentation Index, COVOL for Common Volatility Index, RealUN for JNL Real Economic Uncertainty Index, MacroUN for JLN Macro Uncertainty Index. FinUn for Financial Uncertainty Index and EqSegm for Equity Market Segmentation. The cluster analysis was based on a subset of global geopolitical indicators with at least quarterly frequency.

GaR LASSO analysis

This section presents the core results of the LASSO-based indicator selection applied within a GaR framework. The goal is to isolate the most informative indicators for forecasting downside risks to GDP growth, using a non-crossing quantile regression (QR) approach, which includes LASSO regularisation.

We begin with a baseline GaR model specification, similar to the strategy adopted by the ESRB Working Group on Policy Stance. The regressors include a constant, the lag of quarterly GDP growth, and two standard macro-financial controls: the CLIFS and the CCI. CCI was selected over the SRI owing to its high correlation ($\rho > 0.8$), persistent behaviour (unit root presence) and broader country availability and consistency.

Unit root tests – augmented Dickey–Fuller (ADF) and Kwiatkowski-Phillips-Schmidt–Shin (KPSS) – confirmed high persistence for several indicators (**Table A.3**), which further guided selection. Indicators that were conceptually weak, statistically redundant or unstable across model specifications were excluded from final testing.

In-sample results revealed that uncertainty indicators tend to affect both tails of the conditional GDP distribution, raising both downside risk (left tail) and upside potential (right tail). However, when the models were re-estimated over a pre-COVID sample (ending in the first quarter of 2020), the positive effect on the right tail disappeared, confirming that this effect was likely to be an artefact of COVID rebound dynamics. This underlines the importance of sample robustness in interpreting coefficient behaviour in GaR models. Both Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC)[6] were used as model selection criteria. BIC proved more stringent, favouring parsimonious models, while AIC tended to allow more correlated variables. Together, they provide a balance between robustness and flexibility.

[6] AIC and BIC are penalised likelihoods, which differ in the penalisation term. BIC includes both the number of parameters and the number of datapoints, while the AIC penalisation term includes solely the number of the parameters.

Table A.3

Unit root test results for selected countries and indicators

Indicators	Stationary	Indecisive	Non-stationary
GDP growth (qoq)	12 of 13	1 of 13	
Country-Level Indicator of Financial Stress (CLIFS)		7 of 13	6 of 13
Common Composite Indicator (CCI)			13 of 13
World Uncertainty Index (WUI)		1 of 1(1)	
World Uncertainty Index (WUI), country specific	3 of 13	10 of 13	
Economic Policy Uncertainty Index (EPU)			1 of 1
Economic Policy Uncertainty Index (EPU), country specific		1 of 7	6 of 7
Energy-related Uncertainty Index (EUI)			1 of 1
JLN Real Uncertainty Index (RealUn)			1 of 1
JLN Macro Uncertainty Index (MacroUn)			1 of 1
Geopolitical Fragmentation Index (Frag)			1 of 1
Geopolitical Risk Index (GPR)		1 of 1	
Geopolitical Risk Index (GPR), country specific		10 of 10	
Geopolitical Risk Threats (GPRT)		1 of 1	
Geopolitical Risk Acts (GPRA)			1 of 1
Bondarenko Geopolitical Risk Perceptions (GPRP)		1 of 1	
Bondarenko Geopolitical Risk Perceptions (GPRP), country specific		1 of 5(1)	4 of 5
Bilateral Indicator of Local Perception of Geopolitical Risk (BiGPR)			6 of 6
National Security Policy EMV Tracker (EMVsec)			1 of 1
Number of Conflict Events (NoConfl)			1 of 1
Number of International Armed Conflicts (NoArmedConfl)			1 of 1
Trade volume (% of GDP) or trade openness (TO), yoy difference	10 of 13	3 of 13	
Global Supply Chain Pressure Index (GSCPI)		1 of 1	
Trade Policy Uncertainty Index (TPU)			1 of 1
World Trade Uncertainty Index (WTUI)		1 of 1	
Trade Policy EMV Tracker (EMVtp)			1 of 1
Trade Fragmentation Index (TFrag)			1 of 1
JLN Financial Uncertainty Index (FinUn)			1 of 1
Common Volatility (COVOL)		1 of 1	
Financial Fragmentation Index			1 of 1
Euro Area Equity Market Segmentation (EqSegm)			1 of 1
Global Sanctions Intensity Index (GSI)		1 of 1	
Migration Fear Index (MigFear)			1 of 1
Migration Policy Uncertainty Index (MigPU)			1 of 1
Elections & Political Governance EMV Tracker (EMVelec)		1 of 1	
Mobility Fragmentation Index (MobFrag)			1 of 1
Political Fragmentation Index (PolFrag)			1 of 1

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Notes: Qoq stands for quarter on quarter. The table provides a summary of the augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt–Shin (KPSS) test results, Stationary means that both tests indicate that the variable is stationary. Indecisive means that only one test indicates that the variable was stationary. Non-stationary means that both tests show that the variable is non-stationary. The countries included in the analysis are Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, the Netherlands, Austria, Portugal, Finland and Sweden. 1) Non-stationarity is generally linked to the ADF tests. With regard to cases that were indecisive, it is generally the KPSS tests that indicate non-stationarity.

A couple of indicators were found to be less useful for GaR LASSO analysis. The Energy-related Uncertainty Index (EUI) was excluded from the analysis because it lacks the latest data. It was tested for Denmark, Finland and Sweden, but was not selected by the LASSO testing for the GaR model. Trade openness (TO) is generally viewed as a structural variable showing domestic vulnerabilities towards external risks. Moreover, it is very persistent and shows seasonality. The GPR and CLIFS interaction term was tested for Germany and France and proved to have limited predictive value beyond the CLIFS. Moreover, the interaction term has high multicollinearity with the CLIFS and CCI.

The GaR LASSO analysis confirms the relevance of specific uncertainty and volatility indicators, particularly at short and medium-term forecast horizons (**Table A.4**). Indicators representing the General and Capital & Finance categories are more relevant at the one-quarter and four-quarter horizons, namely the JLN uncertainty suite indicators (RealUn, MacroUn and FinUn), COVOL and the geopolitical and financial fragmentation indices. The global EPU and WUI indices are frequently selected at both the one-quarter and four-quarter horizons, whereas the country-specific EPU and WUI indices have a more limited reach. In the Trade category, the WTUI, the TPU Index and the EMVtp Tracker are frequently selected across countries, highlighting their value in capturing tail risks in different horizons and suggesting their robustness as trade policy-related risk measures. Notably, migration fear only gains relevance at the two-year horizon, pointing to its potential as a slow-burning societal risk predictor. By contrast, most indicators from the Military & Infrastructure category were not selected across any horizon, indicating limited additional value beyond core controls. Overall, the results confirm that a subset of high-frequency uncertainty indicators can offer strong marginal contributions to downside risk prediction when added to a baseline specification with the CLIFS and CCI.

Table A.4

Indicator relevance in GaR baseline regressions across forecast horizons

	h=1q	h=4q	h=8q
General			
World Uncertainty Index (WUI) 1)	4	5	0
Economic Policy Uncertainty Index (EPU)	5	9	1
JLN Real Uncertainty Index (RealUn)	11	0	1
JLN Macro Uncertainty Index (MacroUn)	11	5	0
Geopolitical Fragmentation index (Frag), first differences 1)	3	7	0
US-EU Bloc Fragmentation, first differences 1)	3	1	0
Others Bloc Fragmentation, first differences 1)	4	1	0
Military & Infrastructure			
Geopolitical Risk Index (GPR), country specific	0	0	2
GPR Threats (GPRT)	0	1	1
GPR Acts (GPRA)	1	0	0
Local Perception of Geopolitical Risk (BiGPR) 2)	0	1	0
BiGPR China 2)	2	1	1
BiGPR China, relative to other regions 2)	2	2	1
BiGPR Western Bloc 2)	0	0	0
BiGPR Western Bloc, relative to other regions 2)	0	0	2
National Security Policy EMV Tracker (EMVsec) 1)	5	5	2
Number of conflict events (NoConfl), first differences 1)	1	0	0
Number of international armed conflicts (NoArmedConfl), first differences 1)	0	0	1
Trade			
Global Supply Chain Pressure Index (GSCPI)	2	1	3
Trade Policy Uncertainty Index (TPU)	3	7	10
World Trade Uncertainty Index (WTUI)	11	11	1
Trade Policy EMV Tracker (EMVtp) 1)	3	8	6
Trade Fragmentation index (TFrag), first differences 1)	3	4	1
Capital & Finance			
JLN Financial Uncertainty Index (FinUn)	11	11	1
Common Volatility (COVOL)	5	2	0
Financial Fragmentation index (FinFrag), first differences 1)	3	6	0
Politics & Societal			
Sanctions Intensity Index (GSI)	0	1	7
Migration fear index (MigFear)	1	0	8
Migration policy uncertainty (MigPU)	0	0	4
Elections & Political Governance EMV Tracker (EMVelec)	5	3	0
Mobility Fragmentation index (MobFrag)	3	5	3
Political Fragmentation index (PolFrag)	2	3	3
Mobility Fragmentation index (MobFrag), first differences 1)	0	4	3
Political Fragmentation index (PolFrag), first differences 1)	2	7	1

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Notes: The table presents the number of countries for which the coefficient estimate of a particular indicator for the 10th percentile was negative. Bayesian Information Criteria (BIC) are used as model selection criteria. The results shown in this table are based on a subset of countries, namely Denmark, Germany, Ireland, Greece, Spain, France, Italy, Hungary, the Netherlands, Portugal, Finland and Sweden, for which complete time series were available from the second quarter of 2000 onwards for all the indicators included in the baseline specification. 1) Germany, Ireland, France and Hungary, were not included. 2) Tested only for Spain and Italy.

The GaR LASSO results are sensitive for some indicators with the respect to the COVID-19 period. For several countries, GaR LASSO tests were performed excluding the COVID-19 period from the sample. In several cases, the results did not change much, e.g. for most of the Military & Infrastructure indicators. In some instances, indicators became more relevant for GaR analysis, namely the GSCPI, PolFrag and RealUn Indices. However, some indicators became less relevant, especially the trade-related indicators.

Technical descriptions of the exploratory analysis of indicators

This subsection provides the underlying technical formulation of the GaR LASSO estimation.

The empirical specification follows a non-crossing quantile regression (QR) framework (Bondell, Reich, and Wang, 2010), incorporating adaptive LASSO regularisation (Jiang, Wang and Bondell, 2014). The baseline GaR model is given by:

$$\Delta \mathrm{GDP}^{\tau}_{t+h} = \mathrm{const} + \Delta \mathrm{GDP}_t * \beta_{\mathrm{GDP}} + \mathrm{CLIFS}_t * \beta_{\mathrm{CLIFS}} + \mathrm{CCI}_t * \beta_{\mathrm{CCI}} + X^T_t * B_X$$

Where:

- $\Delta \mathrm{GDP}^{\tau}_{t+h}$ is the average quarterly GDP growth from t to t+h, h=1,4,8.
- $\Delta \mathrm{GDP}_t$ is the quarterly GDP growth at t.
- CLIFS_t is the Country-Level Indicator of Financial Stress (CLIFS) Index.
- CCI_t is the national Common Composite Indicator (CCI).
- X^T_t is the vector of possible regressors , such as the geopolitical risk and uncertainty indices.

Quantile crossing (non-monotonically increasing estimated quantiles) is a well-known problem with the QR method. There are two ways of solving this problem:

- ordering the estimated quantiles after estimation (Chernozhukov et al., 2010);
- imposing non-crossing constraints (Bondell, Reich and Wang, 2010) – which was our choice.

The original minimisation:

$$\hat{\beta}_\tau = \mathrm{argmin}_\beta \sum_{i=1}^{n} \rho_\tau(y_i - x_i^T \beta)$$

$$\rho_\tau(u) = u\{\tau - I(u < 0)\}, \quad \tau_1, \dots, \tau_q:\ \hat{\beta}_\tau = \left(\hat{\beta}^T_{\tau_1}, \dots, \hat{\beta}^T_{\tau_q}\right)^T$$

The new minimisation:

$$\hat{\beta}_\tau = \operatorname{argmin}_\beta \sum_{q=1}^{Q} w_{\tau_q} \sum_{i=1}^{n} \rho_\tau(y_i - x_i^T \beta) \text{ s.t. } x^T \beta_{\tau_j} \geq x^T \beta_{\tau_{j-1}},\ x \in D,\ D \subset R^p,\ j = 2, \ldots q$$

We complete our non-crossing frequentist QR method with LASSO-type variable selection, based on Jiang, Wang and Bondell (2014).

LASSO regression performs LASSO 1 (L1) regularisation: it adds a penalty equal to the absolute value of the coefficients. Some coefficients are shrunk to zero and eliminated from the model. Larger penalties shrink coefficient values closer to zero more aggressively, giving simpler models which are easier to interpret.

$$\min \sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{p} x_{ij} \beta_j \right)^2 + \lambda \sum_{j=2}^{p} |\beta_j|$$

$\min \sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{p} x_{ij}\beta_j\right)^2$ with the constraint $\sum_{j=2}^{p} |\beta_j| \leq s$

Note: the intercept and the coefficient of the lag of GDP are exempt from shrinkage. The final minimisation (see Szendrei and Varga, 2023):

$$\hat{\beta}_\tau = \operatorname{argmin}_\beta \sum_{q=1}^{Q} w_{\tau_q} \sum_{i=1}^{n} \rho_\tau(y_i - x_i^T \beta) \text{ s.t. } x^T \beta_{\tau_j} \geq x^T \beta_{\tau_{j-1}},\ x \in D,\ D \subset R^p,\ j = 2, \ldots q$$

$$\sum_{q=1}^{Q} \sum_{k=1}^{K} w_{k,\tau_q} \left|\beta_{k,\tau_q}\right| \leq t^*$$

Where $w_{k,\tau_q} = \left|\theta_{k,\tau_q}\right|^{-1}$ are the estimated coefficients of a regular QR with a full design matrix and t^* is a global variation parameter, which is non-quantile specific.

To choose the optimal t^*, a grid search is employed. The model with the lowest AIC and BIC is chosen as the optimal model.

Measuring geopolitical risk spillovers to financial stress

This section provides supplementary information supporting the analysis presented in Section 5.1 of the report. This analysis section explores the interconnectedness of financial markets during periods of geopolitical stress, potentially giving rise to spillovers across markets, asset classes and countries. Analysing how stress linked to geopolitical factors spreads within the financial system made it possible to identify the evolving systemic importance of different financial markets over time.

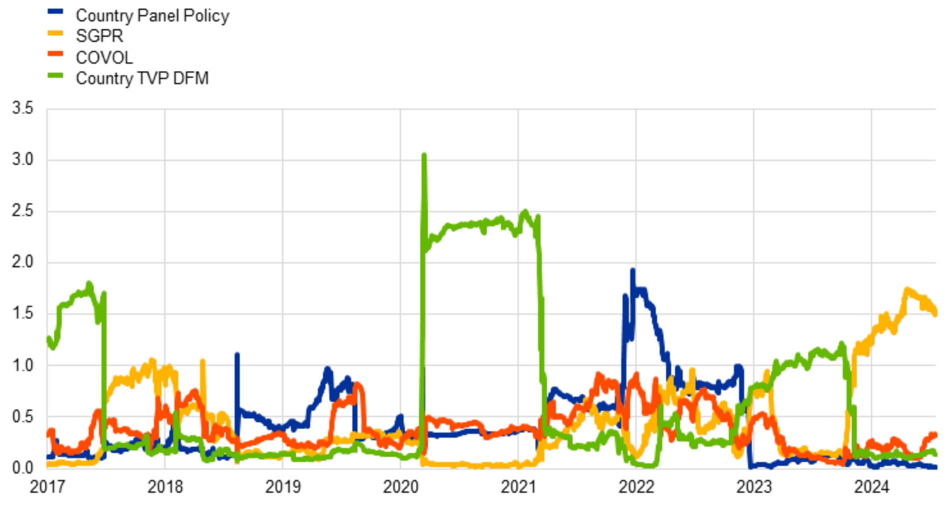
The methodological approach built on the spillovers framework in Diebold-Yilmaz (2012). This methodology is based on forecast error variance decomposition (FEVD) and captures the extent to which volatility from geopolitical risk transmits within the financial system. It measures directional spillovers between different market-based indicators, directional spillovers being defined as the amount of variation in one indicator accounted for by changes in another. The set of indicators used in the analysis includes the geopolitical risk indicators indicated in Section 3 (the GPR Index and COVOL Index), as well as metrics from financial markets themselves, such as those for country ETFs, foreign exchange rates and energy markets, all capturing different aspects of financial risk across markets (**Table 3** of the report). The individual indicators are combined to extract volatility signals using econometric and machine learning tools, as well as DFMs and principal component analyses (PCAs).

The variance decomposition reveals individual spillover channels, with shifts in the relative importance of the transmission channels over time. Three indicators stand out in their relevance for spillovers to the other indicators, i.e. their respective contributions to explaining variations in the rest of the dataset. Intuitively, these measures track which indicator is the strongest source of variation for all other variables included in the model. The GPR Index started gaining importance in risk transmission from the beginning of 2022, when the Country Time-varying Parameter Dynamic Factor Model (TVP DFM) Index was the dominant indicator, but became the most important shock transmitter in 2024, highlighting a structural shift in systemic influence (**Chart 27**).The structural shift is all the more remarkable given that the Country TVP DFM Index, which covers global equity and foreign exchange markets, has been a leading shock transmitter in multiple previous episodes from the beginning of 2020 (**Chart A.13**). The main reason for this is that the Country TVP DFM Index captures spillover episodes when volatility is spread across markets. Between the end of 2021 and throughout 2022, the sources of volatility were, however, more concentrated in the equity and foreign exchange markets of the largest economies, as captured by the Country Panel Policy Index.[7] Interestingly, even though the GPR Index did not perform statistically well in GaR regressionsly frequency series can be valuable in explaining market dynamics, as was particularly evident after the onset of the Russian invasion of Ukraine. These results highlight the importance of complementing macro-financial data with high-frequency market information to obtain a broader view of the transmission mechanism for geopolitical risks.

[7] The index is a policy weighted average of country equity and foreign exchange volatilities that takes into account the country's market capitalisation, government debt and trade weightings. Major economies play a predominant role in the panel.

Chart A.13

Spillovers between financial stress and geopolitical risk indices for the EU



Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation, based on the framework in Diebold-Yilmaz (2012).
Notes: This chart figure shows the dynamics of spillovers estimated using the Diebold-Yilmaz methodology between the country cross-linkage indicator (country time-varying parameter dynamic factor model or TVP DFM) – based on financial stress indicators – combined with three indices that capture geopolitical risk: the Geopolitical Volatility Index, calculated as a dynamic panel across countries (Country Panel), the Standard Geopolitical Risk (SGPR) Index and the Common Volatility (COVOL) Index.

2 Econometric models

2.1 Geopolitical shocks and their euro area transmission

Empirical evidence shows that geopolitical events can be transmitted through the economy either as supply shocks, which constrain production and push up prices, or as demand shocks, which reduce consumption and investment, and push down prices owing to heightened uncertainty. Both channels are relevant, but their relative importance differs across events, underscoring the benefits of a case-by-case analysis. The analytical framework used here is a Bayesian structural vector autoregressive (B-SVAR) model with non-Gaussian innovations based on Anttonen and Lehmus (2025). This framework identifies multiple macroeconomic shocks and traces their effects on euro area Harmonised Index of Consumer Prices (HICP) inflation and GDP.[8]

A key feature of the model is that it does not treat geopolitical events as homogeneous. Instead, it maps specific events to combinations of identified macroeconomic shocks – such as supply, demand, industry-specific demand and oil price shocks – allowing for event-specific causal inference and ensuring both robustness and interpretability. A homogeneous global geopolitical risk shock is included to absorb the average effects of the heterogeneous geopolitical events, leaving other shocks (at least mean) independent.

The results illustrate how transmission channels differ across two recent geopolitical shocks, the Russian invasion of Ukraine and the Israel-Hamas war. The Russian invasion of Ukraine in February 2022 triggered a strong supply shock that amplified energy inflation **(Chart A.14)**. A concurrent positive industry-specific demand shock helped to offset the expected decline in industrial production, reflecting the low price elasticity of demand. Inflation peaked at 10.6% in the euro area, compared with a counterfactual peak of around 8% when disregarding the geopolitical risk, supply and industrial production demand shock.[9]

By contrast, the Israel-Hamas war in October 2023 primarily operated through the uncertainty channel, generating negative demand shocks. This led to a deflationary impact on inflation and a temporary decline in GDP of about 0.5 percentage points for the euro area. The identification of an industry-specific demand shock, distinct from aggregate demand, highlights the importance of sectoral heterogeneity. This type of shock played a significant role in both episodes,

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8 Macroeconomic shocks are statistically identified in a non-Gaussian SVAR model using higher-order moments and the assumption of shock independence, allowing for identification without a priori restrictions. Structural interpretation is achieved through minimal, informed zero and sign restrictions.

9 For the Russian invasion of Ukraine, the shocks associated with the outbreak, and thus set to zero, in the counterfactual are the supply shock, the industry-specific demand shock and the geopolitical risk shock. For the Israel-Hamas war, the shocks set to zero in the counterfactual are the demand shock, the industry-specific demand shock and the geopolitical risk shock.

suggesting that industry-specific dynamics can substantially influence aggregate outcomes, particularly under supply constraints.

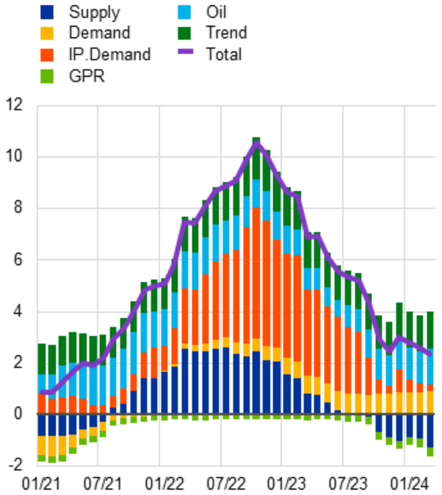
Chart A.14

Euro area inflation following geopolitical shocks

Russian invasion of Ukraine in February 2022

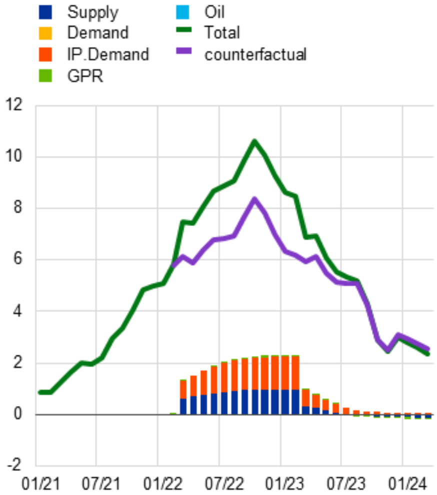
a) Shock-related EU inflation

(percentage points)



b) Counterfactual EU inflation in the absence of a shock

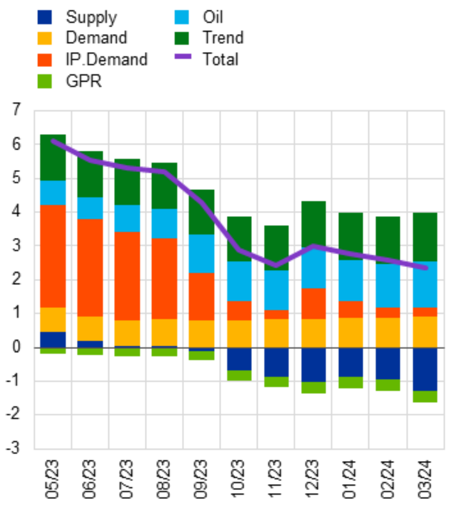
(percentage points)



Israel-Hamas war in October 2023

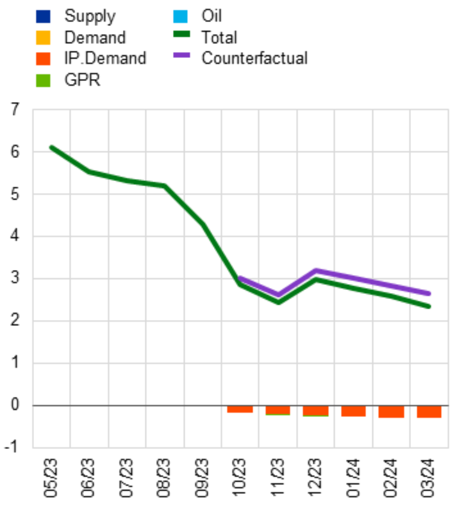
a) Shock-related EU inflation

(percentage points)



b) Counterfactual EU inflation in the absence of a shock

(percentage points)



Source: Anttonen and Lehmus (2025).
Notes: IP stands for investment position. The counterfactual assumes that the geopolitical event never took place. The difference between the shock-based inflation and the counterfactual is the causal estimate of the effect of the geopolitical shock.

A nuanced, event-specific approach is essential for effective risk assessment and policy design. The net effect on financial stability depends on the dominant transmission channel, which varies across events. A context-sensitive framework that accounts for the nature of each event and its transmission mechanisms is particularly useful for the design of policy responses. The approach presented here offers a practical tool for incorporating geopolitical risk into scenario analysis and stress testing, helping to distinguish between inflationary and deflationary risks and to evaluate sectoral vulnerabilities that may amplify or dampen macroeconomic shocks.[10]

2.2 Factor-augmented VAR model (Section 4.2 of the report)

The empirical framework in Section 4.1 of the report is based on the Factor-Augmented Vector Autoregressive (FAVAR) model described in Bernanke et al. (2005). Let $\boldsymbol{X}_{\mathrm{t}}$ denote an $n \times 1$ vector of macroeconomic and financial variables observed in month $t = 1, 2, \ldots, T$. In addition, $\boldsymbol{F}_{\mathrm{t}}$ represents an $r \times 1$ vector of common factors. The number of time series is large ($n > T$) and much greater than the number of common factors ($N > r$). The factors can be decomposed into an $m \times 1$ vector of observed factors $\boldsymbol{G}_{\mathrm{t}}$ and a $k \times 1$ vector of unobserved factors $\boldsymbol{H}_{\mathrm{t}}$, i.e. $\boldsymbol{F}_{\mathrm{t}}$ = $[\boldsymbol{G}_{\mathrm{t}}', \boldsymbol{H}_{\mathrm{t}}']'$. Here, $\boldsymbol{G}_{\mathrm{t}}$ is the GPR Index developed by Caldara and Iacoviello (2022), such that $m = 1$. Using an informal criterion, the number of unobserved factors is set to $r = 7$, as a total of $r + m = 8$ factors are required to explain at least 50% of the variance in the variables $\boldsymbol{X}_{\mathrm{t}}$. The factors are related to the variables $\boldsymbol{X}_{\mathrm{t}}$ through the following dynamic factor model: $\boldsymbol{X}_{\mathrm{t}} = \Lambda \boldsymbol{F}_{\mathrm{t}} + \boldsymbol{e}_{\mathrm{t}}$, where $\boldsymbol{e}_{\mathrm{t}}$ is an $n \times 1$ vector of idiosyncratic components and Λ is an $n \times r$ matrix of factor loadings. The idiosyncratic components are stationary with zero mean and may exhibit weak cross-sectional and serial correlation. The factors are mutually orthogonal and uncorrelated with the idiosyncratic components. The factors are modelled using a VAR of the following reduced form: $\boldsymbol{F}_{\mathrm{t}} = C + \Phi(L)\boldsymbol{F}_{t-1} + \boldsymbol{u}_{\mathrm{t}}$, where $\Phi(L)$ is a finite-order polynomial in the lag operator, and $\boldsymbol{u}_{\mathrm{t}}$ is an $r \times 1$ vector of reduced-form innovations that are independently and identically distributed with zero mean and variance-covariance matrix Σ_u.

The FAVAR model described here is estimated using a two-step principal component approach. In the first step, consistent estimates of the latent factors $\boldsymbol{H}_{\mathrm{t}}$ are obtained using PCA, which capture the common dynamics in $\boldsymbol{X}_{\mathrm{t}}$ after removing the fluctuations in the observed factors $\boldsymbol{G}_{\mathrm{t}}$ using standard techniques. In the second step, the parameters of the VAR for the joint dynamics of the observed and unobserved factors are estimated using ordinary least squares. The model is estimated over the period between January 1990 and November 2023, with three lags of the endogenous variables. The number of lags was determined using AIC.

[10] The role of inflation in financial stability is discussed in Albertazzi et al. (2024).

Scenario analysis

The set of scenarios assumes geopolitical tensions, modelled through (i) increases in geopolitical risk combined with heightened volatility (reflected in the COVOL Index), replicating the rise in these indicators observed at the beginning of the Russian invasion of Ukraine (main text); (ii) a spike in economic policy uncertainty as observed at the onset of COVID-19 in 2020; and (iii) supply constraints, defined by the rises in the GSCPI observed in 2021 during the COVID-19 period.[11] The scenarios use an estimated Bayesian VAR based on Crump et al. (2025) captures interactions among 72 macroeconomic and financial variables spanning both the euro area and the United States forecasts average outcomes for the economy and the financial system.[12]

Under a scenario of increased economic policy uncertainty, the analysis indicated broad-based adverse impacts across financial markets and the real economy (Chart A.15). Equity markets contracted significantly, while Brent spot oil prices showed a sustained decline, reflecting heightened risk aversion and deteriorating economic sentiment. Both two-year and ten-year government bond yields fell in response to the weakening macroeconomic environment. Credit to non-financial corporates also declined, underscoring tighter financial conditions. Output and prices decreased, signalling suppressed demand and broader macroeconomic weakness.

Financial stress, as measured by the CISS, rose substantially, while the VIX Index increased and credit spreads widened, all pointing to elevated market volatility and risk premiums.

11 Scenario paths are constructed by estimating an AR(1) model with an intercept for each geopolitical risk variable up to the fourth quarter of 2024. For the GPR Index and COVOL Index, the residual from the one-quarter-ahead forecast for the first quarter of 2022 – using data up to the fourth quarter of 2021 – calibrates the generic conflict scenario. This shock is added to the forecast for t+1 (the first quarter of 2025), with subsequent quarters projected iteratively. The same approach is used for EPU Index, with the scenario calibrated to the pandemic shock in the second quarter of 2020. For the Global Supply Chain Pressure Index, four consecutive shocks were applied for the first four quarters of 2021 to capture COVID-related supply chain disruptions; otherwise, the procedure is the same.

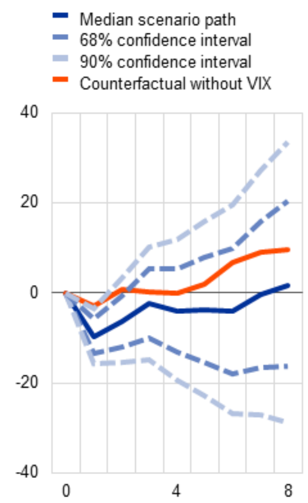
12 The estimation sample covers the period from the second quarter of 2000 to the fourth quarter of 2024, with three lags included in the model. The scenario analysis considers a forecast horizon of up to eight quarters.

Chart A.15

Macro-financial implications of an increased economic policy uncertainty scenario

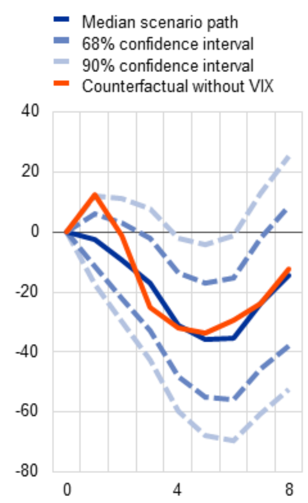
a) Euro Stoxx

(percentage changes)



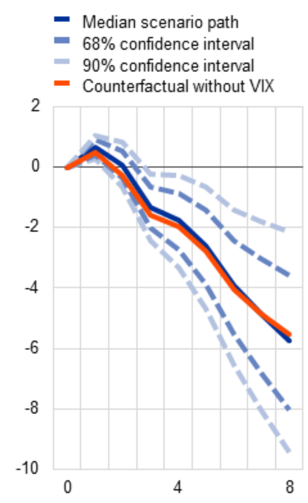
b) Brent spot oil price in EA

(percentage changes)



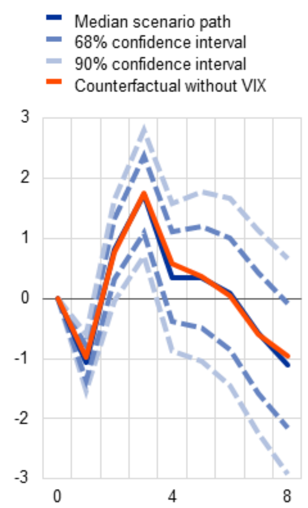
c) Credit to non-financial corporates in EA

(percentage changes)



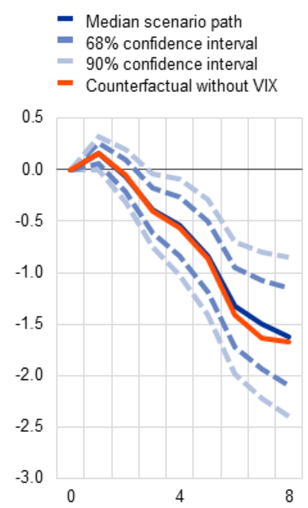
d) Two-year benchmark government yields in EA

(percentage changes)



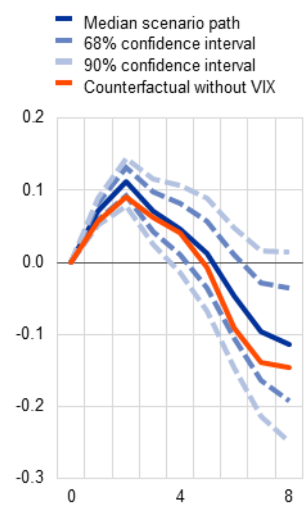
e) Ten-year benchmark government yields

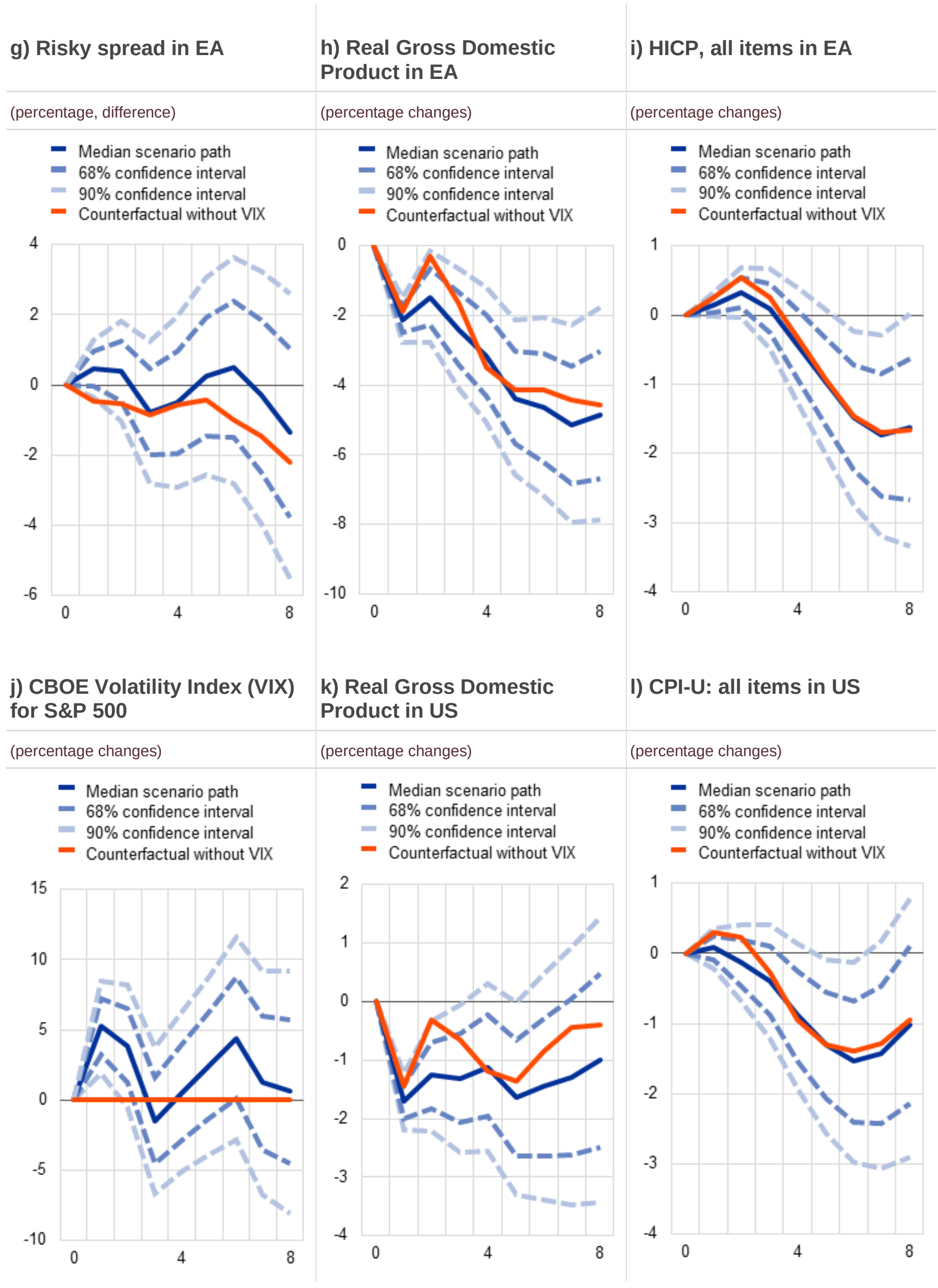
(percentage changes)



f) Financial stress in EA

(percentage changes)





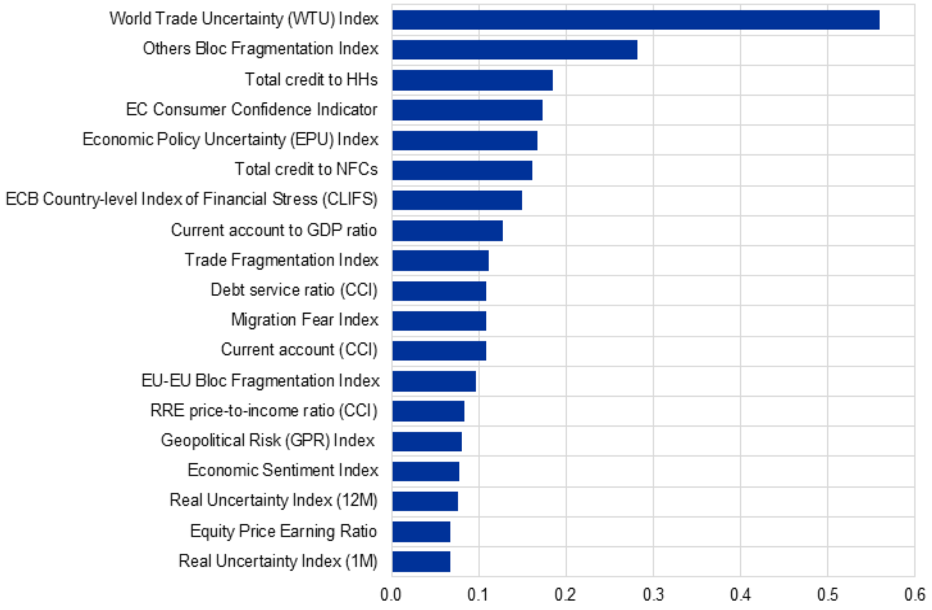
Sources: Baker et al. (2016), Haver Analytics, Federal Reserve Economic Data and ESRB calculations.
Notes: The blue lines denote the median scenario paths with shaded 68% (dark blue) and 90% (light blue) showing the coverage intervals. The red dashed lines show the counterfactual median paths for a scenario in which the VIX Index does not respond throughout the scenario.

2.3 Growth-at-risk (Section 4.3.2 of the report)

Given the large size of the compiled geoeconomic indicators database, we resort to variable selection using machine learning techniques and use a Light Gradient Boosting Machine Regressor (LGBM), owing to its advanced features, such as handling missing data and custom loss options, including quantile loss. We use a parameter grid search optimisation method to identify the best set of parameters and evaluate the results of the model using the quantile loss and the empirical coverage measures, with the Shapley values being used to rank the best performing indicators by their marginal contribution to the outcome of the model (**Chart A.14**).

Chart A.16

Shapley average values for the best predictors (20th percentile)



Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: HHs stands for households, NFCs for non-financial corporations, CCI for the Common Composite Indicator, RRE for residential real estate and M for months.

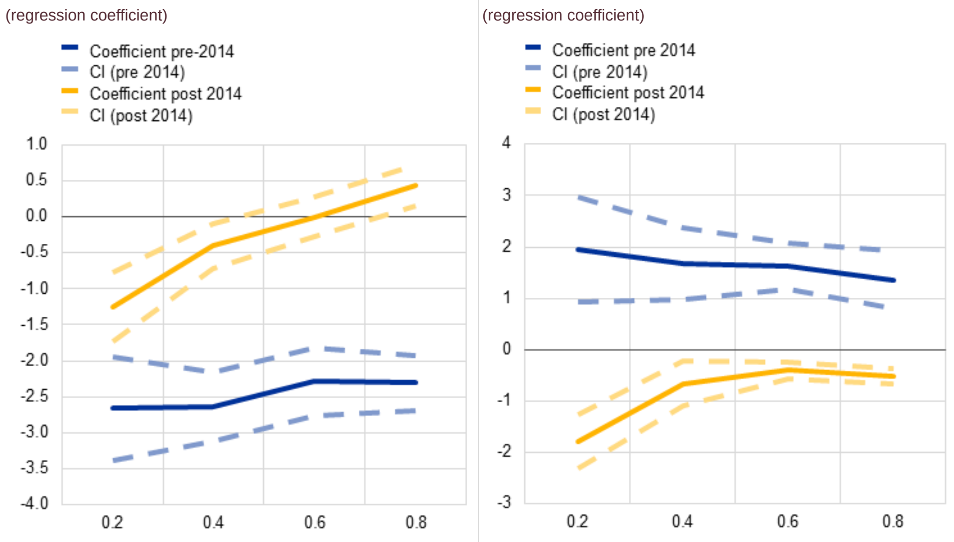
Having trimmed down the GEO dataset to a set of relevant indicators, we proceeded to estimate a benchmark EU PQR model, in a similar manner to the work done in previous ESRB workstreams.

We include country fixed effects to allow for country heterogeneity and estimate the results over a range of quantiles, while standardising the data to obtain more stable results. Furthermore, we split the sample at 2014 to allow for further interpretation of the results based on the timeframe considered (e.g. recently geoeconomic risks have been playing a more important role y than in the past). The results analysed shed light on two important perspectives: the non-linear impact of geoeconomic risks on the distribution of economic growth, through quantile process plots (elasticity coefficients plotted over a range of quantiles); and the “value added” gained from adding geoeconomic indicators to the benchmark specification, through computing the differences in the pseudo R-squared measures (making comparison possible between the likelihood of the augmented and baseline models).

Chart A.17

Quantile process plots for economic policy uncertainty and trade policy uncertainty

a) Economic policy uncertainty | **b) Trade policy uncertainty**

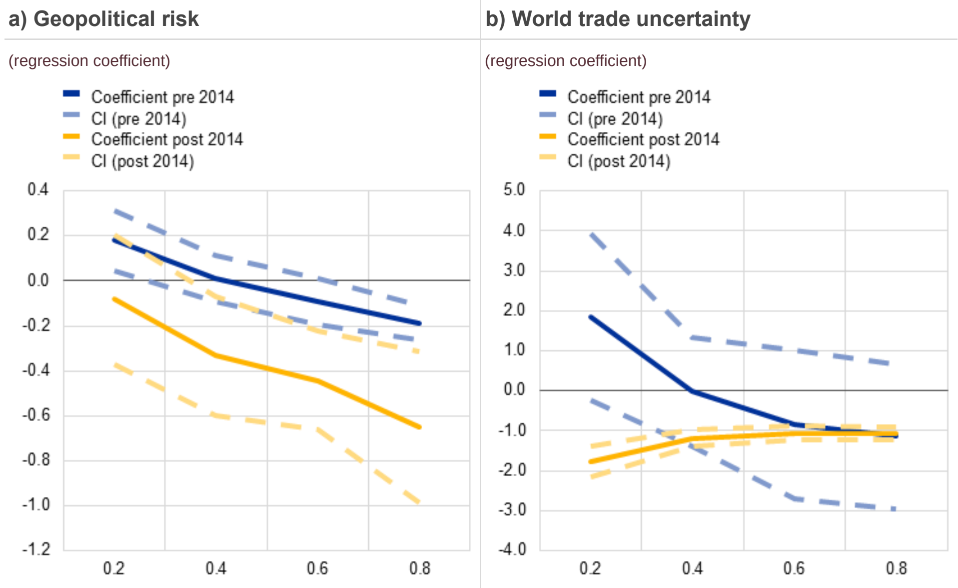


Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.

Estimating the EU panel GaR model yields some heterogeneous results in terms of coefficient plots – we ascertain that some indicators, such as the EPU and TPU (**Chart A.15**), have intuitive shapes and signs for the post-2014 period (negative and upward-sloping), while others, such as GPR or WTUI (pre-2014), do not share these characteristics (**Chart A.16**). Moreover, we find that, in accordance with our prior beliefs, post-2014 results exhibit a clearer upward tendency and more pronounced negative effects in the tails of the growth distribution, confirming once again the increasing importance of these events for the financial sector and the global economy.

Chart A.18

Quantile process plots for geopolitical risk and world trade uncertainty



Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.

Finally, we rank the models in terms of the geoeconomic variables which allow for a better fit in terms of likelihood, against a baseline model. We compute and compare the pseudo R-squared for each variable and order the models by absolute differences.

Our results show that trade-related indicators, such as the WTUI and TPU, currently rank highest in terms of value added when included in the baseline EU GaR model. Other relevant variables are related to the US-EU bloc, trade and political fragmentation, but also the EPU, which ranked high in both the pre- and post-2014 period. Other frequently used geoeconomic indicators, such as the GPR Index and its subcomponents and the WUI, show only modest improvement in model fit when included in the baseline specification, in line with our previous findings presented in Chapter 3 of the report.

Table A.5

Model ranking in terms of (pseudo) R-squared results

(GDP at 20th percentile)

Variable	R-sq. (baseline)	R-sq. (incl. geopolitical indicator)	Delta R-sq.
WTUI	9.08%	17.87%	8.79%
TPU	8.79%	11.16%	2.37%
US-EU Frag. Index	8.79%	11.01%	2.22%
Financial Uncert. Index	8.79%	10.97%	2.18%
Trade Frag. Index	8.79%	10.59%	1.80%
EPU (Global)	8.95%	10.51%	1.57%
EMV	8.86%	9.99%	1.13%
Political Frag. Index	8.79%	9.71%	0.92%
Financial Frag. Index	8.79%	9.40%	0.61%
EPU (country)	11.00%	11.54%	0.54%
Macro Uncert. Index	8.79%	9.24%	0.45%
GPRI (Western)	8.38%	8.79%	0.41%
WUI	7.96%	8.29%	0.34%
GPRI (China)	8.38%	8.63%	0.25%
Migration Fear Index	9.12%	9.34%	0.22%
Mobility Frag. Index	8.79%	8.99%	0.20%
GPRI (global)	8.86%	9.01%	0.14%
GPRI (Middle East)	8.38%	8.52%	0.14%
GPRI (country)	7.57%	7.63%	0.06%
No. of conflict events	9.24%	9.28%	0.04%
Real Uncert. Index	8.79%	8.82%	0.03%
COVOL	9.60%	9.60%	0.00%

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Notes: WTUI stands for World Trade Uncertainty Index, TPU for the Trade Policy Uncertainty Index , EMV for Equity Market Volatility Tracker, GPRI for Global Geopolitical Risk Index, WUI for World Uncertainty Index and COVOL for the Common Volatility Index. The pseudo R-squared is computed using the check loss function related to an intercept only model and the Delta R-squared is the simple difference between the extended and baseline models. Differences appear in the values for the baseline model owing to different lengths of the dataset, depending on the availability of the geopolitical indicators.

2.4 Quantile Vector autoregression (Section 4.3.2 of the report)

In order to estimate the transmission of geopolitical shocks to macro-financial variables, the structural quantile vector autoregressive (QVAR) model proposed in Chavleishvili et al. (2021) and Bochmann et al. (2023) is used. This choice of VAR was dictated by the need for both interaction of all the endogenous variables over time and transparent identification of structural shocks for counterfactual scenarios. The quantile regression (QR) method, in turn, made it possible to estimate the dynamic properties of the system with coefficients differentiated across quantiles. The empirical model thus combines the advantages of a standard (linear) VAR with those of quantile regressions, which can capture potential non-linearities in the propagation of structural shocks (see Section 1.2 of this Annex).[13]

The estimated model combines not only the geopolitical indicator but also real GDP growth, with variables for financial vulnerabilities and systemic stress. A four-variable QVAR was used to forecast the entire distribution of the three macro-financial variables. Vulnerabilities to the economy were captured by the SRI, developed in Lang et al. (2019), and systemic stress is measured by the ECB's CISS, as originally introduced in Holló et al. (2012). The CISS is a summary measure of the level of financial stress and includes 15 market-based financial indicators split into five sub-indices: financial intermediaries, money markets, equity markets, bond markets and foreign exchange markets. The aggregation for the overall index takes into account the time-varying cross-correlations between sub-indices. This means that the CISS takes higher values when stress prevails in several market segments at the same time. High CISS values are observed during the recession in 1992, the global financial crisis in 2008-09 and during the euro area sovereign debt crisis between 2010 and 2012. In each case, elevated systemic stress is associated with negative GDP growth. The SRI measures medium-term variations in financial imbalances, captured primarily by elevated credit growth and exuberant asset price inflation. It takes high values when there is elevated growth in bank lending, total non-financial credit, house prices and asset prices, as well as a widening of external imbalances.

The four variables are stacked in the vector $\tilde{x}_t$ and the QVAR for a fixed quantile γ is given by:

$$\tilde{x}_{t+1} = \omega^{\gamma} + A_0^{\gamma}\tilde{x}_{t+1} + A_1^{\gamma}\tilde{x}_t + \epsilon_{t+1}^{\gamma}$$
$$P\left(\epsilon_{t+1}^{\gamma} < 0|\mathrm{F}_{it}\right) = \gamma \text{ for } i = 1, 2, 3,$$

where ϵ_{t+1}^{γ} represents the vector of structural quantile residuals.[14]

The recursive identification of the structural residuals is achieved by restricting the 4×4 matrix A_0^{γ} to a lower triangular, with zeros along the main diagonal. This places the geopolitical indicator first, real GDP growth second, systemic risk third and systemic stress last. The identification strategy means that the systemic stress variable (placed fourth) can react contemporaneously to geopolitical, macroeconomic and systemic risk shocks. Meanwhile systemic risk (placed third) can only react contemporaneously to shocks to geopolitical risk and output growth, and real output growth (placed second), reacting to a contemporaneous geopolitical shock, only reacts with a lag to shocks to systemic risk and to the stress indicator.[15] This follows standard assumptions in the empirical literature, such as Christiano et al. (1999), Kilian (2009), and Gilchrist and Zakrajsek (2012). The estimated model

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[13] In addition, the QR parameter estimates are less sensitive to outliers relative to their least squares counterparts. This robustness feature is welcome given that financial variables face abrupt and large changes.

[14] The estimation for a single quantile can be expanded to consider multiple quantiles. Technically, this is done by stacking the equations for the individual quantiles. See the companion paper Chavleishvili et al. (2021).

[15] The available information for each variable at each point in time is determined as follows. For the first variable, the information set is $\mathrm{F}_{1t} = \{\tilde{x}_{t,}\tilde{x}_{t-1}, \dots\}$ and for subsequent variables, it is $\mathrm{F}_{it} = \{\tilde{x}_{i-1,t+1,}\mathrm{F}_{i-1,t}\}$ for $i \in \{2,3\}$.

and its identification strategy allow us to quantify amplifications of risks for future economic activity caused by elevated levels of financial imbalances and by systemic stress. This is relevant for forecasting the variables over time and for counterfactual scenarios.

Scenario analysis

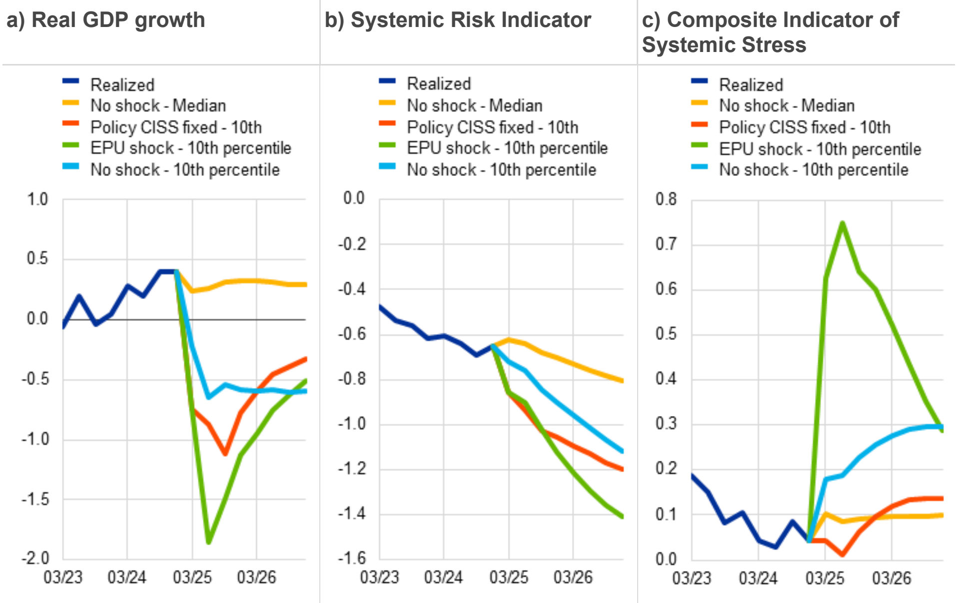
The scenario based on the QVAR assumes geopolitical tensions, modelled through a spike in economic policy uncertainty as observed at the onset of COVID-19 in 2020.[16] The analysis shows that following an economic policy uncertainty shock, quarterly real GDP growth at the 10th percentile falls by more than one percentage point (**Chart A.19, red line**), reflecting both the sizeable shock and the downward risks to the economy. The high persistence of the shock let real GDP recover only slowly, partly owing to the fact that the SRI declined throughout the two-year forecast horizon.

A stabilisation of the financial system, by maintaining the CISS at its pre-scenario level, had positive effects on GaR and the SRI, but differed compared with the geopolitical risk shock. In particular, the stabilisation did not lead to a redress of GaR above the baseline levels. The stabilisation did, however, have a stronger impact on the SRI, which came closer to its baseline.

[16] Scenario paths are constructed by estimating an AR(1) model with an intercept for each geopolitical risk variable up to the fourth quarter of 2024. For the GPR Index and COVOL Index, the residual from the one-quarter-ahead forecast for the first quarter of 2022 – using data up to the fourth quarter of 2021 – calibrates the generic conflict scenario. This shock is added to the forecast for t+1 (the first quarter of 2025), with subsequent quarters projected iteratively. The same approach is used for EPU Index, with the scenario calibrated to the pandemic shock in the second quarter of 2020. For the Global Supply Chain Pressure Index, four consecutive shocks were applied for the first four quarters of 2021 to capture COVID-related supply chain disruptions; otherwise, the procedure is the same.

Chart A.19

Implications for tail risks after an increase in the Economic Policy Uncertainty Index



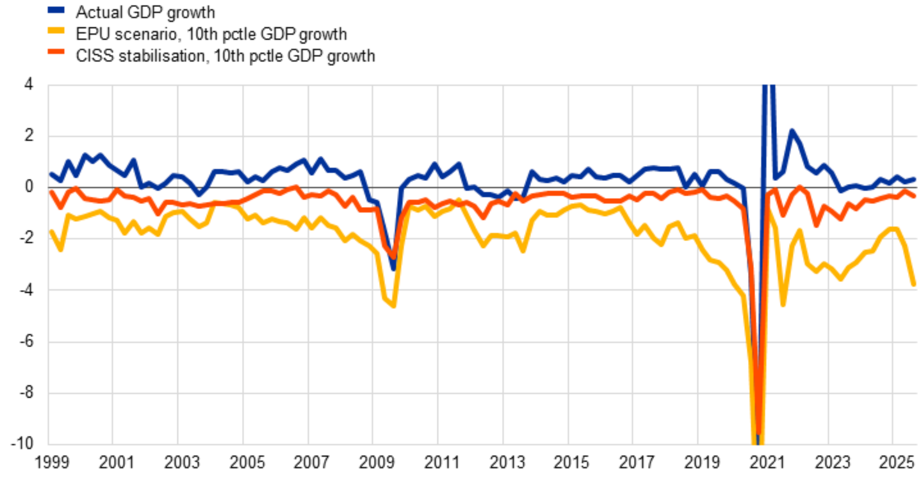
Source: Baker et al. (2016).
Notes: The green dotted lines show the baseline median forecast, the blue dashed lines depict the baseline 10th percentile (unconditional forecast of the 10th, 50th and 90th percentiles of the variable). The solid red lines depict the 10th-90th percentiles of the variable under the scenario of a joint geopolitical and volatility shock, and the dashed purple line represents the scenario in which policy stabilises financial stress (Composite Indicator of Systemic Stress or CISS) at the level before the geopolitical scenario materialised.

An additional type of analysis based on the QVAR considers a given set of shocks and creates historical counterfactuals to evaluate the implications of geopolitical risks for macro-financial risks since the beginning of EMU. For this, a one-off shock to economic policy uncertainty[17] is assumed and applied at every point in time. The forecast under the scenario is then summarised by the average GaR over a four-quarter forecast horizon. This method makes it possible to identify episodes in which the economy and the financial system have been more vulnerable to economic policy uncertainty.

[17] For the economic policy uncertainty shock, a shock of the same size as that indicated above was chosen, computed as the residual from an AR(1) model during the onset of the pandemic in the first quarter of 2022.

Chart A.20

Euro area macro-financial stress test for economic policy uncertainty shocks



Sources: Baker et al. (2016) and AWG/MPAG workstream on financial stability risks from geoeconomic fragmentation.
Notes: The blue line depicts quarterly real GDP growth at each point in time. The yellow economic policy uncertainty (EPU) line depicts recursive (in-sample) one-quarter ahead GDP growth at the tenth percentile applying an EPU shock of the size observed in the first quarter of 2022. The red Composite Indicator of Systemic Stress (CISS) stabilisation line depicts the GDP growth forecast with an EPU shock and considering a counterfactual in which the CISS is kept stable at its current level.

The macro-financial stress test reveals the vulnerability of the financial system to economic policy uncertainty shocks. While the economic policy uncertainty shock size is identical over the different time periods, the macro-financial conditions determined by GDP growth, the SRI and the CISS differ and modulate the transmission. Three episodes since the start of EMU stand out, in addition to the sharp declines in the 10th percentile during the global financial crisis and the pandemic (**Chart A.20**). First, GaR was slightly lower during the build-up of financial imbalances between 2006 and 2008, while realised GDP growth exceeded the long-term average. Second, the 2018-20 episode was characterised by increasing economic policy uncertainty, with detrimental effects for GaR. Finally, the post-COVID-19 period was strongly affected by geopolitical events that also entailed elevated economic policy uncertainty. Specifically, 2021-24 saw a combination of spikes in financial stress due to the Russian invasion of Ukraine, which made the euro area economy even more vulnerable to additional shocks such as those arising from economic policy uncertainty. Macro-financial stress tests of this type can serve as a useful monitor for policymakers to detect downside risks in real time and, if necessary, take mitigating action.

2.5 Diebold-Yilmaz framework (Section 5.1 and 5.2 of the report)

The Diebold-Yilmaz spillover framework (Diebold-Yilmaz, 2012) provides a methodology for quantifying the extent to which shocks in one variable or market contribute to the forecast error variance of other variables or markets. It builds on earlier work in Diebold and Yilmaz (2009), refining the approach by employing the generalised forecast error variance decomposition (GFEVD) developed in Pesaran and Shin (1998), which is invariant to the ordering of variables in the VAR model.

- **Methodological foundation**

The VAR model was estimated using an N-dimensional, covariance stationary vector autoregressive process of order $p\left(\mathrm{VAR}(p)\right)$: $\boldsymbol{y}_{\mathrm{t}} = \sum_{i=1}^{p} \boldsymbol{\Phi}_i \boldsymbol{y}_{i-\mathrm{t}} + \epsilon_t$, where $\boldsymbol{y}_{\mathrm{t}}$ is an $N \times 1$ vector of variables, $\boldsymbol{\Phi}_i$ are coefficients matrices, and ϵ_t is a vector of serially uncorrelated disturbances with covariance matrix Σ.

The moving average representation of the VAR is: $\boldsymbol{y}_{\mathrm{t}} = \sum_{h=0}^{\infty} \mathbf{A}_h \epsilon_{t-h}$.

- **Generalised forecast error variance decomposition (GFEVD)**

The key element is the decomposition of the H-step-ahead forecast error variance of each variable into parts attributable to shocks in each variable, based on the **generalised VAR framework**. The GFEVD is given by:

$\theta_{ij}{}^{(H)} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma\, e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma\, A_h' e_i\right)}$, where:

$\theta_{ij}{}^{(H)}$ is the proportion of the H-step-ahead forecast error variance of variable i explained by shocks to variable j, σ_{jj} is the standard deviation of the error term for variable j, e_i is a selection vector with one in the i-th position and zeros elsewhere.

Because GFEVDs do not sum to one across j, they are normalised as: $\tilde{\theta}_{ij}^{(H)} = \frac{\theta_{ij}{}^{(H)}}{\sum_{j=1}^{N} \theta_{ij}{}^{(H)}}$.

- **Spillover measures**

From the normalised GFEVDs, a Total spillover index as implemented in Section 5.2 can be defined as: $S^{(H)} = \frac{\sum_{i=1}^{N} \sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{(H)}}{N} \times 100.$

which measures the overall contribution of spillovers across all variables. The directional spillovers transmitted by $\boldsymbol{i}$ to all others (implemented in Section 5.1) is:

$S_{i\rightarrow\cdot}^{(H)} = \sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{(H)}$.

- **Time-varying spillovers**

To capture the evolution of interconnectedness over time, the method is implemented in a **rolling-window framework**: the VAR is estimated over a moving window of fixed length, and spillover indices are recalculated for each window. This produces a time series of spillover measures that reflect dynamic changes in market interdependencies.

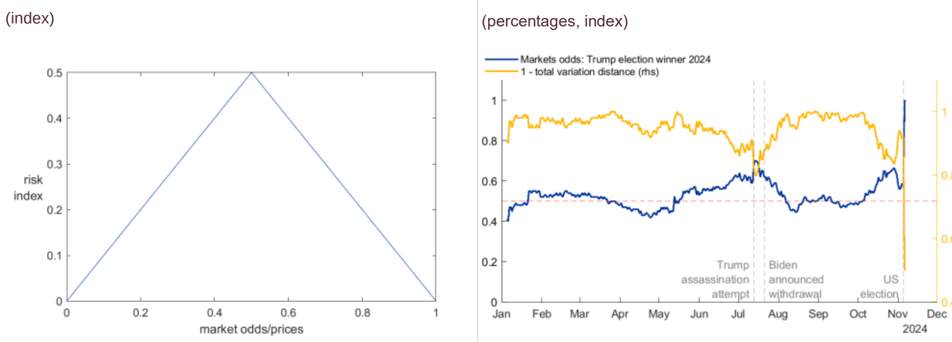
2.6 Financial markets reactions to US political risk shocks (Section 5.3 of the report)

Prediction markets can provide a market view of political risks. The US Political Risk Prediction Market Index is constructed by aggregating the risk associated with a broad set of prediction markets linked to US politics. Prediction markets are bets placed on events; Polymarket is the largest decentralised prediction market and has recorded monthly trading volumes of USD 1.17 billion since June 2025. Polymarket is structured around events and markets, i.e. events linked to real-world issues, such as elections and market outcomes, with contracts corresponding to binary bets with “Yes” and “No” outcomes. Market participants purchase contracts (event derivatives) for “Yes” or “No” outcomes, which trade at a price between USD 0 and 1. After the resolution of such an event the participants receive USD 1 if the event resolved in their favour and if not they receive nothing. The purchase price can therefore be interpreted as a market-implied probability of a specific event occurring or, alternatively, the participant’s view of the probability of an event occurring.[18] The total variation distance of probability measures is the largest absolute difference between the probabilities that the two probability distributions assign to the same event. The total variation (TV) distance from an equal distribution in a binary distribution is: TV = $|p - 0.5|$ with p success probability. The greatest risk associated with a single market occurs when the market-implied probability is at 50%. The closer the market-implied probability is to 0% or 100%, the lower the risk. The total variation in market-implied probability can therefore be transformed into a risk index component (**Chart A.4, panel a).** The risk varies over time and upon the resolution of the event the risk is resolved. One benefit of this approach is that the risk is agnostic with regard to the outcome of any given political event, instead capturing the uncertainty associated with that event. It is therefore neutral in terms of political orientation.

Chart A.21

Transformation of market-implied odds/prices into a risk index

a) Risk Index / Market-implied probability | **b) Market odds**



Source: Polymarket, ECB calculations.
Notes: Lhs stands for left-hand scale and rhs for right-hand scale. Panel a) shows the transformation from market-implied probability into a risk index. Panel b) shows the changes in the market odds for Trump winning the US presidential election in 2024 and a 1-total variation distance.

[18] Eichengreen et al. (2025).

The aggregation of individual markets to a single index is a capped weighted average. The Risk Index is constructed by aggregating the individual markets[19] by a capped volume weight:

$$\text{US political risk}_t = \sum_{i=1}^{\bar{N}} w_{i,t}\,(0.5 - (|p_{i,t} - 0.5|))$$

$$\text{with the weights } \widetilde{w_{i,t}} = \frac{m_{i,t}}{\sum_{i=1}^{N_t} m_{i,t}}$$

The amount of money invested in a single market at each time point is $m_{i,t}$.

To limit the impact of a single market and ensure that excessive weight is not given to any single event, the weights are capped relative to an equal weight factor:

$$w_{i,t} = \max\left(w_{eq,t} \times \gamma_{max}, \widetilde{w_{i,t}}\right)$$

with $w_{eq,t}$ representing the equal weight and γ_{max} the maximum factor set to 3. The excess weight mass is proportionally distributed to the other markets below the limit of 3 times the $w_{eq,t}$.

Table A.6

Sign and zero identification for the structural Bayesian vector autoregression

	Restrictive EA MP	Positive EA macro news	Restrictive US MP	Positive US macro news	Positive Global macro risk	Reduction US Political
EA long-term yields	+	+	+	+	+	0
EA equity prices	-	+			+	
US equity prices			-	+	+	+
USD/EUR exchange rate	+	+	-	-	+	-
EA-US long-term yield spread	+	+	-	-	-	
US political Risk index Prediction Marker	0	0			0	-

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: EA stands for euro area and MP for monetary policy.

A combination of sign and zero restrictions identifies a structural US political risk shock using a Metropolis–Hastings algorithm to estimate the model.[20,21] A US political risk shock has broad implications for financial markets. The assumption is that a reduction in US political risk has a positive effect on US equity and a beneficial impact on the US dollar relative to the euro. It is assumed that euro area long-term yields are not impacted. The impact on euro area equity prices is left unconstrained to allow the data during the estimation to determine this. Furthermore, shocks arising from euro area monetary policy, euro area macro news and global macro news are assumed to have zero impact on the US Political Risk Prediction

[19] Only markets that trade for at least 15 days are considered in constructing the index.

[20] Dieppe et al. (2016).

[21] Arias et al. (2018).

Market Index. The rest of the variables follows the original daily cross-asset structural BVAR framework[22] and are specified in differences or log differences.

2.7 Impact of the Russian invasion of Ukraine on bank lending (Section 6.1 of the report)

To assess the impact of the energy shock on credit conditions at the bank-firm level, the following regression model was estimated:

$$y_{ibt} = \beta_0 + \beta_1 POST_t + \beta_2 Energy_i + \beta_3 (Energy_i * POST_t) + \beta_4 X_{bt} + \alpha_{ib} + \varepsilon_{ibt}$$

Where:

y: credit conditions at the bank-firm level, as outlined below;

Energy: dummy = 1 if the firm belongs to an energy-intensive sector;

POST: dummy = 1 if after Q1 2022;

X: bank controls, as outlined below;

α: bank-firm fixed effects;

ε: Standard errors are clustered at the bank-firm level.

For analysis within the energy-intensive sectors, a dummy was used to capture firm vulnerability, i.e. a dummy = 1 if the firm's annual turnover/total assets was in the 1st quartile in 2021.

All the regressions exclude the period of the shock, i.e. Q1 2022.

The credit conditions at the bank-firm level include:

- logarithmic change in loan volume;
- logarithm of the new lending amount;
- absolute difference in average interest rate;
- absolute difference in average residual maturity;
- new lending interest rate;
- new lending maturity.

The bank characteristics used as controls (X^{it}) were the following:

[22] Brandt et al. (2021). The original framework is a widely used by centrals banks, recently it also acquired popularity among commercial banks and financial data providers.

- lag of management buffer – capital above regulatory requirements and pillar 2 guidance;
- lag of average risk weight – total risk-weighted exposure over total exposure;
- lag of provisions ratio – provisions over total assets;
- lag of market discipline – ratio of non-deposit liabilities over total liabilities;
- lag of size – logarithm of total assets;
- lag of the sum of the overall capital requirement and pillar 2 guidance.

Country comparison: POST-invasion effects on credit conditions in peripheral euro area economies

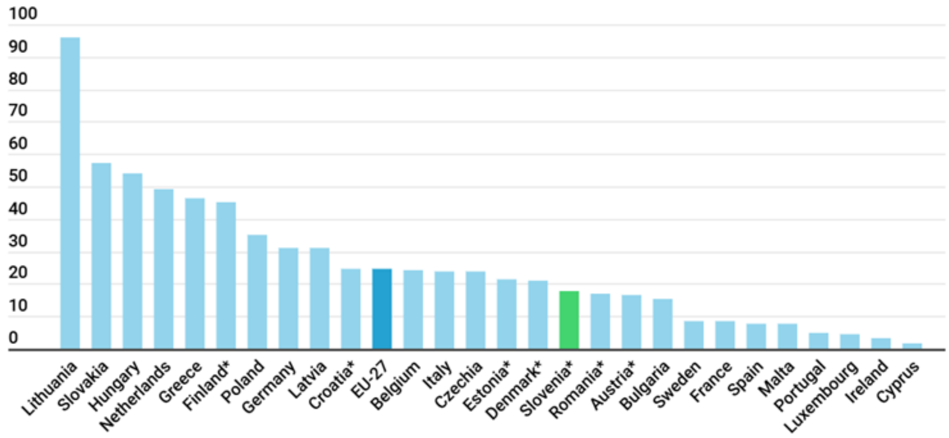
Portugal, Spain and Slovenia are bank-based euro area economies with shallow corporate bond markets and a high share of small and medium-sized enterprises (SMEs) that are reliant on bank intermediation. Their banking systems feature concentrated lenders, substantial exposures to domestic corporates and broadly similar prudential regimes, but with heterogeneous capital headroom and national support-scheme intensity. Comparing these countries helps identify whether bank capital buffers shape the transmission of a common geopolitical shock where capital market substitutes are limited and bank pricing/quantity decisions dominate. In 2020, before the energy shock, EU Member States' displayed wide heterogeneity in their dependence on Russian gas, although the three countries analysed in detail (Portugal, Spain and Slovenia) were among the least exposed (**Chart A2.1, panel a**). However, gas import dynamics diverged across all three countries (**Chart A2.1, panel b**).

Chart A.22

Available energy imported to the EU from Russia in 2020

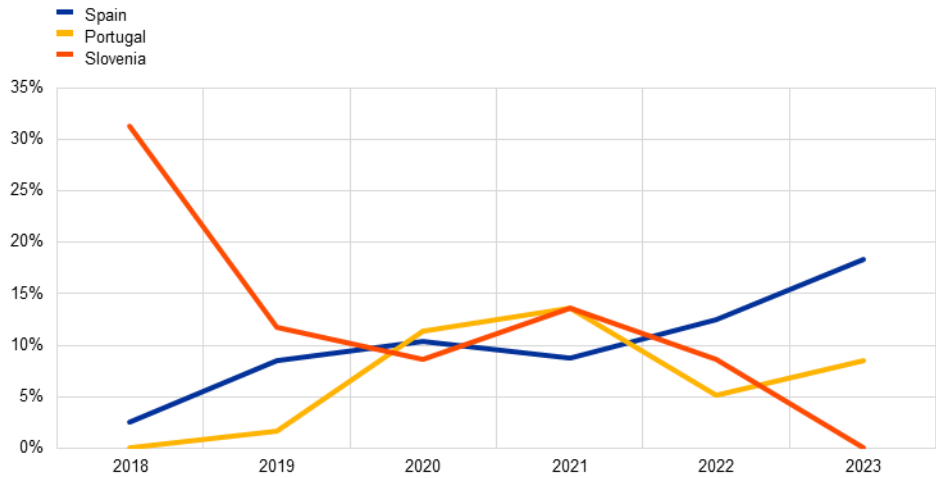
a) EU-27 share of available energy imported

(percentages)



b) Share of natural gas imports by EU Member State

(percentages)



Source: Eurostat data and Statistical Office of the Republic of Slovenia.
Note: * indicates estimates.

Portugal had almost no Russian gas in 2018, but imports grew rapidly thereafter, peaking at around 13-14% in 2021, before falling sharply in 2022 and then partly recovering in 2023. Slovenia started with high dependence (over 30% in 2018), but reduced it dramatically year by year, reaching zero reliance on Russian gas by 2023. Spain steadily increased its share of natural gas imports from Russia, rising from around 2-3% in 2018 to nearly 18% by 2023, despite a brief dip in 2021.

Although the 2022 energy shock primarily affected countries heavily reliant on Russian gas, it fed through relatively strongly to costs and cashflow volatility across all euro area countries.

Data and specification

Data: AnaCredit datasets linked to supervisory data, including data for both significant institutions (SIs) and less significant institutions (LSIs).

Specification: The same sample window (Q1 2021 to Q1 2023), same pre/post demarcation (pre: Q1 2021 to Q4 2021; post: Q2 2022 to Q1 2023), same outcomes, controls and bank-firm fixed effects as in the analysis in Sections 6.1.1 and 6.1.3 for the euro area.

The main findings reveal that well-capitalised banks in Spain, Portugal and Slovenia acted as shock absorbers by granting better-priced credit, including to energy-intensive sectors, the breakdown being as follows.

Loan growth (stocks): In Spain and Slovenia, post-invasion declines are larger for energy-intensive firms than for others. In Portugal, however, this difference is not statistically significant. In Portugal and Spain, higher-capitalised banks are associated with higher lending growth for energy firms.

New lending (flows): In Spain and Slovenia, without conditioning on the management buffer, energy firms receive smaller new-loan amounts than non-energy firms. With management buffers, the POST-invasion effect does not differ between non-energy and energy firms.

Interest rates (stocks): In Spain and Portugal, rates rise post-invasion and capital headroom had a stabilising effect, with the latter more pronounced for energy-intensive firms.

Interest rates (flows): In all three countries, new-loan rates increase post-invasion, although higher buffers are associated with lower new-loan pricing, corroborating a stabilising price effect.

Table A.7

Summary of the results

Outcome (bank-firm)	Unit	Portugal: Non-energy	Portugal: Energy	Spain: Non-energy	Spain: Energy	Slovenia: Non-energy	Slovenia: Energy
Loan growth (stocks)	Post (%)	-4.69***	-4.67***	-2.02***	-2.65***	−1.62%*	−4.18%***
	Post x MB (%)	0.50***	0.66***	+0.52***	+0.74***	(ns)	(ns)
Interest rate (stock)	Post (bps)	+75.7***	+76.8***	+12.1***	+9.7***	+22.1***	+18.5***
	Post x MB (bps)	-1.54***	-3.61***	-1.47***	-0.80***	+42.01***	+38.00***
New-loan amount	Post (%)	-17.8***	-20.0***	+9.36***	+5.48***	+26.7%**	+57.6%***
	Post x MB (%)	+7.97***	7.34***	(ns)	(ns)	(ns)	(ns)
New-loan interest	Post (bps)	+140***	+138***	26.7***	17.0***	+148***	+161***
	Post x MB (bps)	-18.00***	-17.51***	-28.85***	-24.17***	-85.74***	-101.75***

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Notes: Significance: *** p<0.01, ** p<0.05, * p<0.10, ns = not significant. "%" indicates that the rows are semi-elasticities from log outcomes. Post stands for post-invasion, MB for management buffer and "bps" for basis points.

Descriptive statistics

Table A.8

Descriptive statistics of the dependent variables

Variable Outstanding credit		Year	N Energy	Mean Energy	N NonEnergy	Mean NonEnergy	Diff	t-stat	p-value
Outstanding loans (EUR thousands)		2021	142,148	568	2,349,915	462	106	13.51	0.00
		2022	135,215	567	2,252,198	467	100	7.14	0.00
Interest rates (%)		2021	139,469	2.10%	2,287,735	1.98%	0.00	32.01	0.00
		2022	132,093	2.62%	2,201,400	2.33%	0.00	67.42	0.00
Residual maturity (years)		2021	141,702	4.10	2,345,935	6.31	-2.21	-171.88	0.00
		2022	134,694	3.87	2,247,311	6.17	-2.30	-173.55	0.00
New credit		**Year**	**N Energy**	**Mean Energy**	**N NonEnergy**	**Mean NonEnergy**	**Diff**	**t-stat**	**p-value**
New loans (EUR thousands)		2021	24,243	310	256,970	394	-85	-2.44	0.01
	ES	2021	10,832	347	83,600	1,527	-1180	-1.66	0.10
	PT	2021	1,801	136	14,461	124	12	1.94	0.05
		2022	23,226	289	243,624	436	-147	-2.64	0.01
	ES	2022	11,029	368	88,209	1,048	-680	-1.51	0.13
	PT	2022	1,894	133	15,237	135	-2	-0.29	0.77
Interest rate (%)		2021	37,641	2.11%	449,330	1.91%	0.20	23.90	0.00
	ES	2021	8,358	3.15%	65,679	3.13%	0.02	0.86	0.39
	PT	2021	1,617	3.25%	12,758	3.24%	0.00	0.13	0.90
		2022	50,415	2.95%	603,462	2.69%	0.00	30.96	0.00
	ES	2022	8,495	4.71%	69,774	4.73%	-0.01	-0.62	0.53
	PT	2022	1,694	5.28%	13,802	5.11%	0.00	3.34	0.00
Residual maturity (years)		2021	37,641	3.62	449,330	5.56	-1.94	-70.81	0.00
		2022	50,415	3.90	603,462	5.96	-2.06	-86.69	0.00

	Year	Share
Higher-capitalised banks' share of outstanding loans (%)	2021	55%
	2022	51%

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Notes: Diff stands for the difference between Mean Energy and Mean Non Energy, N for the number of observations, and t-stat for t-statistic. More Highly capitalised banks have a management buffer above the median in the fourth quarter of 2021.

Marginal effects of the analyses in Sections 6.1.1 and 6.1.3 of the report for the euro area

Table A.9

Impact of post-invasion effects on the logarithmic change in loan volume per sector

	Delta-method					
	dy/dx	Std err.	Z	P>|z|	[95% conf. interval]	
0.post	(base outcome)					
1.post						
Energy sector						
0	-.0102456	.0003147	-32.56	0.000	-.0108624	-.0096288
1	-.0235359	.0010393	-22.65	0.000	-.0255729	-.021499

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Table A.10

Impact of post-invasion effects on the logarithm of new lending amount per sector

	Delta-method					
	dy/dx	Std err.	Z	P>|z|	[95% conf. interval]	
0.post	(base outcome)					
1.post						
Energy sector						
0	.1495748	.0040387	37.04	0.000	.1416592	.1574905
1	.126657	.0076257	16.61	0.000	.1117109	.1416031

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Table A.11

Impact of post-invasion effects on the logarithm of new lending amount according to firm vulnerability within energy-intensive sectors

	Delta-method					
	dy/dx	Std err.	z	P>|z|	[95% conf. interval]	
0.post	(base outcome)					
1.post						
Vulnerable						
0	.1511873	.0113277	13.35	0.000	.1289855	.1733891
1	.010123	.057962	0.17	0.861	-.1034804	.1237264

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Table A.12

Impact of post-invasion effects on the absolute difference in the average interest rate

	Delta-method					
	dy/dx	Std err.	Z	P>|z|	[95% conf. interval]	
0.post	(base outcome)					
1.post						
Energy sector						
0	.0001399	4.34e-06	32.22	0.000	.0001314	.0001484
1	.0005926	.0000133	44.55	0.000	.0005666	.0006187

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Table A.13

Impact of the post-invasion effects on the absolute difference in residual maturity

	Delta-method					
	dy/dx	Std err.	Z	P>|z|	[95% conf. interval]	
0.post	(base outcome)					
1.post						
Energy sector						
0	-51.24499	.3035239	-168.83	0.000	-51.83988	-50.65009
1	-65.64166	.8824623	-74.38	0.000	-67.37125	-63.91206

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Table A.14

Impact of post-invasion effects on the interest rate for new lending

	Delta-method					
	dy/dx	Std err.	Z	P>|z|	[95% conf. interval]	
0.post	(base outcome)					
1.post						
Energy sector						
0	.0073794	.0000668	110.52	0.000	.0072485	.0075103
1	.0064641	.0001395	46.34	0.000	.0061907	.0067375

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Table A.15

Impact of post-invasion effects on the interest rate for new lending (controlling for 10-year yields)

	Delta-method					
	dy/dx	Std err.	Z	P>|z|	[95% conf. interval]	
0.post	(base outcome)					
1.post						
Energy sector						
0	-.0066964	.0000725	-92.32	0.000	-.0068385	-.0065542
1	-.0074771	.0001325	-56.42	0.000	-.0077369	-.0072174

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Table A.16

Impact of post-invasion effects on the maturity of new lending

	Delta-method					
	dy/dx	Std err.	z	P>|z|	[95% conf. interval]	
0.post	(base outcome)					
1.post						
Energy sector						
0	-1.215365	3.679101	-0.33	0.741	-8.426269	5.99554
1	.613745	5.34328	0.11	0.909	-9.858892	11.08638

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Post stands for post-invasion and std err. for standard error.

Table A.17

Impact of post-invasion effects on the interest rate for new lending according to firm vulnerability within energy-intensive sectors

	Delta-method					
	dy/dx	Std err.	z	P>|z|	[95% conf. interval]	
0.post	(base outcome)					
1.post						
vulnerable						
0	.0068968	.0002105	32.77	0.000	.0064842	.0073093
1	.0084625	.0009389	9.01	0.000	.0066222	.0103027

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Table A.18

Effect of a 1 percentage point increase in the management buffer on the logarithmic change in the loan volume per sector and period

	Delta-method					
	dy/dx	Std err.	Z	P>|z|	[95% conf. interval]	
energysector#post						
0 0	1.092297	.0316748	34.48	0.000	1.030216	1.154379
0 1	1.495068	.0334465	44.70	0.000	1.429514	1.560622
1 0	.9894473	.114343	8.65	0.000	.765339	1.213555
1 1	.958243	.1207193	7.94	0.000	.7216375	1.194848

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Table A.19

Effect of a 1 percentage point increase in the management buffer on the logarithm of the new lending amount per sector and period

	Delta-method					
	dy/dx	Std err.	Z	P>|z|	[95% conf. interval]	
energysector#post						
0 0	3.381557	.2726797	12.40	0.000	2.847115	3.916
0 1	4.271186	.3885178	10.99	0.000	3.509705	5.032667
1 0	4.121846	.664144	6.21	0.000	2.820148	5.423544
1 1	6.396621	1.039714	6.15	0.000	4.358819	8.434424

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Table A.20

Effect of a 1 percentage point increase in the management buffer on the absolute difference in the average interest rate

	Delta-method					
	dy/dx	Std err.	z	P>|z|	[95% conf. interval]	
energysector#post						
0 0	-.0393029	.0003672	-107.02	0.000	-.0400227	-.0385831
0 1	-.0353521	.0003788	-93.33	0.000	-.0360945	-.0346096
1 0	-.0326558	.0012747	-25.62	0.000	-.0351542	-.0301573
1 1	-.0274762	.0013066	-21.03	0.000	-.030037	-.0249154

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Table A.21

Effect of a 1 percentage point increase in the management buffer on the absolute difference in the average residual maturity

	Delta-method					
	dy/dx	Std err.	z	P>|z|	[95% conf. interval]	
energysector#post						
0 0	-144.7791	24.54007	-5.90	0.000	-192.8767	-96.68143
0 1	445.1885	25.59546	17.39	0.000	395.0223	495.3547
1 0	-615.5812	82.7593	-7.44	0.000	-777.7865	-453.3759
1 1	192.2406	84.32341	2.28	0.023	26.9698	357.5115

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Table A.22

Effect of a 1 percentage point increase in the management buffer on the interest rate for new lending

	Delta-method					
	dy/dx	Std err.	z	P>|z|	[95% conf. interval]	
energysector#post						
0 0	-.3559605	.0055365	-64.29	0.000	-.3668118	-.3451092
0 1	-.2889564	.005887	-49.08	0.000	-.3004948	-.277418
1 0	-.4321068	.0165268	-26.15	0.000	-.4644989	-.3997148
1 1	-.3273616	.0190502	-17.18	0.000	-.3646993	-.2900238

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Post stands for post-invasion and std err. for standard error.

Table A.23

Effect of a 1 percentage point increase in the management buffer on the maturity of new lending

	Delta-method					
	dy/dx	Std err.	z	P>|z|	[95% conf. interval]	
energysector#post						
0 0	406.3327	207.8924	1.95	0.051	-1.128911	813.7943
0 1	-1397.743	411.1861	-3.40	0.001	-2203.653	-591.8331
1 0	2123.527	478.0962	4.44	0.000	1186.476	3060.579
1 1	1943.716	811.7551	2.39	0.017	352.7056	3534.727

Source: ECB/ESRB workstream on financial stability risks from geoeconomic fragmentation.
Note: Post stands for post-invasion and std err. for standard error.

Acknowledgements
This report was prepared jointly by the ESRB Advisory Technical Committee and Eurosystem Financial Stability Committee.

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The cut-off date for the data included in this report was June 2025

For specific terminology please refer to the ESRB glossary (available in English only).