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Trade under Tensions: Insights from Media-Reported Bilateral Events

Nathan Chevalier, Matthieu Crozet, Charlotte Emlinger & Daniel Mirza

Highlights

- We propose a new dataset that captures the exposure of country pairs to all types of geopolitical frictions, including low- and medium-importance events.
- Our analysis confirms that geopolitical tensions create an unfavorable climate for international trade.
- An increase of one standard deviation in our tension indicator has an effect on trade equivalent to a tariff ranging from 0.06% to 8.19%, depending on the specification.

Abstract

A growing number of studies show the significant impact of major geopolitical events and alignments between countries on international trade. We propose a new dataset, based on the GDELT database, that captures the exposure of country pairs to all types of geopolitical frictions, including low- and medium-importance events. The statistical indicators, which are monthly and bilateral, provide information on the geopolitical climate surrounding the relations between each country pair over time. The database covers 201 countries over nearly 10 years. Our econometric analysis confirms that geopolitical tensions create an unfavorable climate for international trade. We estimate that An increase of one standard deviation in our tension indicator has an effect on trade equivalent to a tariff ranging from 0.06% to 8.19%, depending on the specification. We also observe that the sensitivity of international trade to geopolitical events has increased significantly since the COVID-19 crisis.

Keywords

Geoeconomics, International Trade, Risk, GDELT.

JEL

F14, F51.

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RESEARCH AND EXPERTISE
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Trade under Tensions: Insights from media-reported bilateral events

Nathan Chevalier*, Matthieu Crozet†, Charlotte Emlinger‡, and Daniel Mirza§

1 Introduction

"In a system, small or modest actions can, through their accumulation or interaction, produce consequences far greater than one would have anticipated."

— Robert Jervis, "System Effects: Complexity in Political and Social Life", Princeton University Press, 1997.

In a world increasingly affected by geopolitical instability, trade in goods and services, cross-border investments, and international travel can be significantly hindered by major events such as wars, civil conflicts, terrorism, piracy, sanctions, and unilateral protectionist policies. Nevertheless, international business can also be impacted by underlying tensions expressed through a series of low- to mid-salience events.

The media plays a crucial role in reporting on the state of international relations, which can influence public perceptions of the current and future costs associated with international trade. Negative events related to a specific country can decrease trade flows, by directly affecting trade costs (e.g. in case of military conflict, trade wars, visa restrictions, or natural disasters). But less salient negative events (such as hostile statements or expressions of rivalry) may also play a role by prompting exporters and importers to reevaluate their exposure to risk. Systematic measures of these tensions or frictions are still scarce. Existing datasets often focus primarily on conflicts, diplomatic crises, and their hard policy responses (such as sanctions), failing to capture the perceptions of trade-makers regarding the broader range of events that influence international economic relations. At the same time, empirical research in international trade has long highlighted the importance of political stability and institutional quality but has lacked comprehensive indicators of geopolitical tensions that are available at a high frequency for empirical analysis.

This paper measures the impact of bilateral political tensions reported in the media on international trade. It is based on original statistical indicators built from the information gathered by the GDELT project (*Global Database of Events, Language, and Tone*, Leetaru and Schrodt

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(2013)).[1] We extract from GDELT all press articles or agency reports provided by national press agencies around the world, covering the whole spectrum of events in the database. We then rearrange the information covered by the reports and aggregate them up into two indicators expressing the *Shade* and *Intensity* of the relations across pair of countries, overtime. Our indicators are constructed using the tone – negative, positive or neutral – provided by GDELT and associated to each article/press report, which is a novelty compared to the prior economic research which uses GDELT. We define the *Shade* indicator, our main measure, by the share of all negative-tone reports in a given time to all press reports involving a pair of countries. Thus, the *Shade* represents the extent of the negative geopolitical climate surrounding a given dyad of countries. The *Intensity* measure is the ratio of media reports mentioning the two countries, per pair, to the number of articles reported for either of these countries with the rest of the world. The *Intensity* indicator therefore measures, for a given country, the importance of each foreign nation in the media coverage of international events. These two indicators are computed for 12,766 dyads formed by 201 countries, and each month between March 2015 and July 2025. The resulting database – the *IntenSE* Dataset – is made readily available online by the CEPII.[2]

We use these two newly constructed bilateral indicators to quantify how a deterioration in the geopolitical climate between two countries affects their bilateral trade in goods. A worsening of bilateral relations is captured by an increase in the Shade indicator, which summarizes the polarity of media coverage, and can be interacted with the Intensity indicator to account for the relative importance of the relationship in global news. Together, these indicators allow us to measure not only the tone of geopolitical interactions but also their salience in international media. Our empirical analysis proceeds in two steps. We first examine the dynamic response of bilateral trade to a deterioration in the geopolitical climate. Using local projections (Jordà, 2005; Montiel Olea and Plagborg-Møller, 2021), we show that an increase in negative news articles explicitly mentioning both countries leads to an immediate and persistent decline in bilateral trade flows. This result goes beyond the general observation that trade reacts to rising uncertainty or geopolitical risks: the bilateral nature and high frequency of our indicators allow us to identify shocks that are specific to a given pair of countries, while controlling for broader trends affecting global import and export capacities. We then turn to a structural gravity framework to estimate the short-term effects of geopolitical tensions on trade. Following the recommendations of the empirical trade literature (Larch et al., 2025; Mulabdic and Yotov, 2025), we complement bilateral trade data with domestic trade flows. Using these as a benchmark for international transactions enables us to isolate the global impact of a deterioration in bilateral geopolitical relations on cross-border trade. Across specifications, we find robust evidence that geopolitical tensions exert a significant and economically meaningful negative effect on international trade. Across both empirical approaches – local projections and structural gravity estimations – we find that the magnitude of the estimated effects does not differ significantly when distinguishing between violent and non-violent events. This consistency indicates that our results are not driven by a particular subset of geopolitical incidents. Instead, it is the

[1]See GDELT website: https://www.gdeltproject.org
[2]See CEPII website: https://www.cepii.fr

broader deterioration of the bilateral geopolitical climate, as captured by our indicators, that systematically depresses international trade.

The literature on the impact of geopolitical shocks on international trade is long-standing, but it has mushroomed in recent years (see Mohr and Trebesch (2025) and McGuirk and Trebesch (2025) for comprehensive overviews of the rapidly expanding body of research in geoeconomics). A first strand of this literature concentrates on military and other violent forms of disputes.[3] Early influential papers, Glick and Taylor (2010) and Martin et al. (2008) investigate the impact of militarized interstate disputes on trade using Correlates of War (CoW) database (Gleditsch, 2004; Sarkees and Wayman, 2010), which records all international events characterized by display of military force. The latter isolate a significantly negative and persistent effect of wars on bilateral trade that can last up to 20 years. Multilateral trade liberalization in turn is shown to increase the probability of occurrence of a bilateral conflict, through the reduction of their bilateral dependencies. Other databases, complementary to CoW, record conflicts and other violent actions in international relations. In particular, indicators from the Uppsala Conflict Data Program (UCDP) (Harbom et al., 2008; Davies et al., 2024), the Armed Conflict Location and Events Dataset (ACLED) (Raleigh et al., 2023), and the Global Terrorism Database (GTD)[4] have been widely used as variables of interest or control in studies related to trade, migration, and foreign investment.[5]

The second body of the literature concentrates on geopolitical (mis)-alignments. A large body of literature (e.g. Fuchs and Klann (2013), Rose (2007)) has exploited official state visits or embassy network to demonstrated the influence diplomatic actions on trade. Fernando Broner (2025) construct a database of 77,000 international treaties over more than two centuries and show how they influence trade patterns. Gopinath et al. (2025) witness the resurgence of disputes in geopolitics by highlighting the emergence of a new cold war, based on evidence given by trade, financial, and foreign direct investment (FDI) data. The authors find evidence of trade and investment fragmentation along geopolitical lines, exploiting the widely used "Ideal Point Distance" (IPD) indicator developed by Bailey et al. (2017). The measure is bilateral and based on the similarity of the respective voting of countries at the United Nations General Assembly.[6] One critique made regarding the IPD use is that as many countries' voting mimics those of the leading countries in the U.N. assembly (US, Russia, China), the measure suffers from insufficient variations within dyads overtime. Fan et al. (2025) present a new measure of geopolitical alignments which overcomes the insufficient variation in the ideal point distance measure. They use Large Language Models (LLM), by picking all *major* political events between country pairs (with a country originating an event on a target country), listed by Gemini 2.5 Pro. They then assign a Goldstein scale (Goldstein, 1992) value for each type of those events,

[3]For an historical perspective on this topic, see the work of Findlay and O'Rourke (2007). They demonstrate how geopolitics and wars have shaped international trade patterns in the long term.

[4]See START website: https://www.start.umd.edu/data-tools/GTD

[5]Kamin (2022) on UCDP data, Eberhard-Ruiz (2024) on ACLED, or de Sousa et al. (2018) on GTD, provide recent examples.

[6]Aiyar et al. (2024) and Bosone and Stamato (2024) provide other examples using the IPD indicator. The votes at the United Nations is also one of the many variables that contribute to the synthetic measure of geopolitical fragmentation built by Fernàndez-Villaverde et al. (2025).

and aggregate them up at the country level to measure geopolitical alignments across pairs for 193 countries and over a long period (1950-2024). The authors then run Local Projections (i.e. see Jordà (2005) and Montiel Olea and Plagborg-Møller (2021)) using a dynamic version of gravity equations and controlling for multiple trade and geopolitical relations lags. They estimate that a one-standard-deviation improvement in geopolitical alignment increases bilateral trade by 20 percent over ten years. They further find that deteriorating geopolitical relations have reduced trade globally, by 7 percentage points between 1995 and 2020.

There is also a literature which looks at how risks of different nature (like regional war shocks, president or prime minister assassinations, financial crises, etc.) leading to important uncertainty, can affect trade. Novy and Taylor (2019) extend Bloom's (2009) Volatility Exchange Options index, as a measure of uncertainty about future stock market developments, to find that US trade is clearly more affected by this indicator than domestic production.[7] Mulabdic and Yotov (2025) investigate the impact of global geopolitical risk on bilateral trade, in a structural gravity model, by mobilizing the global *GeoPolitical Risk Index, GPR* introduced by Caldara and Iacoviello (2022), where inter and intra-trade flows are being considered. The *GPR* index measures the global risk overtime in the world. It is obtained from information extracted from 10 major newspapers in English. Mulabdic and Yotov (2025) interact a high-risk time-dependent dummy variable based on *GPR* with an international border dummy variable, to get a proxy for doing business across borders (with respect to internal borders' trade) overtime. The authors highlight an effect of GPR peaks on international trade (compared to intra-trade) equivalent to an increase in tariffs of 14%. They also investigate product heterogeneity, showing that services and agricultural goods are mostly affected.

The last body of the literature concentrates on the impact of geopolitical pressures on trade. The geoeconomic pressure variables express higher costs to trade. They are not related to uncertainty, *a priori*. One well known geopolitical pressure is the use of sanctions. In a series of articles, initiated by Felbermayr et al. (2020) and which have been surveyed recently by Felbermayr et al. (2025), the authors examine and review extensively this literature, which uses mainly the Global Sanctions Database (GSDB)[8]. One main result provided by these authors from this literature is that "the primary effects of sanctions on the target states are negative, large, and often long-lasting". A recent work however by Clayton and Maggiori (2025) goes beyond the indicators of sanctions provided by the GSDB database, by defining and systematically classifying geoeconomic pressure (beyond traditional sanctions) using an LLM-based text classification on economic discourse on limited well defined instruments such as tariffs, export controls or investment screenings. They classify which governments apply pressure to which foreign targets, across which different types of instruments, firms, and products. The paper shows that firms' economic responses differ systematically by policy tool: price passthrough for tariffs, R&D for export controls, and nuanced responses to sanctions and threats.

[7]The authors provide an elegant theoretical explanation of such effect: order costs of foreign inputs purchased by firms are higher than ordering costs linked to the purchase of domestic inputs. After an important shock, the firms choose an optimal waiting option by cutting more orders addressed to foreign suppliers than those directed to domestic ones, which then clearly leads to a higher contraction of imports than production but then a greater increase in imports during economic recovery.

[8]See GSDB website: https://www.globalsanctionsdatabase.com

Furthermore, several recent research have used the GDELT rich database to construct geopolitical related indicators and relate them to trade related subjects too. All of these have the particularity to use either the Goldstein scale to compute synthetic indicators, or the CAMEO classification which provides the general type in which fits each event. The Goldstein scale is a numerical score running from –10 (extreme conflict) to +10 (extreme cooperation), assigned to political events, ordered from highly conflictual to highly cooperative interactions. A CAMEO event code (Conflict and Mediation Event Observations code) is a qualitative version of the Goldstein one. It classifies events into a structured hierarchy (e.g., "Fight", "Threaten", "Protest", "Provide aid"). Among these research, Desbordes (2026) uses CAMEO codes, to offer a long term stock-based Interstate Conflict Relation Index (ISCRI) based on GDELT. Hinz (2023) constructs some indicators which are relatively close to ours but through the use of the CAMEO measure as well, not through the use of articles' tones as we do. He then finds that geopolitical relations affect the choice of partners in signing trade agreements and the depth of these agreements. Hardwick (2025) proposes again a GDELT-sourced indicator which makes use of the Goldsetin scores and a particle filter. He then finds that being part of international trade institutions like the WTO, increases trade even between highly-geopolitical distant partners.[9]

The value added of our work compared to most of the cited literature lies in the broad information our dataset conveys: we do not consider only some major geopolitical events as in Fan et al. (2025), we do not consider neither some well-defined instruments of coercion as in Clayton and Maggiori (2025).

Besides, and in sharp contrast to much of the existing literature using GDELT, our measures are not directional. Specifically, we do not exploit the reported source and target actors of each geopolitical event, as this information is often inconsistently or inaccurately coded. Further, and even more importantly, we also depart from the standard use of GDELT by not relying on the Goldstein scale or the associated CAMEO classifications, except for CAMEO categories directly related to violence and armed conflict. For all other events, we construct our measures using the sentiment (tone) of the underlying news articles rather than the ex-ante Goldstein scores or the event-type classification. In fact, the CAMEO category and its associated Goldstein score do not necessarily reflect the overall tone of the reporting. For example, an event coded as humanitarian assistance (typically cooperative and thus positive in the CAMEO/Goldstein classification) may be covered in a strongly negative context, such as aid delivered while ongoing bombings. By relying on article-level sentiment, we aim to capture the broader informational environment surrounding geopolitical events rather than the mechanical polarity embedded in the coding scheme.

To anticipate our presentation and discussion of our results, our findings indicate that geopolitical tensions produce an unfavorable climate for doing business across countries. We estimate that a standard deviation increase in our tensions' indicators, typically produces from 0.06 to as much as 8.19% ad-valorem tax equivalent on bilateral trade, depending on the selected in-

[9] Saadaoui et al. (2026) use the Political Relationship Index (PRI), a Chinese focused indicator, to study how extreme geopolitical events affect Chinese firms' exports. PRI is developed by Tsinghua University regarding Chinese state of relations with 12 other countries. Again the indicator is based on a Goldstein measure. Interestingly, Chinese exporters are found to react more strongly to diplomatic improvements than to deterioration.

dicator of geopolitical tensions we are exploiting, the short or long run price-elasticities being considered and most importantly, the period considered, as well as whether or not internal trade data are being included.

The remainder of the paper is organized as follows. Section 2 describes in detail the construction of the IntenSE database. Section 3 presents our empirical application to international trade, divided between dynamic and structural estimations. Section 4 quantifies the extent of the effect of tensions on trade. Section 5 concludes.

2 IntenSE Database Construction

2.1 Main Data Source: GDELT

The CEPII *Intensity and Shade of Events* (IntenSE) database is constructed from version 2.0 of the *Global Database of Events, Language, and Tone* (GDELT) (Leetaru and Schrodt, 2013). GDELT provides structured information on international events extracted from global news sources using automated text-processing techniques. These data include event dates, actors, and their classification under the *Conflict and Mediation Event Observation* (CAMEO) framework (Gerner et al., 2002). Our construction relies primarily on the *events* and *eventmentions* tables, which respectively record standardized events and the underlying articles from which these events are derived.

Because the mapping between articles and events is not one-to-one – multiple articles may refer to the same occurrence, while a single article may generate several coded events – we conduct the analysis at the article level, using the CAMEO codes they report. To ensure consistency and data quality, we rely exclusively on GDELT version 2.0, which is available from March 2015 onward.[10] We further limit the sample to articles published by 164 press agencies located in 154 countries (see Table 9 in Appendix A.4). This filtering step helps retain the most factual reporting and focuses on sources that are most likely to be accurately processed by GDELT's algorithm – typically brief, descriptive articles, often written in English and containing minimal journalistic commentary.[11]

2.2 Event Classification and Aggregation

The CAMEO taxonomy (Gerner et al., 2002) comprises 149 distinct event codes and is therefore both highly granular and heterogeneous (Table 10 in Appendix A.5). To make the information contained in GDELT articles tractable and interpretable, these codes are grouped into broader categories reflecting the nature of the reported interaction. We rely on the three-digit structure of the CAMEO classification to differentiate between violent and non violent events. We then exploit the tone of the underlying article provided by GDELT to further refine this classification. Specifically, within the non violent categories, we distinguish between positive and negative

[10] Version 2.0 expands language coverage and introduces the *eventmentions* table, which is not available before March 2015.

[11] Appendix A documents the full data-processing pipeline.

interactions based on whether the article conveys a positive or negative tone. [12]

This two-step procedure results in three mutually exclusive categories: violent articles (irrespective of article tone) non-violent articles with a negative tone, and non-violent articles with a positive tone. In addition, violent and non-violent articles with a negative tone can be aggregated into a single negative category, while non-violent articles with a positive tone are grouped into a positive category. This broader classification now yields two categories covering all articles: negative, and positive.

Figure 1 illustrates the distribution of articles across the three broad categories defined above for the United States and a selected set of partner countries in 2024. Mentions of EU member states are aggregated under a single EUR label. The patterns displayed in the figure closely mirror the geopolitical landscape of U.S. foreign relations in 2024, suggesting that this aggregation captures meaningful variation in bilateral interactions. In particular, the United States and Israel are frequently co-mentioned in articles classified as Negative, including both violent and non-violent events, reflecting the escalation of the conflict in Palestine. A similar concentration of negative coverage is observed for Russia (RUS), consistent with the ongoing war in Ukraine and the associated sanctions regime.

With the exception of the European Union (EUR), Turkey (TUR), and Saudi Arabia (SAU), most bilateral relationships are predominantly associated with negative articles. This descriptive evidence underscores the extent to which U.S. foreign relations in 2024 were shaped by unfavorable geopolitical developments and motivates the construction of monthly bilateral indicators that summarize both the intensity and the nature of interactions between countries.[13]

2.3 Geopolitical Indicators

To characterize the importance and the nature of bilateral relationships, we introduce two indicators. Let $\mathbb{N}$ denote the set of countries in the database, and let a_{ijt} the number of news articles that mention countries $i \in \mathbb{N}$ and $j \in \mathbb{N}$ during month t. The Intensity indicator for country j from the perspective country i, in a given month t is defined as follows:

$$\textbf{Intensity: } \mathbb{I}_{ijt} \equiv \frac{a_{ijt}}{\sum_{s \in \mathbb{N}} a_{ist}} \tag{1}$$

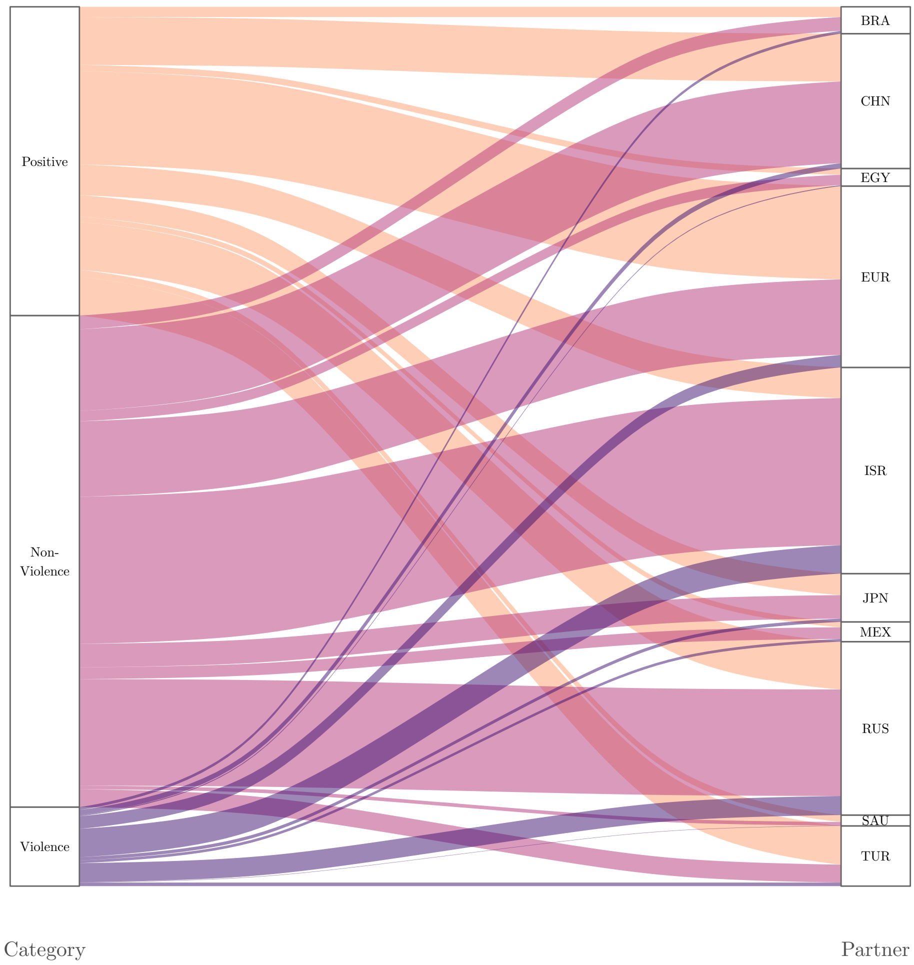
This indicator takes values between 0 and 1, as it represents the proportion of articles mentioning country i that also refer to country j, among all articles mentioning i. A higher value indicates a stronger relationship from the perspective of country i. This Intensity indicator is not symmetric: for any pair of countries i and j and any month t, $\mathbb{I}_{ijt} \neq \mathbb{I}_{jit}$.

This asymmetry is economically significant. Consider, for example, a small open economy such as Belize and a major geopolitical actor such as the United States of America . A substantial share of the news coverage concerning Belize may refer to the USA, resulting in a high value

[12]This marks the main point of departure from the approach adopted by Hinz (2023), who classifies events solely on the basis of their CAMEO code without incorporating information from the underlying articles and the tone they convey.

[13]Comparable visualizations for China (CHN), the European Union (EUR), and Russia (RUS) are provided in Appendix A.6 (Figures 10, 11, and 12), showing different patterns that still closely align with their respective geopolitical climate.

Figure 1: Event Category Breakdown of Press Agency Articles Mentioning the United States and Partner Countries (2024)



of $\mathbb{I}_{BLZ,USA,t}$. By contrast, only a very small fraction of articles about the much larger country USA will mention Belize, yielding a markedly lower $\mathbb{I}_{USA,BLZ,t}$. The Intensity indicator therefore captures directional dependence, visibility, and exposure-key dimensions of the importance of bilateral relations that need not to be reciprocal.[14]

The Shade indicator is defined for each event category and each bilateral relationship. Let $\mathbb{C} \equiv \{\text{Violence, Negative, Positive}\}$ denote the set of broad event categories defined above; and $\mathbb{C}' \equiv \{\text{Negative Action, Positive Action, Negative Declaration, Positive Declaration}\}$. Then, a_{ijct} represent the number of news articles reporting events of category $c \in [\mathbb{C}, \mathbb{C}']$ that involve countries $i \in \mathbb{N}$ and $j \in \mathbb{N}$ during month t. It corresponds to the proportion of articles that fall into category c during month t for country pair (i, j), thereby capturing the "color" or qualitative orientation of their relationship:

$$\textbf{Shade: } \mathbb{S}^c_{ijt} \equiv \frac{a^c_{ijt}}{\sum_{\kappa \in \mathbb{C}} a^{\kappa}_{ijt}} \tag{2}$$

[14]The interpretation of the Intensity indicator is illustrated in greater detail in Appendix B (Figures 13, 14, 15, 16, 17 and Table 15).

This indicator ranges from 0 to 1: values closer to 1 indicate a larger share of articles reporting events in the corresponding category for the country pair (i, j). Because the ordering of actors is not considered, the indicator is symmetric. Formally, for any countries i and j, any month t, and any category c, we have $\mathbb{S}^c_{ijt} = \mathbb{S}^c_{jit}$.

Crucially, the Shade indicator should not be interpreted as a measure of geopolitical alignment or ideological proximity between countries i and j. Instead, it captures the *quality of climate in bilateral relations*, i.e. whether bilateral interactions reported in the news are predominantly embedded in cooperative, neutral, or conflictual environments. In other words, Shade reflects how "favorable" or "unfavorable" the relational environment is, which is precisely the dimension that matters when studying international trade. An exposure of a bilateral relationship to frequently negative events (e.g., diplomatic disputes, sanctions, hostile declarations) is likely to create uncertainty, reduce trust, and hinder business activity, whereas a relationship dominated by or embedded in positive or neutral interactions is more conducive to stable commercial exchanges.

Putting all components together, the resulting bilateral panel contains 484,148 monthly observations from March 2015 to July 2025, covering 201 countries and 12,766 country pairs.

2.4 Stylized Facts

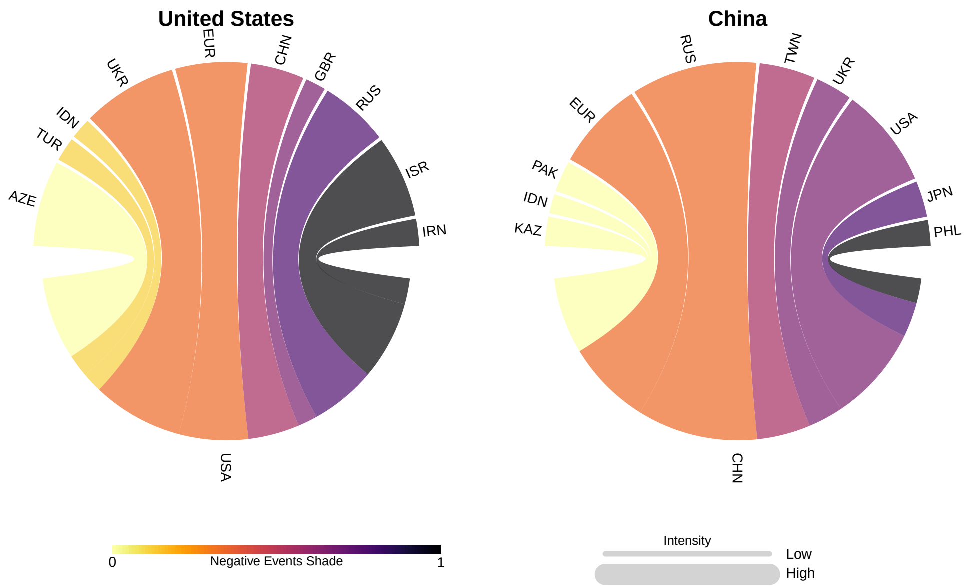
A key strength of the IntenSE database is that it captures bilateral relationships along two complementary dimensions: the first dimension measures the importance of partners in a country's bilateral relations, while the second captures the quality of the climate surrounding these relationships. The two chord diagrams in Figure 2 illustrate the analytical gain from combining these dimensions by jointly displaying the Intensity indicator for the ten most intense bilateral ties (link thickness) and the negative events Shade (color) for the United States and China in 2024.

The diagrams show that both countries have highly intense relationships that may be either positive or negative. For the United States, relations with Ukraine are intense and largely positive, while relations with Israel are intense but predominantly negative. For China, relations with Russia are both intense and positive. Taken together, these patterns reveal the contrasting perspectives of the United States and China on the ongoing Russia-Ukraine conflict.[15] The figures further show that the United States and China are themselves closely connected, though mainly through negative events. The Intensity of this relationship is asymmetric: the United States represents a relatively more important partner for China than China does for the United States in that year. By contrast, Europe displays similar levels of Intensity and negative-event shading in its relations with both countries.

Another important advantage of the IntenSE database is its temporal dimension, as it covers the period 2015-2025, a decade marked by major global disruptions. Figure 4 plots yearly kernel density distributions of the negative events Shade indicator from 2016 to 2024 and highlights substantial variation over time. At the beginning of the period, the distribution is more

[15] Figure 21 in the Appendix D presents similar chord diagrams for the EU and Russia, highlighting the importance of Ukraine for both, but with a high negative events Shade for Russia and a comparatively low one for the EU.

Figure 2: Media-Reported Interaction Patterns for the USA and China (2024)

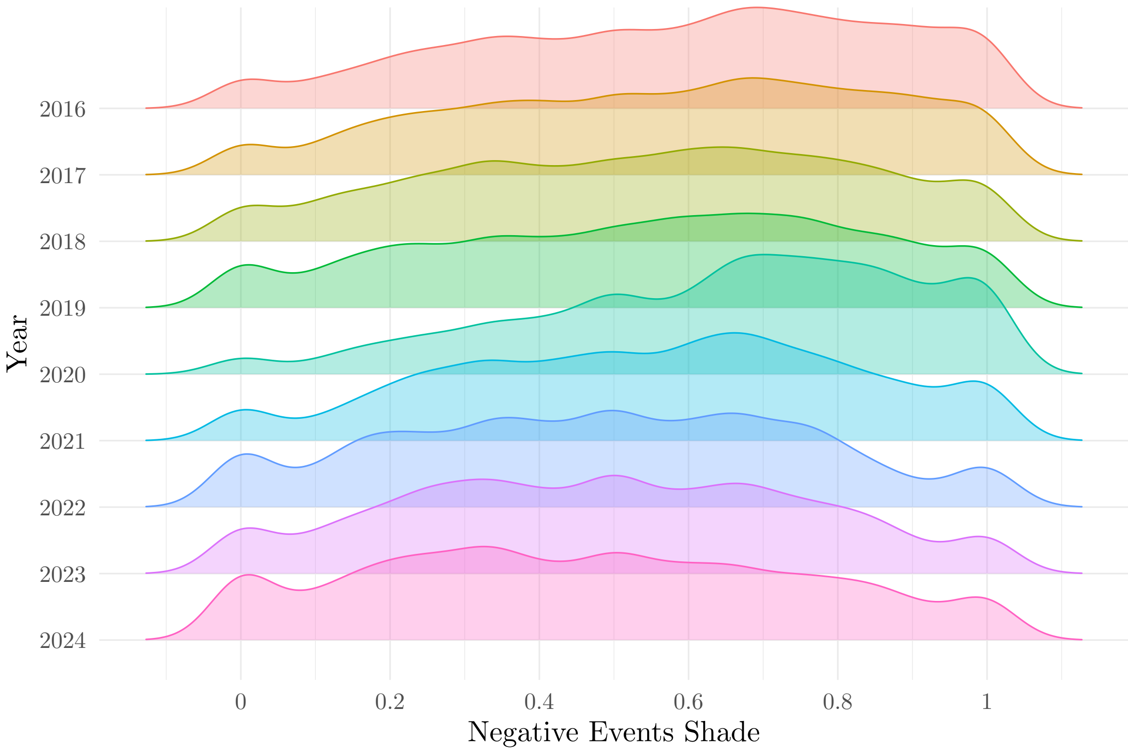


Note: The figure displays the Negative events Shade and Intensity indicators for links between the United States, China, and their ten most intense relationships. Darker lines indicate a more negative bilateral tone (higher Shade), while thicker lines reflect greater relationship Intensity. Country labels follow ISO 3-letter codes.

concentrated toward higher values, indicating a larger share of bilateral relationships characterized by intense negative events. By contrast, toward the end of the period, the distribution displays a trimodal structure: most bilateral relationships are relatively positive, while a smaller but clearly distinct set of relationships remains highly negative. A notable exception to this gradual evolution is the sharp spike observed in 2020, corresponding to the COVID-19 pandemic, negative events then dominated bilateral interactions across most country pairs.[16]

[16]The chord diagrams for Israel and Russia reported in Figures 22 and 23 in the Appendix D show that changes over time are not limited to the negative events Shade indicator. For Israel, the intensity associated with the EU declines between 2021 and 2024, while this relationship is characterized by a higher negative events Shade. For Russia, the intensity associated with the United States decreases, while Iran appears among Russia's ten most intense partners. Figures 25 and 24 further illustrate the evolution of both indicators over time for selected country pairs, showing substantial variation in different directions.

Figure 3: Negative Events Shade Yearly Distribution

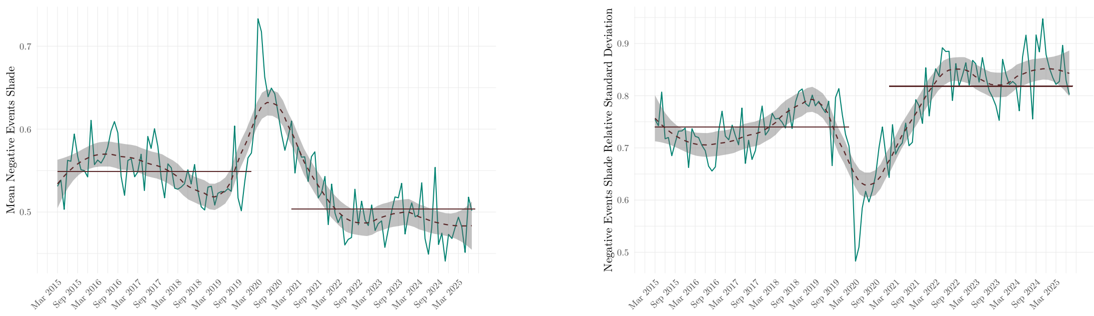


The COVID-19 pattern is also visible in the left panel of the Figure 4 when computing the monthly average of the negative events Shade indicator across all bilateral country pairs. The series exhibits a sharp spike in early 2020, corresponding to the onset of the COVID-19 pandemic, indicating that the climate at that time was predominantly negative. By contrast, the post-COVID period displays a lower average level than the pre-COVID period, suggesting a relative improvement in bilateral relations on average.

This apparent improvement is not necessarily what one might infer from news coverage in recent years, where negative events often appear to dominate reporting. The right panel of the Figure 4 provides additional insight by plotting the monthly relative standard deviation of the negative events Shade indicator across country pairs. It shows a pronounced drop in early 2020, reflecting the fact that bilateral relationships were uniformly affected by negative events related to the COVID-19 pandemic, as the shock was global in scope. By contrast, in the post-COVID period, the relative standard deviation increases markedly. This indicates that the average improvement observed earlier masks substantial heterogeneity across country pairs, with some bilateral relationships improving significantly while others deteriorating sharply.[17] This pattern reflects an increasing fragmentation of the global geopolitical landscape.

[17]The same pattern is observed when the mean and standard deviation of the negative events Shade indicator are computed using Intensity weights (see Appendix D Figure 26).

Figure 4: Monthly Negative Events Shade: Average (left panel) and Standard Deviation (right panel)



Note: The two red straight lines indicate pre- and post-COVID levels, respectively.

3 Trade Impact of Geopolitical Events

3.1 Dynamic Response of Bilateral Trade

We now exploit the Shade and Intensity indicators, $\mathbb{S}_{ijt}$ and $\mathbb{I}_{ijt}$, to assess how political events impact bilateral trade flows. Negative bilateral events, whether violent or non-violent, signal exposure to unrest or tensions for governments, businesses, or citizens in both countries. The occurrence of such events is expected to raise the risks linked to bilateral transactions and/or impose greater restrictions on cross-border mobility and trade, ultimately leading to a decline in trade.

We consider trade data from the United Nations Comtrade database.[18] We extract monthly bilateral import flows at the 4-digit Harmonized System (HS4) level. This level of product disaggregation allows us to better capture countries' supply capacities and demand determinants, including product-specific seasonality effects. At this level of disaggregation, there are about 260 million potential trade flows, and the bilateral shipments of goods are extremely granular. Even for strongly established trade relationships, many products are not exported every month, leading to a disproportionate representation of zero flows. To get a tractable database and reduce the high volatility of monthly trade, we aggregate the data by quarters. The final database gathers 91,757,196 observations, including 59,184,307 with non-zero trade flows. It covers 100 countries[19], 1242 products and 36 quarters from January 2016 to December 2024.

The consequences of political events will likely take time to materialize, and their influence on trade could extend across several quarters. We can also expect $\mathbb{S}_{ijt}$ to be serially correlated. The occurrence and magnitude of negative shocks may follow a random walk, but most take place in a political situation that unfolds gradually. Our first analysis therefore estimate how changes in bilateral Shade of political events will affect bilateral trade, with a lag-augmented local projection (see Jordà and Taylor (2025) and Montiel Olea and Plagborg-Møller (2021)).

[18] See UN Comtrade website: https://comtradeplus.un.org

[19] We retain only the 100 largest actors in international markets on the 2016–2024 period and impose a minimum trade-flow threshold of 2,500$, thereby excluding transactions that are too small to be economically meaningful.

For each time horizon $h \in [\![-6, 6]\!]$, we estimate the following impulse response function:[20]

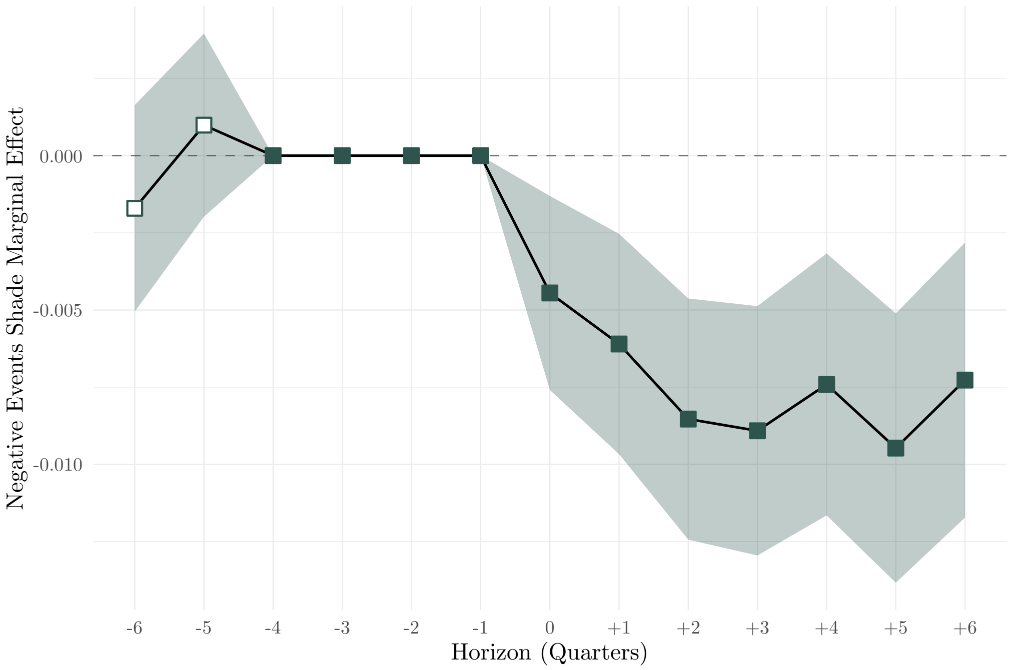
$$ln(M_{ijkt+h}) = \beta_{0,h}\mathbb{S}^N_{ijt} + \sum_{l=1}^{4}\delta_{l,h}ln(M_{ijkt-l}) + \sum_{l=1}^{4}\gamma_{l,h}\mathbb{S}^N_{ijt-l} + FE_{ikt} + FE_{jkt} + FE_{ijk} + \varepsilon_{ijkt}, \quad (3)$$

where M_{ijkt} denotes the value of HS4 product k imported by country j from country i in quarter t, $\mathbb{S}^N_{ijt}$ is the negative events Shade between countries i and j in quarter t. While the Shade indicator can be computed for each specific event category, we choose to aggregate all negative events in our baseline analysis. $\mathbb{S}^N_{ijt}$ is the proportion of articles that mention a violent event, a negative action, or a negative statement among all articles associating countries i and j in quarter t. Given that geopolitical events are likely to be correlated over time and that past events may have influenced past trade flows, we control for the persistence of both variables by including four lags of the outcome and the Shade variable.[21]

The local projections method allows the inclusion of the high-dimensional fixed effects required for estimating a structural gravity model (Head and Mayer (2014) and Larch et al. (2025)). We include importer-product-time, exporter-product-time, and importer-exporter-product fixed effects, denoted FE_{ikt}, FE_{jkt}, and FE_{ijk}, respectively.[22] These fixed effects absorb, in turn, unobserved time-varying demand shocks specific to importer-product pairs, time-varying supply shocks specific to exporter-product pairs, and time-invariant bilateral determinants of trade at the importer-exporter-product level. Therefore, the identification is based on the comparison of within country-pair time variations. The three-way fixed effects are also needed here since variations in $\mathbb{S}^N_{ijt}$ are certainly not as good as random. They are strongly determined by events affecting i (respectively j) independently of j (respectively i), and by cultural, geographical, and historical characteristics that constitute the fundamentals – invariant in the short term – of the relationships between i and j. Note that the presence of lagged logs of trade on the right-hand side of (3) imposes to keep logs on the left-hand side, meaning that we have to ignore the existence of zero flows. This is a limitation of the application of local projection approach to international trade analyzes. However, the following section, which presents PPML estimates of a standard gravity equation, shows that the zeros do not have a significant impact on the estimates. The coefficient $\beta_{0,h}$ captures the response of average bilateral imports at horizon h to a one percentage point increase in negative events Shade at a given date. Standard errors are clustered at the importer-exporter-time level, allowing for possible serial correlation within country pairs.

[20]Fan et al. (2025) use a similar approach.
[21]Figure 29 and Table 22 in Appendix E.1 confirm that our results are robust to the exclusion of lags of $\mathbb{S}^N_{ijt}$.
[22]Estimations are carried out using the *fixest* package for R (Bergé, 2018).

Figure 5: Bilateral Trade Response to Changes in Negative Events Shade



Note: Estimated impulse response ($\beta_{0,h}$). The colored areas are the confidence intervals (10%). Filled marks indicate coefficients statistically different from zero.

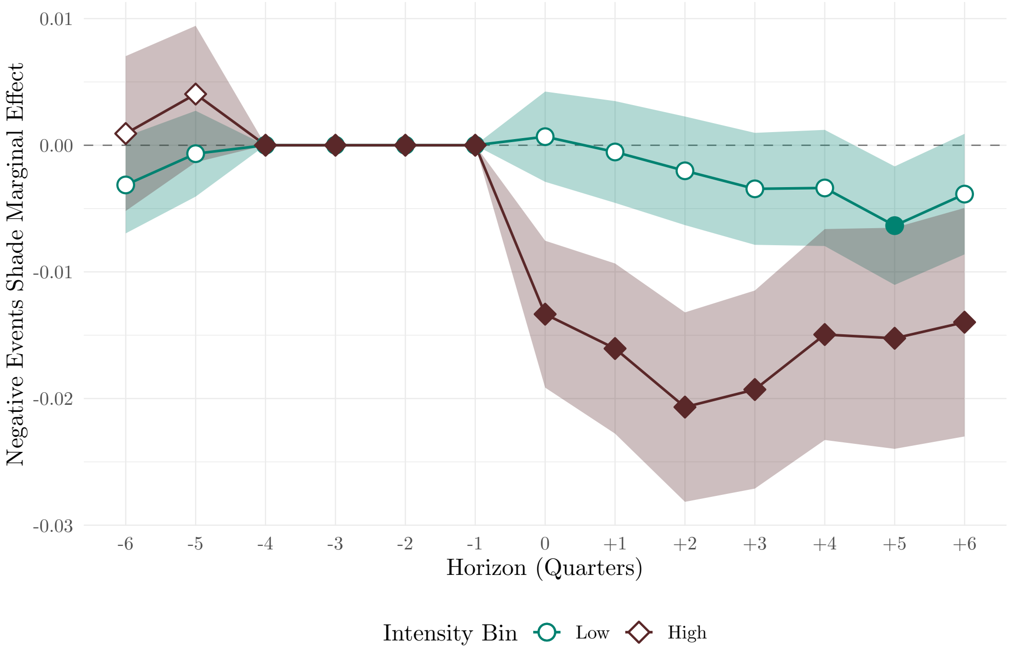
Our data cover 36 quarters, which, given the lags, is not sufficient to cover a very long horizon. We focus on periods of 13 semesters, and estimate equation (3) separately for time horizon $h \in [\![-6, 6]\!]$. The $\beta_{0,h}$ coefficients for $h \in [\![-4, -1]\!]$ are absorbed by the lagged dependent variables used as controls and cannot be estimated. The estimates obtained for horizon $h \in [\![-6, -5]\!]$ provide pre-trend tests, while those for $h \in [\![0, 6]\!]$ indicate the causal impact on trade of a worsening of bilateral Shade over a period of one and half year. Given the number of lags and the range of time horizons h, our estimates indicate the impact of variations in bilateral Shades that occurred between the third quarter of 2018 and the second quarter of 2023.

The baseline results are shown graphically in Figure 5. It displays coefficients $\beta_{0,h}$ for each $h \in [\![-6, 6]\!]$, with the corresponding confidence interval.[23] Each estimate is the impact of a one percentage point increase of $\mathbb{S}^N_{ijt}$ on bilateral imports at horizon h. Although the time frame of our database is too short to provide a comprehensive view of pre-trends, it is reassuring to observe an absence of statistically significant effects five and six quarters before the shock. The suspicion of reverse causality is a potentially serious challenge to our identification. It is plausible that bilateral geopolitical tensions arise, at least in part, as a response to deteriorating economic performance in one and/or a trade shock driven by favorable economic conditions or aggressive industrial policy in the other. The absence of a pre-trend rules out this concern. In contrast, the outbreak of negative events involving two countries leads to an immediate decrease in bilateral trade. An increase of one standard deviation of $\mathbb{S}^N_{ijt}$ in quarter $t = 0$ cuts

[23] See Appendix E.1 Table 22 for detailed results.

current bilateral trade by 0.11% on average.[24] The very short term impact is quite small, but it grows in magnitude over the course of a year and persists over 7 quarters at least. In term $t = 6$, the cumulative impact of a standard deviation increase in $\mathbb{S}^N_{ijt}$ reaches -1.27%.

Figure 6: Bilateral Trade Response to Geopolitical Climate Deterioration for High and Low Intensity Relationships



Note: Estimated impulse response for low ($\beta_{Low,h}$) and high ($\beta_{High,h}$) Intensity relationships respectively. Estimates for country-pairs among the High and Low levels of bilateral average intensity $\overline{\mathbb{I}_{ij}}$ respectively. The colored areas are the confidence intervals (10%). Filled marks indicate coefficients statistically different from zero.

A potential challenge to our identification is related to the COVID pandemic. The crisis has been at the center of global media coverage. It has logically led to an increase in negative Shades for a large number of country pairs, as can be seen in Figure 4. At the same time, lockdowns and restrictions on cross-border movements have directly impacted international trade. These correlations are a potential source of endogeneity. It is most likely captured by the fixed country-product-time effects and lagged variables. Nevertheless, we verify that our results are not dictated by the COVID episode by re-estimating our baseline specification over a period omitting all quarters of 2020. The results, shown in the Appendix E.1 Figure 28 and Table 22, confirm the robustness of our findings. The Appendix E.1 Figure 27 presents another robustness check. Since our estimates are not weighted by trade volumes, this test aims to verify that our results are not due to transactions between small countries that do not significantly impact global trade. Therefore, we re-estimate the local projection 3 using a sample limited to OECD and BRICS exporters. The results are again very consistent with those in Figure 5.

The Shade indicator provides a measure of the tone of the events involving two countries.

[24] Over our sample, the standard deviation of the within country-pair component of $\mathbb{S}^N_{ijt}$ is about 0.25. To give a sense of scale, this is roughly the increase in the negative Shade between Brazil and Argentina that followed the election of Argentina's Javier Milei, whose views starkly contrast with those of Brazil's president.

However, it does not convey the relative importance of these events or the extent of their media coverage. The number of events involving two countries with limited relations is necessarily small. Therefore, sporadic, minor negative events can cause significant changes in the Shade indicator, even though there are no substantial changes in bilateral relations or threats to trade. As a result, we can anticipate that the impact of Shade on imports from country i to j will be more pronounced when i plays a crucial role in country j's international relations. We test this hypothesis by estimating the following impulse function:

$$\begin{aligned} ln(M_{ijkt+h}) =& \beta_{Low,h}\mathbb{S}^{N}_{ijt} \times \mathbb{1}_{\{Low\ \bar{\mathbb{I}}_{ij}\}} + \beta_{High,h}\mathbb{S}^{N}_{ijt} \times \mathbb{1}_{\{High\ \bar{\mathbb{I}}_{ij}\}} \\ &+ \sum_{l=1}^{4}\delta_{l,h}ln(M_{ijkt-l}) + \sum_{l=1}^{4}\gamma_{l,h}\mathbb{S}^{N}_{ijt-l} + FE_{ikt} + FE_{jkt} + FE_{ijk} + \varepsilon_{ijkt}. \end{aligned} \tag{4}$$

Here, the bilateral negative Shade variable, $\mathbb{S}^{N}_{ijt}$, is interacted with dummies indicating whether the relationship Intensity of dyad (i,j) is among the 10% or the bottom 90% of the distributions, with $\mathbb{1}_{\{Low\ \bar{\mathbb{I}}_{ij}\}} + \mathbb{1}_{\{High\ \bar{\mathbb{I}}_{ij}\}} = 1$. Formally, we calculate, for all possible combinations of countries (s,s'), the average Intensity over the sample period, $\bar{\mathbb{I}}_{ss'}$. The dummy $\mathbb{1}_{\{High\ \bar{\mathbb{I}}_{ij}\}}$ takes the value of one either if the average Intensity of j from the perspective of i, $\bar{\mathbb{I}}_{ij}$, belongs to the top 10% of intensities from i, or, inversely, if $\bar{\mathbb{I}}_{ji}$ is in the top 10% of intensities from j.[25] The probability of two countries having low or no trading relationship for a given good is higher when the intensity of events is low. Consequently, the $\mathbb{1}_{\{High\ \bar{\mathbb{I}}_{ij}\}}$ dummy variable covers a large proportion of the sample. It accounts for about 40% of the observations and more than 70% of the total trade value recorded in our database. The local projection estimates of equation 4 are shown graphically in Figure 6. The coefficients $\beta_{Low,h}$ are negative but much small in magnitude and statistical significance than the baseline estimates (figure 5). By contrast, the point estimates for $\beta_{High,h}$ are relatively large in absolute value. They indicate a trade impact twice larger than the benchmark estimate for dyads with a relatively more intense bilateral relationship. For these pairs of countries the cumulative impact over seven quarters $(t+6)$ of a standard deviation increase in the Shade of negative events is a 2.7% decrease.[26]

Figure 7 illustrates how imports respond to an upsurge in violent events compared to non-violent negative events. To do this, we split the negative Shade variable in two distinct components: $\mathbb{S}^{V}_{ijt}$ is the Shade indicator for violent events, and $\mathbb{S}^{NnV}_{ijt}$ is the one for negative but non-violent ones. The estimated impulse function is:

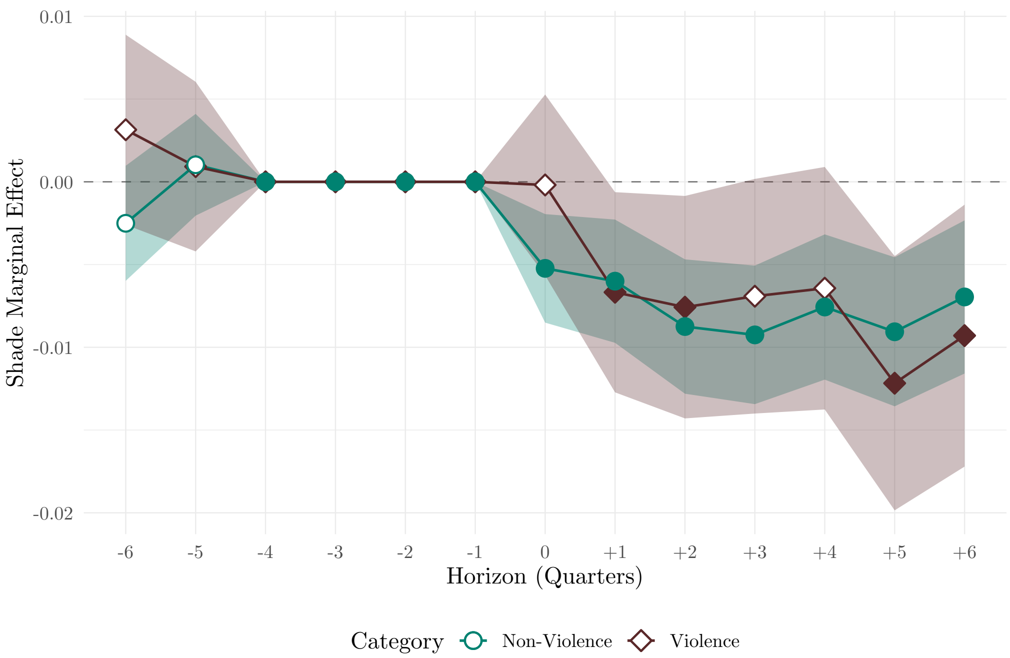
[25]Remember that Intensities are asymmetric: $\bar{\mathbb{I}}_{ij} \neq \bar{\mathbb{I}}_{ji}$. Although our empirical setting reveals the impact of a change in $\mathbb{S}^{N}_{ijt}$ on bilateral trade, it does not allow us to determine the extent to which this reaction results from a change in the behavior of importers in country j rather than exporters in country i. It is therefore necessary for the two dummy variables in equation 4 to be symmetrical with respect to i and j.

[26]Figure 32 in Appendix E.1 shows the $\beta_{Low,h}$ and $\beta_{High,h}$ coefficients obtained from a specification without lags of negative Shades. Figures 30 and 31 display the results obtained without the COVID period and for Large exporters only.

$$
\begin{aligned}
ln(M_{ijkt+h}) = & \beta_{V,h}\mathbb{S}^{V}_{ijt} + \beta_{NnV,h}\mathbb{S}^{NnV}_{ijt} + \sum_{l=1}^{4}\delta_{l,h}ln(M_{ijkt-l}) \\
& + \sum_{l=1}^{4}\gamma_{l,h}\mathbb{S}^{V}_{ijt-l} + \sum_{l=1}^{4}\omega_{l,h}\mathbb{S}^{NnV}_{ijt-l} + FE_{ikt} + FE_{jkt} + FE_{ijk} + \varepsilon_{ijkt}.
\end{aligned} \tag{5}
$$

The results, shown in figure 7, are striking. The coefficients $\beta_{V,h}$, which serve to quantify the impact of violent episodes on trade, are less precisely estimated, but are not larger than the coefficients associated with non-violent events. This result supports our belief that analyses of the economic impact of geopolitical turmoil should not overlook weak signals of tension. Violent events occur much less frequently than non-violent negative statements or actions. Limiting data to major and/or violent shocks therefore means ignoring most of the sources of uncertainty to which international businesses react.

Figure 7: Bilateral Trade Response to Geopolitical Climate Deterioration: Violent vs. Non-Violent Events



Note: Estimated impulse response, for violent ($\beta_{V,h}$) and negative non-violent ($\beta_{NnV,h}$) Shades respectively. The colored areas are the confidence intervals (10%). Filled marks indicate coefficients statistically different from zero.

3.2 Structural Gravity

In this section, we turn to estimating a structural gravity framework, more standard in the empirical trade literature. The purpose of this exercise is to complement the inspection of the dynamic effects of negative geopolitical events on trade with local projections shown in the previous section. The gravity framework first provides a robustness check by allowing to take into account zero trade flows. This is important because our political event indicators cover a very large number of country pairs, many of which do not have uninterrupted trade relations. Given the fixed effects, it is unnecessary to create zero flows for exporter-importer-product triads that never report any trade. Nevertheless, with data disaggregated by product and sub-annual frequency, the database exceeds 52 million observations and contains a substantial proportion of zeros (35.5%). This wealth of data enables a detailed analysis of the impact of political tensions on trade, by product, time period, and type of trading partners.

The structural gravity equation is:

$$\pi_{ijkt} = \exp[\alpha \widetilde{\mathbb{S}^N}_{ijt-1} + FE_{ikt} + FE_{jkt} + FE_{ijk}]\varepsilon_{ijkt} \quad \forall\, i \neq j. \tag{6}$$

We estimate equation 6 with a Pseudo-Poisson Maximum Likelihood estimator, on quarterly data ranging from the second quarter of 2016 to the last of 2024. The left-hand side variable, π_{ijkt}, is country's i share in importing country j for product k at quarter t.[27] The exporter-product-time and importer-product-time fixed effects (FE_{ikt} and FE_{jkt}) capture the "capabilities" of exporter i and the characteristics of the importing market, respectively. The fixed effect FE_{ijk} absorbs all time invariant source of deviation of bilateral trade, including trade costs, linguistic and cultural heterogeneity, but also much of the geopolitical alignment and degree of political interconnectedness of countries.[28] As in the previous section, the trade impact of geopolitical tensions is identified in short-term variations that occur within bilateral relationships. The dynamic analysis in the previous section showed that the effects of a change in Shade are spread over several quarters. To account for the adjustment delays in international trade responses, the negative events Shade indicator is lagged by one quarter. Moreover, to avoid giving too much importance to sudden but short-lived events, the variable of interest, $\widetilde{\mathbb{S}^N}_{ijt-1}$, is smoothed over two quarters. Specifically, it is defined as the share of negative-tone articles among all articles mentioning countries i and j over a rolling two-quarter window $(t-2, t-1)$. This broader aggregation window enables us to capture part of the effect that may unfold beyond a single quarter following an increase in negative events Shade.[29] All standard errors are clustered at the importer-exporter-time level, allowing for arbitrary correlation of errors over time within country pairs.

3.2.1 Benchmark Results and Post-COVID World

The baseline estimation of equation 6, displayed in column 1 of Table 1 confirms the Local Projections results. The estimated value for α, -0.0216, indicates that a political tension resulting in a one standard deviation of the bilateral Shade of negative events (i.e. 0.25) reduces trade by an average of 0.54% on the short run. In columns 2 and 3, we enrich the specification by looking at whether the impact is more pronounced for pairs of countries with political relations that generate more frequent media coverage. In column 2, we simply interact the Shade vari-

[27]Following Head and Mayer (2022), we use the trade share as a dependent variable, which reduces the importance given to very large trade flows in count regression models.

[28]Note that they are directional country-pair fixed effects, i.e. $FE_{ijk} \neq FE_{jik}$.

[29]In addition, we conduct the same regression using the original quarterly negative events Shade indicator in Table 23 in Appendix E.2.

Table 1: Impact of Negative Events on Bilateral Trade - Gravity Estimates

Dep. Var.	Import $\text{Share}_{\text{ijkt}}$					
	Full Sample			Excl. Zero Trade Flows		
	(1)	(2)	(3)	(4)	(5)	(6)
Shade $\text{Negative}_{\text{ijt-1}}$	-0.0216***	-0.0233***		-0.0117***	-0.0141***	
	(0.0063)	(0.0066)		(0.0028)	(0.0029)	
Shade $\text{Negative}_{\text{ijt-1}}$ $\times \ln(\widetilde{\mathbb{I}}_{ij})$		-0.0110*			-0.0168***	
		(0.0059)			(0.0027)	
Shade $\text{Negative}_{\text{ijt-1}}$ $\times \mathbb{1}_{\{Low\ \widetilde{\mathbb{I}}_{ij}\}}$			-0.0060			0.0021
			(0.0068)			(0.0033)
Shade $\text{Negative}_{\text{ijt-1}}$ $\times \mathbb{1}_{\{High\ \widetilde{\mathbb{I}}_{ij}\}}$			-0.0483***			-0.0350***
			(0.0112)			(0.0047)
Observations	52,178,430	52,178,430	52,178,430	37,325,542	37,325,542	37,325,542
Pseudo R^2	0.38	0.38	0.38	0.36	0.36	0.36

Note: PPML estimations. All specifications include exporter-product-quarter, importer-product-quarter, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-quarter level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

able with the average bilateral Intensity, $\widetilde{\mathbb{I}}_{ij}$.[30] Column 3 adopts the specification used for local projections, where the Shade variable interacts with dummies indicating whether the bilateral relations are among the most intense ones for either the exporter or the importer. Both columns 2 and 3 confirm the impact of variations of negative Shades is greater for larger dyadic Intensities. For the country pairs sharing a high Intensity of events (cf. column 3), the estimated impact is more than twice higher than the average effect: A standard deviation increase in Shade results in a loss of 1.2% of bilateral trade.

Columns 4 to 6 of Table 1 show the same specifications but on a sample excluding zero flows. This robustness test is designed to verify that the impact of bilateral Shade is not entirely due to the inclusion of the zeros. This is indeed not the case, as the results are qualitatively similar to those in columns 1 to 3. However, it appears that the extensive trade margin plays a significant role. Without the zeros, all the coefficients are lower in magnitude. This suggests that a substantial portion of the impact of an increase in negative Shade stems from an interruption in trade relations, in addition to a reduction in trade values.[31]

Table 2 examines how the short term impact of political events captured by the gravity equation has evolved over time. More specifically, we estimate the impact separately for the pre-COVID period (2016-2019) and the post-COVID period (2021-2024). The pandemic appears to have marked a turning point in the consideration of geopolitical risks. The unsynchronized lockdowns in different major countries revealed the fragility of global value chains, and since then, there has been a proliferation of calls for greater strategic autonomy and de-risking measures. The instability generated, among other things, by the intensification of large-scale war in Ukraine in 2022 and the multiplication of international sanctions has reinforced this trend.

[30] We symmetrize the Intensity measure by computing the geometric mean of the two directional values, that is, for dyads (i, j) and (j, i). This procedure yields a single, symmetric indicator for each country pair: $\widetilde{\mathbb{I}}^s_{ijt} \equiv \widetilde{\mathbb{I}}^s_{jit} \equiv \sqrt{\mathbb{I}_{ijt} \times \mathbb{I}_{jit}}$. The interaction variable is the average of this symmetric indicator over the sample period.

[31] In Appendix E.2, Table 24 further distinguishes between violent and non-violent negative events.

Table 2: Impact of Negative Events on Bilateral Trade: Pre- and Post-Covid Periods

Dep. Var.	Import Share$_{ijkt}$			
	Pre-COVID	Post-COVID	Pre-COVID	Post-COVID
	(1)	(2)	(3)	(4)
Shade Negative$_{ijt-1}$	-0.0171***	-0.0409***		
	(0.0044)	(0.0141)		
Shade Negative$_{ijt-1}$			-0.0146***	-0.0160
$\times \mathbb{1}_{\{Low\ \mathbb{I}_{ij}\}}$			(0.0048)	(0.0159)
Shade Negative$_{ijt-1}$			-0.0221**	-0.0747***
$\times \mathbb{1}_{\{High\ \mathbb{I}_{ij}\}}$			(0.0086)	(0.0222)
Observations	23,745,931	20,235,907	23,745,931	20,235,907
Pseudo R^2	0.39	0.39	0.39	0.39

Note: PPML estimations including zero trade flows. All specifications include exporter-product-quarter, importer-product-quarter, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-quarter level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The estimates in columns 1 and 2 indicate that the negative Shade had a stronger impact on trade from 2021 to 2024 than in the years before the pandemic. The coefficient is more than twice as high, indicating a greater attention to geopolitical issues in international business after COVID-19. The results in columns 3 and 4 differentiate the effects according to the Intensity of bilateral relationships. They show that the greater sensibility to political events is mainly for the most important partners. For dyads with highest Intensity, the impact of Shade on trade is nearly four times higher after the pandemic than in the previous period. The -0.0747 coefficient suggests that an increase of one standard deviation in Shade leads to a short-term drop in trade of nearly 1.9%. For low-intensity dyads, however, the estimated coefficient changes little from one period to the next, even though it is less precisely estimated in the most recent period.[32]

3.3 Robustness Checks

Table 3: Robustness Checks: Removing the COVID Period and Major Countries

Dep. Var.:	Import Share$_{ijkt}$				
	Excl. COVID	Excl. RUS&UKR	Excl. ISR	Excl. CHN	Excl. USA
	(1)	(2)	(3)	(4)	(5)
Shade Negative$_{ijt-1}$	-0.0272***	-0.0251***	-0.0222***	-0.0230***	-0.0179***
	(0.0070)	(0.0063)	(0.0064)	(0.0040)	(0.0065)
Observations	45,864,352	47,999,350	50,810,210	47,791,815	47,250,372
Pseudo R^2	0.38	0.38	0.38	0.38	0.39

Note: PPML estimations including zero trade flows. All specifications include exporter-product-quarter, importer-product-quarter, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-quarter level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We verify in Table 3 that these results are not driven by few exceptional geopolitical events that have deeply disrupted international trade. First, we exclude all quarters of 2020 that correspond to the COVID-19 pandemic. This major shock was a crucial determinant of trade variations during this period. As can be seen in Figure 4, it also profoundly influenced our Shade indicators. However, the results confirm that the estimated relationship between the negative

[32]In Appendix E.2, Table 25 further distinguishes between violent and non-violent negative events.

Shade and trade cannot be attributed to this crisis. Compared to the similar specification in column 1 of Table 1, the coefficient is stronger outside the pandemic period than for the sample as a whole. Columns 2 to 5 of Table 3 exclude countries (both as importers or exporters) that were involved in major geopolitical crises during our sample period: Russia and Ukraine, Israel, China and the USA. The results are very close to the baseline estimates. This confirms, once again, that a comprehensive analysis of how geopolitical risk reshape international trade should not focus solely on major events. Tensions involving countries that do not make global headlines also matter. Table 26 in Appendix E.2 runs the same analysis but separating Low and High mean Intensity relationships, yielding results that are also close to baseline estimations.

Table 4 augments our specification with controls for alternative indicators of bilateral geopolitical tension that are widely used in the literature: ACLED (Raleigh et al., 2023) and the Ideal Point Distance between United Nations votes (Bailey et al., 2017). The ACLED database focuses on violent events and its coverage is much less extensive than that of IntenSE.[33] Therefore, we start by reporting in Column 1 the estimate for our benchmark specification obtained on the limited sample covered by ACLED. Then, we test the two alternative indicators of bilateral geopolitical tension. Bilateral negative events reported by ACLED have an expected negative impact on trade. Conversely, the Ideal Point Distance yields an unexpectedly positive coefficient.[34] This result might reflect the yearly frequency of this indicator, which does not align with the quarterly variation in our data. Besides, alignments or misalignments across pairs are relatively persistent over time and might be largely picked-up by our triad (exporter-importer-product) fixed effect.

Table 4: Robustness Checks: Control for other Geopolitical Measures

Dep. Var.	Import Share$_{ijkt}$				
		ACLED		UN Voting	
	(1)	(2)	(3)	(4)	(5)
Shade Negative$_{ijt-1}$	-0.0272***		-0.0257***		-0.0253***
	(0.0082)		(0.0082)		(0.0068)
ACLED Negative Events$_{ijt-1}$		-0.0269***	-0.0268***		
		(0.0035)	(0.0035)		
ln(Ideal Point Distance$_{ijt-1}$)				0.0059**	0.0057**
				(0.0027)	(0.0027)
Observations	40,891,672	40,891,672	40,891,672	47,858,789	47,858,789
Pseudo R^2	0.39	0.39	0.39	0.38	0.38

Note: PPML estimations including zero trade flows. All specifications include exporter-product-quarter, importer-product-quarter, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-quarter level in parentheses. Ideal Point Distance is measured annually; the annual value is assigned to all quarters of the corresponding year and lagged by one quarter to align with the lag structure of the analysis. *** p<0.01, ** p<0.05, * p<0.1.

Even more reassuring, our coefficient of interest is merely unaffected by these additional controls. This is actually not surprising, as the Shade indicator differs substantially from the other two. It does not measure diplomatic alliances, as the UN does, and the violent episodes recorded in the ACLED database represent only a relatively small proportion of the events cap-

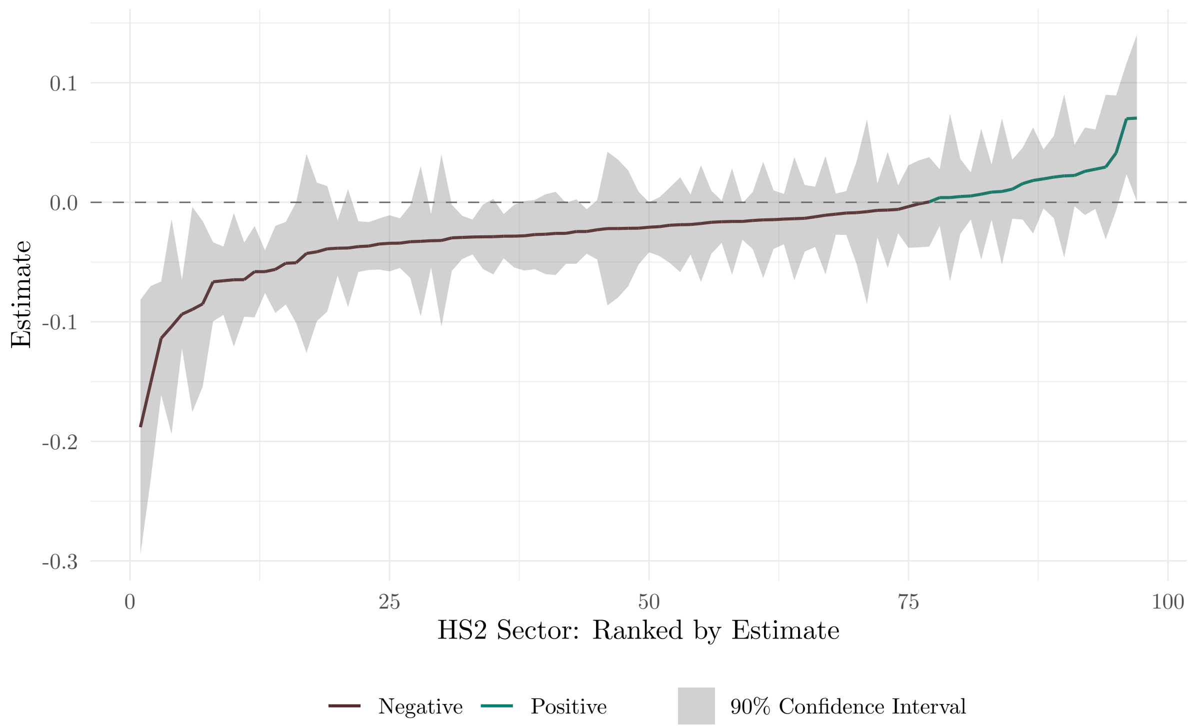
[33]See Appendix C for a detailed comparison of the databases.

[34]The Ideal Point Distance measures the degree of misalignment of U.N. votes, i.e. the political remoteness between countries. It is expected to be negatively correlated with bilateral trade.

tured by our indicator.

Figure 8 shows the estimates obtained for each HS2 family of products separately.[35] This is primarily a robustness test addressing concerns that the results based on pooled data may be driven by a few specific products. From Figure 8, one can see that this is clearly not the case. The vast majority of coefficients are negative. Among the 97 HS2 products, 78.35% (76 HS2 products) show the expected negative reaction to a surge of negative events, and the estimated coefficient is significantly negative for 33 products. All together these 33 products make 37% of world trade. Twenty one products show a positive although almost never statistically significant impact. Only two HS2 products have a significantly positive coefficient: Prepared feathers and down (HS67) and Other base metals (HS81).

Figure 8: Impact of Negative Events on Bilateral Trade for each HS2 Sector



Tables 5 and 6 show the extent to which trade sensitivity to geopolitical tensions depends on specific product characteristics. In table 5, between the negative Shade variable and dummies that characterize the degree of complexity of the traded product or its position in the global value chains. The indicators are successively the contract intensity (Nunn, 2007),[36] product upstreamness (Antràs et al., 2012),[37] product complexity (Hausmann et al., 2014),[38] the re-

[35]The 1242 HS4 products can be embedded into 97 family of products at the 2 digit levels (i.e. HS2 nomenclature)

[36]The contract intensity indicator measures the extent to which the value-added chain of each good relies on inputs that require relationship-specific investments.

[37]The product upstreamness indicator measures an industry's position within a product's value chain: higher values indicate greater distance from the final-use stage. Antràs et al. (2012) show that developed countries tend to export relatively more products originating from downstream industries.

[38]The product complexity indicator measures the diversity and sophistication of the productive capabilities re-

lationship stickiness (Martin et al., 2026),[39] and the substitution elasticity (Imbs and Mejean, 2015).[40] All indicators used in this section are converted from their original product nomenclature to HS02 at the HS4 level, which is the classification employed in our trade data. The relationship-stickiness indicator, originally available at a finer level of disaggregation, is aggregated to HS4 by taking the mean across its corresponding subcategories.

In Table 6, we use the BEC classification[41] to categorize each product based on either its place in the value-added chain or its final use. To do so, we aggregate the provided categories as follows: Durable, Capital, and Transportation goods are grouped under Durable goods; Capital and Transportation goods are grouped under Capital goods; and Primary, Processed, Parts, and Industrial goods are grouped under Intermediary goods. All remaining categories are classified as Final goods. The last column is based on the Rauch (1999) product classification, which is defined at a more disaggregated level than HS4. To aggregate this information, we assign a value of 1 to an HS4 product if more than half of the corresponding lower-level product categories are classified as differentiated. None of these interactions indicate major differences in sensitivity to geopolitical events based on these product characteristics.

Table 5: Heterogeneity Indicators

Dep. Var.	Import Share$_{ijkt}$									
Product characteristic	Contract Intensity$_k$		Upstreamness$_k$		Complexity$_k$		Relationship Stickiness$_k$		Substitution Elasticity$_k$	
	Top 25%	Top 10%	Top 25%	Top 10%	Top 25%	Top 10%	Top 25%	Top 10%	Top 25%	Top 10%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Shade Negative$_{ijt-1}$	-0.0216***	-0.0206***	-0.0198***	-0.0195***	-0.0231***	-0.0211***	-0.0202***	-0.0203***	-0.0200***	-0.0211***
$\times\mathbb{1}_{\{Top_k=0\}}$	(0.0065)	(0.0066)	(0.0067)	(0.0065)	(0.0066)	(0.0066)	(0.0063)	(0.0063)	(0.0063)	(0.0063)
Shade Negative$_{ijt-1}$	-0.0181**	-0.0200**	-0.0265***	-0.0398***	-0.0142**	-0.0152**	-0.0254***	-0.0334***	-0.0258***	-0.0236***
$\times\mathbb{1}_{\{Top_k=1\}}$	(0.0078)	(0.0084)	(0.0068)	(0.0079)	(0.0070)	(0.0077)	(0.0071)	(0.0080)	(0.0074)	(0.0087)
Wald test p-value	0.419	0.9104	0.2039	0.0021***	0.028**	0.2683	0.1567	0.0151**	0.1529	0.6653
Observations	46,817,561	46,817,561	50,891,734	50,891,734	48,923,253	48,923,253	50,739,385	50,739,385	50,070,589	50,070,589
Pseudo R^2	0.37	0.37	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38

Note: PPML estimations including zero trade flows. All specifications include exporter-product-quarter, importer-product-quarter, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-quarter level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Product Classifications

Dep. Var.	Import Share$_{ijkt}$					
	Intermediary$_k$	Final$_k$	Capital$_k$	Durable$_k$	Non-Durable$_k$	Differentiated$_k$
	(1)	(2)	(3)	(4)	(5)	(6)
Shade Negative$_{ijt-1}$	-0.0194***	-0.0205***	-0.0199***	-0.0200***	-0.0199***	-0.0249***
$\times\mathbb{1}_{\{Indicator_k=0\}}$	(0.0067)	(0.0064)	(0.0065)	(0.0066)	(0.0065)	(0.0057)
Shade Negative$_{ijt-1}$	-0.0201***	-0.0178**	-0.0198***	-0.0198***	-0.0199***	-0.0200***
$\times\mathbb{1}_{\{Indicator_k=1\}}$	(0.0064)	(0.0071)	(0.0067)	(0.0065)	(0.0067)	(0.0071)
Wald test p-value	0.4441	0.2279	0.8638	0.7386	0.9213	0.3450
Observations	54,984,485	54,984,485	54,984,485	54,984,485	54,984,485	55,869,577
Pseudo R^2	0.38	0.38	0.38	0.38	0.38	0.38

Note: PPML estimations including zero trade flows. All specifications include exporter-product-quarter, importer-product-quarter, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-quarter level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Finally, we examine the specific issue of trade dependencies. As mentioned above, this has become an important topic in the diplomatic and economic strategy plans of most countries.

quired to manufacture a given product. Building on this concept, Hausmann et al. (2014) develop a framework to assess the overall complexity of an economy and to account for its development trajectory.

[39]The relationship stickiness measures the average duration of firm-to-firm trade relationships. Martin et al. (2026) observe that uncertainty shocks are more likely to disrupt international trade for less sticky products.

[40]The substitution elasticity measures the extent to which a product can be replaced by another variety. Imbs and Mejean (2015) estimate it using highly disaggregated trade data.

[41]See UNStats website: https://unstats.un.org/unsd/trade/classifications/bec.asp

In the mid-2000s, Western countries began to express a clear, increasingly strong desire to decouple from the Chinese economy to reduce their dependence on it. This discourse has grown louder since then and is no longer limited to China. The 2020 pandemic, the intensification of the war in Ukraine, and US trade wars have led many countries and manufacturers to closely examine the dependencies that could affect their entire value chains. For an importer, the risk of being overly dependent on a supplier is the extra costs and/or shortages that could result from an inability to switch to other sources in the event of a geopolitical shock affecting the main exporting country. Our empirical results exposed above confirm that when adverse events occur, firms reduce their business in risky markets. However, they are more likely to do so if they have the opportunity to source from alternative and reliable suppliers. In cases of high trade dependence, importers do not have this option. We therefore expect greater sensitivity of trade to an increase in negative Shade for products with a wide choice of suppliers. In order to test this conjecture, we measure the concentration of world exports on the pre-COVID period for each HS4 product with an Herfindahl-Hirschman index (HHI). In the two first columns of table 7 we interact the Shade variable in order to estimate separately the effect on trade for highly (versus weakly) concentrated products. In the first column, we cut the HHI distribution between the third and fourth quartiles, while in column (2), we isolate the top 10% of the most concentrated products. As expected, Shade has no significant effect for products that are highly concentrated among a small number of exporters and offer limited supplier variety. Restricting the sample to the top 10% of products by HHI even yields a coefficient that significantly differs from the baseline.

In column (3) we take the analysis further considering trade dependence at the product-importer level. To identify import dependent product for each importer, we follow Lefebvre and Wibaux (2024). Their product-dependence indicator is constructed using three criteria. The first is satisfied when the import HHI for a given importer-product-year exceeds 0.4. The second applies the same threshold to a product-year HHI computed from global exports. The third criterion captures product substitutability, measured as the ratio of imports to exports for each importer-product-year, and is met when this ratio exceeds one.[42] A product imported by a given country is classified as dependent in a given year if all three criteria are satisfied in at least two of the three years within a rolling window. The interaction between negative Shade and this indicator yields a non-significant coefficient. This suggests that for importers highly dependent on a given product, increases in negative geopolitical events do not translate into measurable changes in trade flows. Because these importers face very limited substitution possibilities, their exposure to geopolitical tensions does not alter their sourcing behavior: even when negative events intensify, they cannot easily replace the product they rely on.

[42] When exports are zero, the ratio is assigned a large value to reflect the absence of domestic supply.

Table 7: Impact of Negative Events on Trade-Dependent Relationships

Dep. Var.	Import Share$_{ijkt}$		
	Top 25% HHI$_k$	Top 10% HHI$_k$	Dependent$_{jk}$
	(1)	(2)	(3)
Shade Negative$_{ijt-1}$	-0.0232***	-0.0232***	-0.0218***
$\times \mathbb{1}_{\{Top_{jk}=0\}}$	(0.0060)	(0.0061)	(0.0075)
Shade Negative$_{ijt-1}$	-0.0151	0.0004	-0.0166
$\times \mathbb{1}_{\{Top_{jk}=1\}}$	(0.0093)	(0.0121)	(0.0290)
Wald test p-value	0.1744	0.008***	0.8359
Observations	52,178,430	52,178,430	40,942,371
Pseudo R^2	0.38	0.38	0.39

Note: PPML estimations including zero trade flows. All specifications include exporter-product-quarter, importer-product-quarter, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-quarter level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4 Quantification of the Overall Effect of Negative Events on Trade

The estimates of the impact of negative Shade on bilateral trade presented in previous sections are statistically significant and robust. However, their magnitude is relatively small. Local projections give us a coefficient the negative Shade variable of -0.0044 at $t = 0$, reaching -0.0089 at $t = 3$. In our log-level specification, this corresponds to the effect on trade of a one percentage point increase in negative Shade. An isolated event limited to two countries that causes a temporary variation of one standard deviation (i.e., 25 percentage points) in bilateral negative Shade would reduce trade by -0.11% and -0.223% at $t = 0$ and $t = 3$, respectively. The cumulative effect of a shock at t=0 over seven quarters would reduce bilateral trade by 1.27%. The results of the gravity equation estimates provide comparable orders of magnitude. The baseline coefficient in Table 1 is -0.0216. This corresponds to a short-term decline in trade of 0.54% following a one-standard-deviation increase in bilateral Shade. The coefficient increases to -0.0483 for country pairs with intense relations and to -0.0747 for these dyads during the post-COVID period. A 25-percentage-point increase in Shade would reduce trade by 1.21% and 1.87%, respectively.

Table 8: Overall Impact of Negative Events on International Trade

Dep. Var.	Import Share$_{ijkt}$					
	Full Sample	Pre-COVID	Post-COVID	Full Sample	Pre-COVID	Post-COVID
	(1)	(2)	(3)	(4)	(5)	(6)
Shade Negative$_{ijt}$	-0.1056***	-0.0405***	-0.2284***			
	(0.0142)	(0.0142)	(0.0723)			
Shade Negative$_{ijt}$				-0.0481***	-0.0167	-0.1299**
$\times \mathbb{1}_{\{Low\ \bar{\mathbb{I}}_{ij}\}}$				(0.0126)	(0.0154)	(0.0570)
Shade Negative$_{ijt}$				-0.2454***	-0.1088***	-0.3937***
$\times \mathbb{1}_{\{High\ \bar{\mathbb{I}}_{ij}\}}$				(0.0313)	(0.0267)	(0.1388)
Observations	2,853,556	1,706,087	596,201	2,853,556	1,706,087	596,201
Pseudo R^2	0.43	0.44	0.42	0.43	0.44	0.42

Note: PPML estimations including zero trade flows. Trade flows are from the ITPD-E database. All specifications include exporter-product-year, importer-product-year, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The relatively small scale of these effects is not surprising. First, because unlike many studies that examine the link between geopolitical shocks and trade (e.g., Fan et al. (2025); Mulabdic and Yotov (2025)), we do not focus on major shocks. Instead, our indicators are comprehensive and capture low-intensity tensions. Hostile or disparaging statements, diplomatic visits, international symposia, and the involvement of international NGOs in humanitarian disasters do not necessarily have a direct impact on international trade. However, they shape or reflect the climate of the bilateral relations, which can influence trade by altering consumer preferences, increasing administrative hassles at borders, complicating visa applications, or prompting a desire to protect value chains from future geopolitical risks. Second, our indicator operates on a high-frequency basis, and the gravity estimates presented in the previous section only assess very short-term effects. Third, our econometric specifications are very demanding. Large, meaningful events, such as natural disasters, armed conflicts, sanctions or trade wars, likely have a large effect on all of a country's imports and exports, regardless of trading partners. Even when tensions arise between two countries, trade with third countries is often impacted as well. For example, when a country violates WTO rules by imposing tariffs on specific bilateral trade flows, it may create a deterrent effect on all exporters, even those not directly targeted by the tariff. Similarly, when two countries engage in martial rhetoric, trade between them is expected to falls. But all exporters (regardless of origin) are also likely to anticipate an escalation of the conflict and reduce their activity in these countries. When a country is involved in political turmoil or experiences a significant event, all of its bilateral Shades tend to evolve together, and all its trade is likely affected. In the case of a major event or political crisis, bilateral flows tend to evolve in tandem. The same applies to Shades. Crises are negative events and, regardless of the degree of affinity with a third country, this negative tone will be captured by our variable. Our exporter-product-time and importer-product-time fixed effects systematically absorb these multilateral trade impacts of political events, so our estimates only measure the net bilateral effects. They capture additional reactions, specific to each dyad when both countries are relatively strongly involved in the event.

We can rely on intra-national flows to assess the overall impact of geopolitical shocks on international trade. Integrating these flows into a gravity analysis allows us to identify the difference in reaction between bilateral flows that cross borders and intra-national flows. The gravity equation to be estimated becomes:

$$\pi_{ijkt} = \exp[\psi(\mathbb{1}_{\{i \neq j\}})\mathbb{S}^N_{ijt} + FE_{ikt} + FE_{jkt} + FE_{ijk}]\varepsilon'_{ijkt} \quad \forall\, i \neq j \;\; or \;\; i = j, \tag{7}$$

where $\mathbb{1}_{\{i \neq j\}}$ is a dummy that takes the value one for cross-border flows (i.e. when $i \neq j$) and ψ is the coefficient of interest.[43] It captures the variation in international trade arising from the increase in negative bilateral Shade, relative to changes in intra-national trade. The econometric identification is based on the assumption that events that cause instability in a country impact international trade more than intra-national transactions. Therefore, we measure here

[43] Note that $\mathbb{S}^N_{iit}$ does not appear in equation 7 because this variable is systematically absorbed by the country-product-time fixed effects.

the portion of the total consequences of instability on trade that acts as an international trade cost. The remaining portion, which is channeled primarily through changes in the country's output and revenue (which can be large, in particular in cases of military conflicts, riots, or natural disasters) is captured by the fixed effects.

The trade data we use to estimate equation 7 are taken from the International Trade and Production Database for Estimation (ITPD-E), (Borchert et al., 2021), which contains estimates of intra-national flows based on the combination of international trade and production data. Once merged with our $\mathbb{S}_{ijt}^{N}$ variables, the final dataset covers 100 countries[44] and 153 industries over the period 2016–2022. Unfortunately, it only offers yearly data so that the time subscript t in equation 7 refers to years and the negative Shade, $\mathbb{S}_{ijt}^{N}$, is aggregated by year.[45]

The estimation results are displayed in table 8. Column (1) shows the baseline result. Unsurprisingly, the coefficient of interest, -0.1056, is larger than the α coefficient estimated on international flows only. The overall trade impact of an increase in the negative Shade is around 5 times larger than the net bilateral effect.[46] As in the previous section, we then separate the effects estimated on the pre-COVID and post-COVID periods (columns 2 and 3). The previous result are confirmed. Trade has been much more sensitive to geopolitical shocks in the most recent years. The difference is particularly striking, with a coefficient multiplied by 5.6 between the two periods (-0.2284 vs. -0.0405). Finally, in columns 4 to 6, we interact our Shade variable with dummies indicating intense bilateral relations. In line with what we observed previously, the sensitivity of bilateral trade to geopolitical events is more pronounced when they involve a foreign nation that plays an important role in the country's international relations.[47]

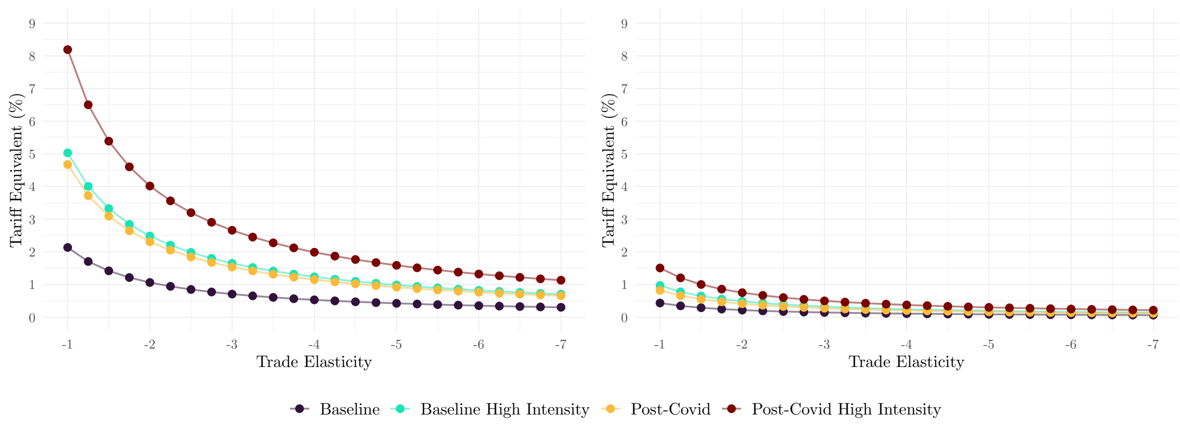
[44]For the sake of consistency, we retain the same set of 100 countries previously selected using Comtrade data. Since we now rely on annual trade flows, we apply a higher minimum-value threshold of 10,000$, ensuring that only economically meaningful transactions are included in this alternative dataset.

[45]In contrast with the quarterly specification, no lagged dependent variable is included here. With annual data, intra-year adjustment dynamics are not observable, making a lag term unnecessary.

[46]See Table 1, column 1: the baseline α coefficient is -0.0216.

[47]In Appendix E.3, Table 27 further distinguishes between violent and non-violent negative events and Figure 33 estimates Equation 7 for each ITPD-E sector.

Figure 9: Tariff Equivalents: Overall International Trade Effects (left panel) and Net Bilateral Trade Effects (right panel)



Since our identification suggests that the estimated coefficients are comparable to trade costs, a useful way to quantify our results is by calculating their tariff equivalent. This represents the increase in customs duties needed to produce a decline in trade that is equivalent to a specific change in the bilateral negative Shade. For this exercise, we retain an increase of 20 percentage points in bilateral negative Shade.[48] The tariff equivalents (in percentage) to an increase in bilateral Shade of 0.20 is $\Delta\tau_k = \left[e^{(0.20\times\psi/\varepsilon)} - 1\right] \times 100$ %, where ε is the trade elasticity, and ψ is our estimate of the impact of negative Shade on bilateral trade.[49] The literature provides a wide range of estimated values for ε. Fontagné et al. (2022) estimates, based on tariff changes at the HS6 level, vary greatly by product, but are centered around a median close to 6. By addressing endogeneity biases and dealing with changes over time, Boehm et al. (2023) obtain much lower values, ranging from -0.76 in the short term to -2.0 in the long run.

Figure 9 shows the tariff equivalent of the various impacts we have estimated, for trade elasticities ranging from -1 to -7. The left panel displays the tariff equivalent of the overall trade impact estimated from equation 7 and the ITPD-E database. The lowest series of estimates is provided by the baseline coefficient (Table 8, column 1). It indicates that a 20 percentage point increase in negative Shade is akin to a tariff hike ranging from 0.3% to 2.13%. The scale is much greater in the post-pandemic period. The tariff equivalent is 0.65% if we assume a trade elasticity of -7, but rises to 4.67% with an elasticity of -1. If we focus on addition on shocks involving a partner with whom we have intense relations, we obtain a fairly high cost of instability: between 1.13% and 8.19%. The panel on the right displays the tariff equivalents derived from the estimations of equation 6, which excludes internal flows. These represent the net bilateral impact of negative events that omit the average effect on the overall trade of the

[48]This value lies between the standard deviations of the Shades aggregated at the annual level (0.16) and by quarters (0.25).

[49]This alternatively the estimates obtained from regressions conducted without intra-national flows (i.e. α in equation 6) and for the ones obtained with intra-national flows (ψ in equation 7).

involved countries. They are, of course, much smaller than the tariff equivalents for the overall effects shown on the left panel. The baseline estimates range from 0.06% (for a trade elasticity of -7) and 0.43% (for an elasticity of -1). Again, the effects are stronger post-COVID and for pairs of countries with higher Intensity of bilateral relationship. The combination of these two conditions leads to tariff equivalents between 0.21% and 1.5%.

5 Conclusion

This paper introduces a new dataset and empirical approach to study the relationship between geopolitical tensions and international trade. By exploiting the tone of media reports collected in GDELT, we construct two high-frequency, bilateral indicators – Shade and Intensity – that capture the informational climate surrounding country pairs. In contrast to existing measures focused on conflicts, sanctions, voting alignment, or pre-classified event types, our indicators aim to reflect the broader perception of geopolitical frictions as conveyed through news coverage. The resulting IntenSE dataset provides a flexible and publicly available tool for researchers interested in the interaction between international relations and economic flows.

Our empirical analysis shows that geopolitical tensions, even when they do not take the form of major conflicts or formal policy actions, are systematically associated with lower bilateral trade. The overall impact of a 20% increase in the share of negative events in the total of events associating two countries is equivalent to a tariff of 0.3% to 2.13% depending on the trade elasticity. Interestingly, the impact is greater when both countries receive significant media coverage of each other. Furthermore, greater sensitivity was observed in the years following to the COVID-19 pandemic, suggesting that this crisis – which exposed the trade dependencies and the fragility of global value chains – prompted firms to pay closer attention to their management of geopolitical risks. Post-COVID, and for countries with intense relationships, the tariff equivalent of a 20% increase in our indicator lies between 1.13 and 8.19%.

The findings contribute to several strands of the literature. First, they complement studies on violent conflicts and sanctions by highlighting the relevance of lower-intensity tensions. Second, they extend the growing body of work on geopolitical fragmentation by providing a measure with substantial time variation at the bilateral level. Third, they relate to the literature on risk and uncertainty by documenting that an adverse informational climate can operate as a trade cost, even in the absence of immediate policy changes.

More broadly, our results suggest that the informational environment surrounding international relations matters for economic integration. Media-reported tensions may affect expectations, increase perceived risk, and alter firms' and consumers' behavior in ways that resemble conventional trade barriers. As geopolitical frictions continue to shape the global economy, measuring and quantifying these softer forms of tension becomes essential.

References

Aiyar, S., D. Malacrino, and A. F. Presbitero (2024). Investing in friends: The role of geopolitical alignment in fdi flows. European Journal of Political Economy 83.

Antràs, P., D. Chor, T. Fally, and R. Hillberry (2012, May). Measuring the Upstreamness of Production and Trade Flows. American Economic Review 102(3), 412–416.

Bailey, M. A., A. Strezhnev, and E. Voeten (2017). Estimating Dynamic State Preferences from United Nations Voting Data. The Journal of Conflict Resolution 61(2), 430–456.

Bergé, L. (2018). Efficient estimation of maximum likelihood models with multiple fixed-effects: the R package FENmlm. DEM Discussion Paper Series. Number: 18-13 Publisher: Department of Economics at the University of Luxembourg.

Bloom, N. (2009). The Impact of Uncertainty Shocks. Econometrica 77(3), 623–685. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA6248.

Boehm, C. E., A. A. Levchenko, and N. Pandalai-Nayar (2023, April). The Long and Short (Run) of Trade Elasticities. American Economic Review 113(4), 861–905.

Borchert, I., M. Larch, S. Shikher, and Y. V. Yotov (2021). The international trade and production database for estimation (itpd-e). International Economics 166, 140–166.

Bosone, C. and G. Stamato (2024). Beyond Borders: How Geopolitics is Reshaping Trade. SSRN Electronic Journal.

Caldara, D. and M. Iacoviello (2022). Measuring Geopolitical Risk. The American Economic Review 112(4), 1194–1225.

Clayton, C. and S. Maggiori (2025). Geoeconomic Pressure. NBER Working Papers.

Davies, S., G. Engström, T. Pettersson, and M. Öberg (2024, July). Organized violence 1989–2023, and the prevalence of organized crime groups. Journal of Peace Research 61(4), 673–693. Publisher: SAGE Publications Ltd.

de Sousa, J., D. Mirza, and T. Verdier (2018). Terror networks and trade: Does the neighbor hurt? European Economic Review 107, 27–56.

Desbordes, R. (2026). An interstate conflictual relations index. SKEMA working paper.

Eberhard-Ruiz, A. (2024). The impact of armed conflict shocks on local cross-border trade: Evidence from the border between uganda and the democratic republic of congo. Economic Development and Cultural Change 72(3), 1151–1187.

Fan, T., M. Wo, and W. Xiang (2025, September). Geopolitical Barriers to Globalization. arXiv:2509.12084 [econ].

Felbermayr, G., A. Kirilakha, C. Syropoulos, E. Yalcin, and Y. V. Yotov (2020). The global sanctions data base. European Economic Review 129(C).

Felbermayr, G., T. C. Morgan, C. Syropoulos, and Y. V. Yotov (2025). Economic sanctions: Stylized facts and quantitative evidence. Annual Review of Economics 17, 175–195.

Fernando Broner, Alberto Martin, J. M. C. T. (2025). Hegemonic globalization. mimeo.

Fernàndez-Villaverde, J., T. Mineyama, and D. Song (2025). Are we fragmented yet? measuring geopolitical fragmentation and its causal effects. mimeo.

Findlay, R. and K. H. O'Rourke (2007). Power and plenty: Trade, war, and the world economy in the second millennium. Princeton University Press.

Fontagné, L., H. Guimbard, and G. Orefice (2022). Tariff-based product-level trade elasticities. Journal of International Economics 137.

Fuchs, A. and N.-H. Klann (2013). Paying a visit: The dalai lama effect on international trade. Journal of International Economics 91(1), 164–177.

Gerner, D. J., P. A. Schrodt, O. Yilmaz, and R. Abu-Jabr (2002). The Creation of CAMEO (Conflict and Mediation Event Observations): An Event Data Framework for a Post Cold War World. American Political Science Association.

Gleditsch, K. (2004). A Revised List of Wars Between and Within Independent States, 1816-2002. International Interactions 30(3), 231–262. Publisher: Taylor & Francis Journals.

Glick, R. and A. M. Taylor (2010). Collateral damage: Trade disruption and the economic impact of war. The Review of Economics and Statistics 92(1), 102–127.

Goldstein, J. S. (1992). A Conflict-Cooperation Scale for WEIS Events Data. The Journal of Conflict Resolution 36(2), 369–385.

Gopinath, G., P.-O. Gourinchas, A. F. Presbitero, and P. Topalova (2025, January). Changing global linkages: A new Cold War? Journal of International Economics 153, 104042.

Harbom, L., E. Melander, and P. Wallensteen (2008, September). Dyadic Dimensions of Armed Conflict, 1946—2007. Journal of Peace Research 45(5), 697–710. Publisher: SAGE Publications Ltd.

Hardwick, S. (2025, September). Trade, Political Distance and the World Trade Organization. arXiv:2509.17303 [econ].

Hausmann, R., C. A. Hidalgo, S. Bustos, M. Coscia, A. Simoes, and M. A. Yildirim (2014, January). The Atlas of Economic Complexity: Mapping Paths to Prosperity. The MIT Press.

Head, K. and T. Mayer (2014). Gravity Equations: Workhorse, Toolkit, and Cookbook. In Handbook of International Economics, Volume 4, pp. 131–195. Elsevier.

Head, K. and T. Mayer (2022). Welfare effects of balkan trade liberalization through the lens of structural gravity. mimeo.

Hinz, J. (2023, February). The ties that bind: geopolitical motivations for economic integration. Review of World Economics 159(1), 51–100.

Hong, D., Z. Fu, X. Zhang, and Y. Pan (2025, October). Research on the Development and Application of the GDELT Event Database. Data 10(10), 158.

Imbs, J. and I. Mejean (2015, July). Elasticity Optimism. American Economic Journal: Macroeconomics 7(3), 43–83.

Jordà, O. and A. M. Taylor (2025, March). Local Projections. Journal of Economic Literature 63(1), 59–110.

Jordà, (2005, March). Estimation and Inference of Impulse Responses by Local Projections. American Economic Review 95(1), 161–182.

Kamin, K. (2022). Bilateral trade and conflict heterogeneity: The impact of conflict on trade revisited. Kiel working paper.

Larch, M., S. Shikher, and Y. Yotov (2025, January). Estimating Gravity Equations: Theory Implications, Econometric Developments, and Practical Recommendations. CGPA Working Papers. Number: 2025001 Publisher: Center for Global Policy Analysis, LeBow College of Business, Drexel University.

Leetaru, K. H. and P. A. Schrodt (2013). GDELT: Global Data on Events, Location and Tone. International Studies Association.

Lefebvre, K. and P. Wibaux (2024). Import dependencies: where does the eu stand? CEPII Policy Brief (47).

Martin, J., I. Mejean, and M. Parenti (2026, October). Relationship Stickiness, International Trade, and Economic Uncertainty. Review of Economics and Statistics, 1–15.

Martin, P., T. Mayer, and M. Thoenig (2008, July). Make Trade Not War? Review of Economic Studies 75(3), 865–900.

Mayer, T. and S. Zignago (2011). Notes on CEPII's Distances Measures: The GeoDist Database. SSRN Electronic Journal.

McGuirk, E. and C. Trebesch (2025, October). Geoeconomics and Conflict: A Review and Open Questions. Kiel Working Papers 2302.

Mohr, C. and C. Trebesch (2025). Geoeconomics. CESifo Working Papers (11564 2024).

Montiel Olea, J. L. and M. Plagborg-Møller (2021). Local projection inference is simpler and more robust than you think. Econometrica 89, 1789–1823.

Mulabdic, A. and Y. V. Yotov (2025). Geopolitical Risks and Trade. World Bank Policy Research Working Paper.

Novy, D. and A. M. Taylor (2019). Trade and uncertainty. The Review of Economics and Statistics 102(4), 749–765.

Nunn, N. (2007). Relationship-specificity, incomplete contracts, and the pattern of trade. Quarterly Journal of Economics 122(2), 569–600.

Raleigh, C., R. Kishi, and A. Linke (2023). Political instability patterns are obscured by conflict dataset scope conditions, sources, and coding choices. Humanities and Social Sciences Communications 10(74).

Rauch, J. E. (1999). Networks versus markets in international trade. Journal of International Economics 48(1), 7–35.

Rose, A. K. (2007). The foreign service and foreign trade: Embassies as export promotion. The World Economy 30(1), 22–38.

Saadaoui, J., V. Strauss-Kahn, and J. Creel (2026, January). How geopolitics influences the exports of chinese firms. SSRN Working Paper.

Sarkees, M. R. and F. Wayman (2010). Resort to War: 1816 – 2007 (Correlates of War). Washington DC: CQ Press.

Wickham, H. and J. Bryan (2024). bigrquery: An Interface to Google's BigQuery API.

A The IntenSE Database: Technical Appendix

A.1 GDELT Filtering

This appendix provides a detailed description of the construction of the CEPII *Intensity and Shade of Events* (IntenSE) database from version 2.0 of the *Global Database of Events, Language, and Tone* (GDELT) (Leetaru and Schrodt, 2013). GDELT is an open-source, high-frequency repository of political events extracted from news articles published in more than 65 languages using automated text-processing techniques. It records the actors involved, the date and location of each event, and its classification according to the CAMEO taxonomy (Gerner et al., 2002). The dataset is organized into several tables hosted on Google BigQuery; our work primarily relies on the *events* and *eventmentions* tables, which respectively contain standardized events and the underlying source articles. Because GDELT's automated coding may split a single real-world event into multiple entries or merge distinct incidents, we base our construction on articles and their associated CAMEO codes rather than on GDELT's event-level aggregation. We restrict attention to version 2.0 of GDELT (available from March 2015 onward) and apply a series of filters to retain only factual reports from international press agencies.

Between March 2015 and July 2025, the *eventmentions* dataset accumulated more than 2.3 billion observations, allowing for the application of several filters based on different characteristics. The first step consists in identifying whether an event mentioned in an article is explicitly described in the text or inferred by GDELT's algorithm. We retain only explicitly described events, a choice that preserves 55.10% of the original *eventmentions* entries. Each article is also assigned a confidence score, ranging from 0 to 100, reflecting the algorithm's assessment of the reliability of the extracted information. To improve data accuracy, we keep only articles with a confidence score of 80 or higher, which removes 41% of previously retained observations. In addition, we keep only articles published within six months of the event date. This filter is intended to avoid capturing commemorations that the algorithm might mistakenly classify as new events (e.g. the anniversary coverage of the Paris terror attacks could otherwise be interpreted as a new incident). After applying this criterion, 99.81% of the remaining observations are preserved.

This table enables the filtering of sources, which are subsequently restricted to 164 press agencies from 154 countries (see Table 9). These outlets publish articles that provide factual reporting, which is more likely to be processed accurately by GDELT's algorithm. A related issue, commonly referred to as "domestic bias", reflects the tendency of news organizations to prioritize domestic events, thus potentially skewing coverage toward occurrences within their own borders. Incorporating sources from a broad set of world regions has been shown to mitigate this bias while enriching the available information. After applying this filter, 2.78% of the previously retained observations remain, corresponding to 21,406,593 rows. The following table reports the links to each source, together with their associated tone values, which range from -10 ("very negative") to 10 ("very positive") for usual values.

The *events* table comprises 817,196,094 observations and offers a wide range of filtering possibilities. To ensure data reliability, only observations from March 2015 onward are retained, corresponding to the introduction of real-time information collection in GDELT 2.0. This restriction preserves 99.42% of the original dataset. The next step involves retaining only those events that constituted the primary focus of the article from which they were originally extracted. Applying this criterion preserves 63.08% of the initial observations, resulting in a final dataset of 812,427,471 rows. The resulting table offers a comprehensive overview of event locations, the pair of countries involved in each interaction, and the corresponding CAMEO classification codes at both the 2- and 3-digit levels.

Each of the filtering steps described above is implemented through SQL queries. These queries are executed in Google BigQuery and are sent from R via its Application Programming Interface (API). The *bigrquery* package, developed by Wickham and Bryan (2024), provides the interface required for this workflow. The final query merges the two tables using the unique event identifier, after which the resulting dataset is imported into R. Due to the large volume of data and the storage constraints imposed by Google BigQuery, this procedure must be performed separately for each day in the sample period. The final dataset comprises 15,067,562 observations.

The next step consists in removing irrelevant observations and restructuring the remaining data so that they can be used in an econometric setting. This step raises a specific challenge: a single source article may generate multiple events, and therefore multiple CAMEO codes.

- **Example 1:** Japan increases reinforcements to rescue earthquake victims, the tone of the article is -5.6, event classified under the 073 CAMEO code (provide humanitarian aid).
- **Example 2:** South Korean political opponent stabbed in the neck, the tone of the article is -7, event classified under the 042 CAMEO code (visit).

Events that appear positive may nonetheless be associated with articles conveying negative sentiments, and the reverse can also occur. To limit this type of misclassifications, we adopt a conservative filtering strategy: whenever an article contains at least one violent CAMEO code, all non-violent codes reported in the same article are removed. This procedure reduces the likelihood of false negatives by ensuring that the presence of a violent event is not overshadowed by more benign actions mentioned in passing.

Example 1 further illustrates the situation in which a “positive event occurs within a negative context”. In such cases, the positive action, captured, for instance, by CAMEO code 073 (“provide humanitarian aid”), is embedded in a broader narrative shaped by adverse circumstances such as an earthquake. Our aim is to construct indicators that are meaningful for an econometric analysis of international trade. From this perspective, bilateral trade flows are plausibly affected by major disruptive shocks, whereas the subsequent provision of humanitarian assistance is far less likely to exert an independent influence. For this reason, positive events that arise solely as a reaction to an underlying negative shock fall outside the conceptual scope of our study and are excluded from the final dataset.

In addition, the 042 CAMEO code (“visit”) often generates the reciprocal 043 code (“host a visit”), leading to duplicate entries for the same event. To mitigate this, a filtering procedure is applied at the 2-digit CAMEO level (04 in this case) to retain only one of the duplicates. Finally, some news agencies tend to re-post identical articles under different URLs, artificially inflating the number of references to a single event. These duplicates[50] are removed so that only one article is retained.

A.2 Event Location and Actors

It appears that GDELT's algorithm encounters difficulties in accurately identifying the geographical location of events described in textual sources. In many cases, the location field is either missing or incorrectly substituted with one of the actors involved:

- **Example 3:** UN to stop Gaza aids due to too dangerous routes, located in Israel, while the text clearly specifies a location in the Gaza Strip. The tone of the article is -7.4, event classified under the 112 CAMEO code (accuse, not specified below).
- **Example 4:** Russian oligarch elected at the head of the world fencing federation, located in Russia while the election took place in Switzerland. The tone of the article is -7.4, event classified under the 043 CAMEO code (host a visit).

To address this issue, we incorporate the identified location into the set of actors associated with each event. This approach rests on the assumption that when an event takes place within a given country, that country can, by definition, be considered one of the event's participants. This treatment ensures that geographically grounded events are systematically linked to the relevant sovereign state.

Example 4 also illustrates that certain CAMEO codes provide only limited guidance regarding the substantive nature of the event. For instance, CAMEO code 043 ("host a visit") is inherently broad and may refer to a wide range of situations. Incorporating the tone of the underlying news article helps mitigate this ambiguity: sentiment information offers an additional layer of context that refines the interpretation of the event and supports a more accurate classification within our framework.

The ordering of actors provided by GDELT is insufficiently reliable for analytical use. In some cases, the order is even reversed, rendering the variable unusable overall:

- **Example 5:** Article covering the emission of Omani treasury bonds, announced in a conference in Abu Dhabi, but the first actor is referred to as United Arab Emirates and the second as Oman.
- **Example 6:** Article reporting new elections in Taiwan allowed by China, but the first actor is identified as Taiwan and the second as China.

Given the likelihood that GDELT cannot reliably determine the ordering of actors, this information is excluded from the monthly aggregation process used to identify bilateral events. For each indicator, a duplicate of every row is created so as to account for both possible directions of the bilateral relationship.

[50] The duplicated issues, along with additional GDELT-related problems discussed in the following sections, are documented in greater detail by Hong et al. (2025).

GDELT occasionally reports a country-group code instead of a country-specific code. These codes generally correspond to broad geographic entities, such as continents, but may also refer to international organizations (e.g. EUR for the European Union or WST for NATO). To preserve relevant information while avoiding the creation of artificial or non-existent bilateral relationships, these observations are excluded from the dataset.

In addition, all observations are aggregated at the level of sovereign states. This harmonization step is necessary because the GDELT database occasionally reports events or articles referring to sub-national territories or overseas regions. For example, GDELT may identify French Guiana as the location mentioned in a news article; in such cases, we reassign the observation to France, its sovereign state. This procedure ensures consistency in the construction of bilateral relationships and prevents an artificial inflation of the number of geopolitical entities represented in the dataset. It also provides a more coherent framework for applications involving international trade data, where the sovereign state is the relevant unit of analysis.

A.3 Final Source Data Shaping

Following the decision to treat the event location as an additional actor, each observation contains three actors. To construct the bilateral database, all possible dyadic combinations among these three entities are first generated. Observations in which the resulting dyad consists of the same actor twice are then discarded. For instance, an event involving France and Germany that takes place in France produces three dyads, from which the France-France dyad is removed. Country pairs are subsequently selected based on the requirement that each dyad must exhibit a strictly positive number of articles for at least three months per year, a criterion that preserves 54.20% of the observations.

Because raw CAMEO codes in GDELT are highly heterogeneous and often difficult to interpret consistently, aggregating them into broader categories yields a more reliable representation of media-reported events. We therefore rely on the three-digit CAMEO nomenclature (see Table 10) to classify articles into three categories based on their reported codes: declaration, action, and violence. For articles falling into the declaration and action categories, we further use the article's tone to distinguish between positive and negative declarations, and positive and negative actions. We thus end up with Violent events are systematically treated as negative, regardless of the tone of the underlying article. This structure allows us to collapse articles into even broader groups, as done in this study: violent events and negative-tone articles are combined into a single negative category, while positive-tone articles form a single positive category.

A.4 Press Agencies

Table 9: Selected Press Agencies

Continent	Country	Press Agency (Website)
Africa	Algeria	Algérie Presse Service (aps.dz)

Continent	**Country**	**Press Agency (Website)**
	Egypt	Middle East News Agency (mena.org.eg)
	Kenya	Kenya News Agency (kenyanews.go.ke)
	Morocco	Maghreb Arabe Presse (map.ma, mapexpress.ma)
	Tunisia	Tunis Afrique Presse (tap.info.tn)
	South Africa	South African Government News Agency (sanews.gov.za)
	Angola	Angola Press Agency (angop.ao)
	Ivory Coast	Agence Ivoirienne de Presse (aip.ci)
	Mauritania	Agence Mauritanienne d'Information (ami.mr)
	Namibia	Namibia Press Agency (nampa.org)
	Rwanda	Rwanda News Agency (rnanews.com)
	Senegal	Agence de Presse Sénégalaise (aps.sn)
	Gabon	Agence Gabonaise de Presse (agpgabon.ga)
	Libya	Libyan News Agency (lana-news.ly, lana.gov.ly)
	Botswana	Botswana Press Agency (dailynews.gov.bw)
	Cape Verde	Inforpress (inforpress.cv)
	Sierra Leone	Sierra Leone News Agency (slena.gov.sl)
	Madagascar	Agence Malagasy de Presse (agencemalagasydepresse.com)
	Mozambique	Agência de Informação de Moçambique (aimnews.org)
	Seychelles	Seychelles News Agency (seychellesnewsagency.com)
	South Sudan	South Sudan News Agency (ssnanews.com, southsudannewsagency.com)
	Burkina Faso	Agence d'Information du Burkina (aib.media, aib.bf)
	Guinea-Bissau	Agencia de Noticias da Guiné (ang.gw)
	Central African Republic	Agence Centrafricaine de Presse (acap.cf, acap-cf.info)
	Democratic Republic of Congo	Agence Congolaise de Presse (acp.cd, acpcongo.com)
	Chad	Tchad Infos (tchadinfos.com)
	Mali	Agence Malienne de Presse (amap.ml)
	Benin	Agence Bénin Presse (agencebeninpresse.info)
	Congo	Agence Congolaise d'Information (aci.cg)
	Ghana	Ghana News Agency (gna.org.gh)
	Haiti	Agence Haïtienne de Presse (haitiahp.blogspot.com)
	Niger	Agence Nigérienne de Presse (anp.ne)
	Sudan	Sudan News Agency (suna-sd.net, suna-news.net)
	Gambia	Gambia News Agency (gamna.gov.gm)
	Guinea	Agence Guinéenne de Presse (agpguinee.com)

Continent	**Country**	**Press Agency (Website)**
	Uganda	Uganda Media Centre (mediacentre.go.ug)
	Zambia	Zambia News and Information Services (zanis.gov.zm)
	Eritrea	Eritrean News Agency (shabait.com)
	Liberia	Liberia News Agency (liberianewsagency.com, liberianewsagency.org)
	Nigeria	News Agency of Nigeria (nannews.ng)
	Somalia	Somalie News Agency (sonna.so)
	Cameroon	Agence Cameroun Presse (agencecamerounpresse.com)
	Djibouti	Agence Djiboutienne d'Information (adi.dj)
	Ethiopia	Ethiopian News Agency (ena.et)
	São Tomé and Príncipe	Agência São-Tomense de Notícias (STP-PRESS) (stp-press.st)
North America	Canada	The Canadian Press (thecanadianpress.com)
	United States	Associated Press (ap.org), United Press International (upi.com), Bloomberg News (bloomberg.com), Voice of America (voanews.com, voa.gov)
	Mexico	Notimex (notimex.gob.mx, notimex.com.mx)
Central America	Guatemala	Agencia Guatemalteca de Noticias (agn.gt, agn.com.gt)
	Belize	Belize Press Office (pressoffice.gov.bz)
	Panama	Agencia de Noticias Panamá (anpanama.com)
South America	Argentina	Télam (telam.com.ar)
	Brazil	Agência Estado (estadao.com.br), Agencia Brasil (ebc.com.br)
	Venezuela	Agencia Venezolana de Noticias (avn.info.ve)
	Colombia	Agencia de Noticias RCN (noticiasrcn.com)
	Peru	Agencia Peruana de Noticias (Andina) (andina.pe)
	Uruguay	UY Press (uypress.net)
	Ecuador	Agencia de Noticias Andes (andes.info.ec)
	Suriname	Algemeen Dagblad Suriname (dbsuriname.com)
	Chile	Mediabanco (mediabanco.co)
	Paraguay	Agencia IP (ip.gov.py)
Asia	China	Xinhua News Agency (xinhuanet.com)
	India	Press Trust of India (PTI) (ptinews.com), United News of India (UNI) (uniindia.com)
	Indonesia	Antara (antaranews.com)
	Iran	Islamic Republic News Agency (IRNA) (irna.ir), Mehr News Agency (MNA) (mehrnews.com)

Continent	Country	Press Agency (Website)
	Japan	Kyodo News (kyodonews.net, kyodo.co.jp), Jiji Press (jiji.com)
	Malaysia	Bernama (bernama.com)
	Pakistan	Associated Press of Pakistan (APP) (app.com.pk)
	Philippines	Philippine News Agency (PNA) (pna.gov.ph)
	Russia	TASS (tass.ru), Interfax (interfax.com, interfax.com.ua, interfax.az, interfax.kz, interfax.ru, interfax.by)
	Turkey	Anadolu Agency (AA) (aa.com.tr, anadoluajansi.gov.tr)
	Vietnam	Vietnam News Agency (VNA) (vietnamnews.vn)
	South Korea	Yonhap News Agency (yna.co.kr, yonhapnews.co.kr)
	Bangladesh	Bangladesh Sangbad Sangstha (BSS) (bssnews.net)
	Taiwan	Central News Agency (CNA) (cna.com.tw)
	Uzbekistan	Uzbekistan National News Agency (UzA) (uza.uz)
	Bhutan	Bhutan News Service (bhutannewsservice.com)
	Armenia	Armenpress (armenpress.am)
	Cambodia	Agence Kampuchea Presse (akp.gov.kh)
	Hong Kong	Hong Kong Information Services Department (isd.gov.hk)
	Sri Lanka	LankaPuvath (lankapuvath.lk)
	Azerbaijan	AZERTAC (azertag.az)
	Kazakhstan	Kazinform (inform.kz)
	Timor-Leste	Agencia Notociosa de Timor-Leste (TATOLI) (tatoli.tl)
	Kyrgyzstan	Kabar News Agency (kabar.kg)
	Tajikistan	Khovar (khovar.tj)
	Afghanistan	Bakhtar (bakhtarnews.af, bakhtarnews.com.af)
	North Korea	Korean Central News Agency (kcna.kp)
	Turkmenistan	Turkmenistan State News Agency (tdh.gov.tm)
	Laos	Khaosan Pathet Lao (kpl.gov.la)
	Macao	Macao News Agency (macaobusiness.com)
	Nepal	Nepal News Agency (nepalnewsagency.com)
	Brunei	Jabatan Penerangan Brunei (information.gov.bn)
	Mongolia	Montsame News Agency (montsame.mn)
	Thailand	Thai News Agency (tna.mcot.net)
Europe	Spain	Agencia EFE (efe.com)
	France	Agence France-Presse (AFP) (afp.com)
	Italy	Agenzia Nazionale Stampa Associata (ANSA) (ansa.it)
	United Kingdom	Reuters (reuters.com, reuters.fr, reuters.tv)
	Sweden	Tidningarnas Telegrambyrå (TT) (tt.se)
	Austria	Austria Presse Agentur (APA) (apa.at)

Continent	Country	Press Agency (Website)
	Belgium	Belga (belga.be)
	Finland	Suomen Tietotoimisto (STT) (stt.fi)
	Greece	Athens-Macedonian News Agency (AMNA) (amna.gr)
	Portugal	Lusa News Agency (lusa.pt)
	Hungary	Magyar Távirati Iroda (MTI) (mti.hu)
	Poland	Polska Agencja Prasowa (PAP) (pap.pl)
	Romania	Agerpres (agerpres.ro)
	Slovenia	Slovenska Tiskovna Agencija (STA) (sta.si)
	Ukraine	Ukrinform (ukrinform.net, ukrinform.ua)
	Cyprus	Cyprus News Agency (cna.org.cy)
	Kosovo	KosovaPress (kosovapress.com)
	Latvia	Leta (leta.lv)
	Albania	Agjencia Telegrafike Shqiptare (ata.gov.al)
	Belarus	BelTA (belta.by)
	Iceland	Ríkisútvarpið (ruv.is)
	Moldova	Moldpres (moldpres.md)
	Bulgaria	Bulgaria National News Agency (bta.bg)
	Baltic States	Baltic News Service (bns.ee, bns.lt, bns.lv)
	Lithuania	ELTA (elta.lt)
	North Macedonia	Macedonian Information Agency (mia.mk)
	Montenegro	Montenegrin News Agency (mina.news)
	Netherlands	Algemeen Nederlands Persbureau (anp.nl)
	Switzerland	Keystone-SDA (keystone-sda.ch)
	Vatican	Vatican News (vaticannews.va)
	Czech Republic	Česká Tisková Kancelář (ctk.cz)
	Slovakia	Tlačová Agentúra Slovenskej Republiky (tasr.sk)
	Bosnia and Herzegovina	Federation News Agency (fena.news, fena.ba)
	Malta	Malta News Agency (maltanewsagency.com)
	Norway	Norsk Telegrambyrå (ntb.no)
	Denmark	Ritzau (ritzau.com)
	Germany	Deutsche Presse Agentur (dpa.com)
Oceania	Australia	Australian Associated Press (AAP) (aap.com.au)
	Fiji	Fiji Live (fijilive.com)
	Pacific Islands	Pacific Islands News Association (pina.com.fj)
	Samoa	Samoa News (samoanews.com)
Middle East	Saudi Arabia	Saudi Press Agency (SPA) (spa.gov.sa)

Continent	Country	Press Agency (Website)
	United Arab Emirates	Emirates News Agency (WAM) (wam.ae, wam.org.ae)
	Israel	Israel News Agency (INA) (israelnewsagency.com)
	Lebanon	National News Agency (NNA) (nna-leb.gov.lb)
	Qatar	Qatar News Agency (QNA) (qna.org.qa)
	Kuwait	Kuwait News Agency (KUNA) (kuna.net.kw)
	Bahrain	Bahrain News Agency (BNA) (bna.bh)
	Iraq	Iraqi News Agency (INA) (ina.iq)
	Jordan	Jordan News Agency (Petra) (petra.gov.jo)
	Oman	Oman News Agency (ONA) (omannews.gov.om)
	Palestine	Palestine News Information Agency (WAFA) (wafa.ps)
	Syria	Syrian Arab News Agency (SANA) (sana.sy)
	Yemen	Saba News Agency (saba.ye, sabanews.net)
Caribbean	Cuba	Prensa Latina (prensa-latina.cu)
	Jamaica	Jamaica Information Service (jis.gov.jm)
	Barbados	Barbados Government Information Service (gisbarbados.gov.bb)
	Dominica	Dominica News Online (dominicanewsonline.com)
	Puerto Rico	Noticel (noticel.com)
	Cayman Islands	Cayman News Service (caymannewsservice.com)
	Antigua and Barbuda	Antigua and Barbuda News (antigua.news)

A.5 CAMEO Codes

Table 10: CAMEO Codes Conversion Table

Description	2-digit CAMEO Code	3-digit CAMEO Code	Category
Make statement, not specified below	01	010	Declaration
Decline comment	01	011	Declaration
Make pessimistic comment	01	012	Declaration
Make optimistic comment	01	013	Declaration
Consider policy option	01	014	Declaration
Acknowledge or claim responsibility	01	015	Declaration
Deny responsibility	01	016	Declaration
Engage in symbolic act	01	017	Declaration
Make empathetic comment	01	018	Declaration

Description	2-digit CAMEO Code	3-digit CAMEO Code	Category
Express accord	01	019	Declaration
Make an appeal or request, not specified below	02	020	Declaration
Appeal for material cooperation, not specified below	02	021	Declaration
Appeal for diplomatic cooperation (such as policy support)	02	022	Declaration
Appeal for aid, not specified below	02	023	Declaration
Appeal for political reform, not specified below	02	024	Declaration
Appeal to yield, not specified below	02	025	Declaration
Appeal to others to meet or negotiate	02	026	Declaration
Appeal to others to settle dispute	02	027	Declaration
Appeal to engage in or accept mediation	02	028	Declaration
Express intent to cooperate, not specified below	03	030	Declaration
Express intent to engage in material cooperation, not specified below	03	031	Declaration
Express intent to engage in diplomatic cooperation (such as policy support)	03	032	Declaration
Express intent to provide material aid, not specified below	03	033	Declaration
Express intent to institute political reform, not specified below	03	034	Declaration
Express intent to yield, not specified below	03	035	Declaration
Express intent to meet or negotiate	03	036	Declaration
Express intent to settle dispute	03	037	Declaration
Express intent to accept mediation	03	038	Declaration
Express intent to mediate	03	039	Declaration
Consult, not specified below	04	040	Declaration
Discuss by telephone	04	041	Declaration
Make a visit	04	042	Declaration
Host a visit	04	043	Declaration
Meet at a ”third” location	04	044	Declaration
Mediate	04	045	Declaration
Engage in negotiation	04	046	Declaration
Engage in diplomatic cooperation, not specified below	05	050	Action
Praise or endorse	05	051	Declaration
Defend verbally	05	052	Declaration
Rally support on behalf of	05	053	Declaration

Description	2-digit CAMEO Code	3-digit CAMEO Code	Category
Grant diplomatic recognition	05	054	Declaration
Apologize	05	055	Declaration
Forgive	05	056	Declaration
Sign formal agreement	05	057	Action
Engage in material cooperation, not specified below	06	060	Action
Cooperate economically	06	061	Action
Cooperate militarily	06	062	Action
Engage in judicial cooperation	06	063	Action
Share intelligence or information	06	064	Action
Provide aid, not specified below	07	070	Action
Provide economic aid	07	071	Action
Provide military aid	07	072	Action
Provide humanitarian aid	07	073	Action
Provide military protection or peacekeeping	07	074	Action
Grant asylum	07	075	Action
Yield, not specified below	08	080	Action
Ease administrative sanctions, not specified below	08	081	Action
Ease political dissent	08	082	Action
Accede to requests or demands for political reform, not specified below	08	083	Action
Return, release, not specified below	08	084	Action
Ease economic sanctions, boycott, embargo	08	085	Action
Allow international involvement, not specified below	08	086	Action
De-escalate military engagement	08	087	Action
Investigate, not specified below	09	090	Action
Investigate crime, corruption	09	091	Action
Investigate human rights abuses	09	092	Action
Investigate military action	09	093	Action
Investigate war crimes	09	094	Action
Demand, not specified below	10	100	Declaration
Demand material cooperation, not specified below	10	101	Declaration
Demand diplomatic cooperation (such as policy support)	10	102	Declaration
Demand material aid, not specified below	10	103	Declaration

Description	2-digit CAMEO Code	3-digit CAMEO Code	Category
Demand political reform, not specified below	10	104	Declaration
Demand that target yields, not specified below	10	105	Declaration
Demand meeting, negotiation	10	106	Declaration
Demand settling of dispute	10	107	Declaration
Demand mediation	10	108	Declaration
Disapprove, not specified below	11	110	Declaration
Criticize or denounce	11	111	Declaration
Accuse, not specified below	11	112	Declaration
Rally opposition against	11	113	Declaration
Complain officially	11	114	Action
Bring lawsuit against	11	115	Action
Find guilty or liable (legally)	11	116	Action
Reject, not specified below	12	120	Declaration
Reject material cooperation	12	121	Declaration
Reject request or demand for material aid, not specified below	12	122	Declaration
Reject request or demand for political reform, not specified below	12	123	Declaration
Refuse to yield, not specified below	12	124	Declaration
Reject proposal to meet, discuss, or negotiate	12	125	Declaration
Reject mediation	12	126	Declaration
Reject plan, agreement to settle dispute	12	127	Declaration
Defy norms, law	12	128	Action
Veto	12	129	Action
Threaten, not specified below	13	130	Action
Threaten non-force, not specified below	13	131	Action
Threaten with administrative sanctions, not specified below	13	132	Action
Threaten with political dissent, protest	13	133	Action
Threaten to halt negotiations	13	134	Action
Threaten to halt mediation	13	135	Action
Threaten to halt international involvement (non-mediation)	13	136	Action
Threaten with repression	13	137	Action
Threaten with military force, not specified below	13	138	Action
Give ultimatum	13	139	Action
Engage in political dissent, not specified below	14	140	Action

Description	2-digit CAMEO Code	3-digit CAMEO Code	Category
Demonstrate or rally, not specified below	14	141	Action
Conduct hunger strike, not specified below	14	142	Action
Conduct strike or boycott, not specified below	14	143	Action
Obstruct passage, block, not specified below	14	144	Violence
Protest violently, riot, not specified below	14	145	Violence
Demonstrate military or police power, not specified below	15	150	Action
Increase police alert status	15	151	Action
Increase military alert status	15	152	Action
Mobilize or increase police power	15	153	Action
Mobilize or increase armed forces	15	154	Action
Mobilize or increase cyber-forces	15	155	Action
Reduce relations, not specified below	16	160	Action
Reduce or break diplomatic relations	16	161	Action
Reduce or stop material aid, not specified below	16	162	Action
Impose embargo, boycott, or sanctions	16	163	Action
Halt negotiations	16	164	Action
Halt mediation	16	165	Action
Expel or withdraw, not specified below	16	166	Action
Coerce, not specified below	17	170	Violence
Seize or damage property, not specified below	17	171	Violence
Impose administrative sanctions, not specified below	17	172	Action
Arrest, detain, or charge with legal action	17	173	Violence
Expel or deport individuals	17	174	Violence
Use tactics of violent repression	17	175	Violence
Attack cybernetically	17	176	Violence
Use unconventional violence, not specified below	18	180	Violence
Abduct, hijack, or take hostage	18	181	Violence
Physically assault, not specified below	18	182	Violence
Conduct suicide, car, or other non-military bombing, not specified below	18	183	Violence
Use as human shield	18	184	Violence
Attempt to assassinate	18	185	Violence
Assassinate	18	186	Violence
Use conventional military force, not specified below	19	190	Violence

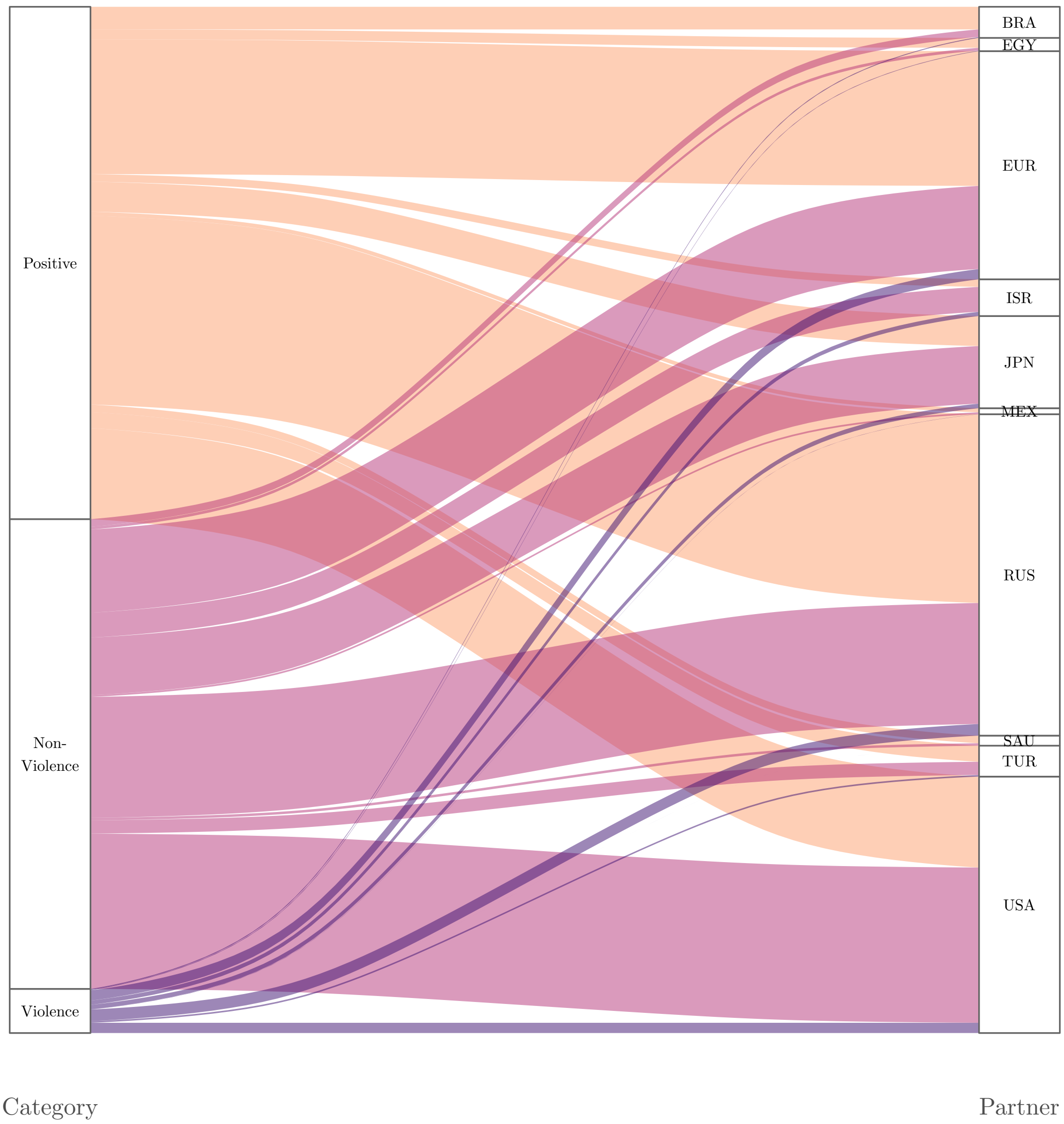
Description	2-digit CAMEO Code	3-digit CAMEO Code	Category
Impose blockade, restrict movement	19	191	Violence
Occupy territory	19	192	Violence
Fight with small arms and light weapons	19	193	Violence
Fight with artillery and tanks	19	194	Violence
Employ aerial weapons, not specified below	19	195	Violence
Violate ceasefire	19	196	Violence
Use unconventional mass violence, not specified below	20	200	Violence
Engage in mass expulsion	20	201	Violence
Engage in mass killings	20	202	Violence
Engage in ethnic cleansing	20	203	Violence
Use weapons of mass destruction, not specified below	20	204	Violence

A.6 Event Category Breakdowns

Figure 10 displays the distribution of articles mentioning China (CHN) and selected partner countries across Positive, Violent, and Non-Violent categories in 2024. The figure highlights both the relative frequency with which each partner appears in China-related news and the share of media attention devoted to each bilateral relationship. The patterns that emerge align closely with the geopolitical context of 2024. China and Russia (RUS) are frequently co-mentioned in articles reporting Negative Violent and Non-Violent events: a configuration consistent with the escalation of the conflict in Ukraine and China's cautious, often ambivalent stance toward it, as reflected in the comparatively limited share of Positive events. A similar distribution characterizes China's coverage of the European Union (EUR), Brazil (BRA), Egypt (EGY), Mexico (MEX), and Saudi Arabia (SAU). By contrast, the United States (USA) appears predominantly in articles classified as Negative, with Non-Violent negative events particularly prominent, mirroring the strained state of Sino-American relations. Comparable patterns arise for Japan (JPN) and, even more markedly, for Israel (ISR), reflecting the ongoing conflict in Palestine. China's media relationship with Turkey (TUR), however, appears more evenly distributed across categories, suggesting a comparatively more balanced bilateral climate.

Figure 11 displays the distribution of articles mentioning European Union member states (aggregated under a single EUR label) and selected partner countries across Positive, Violent, and Non-Violent categories in 2024. The figure summarizes both the frequency with which each partner appears in EU-related news and the relative media space devoted to each bilateral relationship. The patterns observed closely reflect the geopolitical environment of 2024. The European Union and Israel (ISR) are frequently co-mentioned in articles classified as Negative Violent or Non-Violent, a configuration largely driven by the escalation of the conflict in

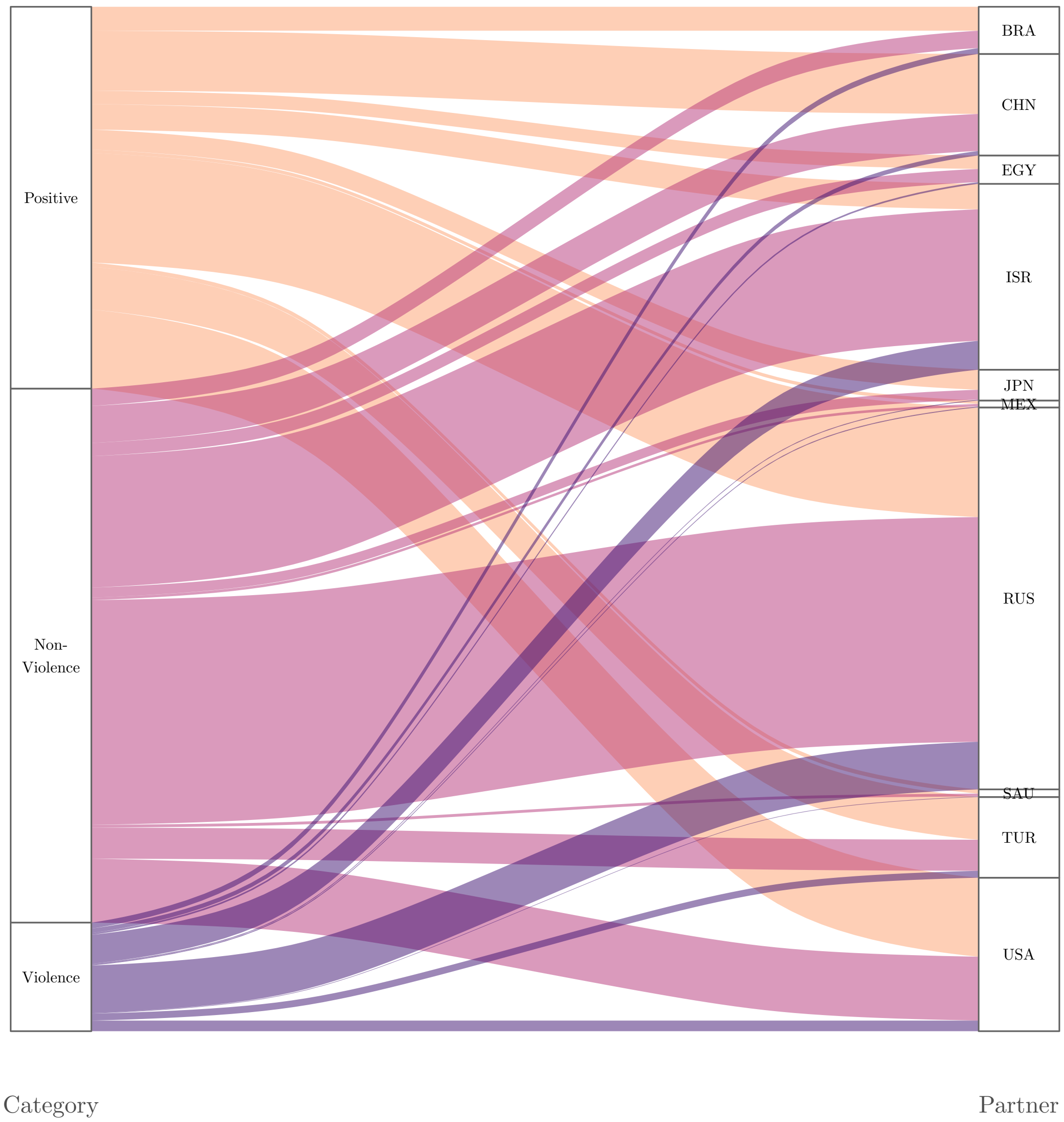
Figure 10: Event Category Breakdown of Press Agency Articles Mentioning China and Partner Countries (2024)



Palestine. A similar distribution emerges for Russia (RUS), consistent with the ongoing war in Ukraine and the sanctions regime in place since 2022. These patterns closely resemble those documented for the United States (USA) in Figure 1, suggesting that the data capture meaningful cross-country similarities in media attention. With the exception of China (CHN), most bilateral relationships appear relatively balanced across categories, indicating a more diversified mix of interactions in EU-related coverage.

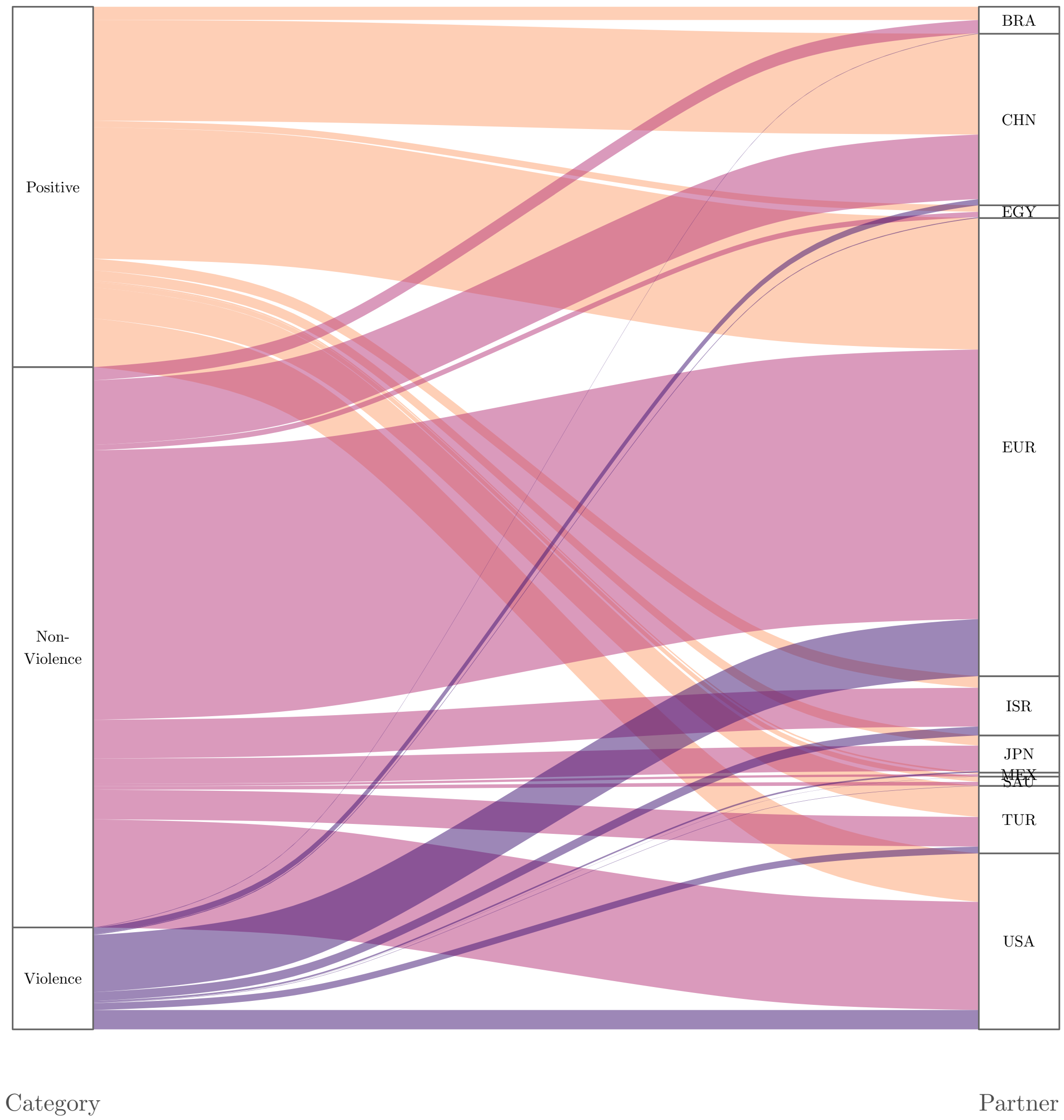
Figure 12 displays the distribution of articles mentioning Russia (RUS) and selected partner countries across Positive, Violent, and Non-Violent categories in 2024. Mentions of European Union member states are aggregated under a single EUR label. The figure summarizes both how frequently each partner appears in Russia-related news and the relative media space devoted

Figure 11: Event Category Breakdown of Press Agency Articles Mentioning the European Union and Partner Countries (2024)



to each bilateral relationship. The patterns observed closely mirror the geopolitical landscape of 2024. Russia and the European Union (EUR) are often co-mentioned in articles classified as Negative Violent or Non-Violent, reflecting the escalation of the conflict in Ukraine and, in particular, the continued enforcement of economic sanctions, an arrangement also visible in Russia's coverage of the United States (USA). A similar distribution emerges for Israel (ISR), consistent with the ongoing conflict in Palestine. As in the case of China (Figure 10), Russia's relationship with China appears predominantly positive, although it occupies a comparatively smaller share of Russia's overall media space. With the exception of Japan (JPN), other bilateral relationships appear either relatively balanced across categories or largely absent from Russia-related coverage.

Figure 12: Event Category Breakdown of Press Agency Articles Mentioning Russia and Partner Countries (2024)



A.7 The Content of IntenSE Database

The resulting bilateral database we shape provides the following variables for 201 countries and 12,766 country pairs over the March 2015–July 2025 period:

- Date: Date in YYYYMM format
- Actor1CountryCode: ISO 3166-1 alpha-3 country code corresponding to the first actor of the concerned dyad
- Actor2CountryCode: ISO 3166-1 alpha-3 country code corresponding to the second actor of the concerned dyad

- Category: Category of the event under consideration among Violence, Negative Action, Positive Action, Negative Declaration, Positive Declaration, Negative, and Positive
- NumEvents: Total number of events recorded in a category and a country during a given month
- NumArticles: Total number of news articles reporting events in a category mentioning two countries during a given month
- Shade: $\mathbb{S}^c_{ijt}$
- Intensity: $\mathbb{I}_{ijt}$

Table 12 presents a sample of our database for the United States-China dyad in June 2016. This period coincides with the first public speech in which Donald Trump outlined his economic agenda, explicitly signaling the possibility of trade retaliation against China. The tone of media coverage captured in our dataset mirrors this political context: articles mentioning both countries during this month predominantly report Negative Declarations. The bilateral relationship is thus overwhelmingly portrayed in negative terms, suggesting that political rhetoric may have had an immediate and measurable impact on the nature of media discourse.

Table 11: IntenSE Database Characteristics

Period	Countries	Country Pairs	Observations
2015/03–2025/07	201	12766	484148

Reshaping the dataset into a wide format (assigning a single Shade value to each event category, country pair, and month) results in a total of 484,148 observations in the IntenSE database. This structure facilitates a comprehensive view of the temporal and cross-country variation captured in the data. Table 11 provides an overview of these core features, highlighting the scale and granularity of the information used in our empirical analysis.

Table 12: IntenSE Database Sample: USA-China, June 2016

Date	Actor 1	Actor 2	Category	# Events	# Articles	Shade	Intensity
201606	USA	CHN	ActionNegative	55	90	0.1446945	0.0561625
201606	USA	CHN	ActionPositive	19	24	0.0385852	0.0561625
201606	USA	CHN	DeclarationNegative	185	337	0.5418006	0.0561625
201606	USA	CHN	DeclarationPositive	107	151	0.2427653	0.0561625
201606	USA	CHN	Negative	256	447	0.7186495	0.0561625
201606	USA	CHN	Positive	126	175	0.2813505	0.0561625
201606	USA	CHN	Violence	16	20	0.0321543	0.0561625

We also report summary statistics for each of our indicators (Shade across all categories and Intensity) in Table 13 and Table 14. By construction, all indicators take values between 0 and 1. The Intensity measure exhibits a markedly skewed distribution, with most observations clustered near the lower end of the scale. This pattern is even more pronounced for the various Shade indicators. In particular, the Violence and Action categories contain an overwhelming share of zeros, reflecting the relative rarity of such events in bilateral media coverage. The aggregate Negative and Positive categories, while perfectly complementary by definition, are likewise dominated by zero values. This prevalence of zeros highlights the strong polarity of many bilateral relationships, which tend to be characterized as either entirely positive or entirely negative within a given month.

Table 13: Bilateral Database Descriptive Statistics I

	Intensity	Shade Negative	Shade Positive	Shade Violence
Min	0	0	0	0
Q1	0.0033	0	0	0
Median	0.011	0.5833	0.4167	0
Q3	0.0377	1	1	0.0244
Max	1	1	1	1
Mean	0.0459	0.5416	0.4584	0.0975
Std.Dev	0.107	0.4083	0.4083	0.2387

Table 14: Bilateral Database Descriptive Statistics II

Shade	Action Negative	Action Positive	Declaration Negative	Declaration Positive
Min	0	0	0	0
Q1	0	0	0	0
Median	0	0	0.2	0.2414
Q3	0.1176	0.0625	0.538	0.6667
Max	1	1	1	1
Mean	0.1205	0.0991	0.3235	0.3594
Std.Dev	0.2497	0.2296	0.3653	0.3847

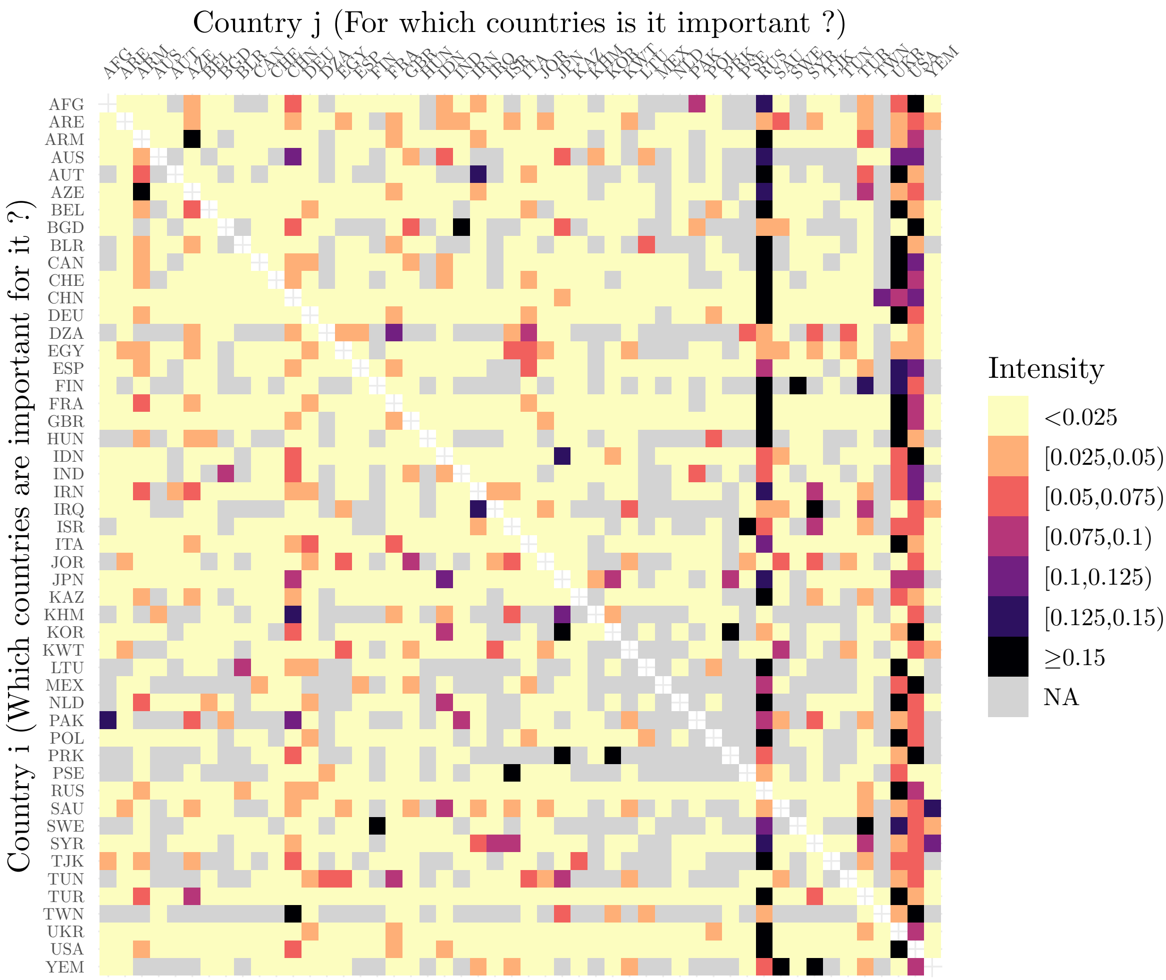
B IntenSE: Stylized facts

To better explain the Intensity indicator, we first plot two different heatmaps for years 2022 and 2024 (Figures 13 and 14, respectively) for the 50 most cited countries of each year.

Focusing first on the year 2022, the heatmap highlights the strong global attention drawn by Russia's invasion of Ukraine. Bilateral relationships involving Russia (RUS) and Ukraine (UKR) rank among the most intense for nearly all other countries. The heatmap also reveals several additional high-Intensity relations, particularly those involving North Korea (PRK) and its neighbors, such as South Korea (KOR) and Japan (JPN). The United States (USA) and China (CHN) likewise appear among the most intense countries, reflecting the prominence of their bilateral relationship.

In 2024, Russia (RUS) continues to appear as a highly intense partner for most countries, alongside Ukraine (UKR), reflecting the ongoing conflict between the two. Israel (ISR) also stands out, driven by the escalation of the conflict in Palestine (PSE). Interestingly, Palestine

Figure 13: Heatmap of Bilateral Interaction Intensity (2022)

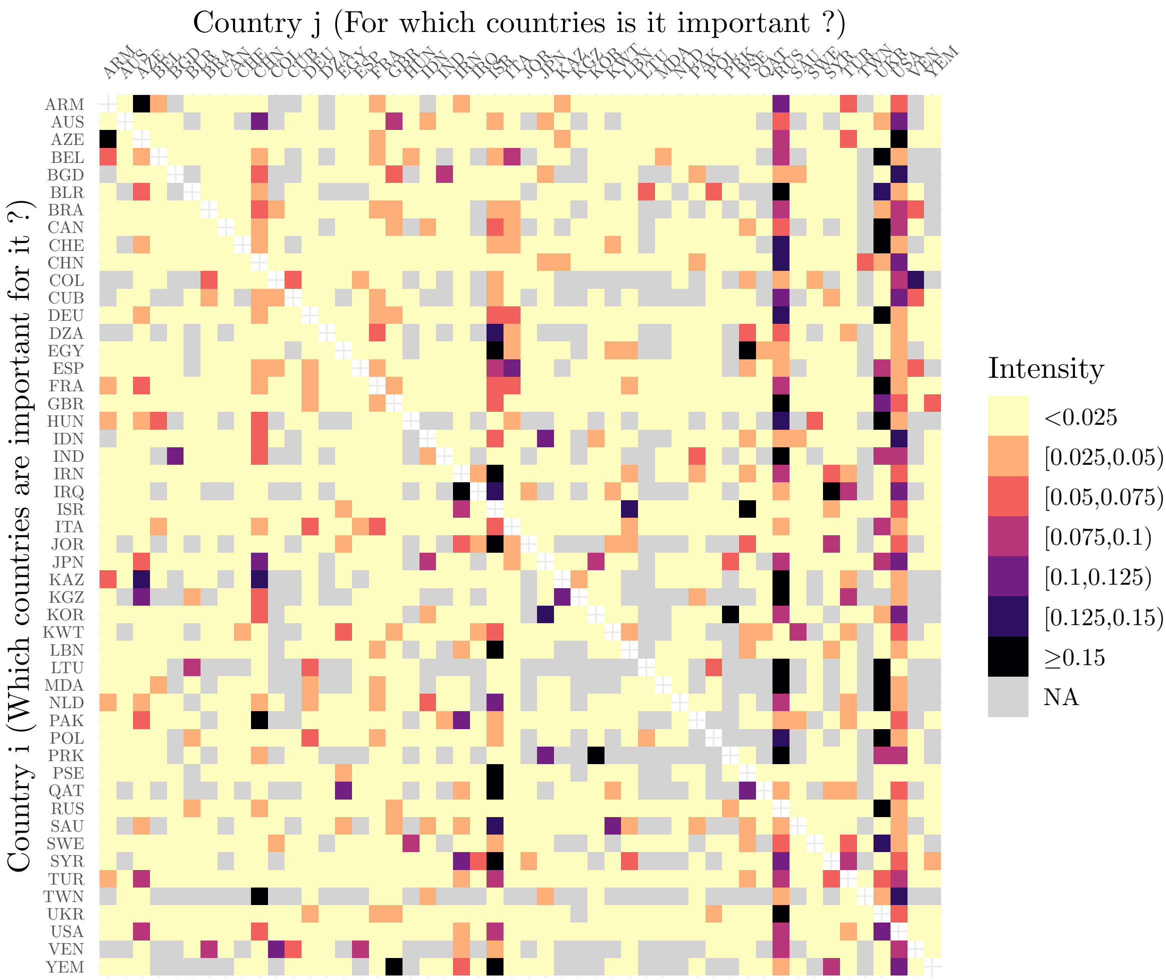


itself does not emerge as particularly prominent, suggesting limited international media attention. As in 2022, several other high-intensity bilateral relationships are visible, notably between the United States (USA) and China (CHN), Armenia (ARM) and Azerbaijan (AZE), and South Korea (KOR) and North Korea (PRK).

Figure 15 focuses on a set of specific bilateral relationships by depicting the evolution of Ukraine's Intensity from the perspective of other countries. Member states of the European Union are grouped under a single EUR category. The colored lines correspond to the ten countries displaying the highest Intensity with Ukraine over the period. Although the conflict between Russia (RUS) and Ukraine dates back to the annexation of Crimea in 2014, Ukraine appeared as an Intense partner for only a limited number of countries prior to the 2022 Russian invasion—primarily Russia and its ally Belarus (BLR). The 2022 invasion marks a sharp and widespread increase in Intensity, visible as a simultaneous spike across most curves. After this peak, Ukraine remains Intense for a narrower group of countries, notably the European Union (EUR), the United Kingdom (GBR), Canada (CAN), and the United States (USA).

Figure 16 examines a set of specific bilateral relationships by tracing the evolution of Palestine's Intensity from the standpoint of other countries. Member states of the European Union

Figure 14: Heatmap of Bilateral Interaction Intensity (2024)



are aggregated into a single EUR category. The colored lines represent the ten countries exhibiting the highest Intensity with Palestine over the period. Prior to the escalation of the conflict with Israel (ISR), Palestine maintained an Intense relationship only with Israel. Following the late-2023 attacks in Israel, Palestine's Intensity rises for several countries, notably its immediate neighbors (Egypt, EGY; Lebanon, LBN; Syria, SYR; Jordan, JOR) as well as for certain Western countries more sensitive to the conflict, including the European Union (EUR) and the United States (USA).

Figure 17 focuses on a set of specific bilateral relationships by depicting the evolution of Afghanistan's Intensity from the perspective of other countries. Member states of the European Union are grouped under a single EUR category. The colored lines correspond to the ten countries displaying the highest Intensity with Afghanistan over the period. Before the taliban regime took the power over the country in 2021, Afghanistan maintained an Intense relationship only with Pakistan (PAK) globally. It became Intense for many countries when the talibans took over in 2021, before becoming less Intense again, except for Pakistan (PAK).

Table15 complements the graphical exploration of indicators by correlating our Intensity measure recomputed at the yearly level with standard gravity variables for 185 countries over

Figure 15: Temporal Dynamics of Ukraine's Bilateral Intensity

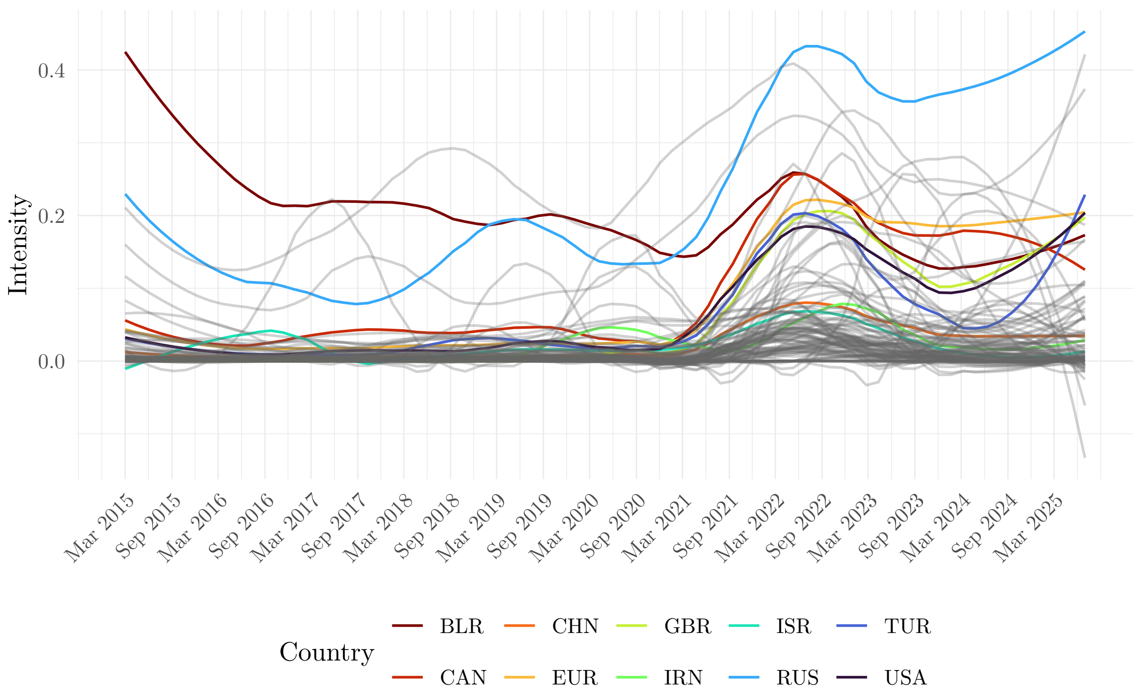
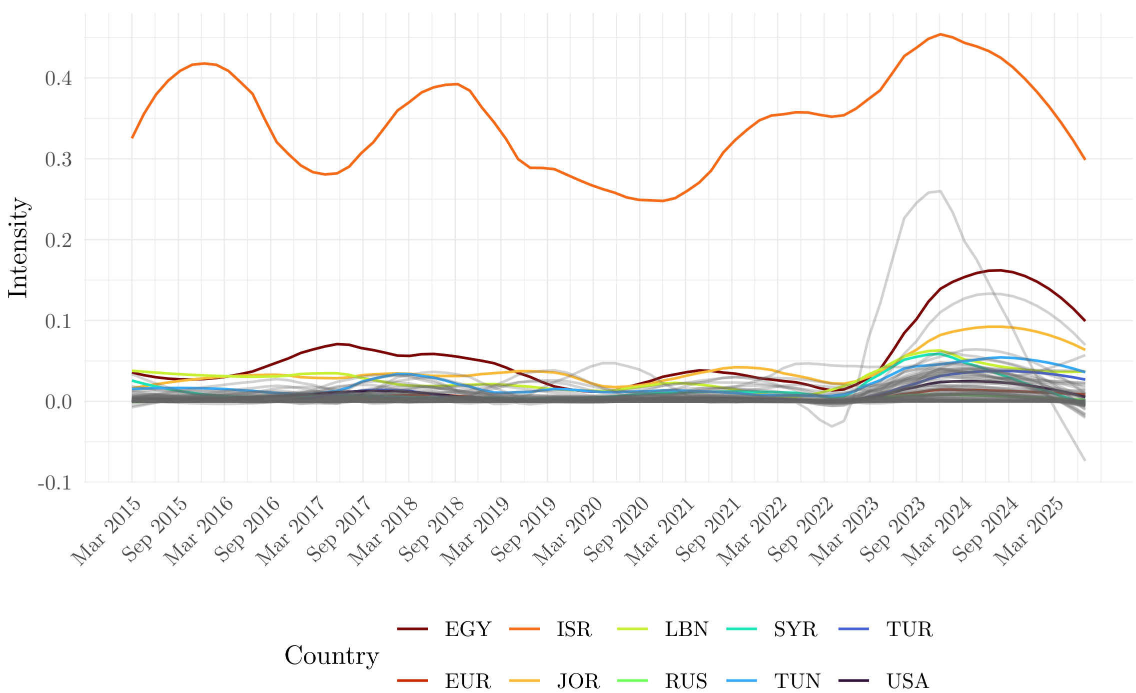
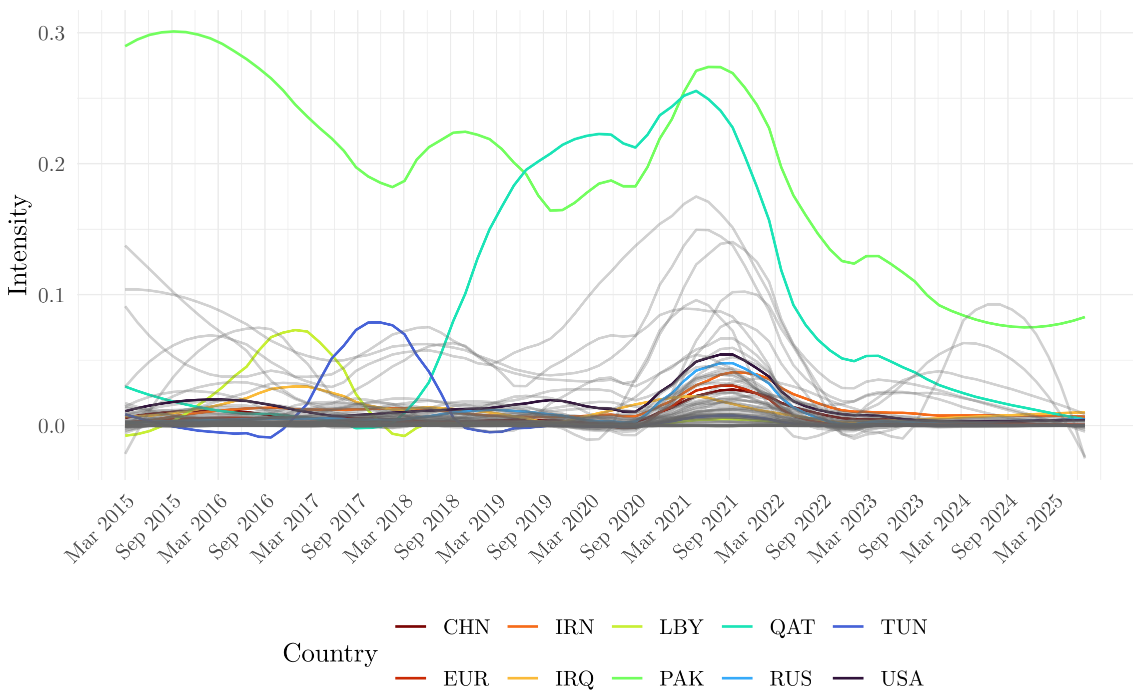


Figure 16: Temporal Dynamics of Palestine's Bilateral Intensity



the 2016–2024 period. Most of these variables are drawn from the CEPII GeoDist database (Mayer and Zignago, 2011) and are symmetric. With the exception of bilateral distance between countries i and j, all variables from this source are binary indicators taking the value 1

Figure 17: Temporal Dynamics of Afghanistan's Bilateral Intensity



when the two countries share a colonial relationship, a common border, a common language, or a common colonizer. In addition, we collect GDP data from the World Development Indicators 2025 (World Bank) to construct a yearly GDP ratio between countries i and j. This ratio captures the degree of asymmetry in the bilateral relationship, a key component of our Intensity indicator. We estimate specifications using the Intensity measure in levels and, subsequently, using its logarithmic transformation.

First, all columns in Table 15 display coefficients with the expected signs. The gravity-type dummies capture the presence of bilateral links between i and j, which naturally increase the Intensity of their relationship. Distance, as in standard trade applications, enters with a negative coefficient: the closer i and j are, the more intense their relationship tends to be. The GDP ratio also behaves as expected. A higher GDP for i relative to j reflects greater asymmetry in the bilateral relationship; in such cases, country j is less Intense for i than the reverse, which translates into a lower overall Intensity measure. Alternative specifications and fixed-effects structures do not materially alter these results. Nevertheless, we retain the logarithmic transformation of the Intensity indicator (or, subsequently, high- and low-Intensity dummies), as it provides a better overall fit with standard gravity variables.

C Comparison with other Geopolitical Databases

When introducing a new database, benchmarking it against existing sources constitutes a crucial step in the validation process. Such comparisons serve two purposes: (1) assessing whether the newly collected information subsumes what is already available, and (2) identifying the

Table 15: Correlation between the Intensity Indicator and usual Gravity Variables

Dep. Var.	Intensity_{ij}		$\ln(\text{Intensity}_{ij})$	
	(1)	(2)	(3)	(4)
$\ln\left(\frac{GDP_{it}}{GDP_{jt}}\right)$	-0.0060***	-0.0029**	-0.2638***	-0.2126***
	(0.0002)	(0.0014)	(0.0020)	(0.0290)
$\ln(\text{Distance}_{ij})$	-0.0056***	-0.0105***	-0.3783***	-0.7138***
	(0.0004)	(0.0004)	(0.0071)	(0.0076)
Contiguity_{ij}	0.0445***	0.0366***	1.090***	0.6444***
	(0.0019)	(0.0016)	(0.0229)	(0.0204)
$\text{Common Language}_{ij}$	0.0133***	0.0021**	0.5509***	0.3663***
	(0.0010)	(0.0009)	(0.0160)	(0.0170)
$\text{Colonial Links}_{ij}$	0.0319***	0.0266***	0.6169***	0.6342***
	(0.0023)	(0.0019)	(0.0285)	(0.0258)
$\text{Common Colonizer}_{ij}$	0.0067***	0.0041***	0.3404***	0.4967***
	(0.0012)	(0.0012)	(0.0216)	(0.0204)
FE: t	Yes	Yes	Yes	Yes
FE: i		Yes		Yes
FE: j		Yes		Yes
Observations	44,838	44,838	44,838	44,838
Adjusted R^2	0.18	0.48	0.41	0.67

Note: OLS estimations. Standard errors clustered at the exporter-importer-quarter level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

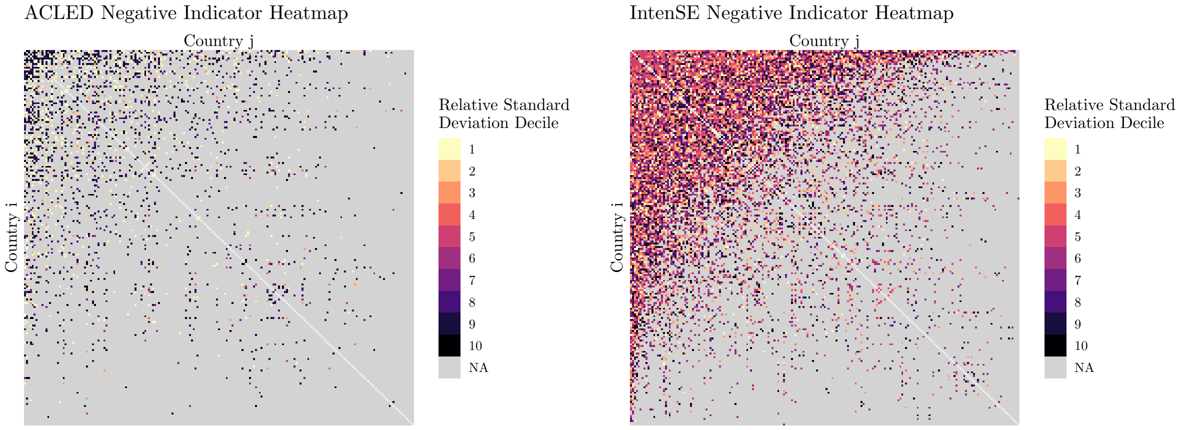
genuinely novel and relevant contributions. To this end, we compare the IntenSE database with two closely related datasets. The *Armed Conflict Location and Event Data* (ACLED) (Raleigh et al., 2023) documents instances of physical conflict, including their date, location, and the actors involved. Its main strength lies in the high level of precision of its event reporting, ranging from exact dating to detailed geocoding. The *United Nations General Assembly Voting Database* (UN Voting Database) (Bailey et al., 2017) measures ideological distances between countries based on their voting patterns. Its key advantage is its extensive coverage: since more than 90% of countries are UN members, the database provides information for the vast majority of possible country pairs worldwide.

C.1 Coverage

To address the first dimension of this comparison, we begin by examining the coverage of the databases. As previously noted, including the UN Voting Database would add little information; we therefore restrict the analysis to ACLED. Figure 18 presents two heatmaps reporting the relative standard deviation of the standardized indicators provided by ACLED and IntenSE for each country pair (i, j), with i on the y-axis and j on the x-axis. Each colored cell indicates whether the corresponding dyad is present in the dataset, while darker Shades denote higher monthly relative standard deviations. Countries are ordered along both axes according to the number of bilateral relationships they form.

The IntenSE database exhibits a substantially broader coverage of country pairs: over the period under study, ACLED provides information for 3,124 dyads, whereas IntenSE covers 12,766. ACLED also appears to capture dyads with markedly polarized patterns. Some display very high relative standard deviations, typically driven by infrequent but sharp spikes in reported events. Others show very low relative standard deviations, especially among dyads for which ACLED

Figure 18: ACLED vs. IntenSE Country Pairs Coverage (2015–2024)

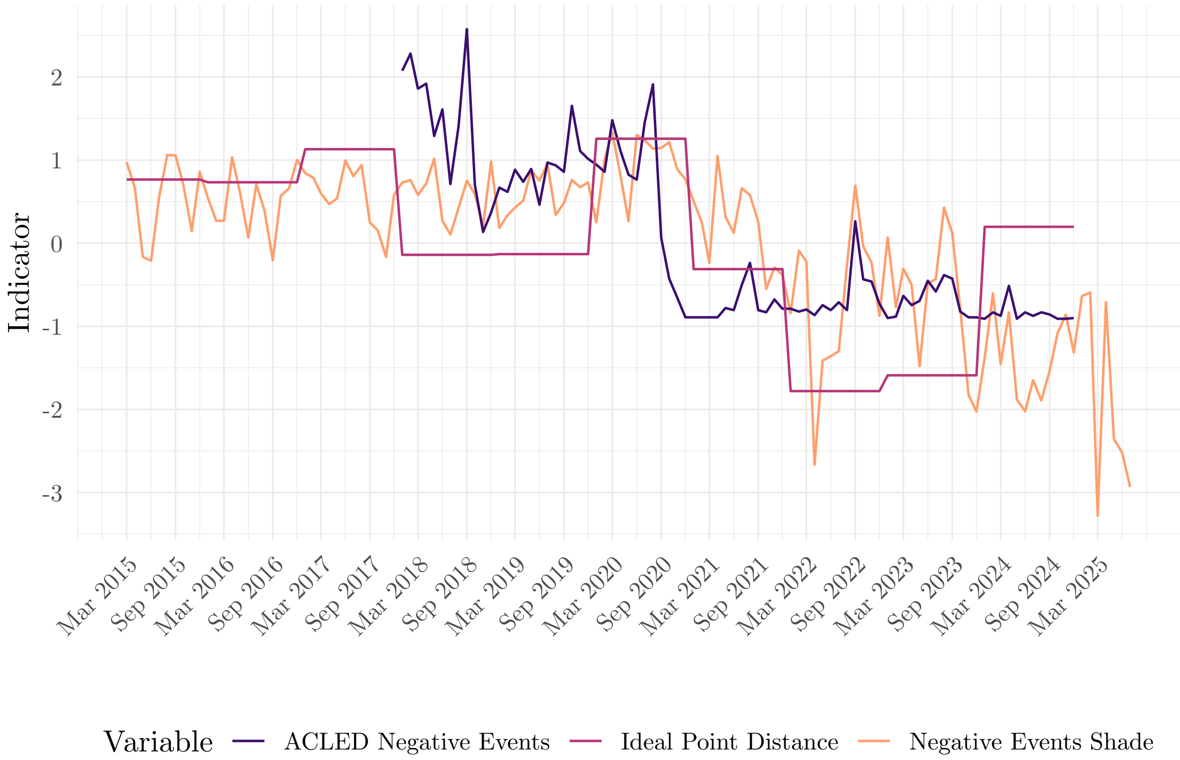


frequently records conflict events. Given ACLED's focus on physical violence, the latter pattern is characteristic of country pairs engaged in sustained conflict throughout much of the period. In contrast, the IntenSE database reveals a more continuous distribution of relative standard deviations, underscoring the heterogeneity of dyadic interactions captured by this broader measure.

C.2 Event Comparison

Extending the comparison to the analysis of specific dyads now makes it possible to incorporate the UN Voting Database into the exercise. Figure 19 displays the evolution of the indicators provided by the three datasets for the Armenia-Azerbaijan dyad, two countries that have experienced intermittent conflict since the dissolution of the Soviet Union. For this pair, we plot the normalized indicator provided by each of the three databases studied: the number of bilateral negative events reported by ACLED, the Ideal Point Distance between countries provided by the UN Voting Database, and the negative events Shade delivered by the IntenSE Database.

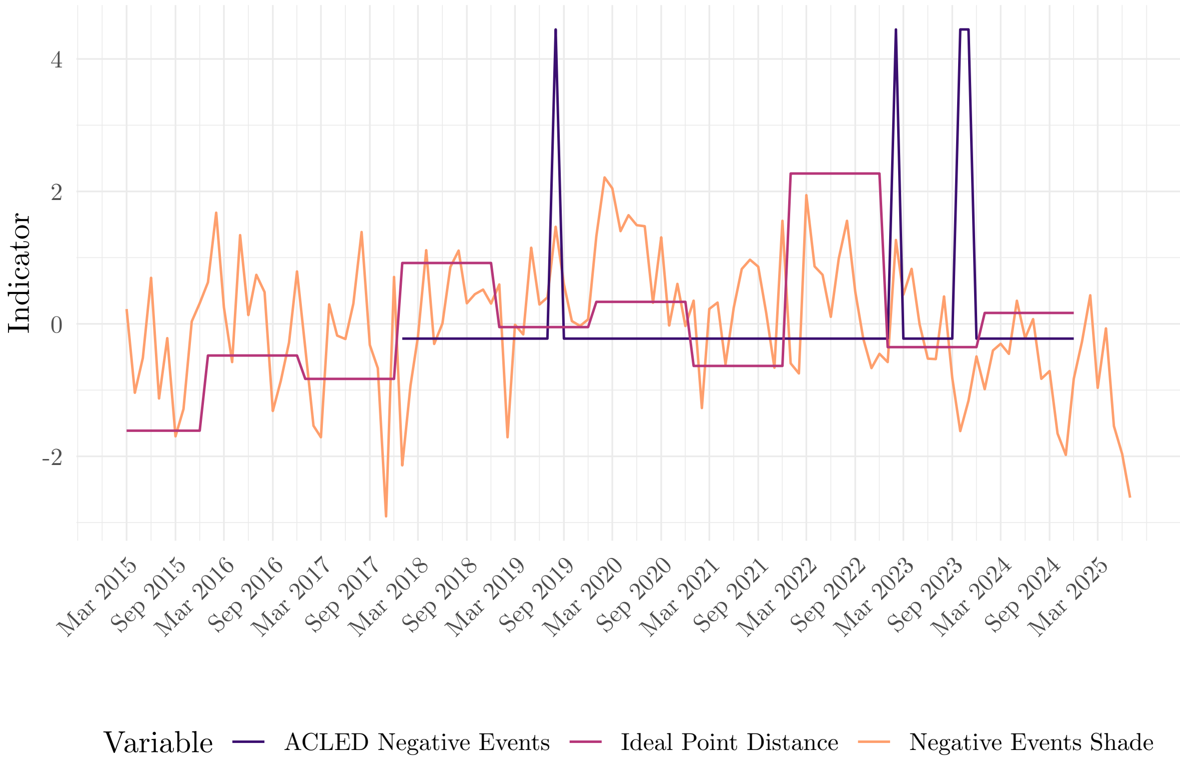
Figure 19: Comparison of Bilateral Indicators from IntenSE, ACLED, and UN Voting for the Armenia-Azerbaijan Dyad



Although the three series broadly align, several differences emerge at first glance. A first discrepancy concerns the coverage period: ACLED begins reporting events for this dyad only in January 2018, whereas IntenSE provides information over a longer horizon. Moreover, because the UN General Assembly meets only once per year, the UN Voting Database offers data at an annual frequency, leaving within-year dynamics unobserved. IntenSE appears to fill this gap by capturing short-term fluctuations. For instance, following the ceasefire signed in September 2020, ACLED reports no events for several subsequent months. The IntenSE database, however, records continued variation, reflecting hostile statements and ceasefire violations that are not captured by the other two datasets.

Similarly, Figure 20 displays the evolution of the indicators provided by the three datasets for the United States-China dyad, a country pair that particularly stands out for its recent geopolitical disputes. For this pair, we also plot the normalized indicator provided by each of the three databases studied: the number of bilateral negative events reported by ACLED, the Ideal Point Distance between countries provided by the UN Voting Database, and the negative events Shade delivered by the IntenSE Database.

Figure 20: Comparison of Bilateral Indicators from IntenSE, ACLED, and UN Voting for the China-USA Dyad



The Ideal Point Distance and the negative events Shade broadly align for this country pair, although the same discrepancy observed earlier remains: IntenSE provides monthly data that effectively fills the gaps left by the annual frequency of the UN Voting Database. Turning to ACLED, the dataset begins reporting events for this dyad in January 2018. The key observation is that, when focusing strictly on physical events, ACLED records almost none for the United States-China relationship (aside from anti-Chinese demonstrations in the United States). Most interactions between the two countries take the form of Negative Declarations or Actions, which are non-physical and therefore not captured by ACLED.

C.3 Correlations

To obtain a more comprehensive perspective, we compute correlations across datasets by sequentially regressing the number of negative events reported in ACLED and the Ideal Point Distance from the UN Voting Database on the negative events Shade indicator provided by IntenSE. The corresponding results are presented in Table 16.

The estimated coefficients remain highly significant even after sequentially introducing time, country-time, and dyad fixed effects. The R^2 provides additional insight into model fit. Once all fixed effects are included, the explanatory power is relatively strong for the Ideal Point Distance, suggesting that its variation is reasonably well accounted for by the negative events Shade, although some residual unexplained heterogeneity remains. By contrast, the explanatory power is markedly lower for the negative events reported in ACLED. This indicates that, while the two

Table 16: Correlations between IntenSE, ACLED and UN Voting Databases

Dep. Var.	ACLED Negative Events$_{ijt}$				Ideal Point Distance$_{ijt}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shade Neg.$_{ijt}$	7.551***	8.645***	7.165***	1.302***	0.1697***	0.1669***	0.0132***	0.0043***
	(0.4796)	(0.5781)	(0.8179)	(0.4223)	(0.0032)	(0.0032)	(0.0028)	(0.0006)
FE: t		Yes				Yes		
FE: i-t			Yes	Yes			Yes	Yes
FE: j-t			Yes	Yes			Yes	Yes
FE: i-j				Yes				Yes
Observations	150,208	150,208	145,516	145,492	444,696	444,696	441,324	441,248
Adjusted R^2	0.0007	0.002	-0.17	0.27	0.006	0.007	0.43	0.97

Note: OLS estimations. Standard errors clustered at the dyad-month level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

measures are correlated, substantial discrepancies persist, likely reflecting the broader set of interaction dimensions captured uniquely by the IntenSE database.

We now assess the predictive performance of the negative events Shade indicator for both physical conflict and the deterioration of diplomatic relations. To do so, we rely on the ACLED and UN Voting databases. All subsequent regressions include country-time fixed effects as well as country-pair fixed effects. The former absorb any time-varying country-specific factors, such as domestic political developments, macroeconomic conditions, or changes in media coverage, while the latter control for all time-invariant characteristics of each bilateral relationship, including geography, historical ties, or structural political affinities. This specification ensures that identification relies exclusively on within-dyad, over-time variation in the indicators of interest.

Physical Conflicts: ACLED

We begin by examining the extent to which the negative events Shade indicator predicts subsequent Violence. To do so, we use the monthly number of Violent events reported by ACLED and regress this outcome on various aggregations of the negative events Shade indicator, each lagged by one month. The results from the initial OLS specifications are presented in Table 17.

Table 17: ACLED Violent Events Prediction I: OLS

Dep. Var.	ACLED Violent Events$_{ijt}$			
	Month	Quarter	Semester	Year
	(1)	(2)	(3)	(4)
Shade Negative$_{ijt-1}$	2.656***	9.088***	11.33***	11.90***
	(0.8539)	(2.387)	(2.908)	(2.873)
Observations	97,592	71,690	61,914	57,642
Adjusted R^2	0.17	0.13	0.12	0.12

Note: OLS estimations. All specifications include country i-month, country j-month, and country i-country j fixed effects. Standard errors clustered at the country i-country j-month level in parentheses. The dependent variable is measured at different temporal aggregations. Column (1) uses the baseline monthly indicator. Column (2) uses a three-month rolling indicator constructed from articles published over months t-1 to t-3. Columns (3) and (4) analogously use six-month and twelve-month rolling indicators, respectively. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

The OLS estimates are positive and statistically significant, and their magnitude increases with the length of the negative events Shade aggregation considered. According to the first column, a ten-percentage-point increase in the negative events Shade lagged by one month is associated with an additional 0.27 violent events reported by ACLED in the subsequent month. However, because the number of violent events is a count variable and is therefore more appropriately modeled using a Poisson distribution, we also estimate PPML specifications. The corresponding results are reported in Table 18.

Table 18: ACLED Violent Events Prediction II: PPML

Dep. Var.	ACLED Violent Events$_{ijt}$			
	Month	Quarter	Semester	Year
	(1)	(2)	(3)	(4)
Shade Negative$_{ijt-1}$	1.110***	2.148***	2.918***	2.913***
	(0.1536)	(0.2832)	(0.3818)	(0.4573)
Observations	33,510	24,234	21,560	19,952
Pseudo R^2	0.99	0.99	0.99	0.99

Note: PPML estimations. All specifications include country i-month, country j-month, and country i-country j fixed effects. Standard errors clustered at the country i-country j-month level in parentheses. The dependent variable is measured at different temporal aggregations. Column (1) uses the baseline monthly indicator. Column (2) uses a three-month rolling indicator constructed from articles published over months t-1 to t-3. Columns (3) and (4) analogously use six-month and twelve-month rolling indicators, respectively. *** p<0.01, ** p<0.05, * p<0.1.

The PPML estimates yield similar results, with positive and statistically significant coefficients. Their magnitude generally increases with the length of the Negative Events Shade aggregation, except for the yearly measure, which is comparable to the semester aggregation. According to the first column, a ten-percentage-point increase in the lagged Negative Events Shade is associated with a 0.11% rise in violent events reported by ACLED the following month. Because PPML drops fixed-effects cells in which the dependent variable is always zero, the number of observations used in these regressions is smaller than in the OLS specifications (see Table 17). This primarily reflects the large share of country pairs that never experience violent events. Given this pattern, it is natural to complement the intensive-margin analysis with an examination of the extensive margin. We therefore construct a binary indicator equal to one whenever ACLED reports at least one violent event in a given month, and zero otherwise, and regress it on the same aggregations of the negative events Shade. The corresponding results are presented in Table 19.

These LPM results are more mixed, with fewer coefficients reaching statistical significance, except for the quarterly aggregation of the negative events Shade. As before, the estimated effects tend to increase with the length of the aggregation window, although the yearly measure is now smaller than the semester aggregation. According to the second column, a ten-percentage-point increase in the quarterly negative events Shade raises the probability that ACLED reports at least one violent event in the following month by 0.16%.

Table 19: ACLED Violent Events Prediction III: LPM

Dep. Var.	ACLED Violent Events Dummy_{ijt}			
	Month	Quarter	Semester	Year
	(1)	(2)	(3)	(4)
Shade $\text{Negative}_{ijt\text{-}1}$	0.0052*	0.0162***	0.0175**	0.0129*
	(0.0027)	(0.0055)	(0.0069)	(0.0074)
Observations	97,592	71,690	61,914	57,642
Adjusted R^2	0.45	0.49	0.50	0.51

Note: OLS estimations. All specifications include country i-month, country j-month, and country i-country j fixed effects. Standard errors clustered at the country i-country j-month level in parentheses. The dependent variable is measured at different temporal aggregations. Column (1) uses the baseline monthly indicator. Column (2) uses a three-month rolling indicator constructed from articles published over months t-1 to t-3. Columns (3) and (4) analogously use six-month and twelve-month rolling indicators, respectively. *** p<0.01, ** p<0.05, * p<0.1.

Diplomatic Relationships Deterioration: UN Voting

Since the negative events Shade encompasses all types of negative geopolitical interactions between two countries, we next examine whether it can predict a deterioration in diplomatic relations. Following the same empirical strategy as in the previous section, we regress the Ideal Point Distance from the UN Voting Database on various aggregations of the negative events Shade. The corresponding OLS results are reported in Table 20.

Table 20: UN Voting Diplomatic Relationships Deterioration Prediction I: Monthly OLS

Dep. Var.	Ideal Point Distance_{ijt}			
	Month	Quarter	Semester	Year
	(1)	(2)	(3)	(4)
Shade $\text{Negative}_{ijt\text{-}1}$	0.0044***	0.0132***	0.0141***	0.0153***
	(0.0006)	(0.0014)	(0.0018)	(0.0019)
Observations	441,902	260,630	203,234	180,952
Adjusted R^2	0.97	0.97	0.98	0.98

Note: OLS estimations. All specifications include country i-month, country j-month, and country i-country j fixed effects. Standard errors clustered at the country i-country j-month level in parentheses. The dependent variable is measured at different temporal aggregations. Column (1) uses the baseline monthly indicator. Column (2) uses a three-month rolling indicator constructed from articles published over months t-1 to t-3. Columns (3) and (4) analogously use six-month and twelve-month rolling indicators, respectively. *** p<0.01, ** p<0.05, * p<0.1.

The estimates are positive and statistically significant, and their magnitude increases with the length of the negative events Shade aggregation. According to the first column, a ten-percentage-point increase in the lagged negative events Shade is associated with a 0.04 rise in the Ideal Point Distance in the following period. It is important to note, however, that the UN Voting Database provides only annual observations, as the UN General Assembly meets once per year. To assess the robustness of these results, we therefore recompute the negative events Shade indicator at an annual frequency and regress the Ideal Point Distance on this yearly measure. The corresponding estimates are reported in Table 21.

Table 21: UN Voting Diplomatic Relationships Deterioration Prediction II: Yearly OLS

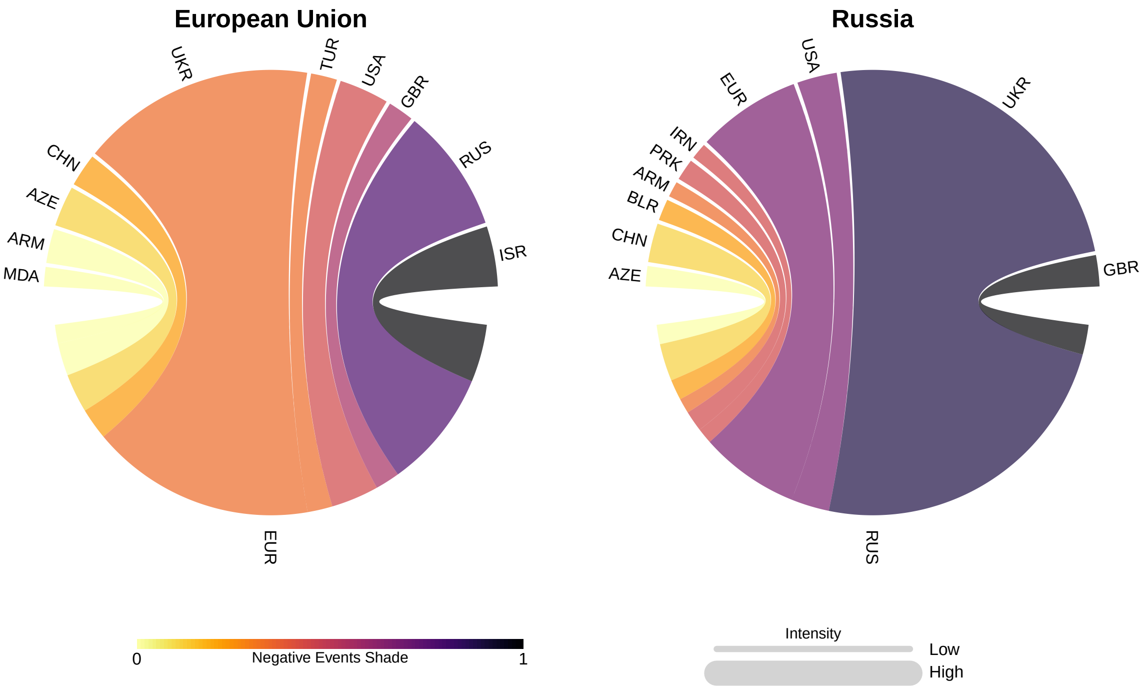
Dep. Var.	Ideal Point Distance$_{ijt}$	
	(1)	(2)
Shade Negative$_{ijt}$	0.0176***	
	(0.0034)	
Shade Negative$_{ijt-1}$		0.0205***
		(0.0036)
Observations	64,212	58,822
Adjusted R^2	0.97	0.97

Note: OLS estimations. All specifications include country i-year, country j-year, and country i-country j fixed effects. Standard errors clustered at the country i-country j-year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Both the contemporaneous and lagged coefficients are positive and statistically significant, with the lagged effect being slightly larger in magnitude. According to the first column, a ten-percentage-point increase in the yearly negative events Shade is associated with a 0.0018 rise in the Ideal Point Distance in the same year. This estimate is very close to the effect reported in column (4) of Table 20, thereby reinforcing the consistency of our previous findings.

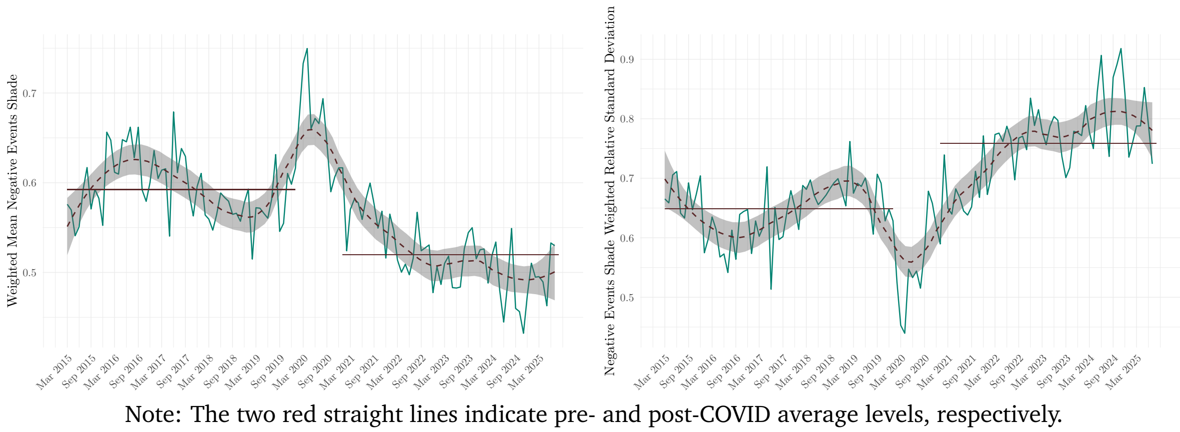
D Additional Stylized Facts

Figure 21: Media-Reported Interaction Patterns for the European Union and Russia (2024)



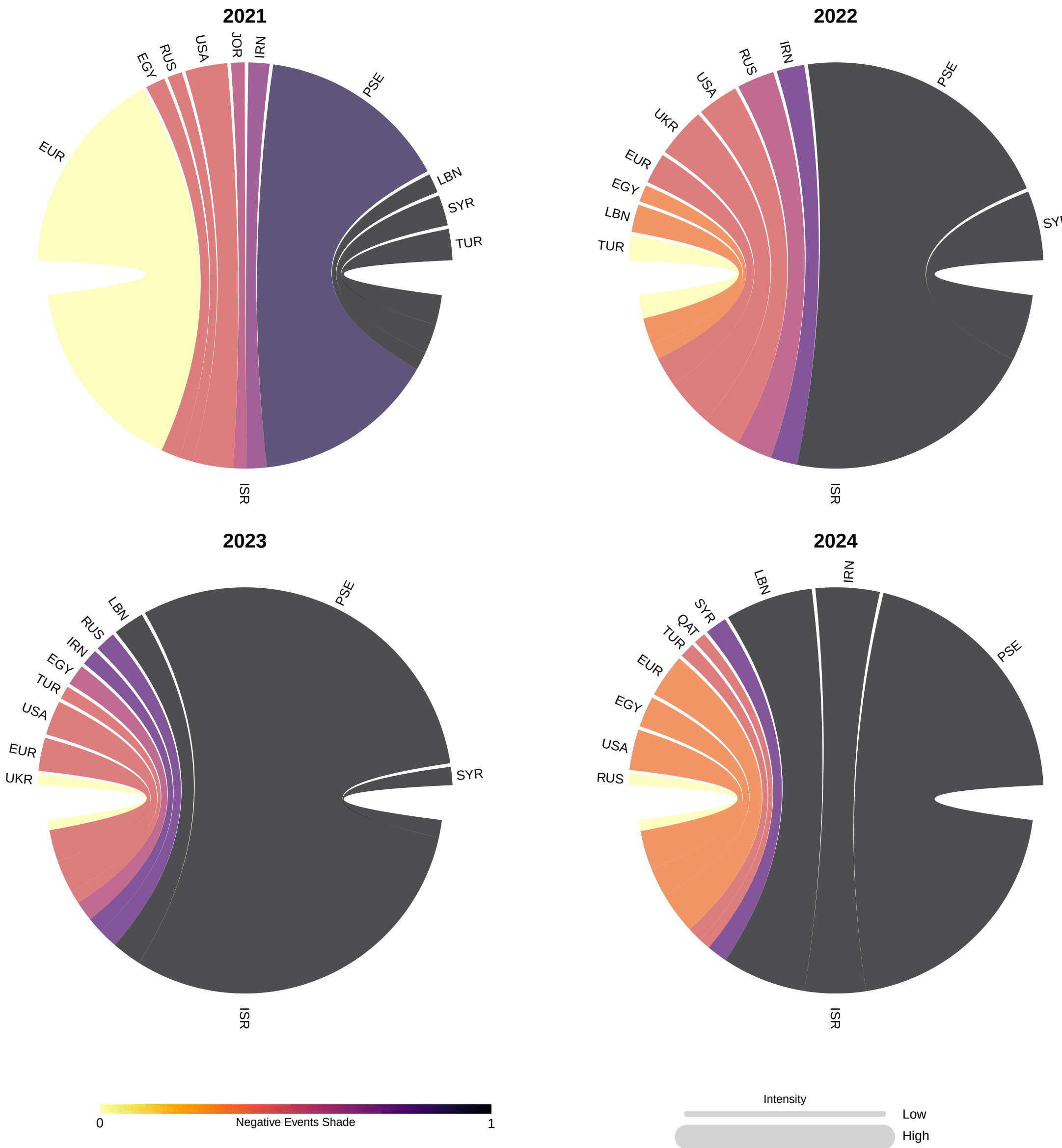
Note: The figure displays the Negative events Shade and Intensity indicators for links between the European Union, Russia, and their ten most intense relationships. Darker lines indicate a more negative bilateral tone (higher Shade), while thicker lines reflect greater relationship Intensity. Country labels follow ISO 3-letter codes.

Figure 26: Monthly Negative Events Shade Weighted Mean (left panel) and Weighted Relative Standard Deviation (right panel)



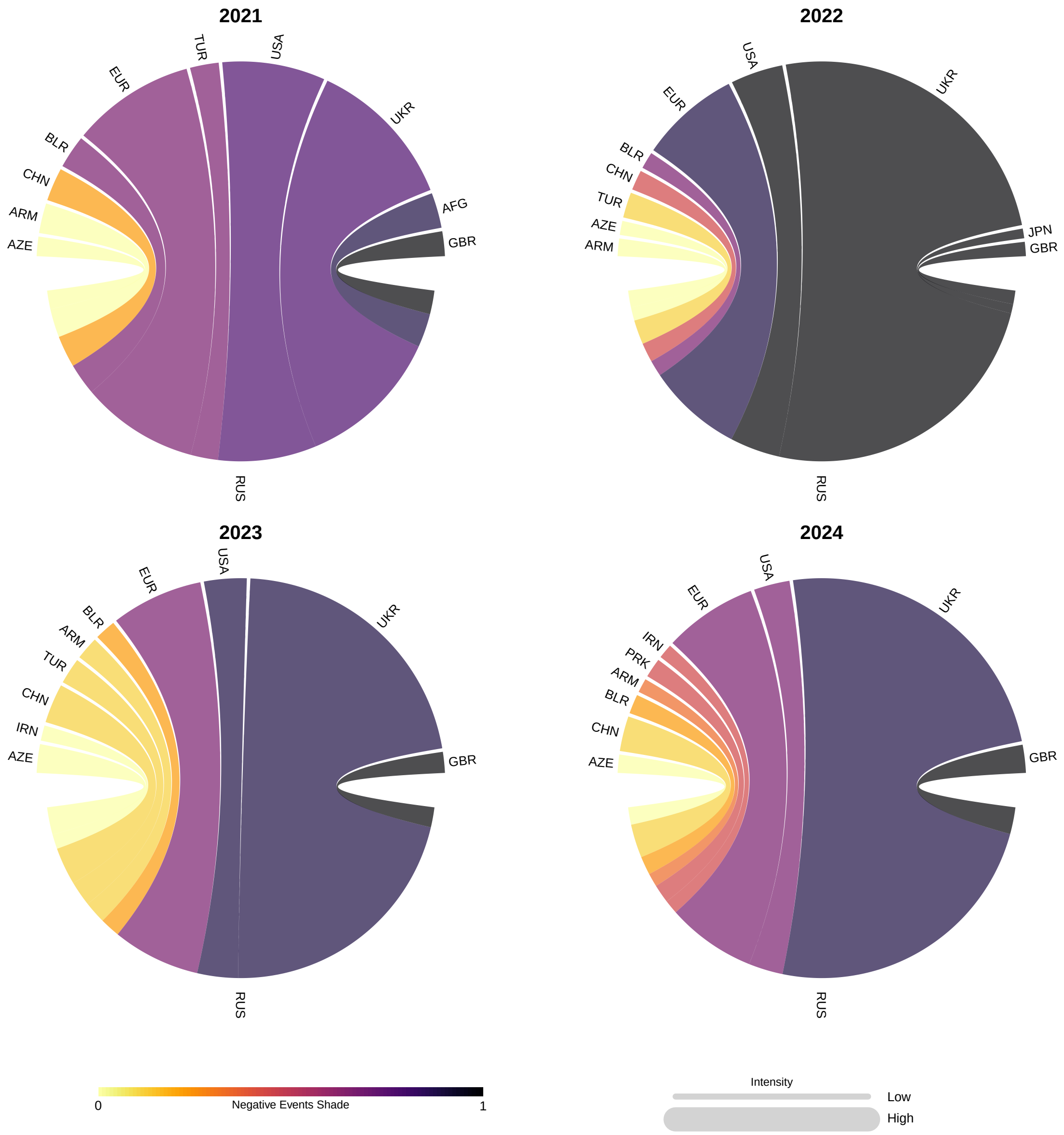
Note: The two red straight lines indicate pre- and post-COVID average levels, respectively.

Figure 22: Media-Reported Interaction Patterns for Israel (2021–2024)



Note: The figure displays the Negative events Shade and Intensity indicators for links between Israel and its ten most intense relationships over the 2021–2024 period. Darker lines indicate a more negative bilateral tone (higher Shade), while thicker lines reflect greater relationship Intensity. Country labels follow ISO 3-letter codes.

Figure 23: Media-Reported Interaction Patterns for Russia (2021–2024)



Note: The figure displays the Negative events Shade and Intensity indicators for links between Russia and its ten most intense relationships over the 2021–2024 period. Darker lines indicate a more negative bilateral tone (higher Shade), while thicker lines reflect greater relationship Intensity. Country labels follow ISO 3-letter codes.

Figure 24: Yearly Negative Events Shade and Intensity Difference (2021–2024) for the USA and China

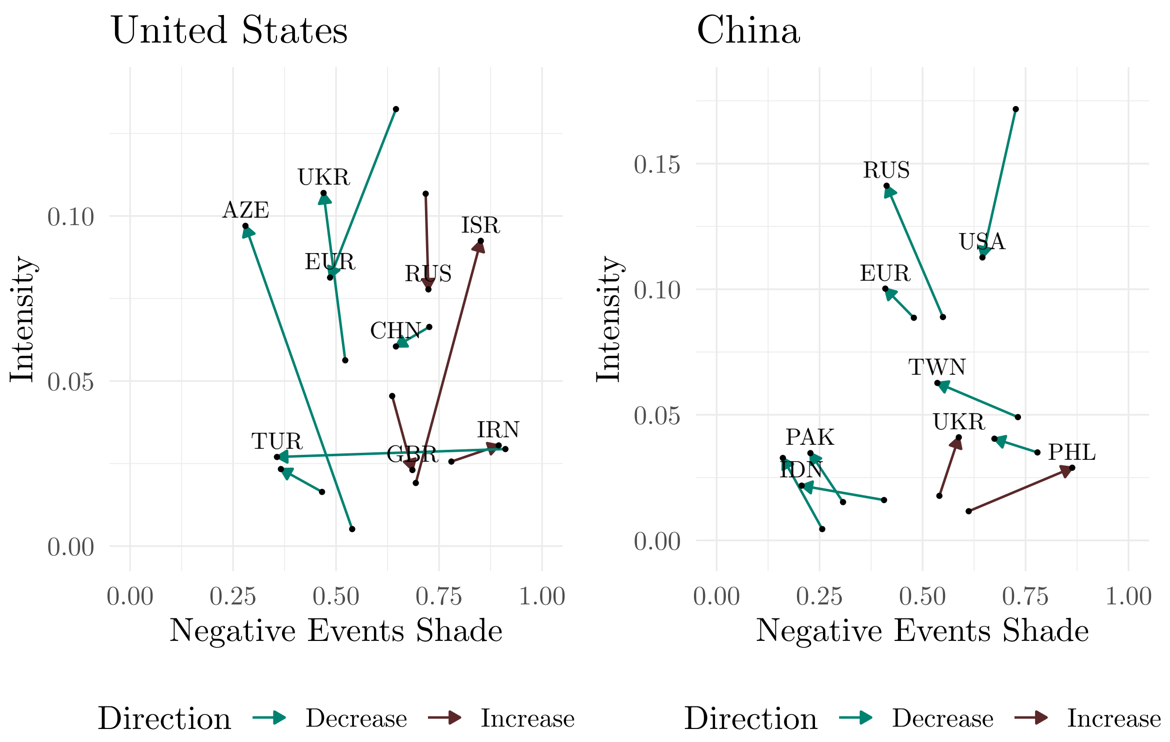
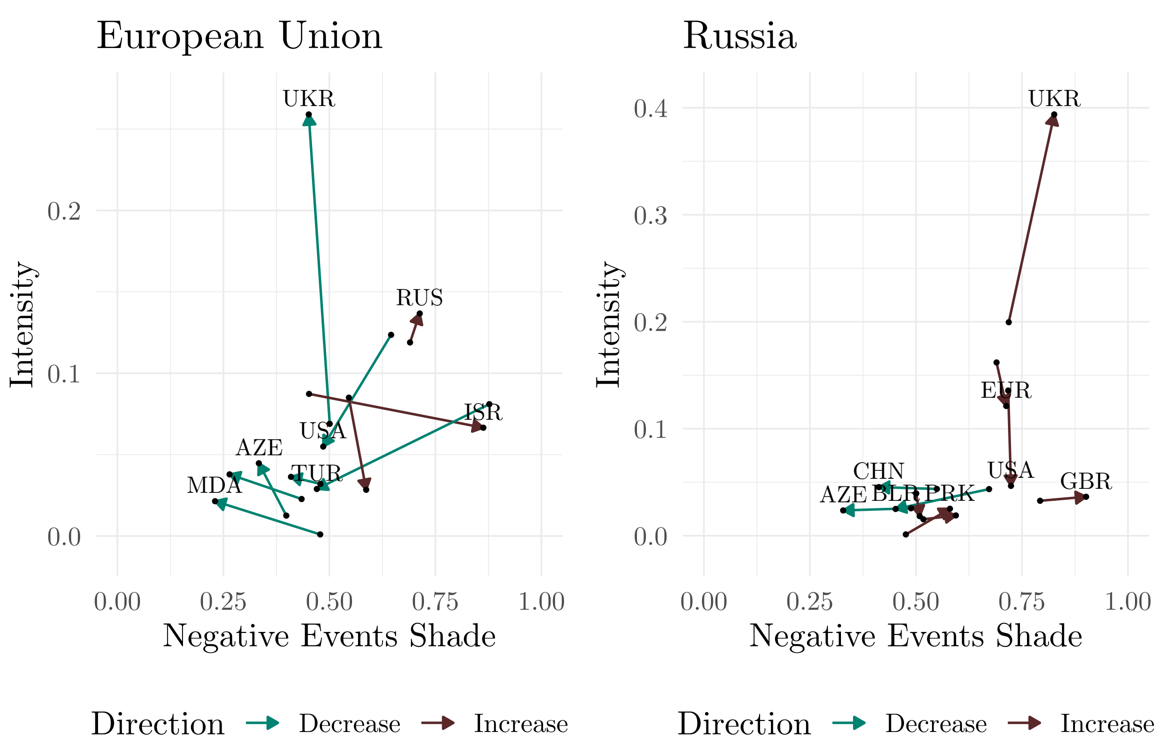


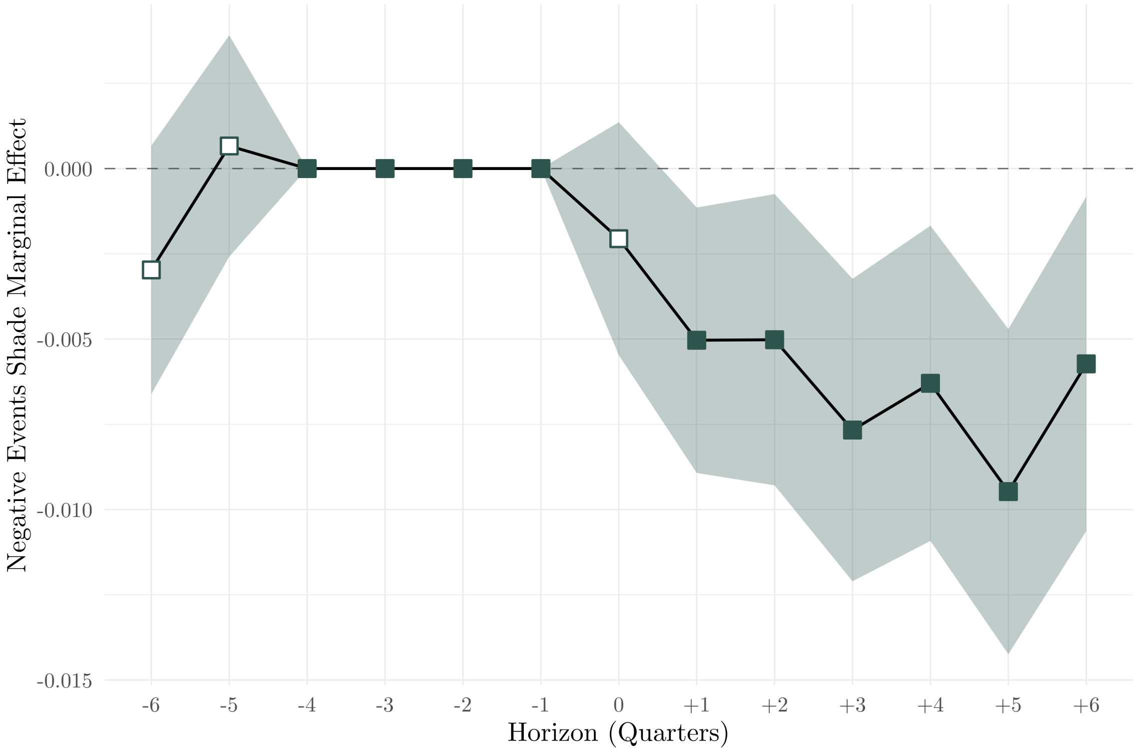
Figure 25: Yearly Negative Events Shade and Intensity Difference (2021–2024) for the European Union and Russia



E Additional Results

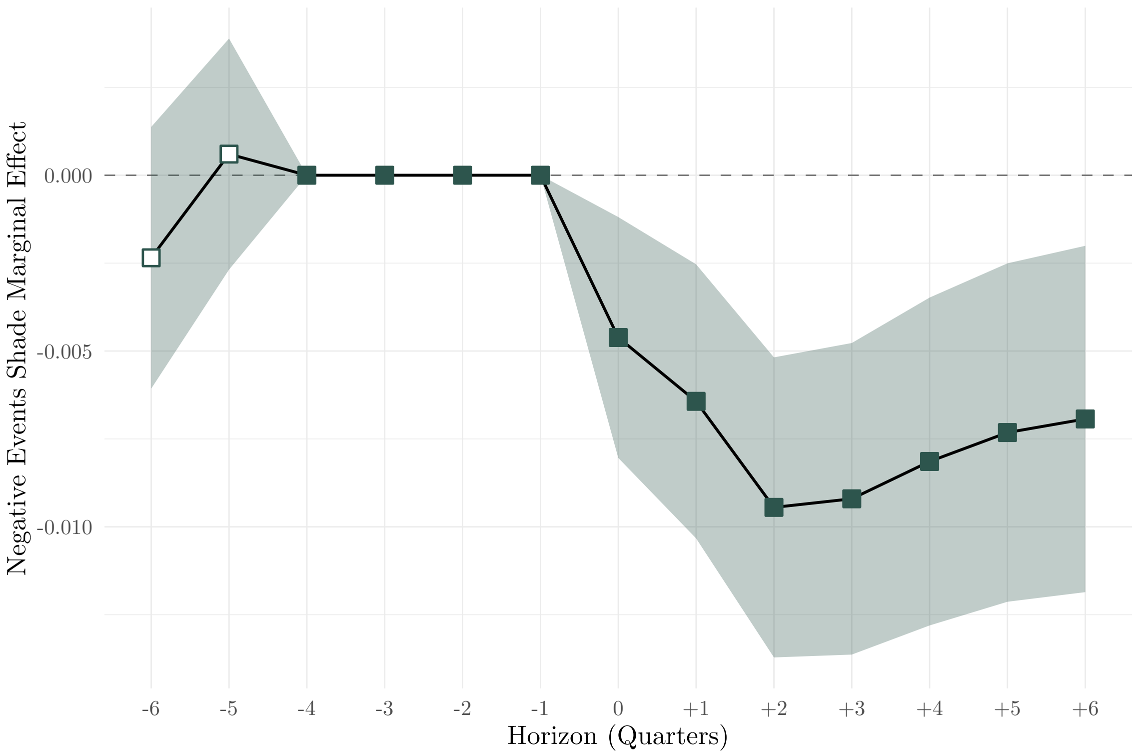
E.1 Local Projections

Figure 27: Bilateral Trade Response to Geopolitical Climate Deterioration: OECD+BRICS Exporters



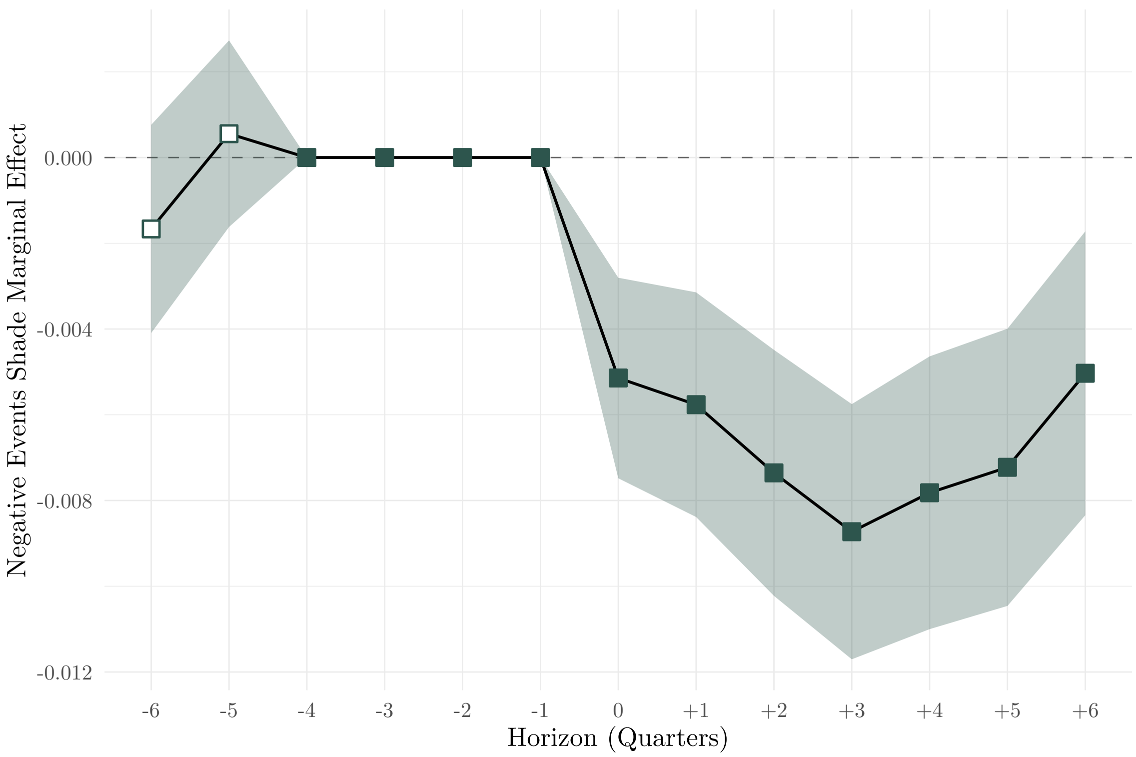
Note: Filled marks indicate significant coefficients at the 10% level.

Figure 28: Bilateral Trade Response to Geopolitical Climate Deterioration: Excluding COVID



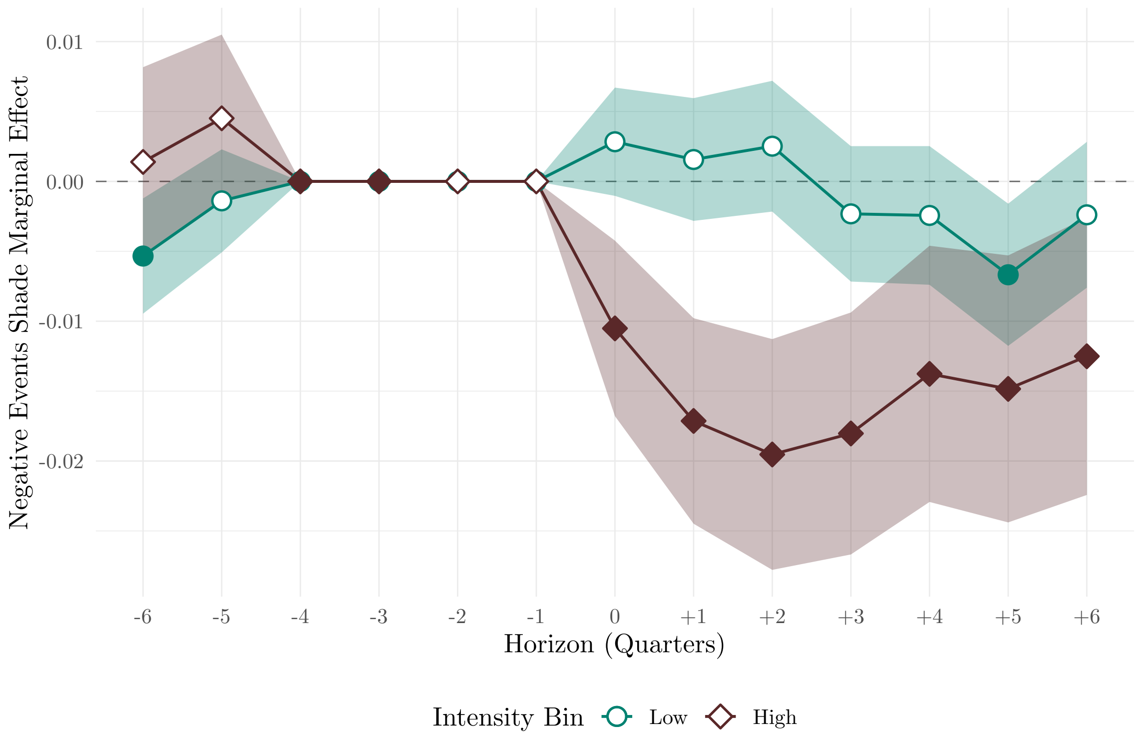
Note: Filled marks indicate significant coefficients at the 10% level.

Figure 29: Bilateral Trade Response to Geopolitical Climate Deterioration: Without Shade Controls



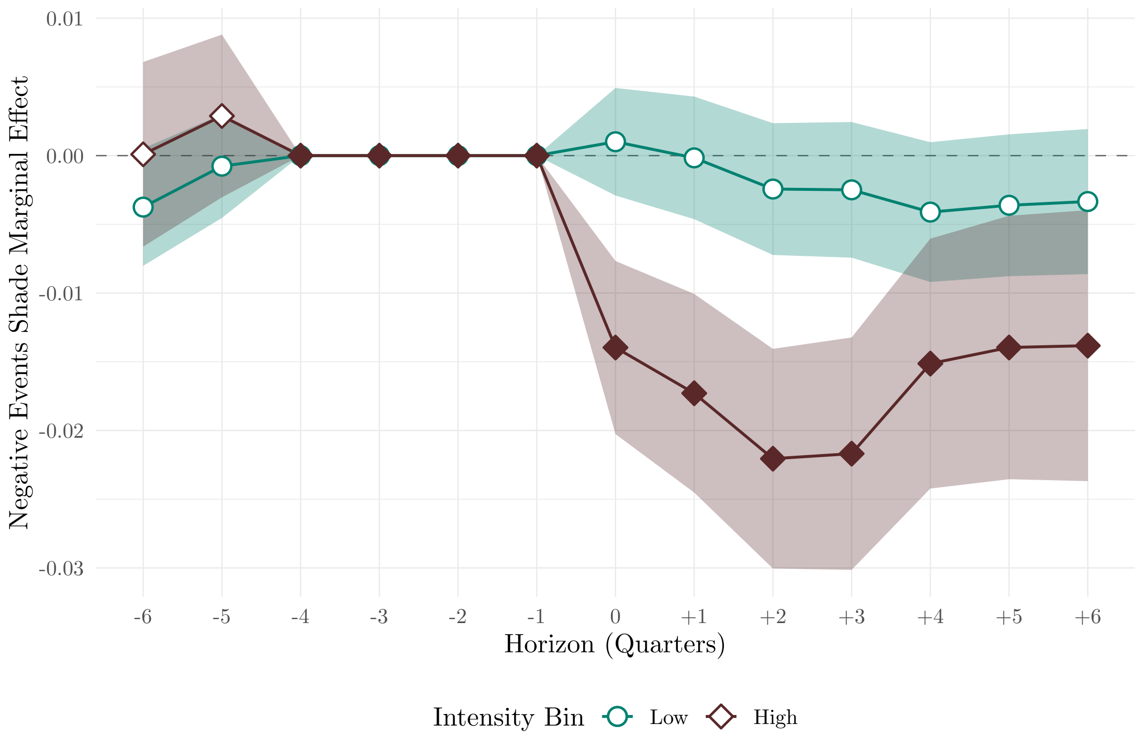
Note: Filled marks indicate significant coefficients at the 10% level.

Figure 30: Bilateral Trade Response to Geopolitical Climate Deterioration for High and Low Intensity Relationships: OECD+BRICS Exporters



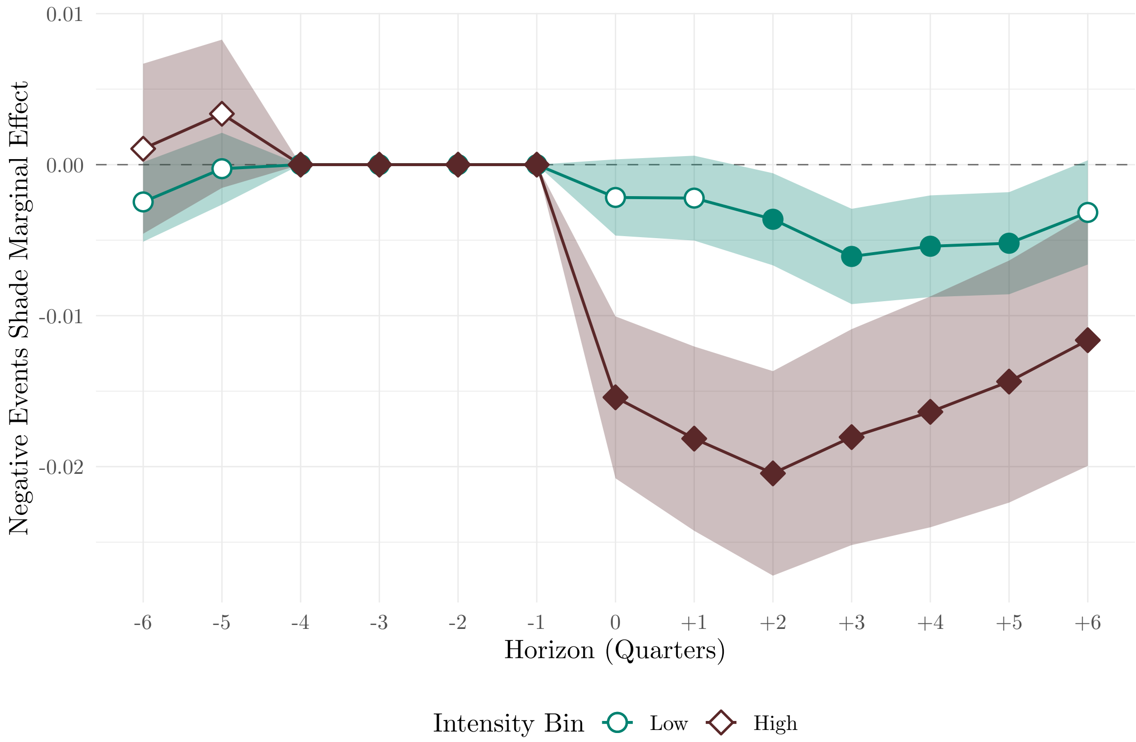
Note: Filled marks indicate significant coefficients at the 10% level.

Figure 31: Bilateral Trade Response to Geopolitical Climate Deterioration for High and Low Intensity Relationships: Excluding COVID



Note: Filled marks indicate significant coefficients at the 10% level.

Figure 32: Bilateral Trade Response to Geopolitical Climate Deterioration for High and Low Intensity Relationships: Without Shade Controls



Note: Filled marks indicate significant coefficients at the 10% level.

Table 22: Local Projections Detailed Results

	$\ln(M_{ijkt-6})$ (1)	$\ln(M_{ijkt-5})$ (2)	$\ln(M_{ijkt})$ (3)	$\ln(M_{ijkt+1})$ (4)	$\ln(M_{ijkt+2})$ (5)	$\ln(M_{ijkt+3})$ (6)	$\ln(M_{ijkt+4})$ (7)	$\ln(M_{ijkt+5})$ (8)	$\ln(M_{ijkt+6})$ (9)
Whole Sample									
Shade Negative$_{ijt}$	-0.0017	0.0010	-0.0044**	-0.0061***	-0.0085***	-0.0089***	-0.0074***	-0.0095***	-0.0073***
	(0.0020)	(0.0018)	(0.0019)	(0.0022)	(0.0024)	(0.0025)	(0.0026)	(0.0027)	(0.0027)
OECD+BRICS Exporters									
Shade Negative$_{ijt}$	-0.0030	0.0007	-0.0021	-0.0050**	-0.0050*	-0.0077***	-0.0063**	-0.0095***	-0.0057*
	(0.0022)	(0.0020)	(0.0021)	(0.0024)	(0.0026)	(0.0027)	(0.0028)	(0.0029)	(0.0030)
Excluding COVID									
Shade Negative$_{ijt}$	-0.0023	0.0006	-0.0046**	-0.0064***	-0.0094***	-0.0092***	-0.0081***	-0.0073**	-0.0069**
	(0.0023)	(0.0020)	(0.0021)	(0.0024)	(0.0026)	(0.0027)	(0.0028)	(0.0029)	(0.0030)
Violent vs. Non Violent Events									
Shade Violence$_{ijt}$	0.0031	0.0009	-0.0002	-0.0067*	-0.0076*	-0.0069	-0.0064	-0.0122***	-0.0093*
	(0.0035)	(0.0031)	(0.0033)	(0.0037)	(0.0041)	(0.0043)	(0.0045)	(0.0047)	(0.0048)
Shade Non-Violence$_{ijt}$	-0.0025	0.0010	-0.0052***	-0.0060***	-0.0087***	-0.0092***	-0.0076***	-0.0091***	-0.0070**
	(0.0021)	(0.0019)	(0.0020)	(0.0023)	(0.0025)	(0.0025)	(0.0027)	(0.0027)	(0.0028)
Whole Sample, Without Shade Controls									
Shade Negative$_{ijt}$	-0.0017	0.0006	-0.0051***	-0.0058***	-0.0074***	-0.0087***	-0.0078***	-0.0072***	-0.0050**
	(0.0015)	(0.0013)	(0.0014)	(0.0016)	(0.0017)	(0.0018)	(0.0019)	(0.0020)	(0.0020)
Whole Sample, Intensity Bins									
Shade Negative$_{ijt}$	-0.0031	-0.0007	0.0007	-0.0005	-0.0020	-0.0034	-0.0034	-0.0063**	-0.0039
$\times\mathbb{1}_{\{Low\ \mathbb{I}_{ij}\}}$	(0.0023)	(0.0021)	(0.0022)	(0.0024)	(0.0026)	(0.0027)	(0.0028)	(0.0028)	(0.0029)
Shade Negative$_{ijt}$	0.0009	0.0040	-0.0133***	-0.0160***	-0.0207***	-0.0193***	-0.0149***	-0.0152***	-0.0140**
$\times\mathbb{1}_{\{High\ \mathbb{I}_{ij}\}}$	(0.0037)	(0.0033)	(0.0035)	(0.0041)	(0.0045)	(0.0048)	(0.0051)	(0.0053)	(0.0055)
Whole Sample, Intensity Bins, OECD+BRICS Exporters									
Shade Negative$_{ijt}$	-0.0053**	-0.0014	0.0028	0.0016	0.0025	-0.0023	-0.0024	-0.0067**	-0.0024
$\times\mathbb{1}_{\{Low\ \mathbb{I}_{ij}\}}$	(0.0025)	(0.0022)	(0.0024)	(0.0027)	(0.0028)	(0.0029)	(0.0030)	(0.0031)	(0.0032)
Shade Negative$_{ijt}$	0.0014	0.0045	-0.0105***	-0.0171***	-0.0195***	-0.0180***	-0.0138**	-0.0148**	-0.0125**
$\times\mathbb{1}_{\{High\ \mathbb{I}_{ij}\}}$	(0.0041)	(0.0036)	(0.0038)	(0.0045)	(0.0050)	(0.0053)	(0.0056)	(0.0058)	(0.0060)
Whole Sample, Intensity Bins, Excluding COVID									
Shade Negative$_{ijt}$	-0.0037	-0.0008	0.0010	-0.0002	-0.0024	-0.0025	-0.0041	-0.0036	-0.0033
$\times\mathbb{1}_{\{Low\ \mathbb{I}_{ij}\}}$	(0.0026)	(0.0023)	(0.0024)	(0.0027)	(0.0029)	(0.0030)	(0.0031)	(0.0031)	(0.0032)
Shade Negative$_{ijt}$	9.49×10^{-5}	0.0029	-0.0140***	-0.0173***	-0.0220***	-0.0217***	-0.0151***	-0.0140**	-0.0138**
$\times\mathbb{1}_{\{High\ \mathbb{I}_{ij}\}}$	(0.0041)	(0.0036)	(0.0038)	(0.0044)	(0.0049)	(0.0051)	(0.0055)	(0.0058)	(0.0060)
Whole Sample, Intensity Bins, Without Shade Controls									
Shade Negative$_{ijt}$	-0.0025	-0.0003	-0.0022	-0.0022	-0.0036*	-0.0061***	-0.0054***	-0.0052**	-0.0032
$\times\mathbb{1}_{\{Low\ \mathbb{I}_{ij}\}}$	(0.0016)	(0.0014)	(0.0015)	(0.0017)	(0.0019)	(0.0019)	(0.0020)	(0.0021)	(0.0021)
Shade Negative$_{ijt}$	0.0011	0.0034	-0.0154***	-0.0181***	-0.0204***	-0.0180***	-0.0164***	-0.0144***	-0.0116**
$\times\mathbb{1}_{\{High\ \mathbb{I}_{ij}\}}$	(0.0034)	(0.0030)	(0.0033)	(0.0037)	(0.0041)	(0.0043)	(0.0046)	(0.0049)	(0.0051)

Note: OLS estimations. All specifications include exporter-product-quarter, importer-product-quarter, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-quarter level in parentheses. Lags -4 to -1 are not reported, as they are absorbed by the lags of the dependent variable included in the regression. *** p<0.01, ** p<0.05, * p<0.1.

E.2 Structural Gravity

Table 23: Impact of Negative Events on Bilateral Trade - Gravity Estimates (Quarterly Negative Events Shade)

Dep. Var.	Import Share$_{ijkt}$					
		Full Sample			Excl. Zero Trade Flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Shade Negative$_{ijt-1}$	-0.0112***	-0.0130***		-0.0056***	-0.0072***	
	(0.0041)	(0.0043)		(0.0018)	(0.0019)	
Shade Negative$_{ijt-1}$ $\times\ln(\bar{\mathbb{I}}_{ij})$		-0.0084**			-0.0075***	
		(0.0036)			(0.0017)	
Shade Negative$_{ijt-1}$ $\times\mathbb{1}_{\{Low\ \bar{\mathbb{I}}_{ij}\}}$			-0.0031			0.0011
			(0.0043)			(0.0020)
Shade Negative$_{ijt-1}$ $\times\mathbb{1}_{\{High\ \bar{\mathbb{I}}_{ij}\}}$			-0.0291***			-0.0205***
			(0.0082)			(0.0034)
Observations	59,650,000	59,650,000	59,650,000	42,047,994	42,047,994	42,047,994
Pseudo R^2	0.38	0.38	0.38	0.36	0.36	0.36

Note: PPML estimations. All specifications include exporter-product-quarter, importer-product-quarter, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-quarter level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 24: Impact of Violent vs. Non Violent Events on Bilateral Trade

Dep. Var.	Import Share$_{ijkt}$					
		Full Sample			Excl. Zero Trade Flows	
	(1)	(2)	(3)	(4)	(5)	(6)
Shade Violence$_{ijt-1}$	-0.0246**	-0.0270**		-0.0135***	-0.0164***	
	(0.0103)	(0.0107)		(0.0047)	(0.0049)	
Shade Non-Violence$_{ijt-1}$	-0.0210***	-0.0226***		-0.0113***	-0.0136***	
	(0.0064)	(0.0067)		(0.0029)	(0.0030)	
Shade Violence$_{ijt-1}$ $\times\ln(\bar{\mathbb{I}}_{ij})$		-0.0180*			-0.0202***	
		(0.0099)			(0.0048)	
Shade Non-Violence$_{ijt-1}$ $\times\ln(\bar{\mathbb{I}}_{ij})$		-0.0097			-0.0162***	
		(0.0061)			(0.0029)	
Shade Violence$_{ijt-1}$ $\times\mathbb{1}_{\{Low\ \bar{\mathbb{I}}_{ij}\}}$			-0.0237**			0.0054
			(0.0115)			(0.0053)
Shade Violence$_{ijt-1}$ $\times\mathbb{1}_{\{High\ \bar{\mathbb{I}}_{ij}\}}$			-0.0291			-0.0442***
			(0.0182)			(0.0083)
Shade Non-Violence$_{ijt-1}$ $\times\mathbb{1}_{\{Low\ \bar{\mathbb{I}}_{ij}\}}$			-0.0028			0.0015
			(0.0070)			(0.0035)
Shade Non-Violence$_{ijt-1}$ $\times\mathbb{1}_{\{High\ \bar{\mathbb{I}}_{ij}\}}$			-0.0521***			-0.0332***
			(0.0114)			(0.0049)
Observations	52,178,430	52,178,430	52,178,430	37,325,542	37,325,542	37,325,542
Pseudo R^2	0.38	0.38	0.38	0.36	0.36	0.36

Note: PPML estimations. All specifications include exporter-product-quarter, importer-product-quarter, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-quarter level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 25: Impact of Violent vs. Non Violent Events on Bilateral Trade: Pre- and Post-Covid Periods

Dep. Var.	Import Share$_{ijkt}$			
	Pre-COVID	Post-COVID	Pre-COVID	Post-COVID
	(1)	(2)	(3)	(4)
Shade Violence$_{ijt-1}$	-0.0176***	-0.0324		
	(0.0065)	(0.0260)		
Shade Non-Violence$_{ijt-1}$	-0.0169***	-0.0423***		
	(0.0046)	(0.0143)		
Shade Violence$_{ijt-1}$			-0.0119	-0.0617**
$\times\mathbb{1}_{\{Low\ \bar{\mathbb{I}}_{ij}\}}$			(0.0073)	(0.0305)
Shade Violence$_{ijt-1}$			-0.0272**	0.0072
$\times\mathbb{1}_{\{High\ \bar{\mathbb{I}}_{ij}\}}$			(0.0121)	(0.0413)
Shade Non-Violence$_{ijt-1}$			-0.0151***	-0.0090
$\times\mathbb{1}_{\{Low\ \bar{\mathbb{I}}_{ij}\}}$			(0.0051)	(0.0163)
Shade Non-Violence$_{ijt-1}$			-0.0208**	-0.0895***
$\times\mathbb{1}_{\{High\ \bar{\mathbb{I}}_{ij}\}}$			(0.0090)	(0.0228)
Observations	23,745,931	20,235,907	23,745,931	20,235,907
Pseudo R^2	0.39	0.39	0.39	0.39

Note: PPML estimations including zero trade flows. All specifications include exporter-product-quarter, importer-product-quarter, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-quarter level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 26: Robustness Checks: Removing the COVID Period and Major Countries for High and Low Intensity Relationships

Dep. Var.:	Import Share$_{ijkt}$				
	Excl. COVID	Excl. RUS&UKR	Excl. ISR	Excl. CHN	Excl. USA
	(1)	(2)	(3)	(4)	(5)
Shade Negative$_{ijt-1}$	-0.0066	-0.0084	-0.0071	-0.0057	-0.0073
$\times\mathbb{1}_{\{Low\ \bar{\mathbb{I}}_{ij}\}}$	(0.0078)	(0.0068)	(0.0069)	(0.0043)	(0.0070)
Shade Negative$_{ijt-1}$	-0.0614***	-0.0547***	-0.0476***	-0.0609***	-0.0390***
$\times\mathbb{1}_{\{High\ \bar{\mathbb{I}}_{ij}\}}$	(0.0123)	(0.0112)	(0.0113)	(0.0080)	(0.0122)
Observations	45,864,352	47,999,350	50,810,210	47,791,815	47,250,372
Pseudo R^2	0.38	0.38	0.38	0.38	0.39

Note: PPML estimations including zero trade flows. All specifications include exporter-product-quarter, importer-product-quarter, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-quarter level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

E.3 Quantification of the Overall Effect of Negative Events on Trade

Table 27: Overall Impact of Violent vs. Non Violent Events on Bilateral Trade

Dep. Var.	Import Share$_{ijkt}$					
	Full Sample (1)	Pre-COVID (2)	Post-COVID (3)	Full Sample (4)	Pre-COVID (5)	Post-COVID (6)
Shade Violence$_{ijt}$	-0.1601***	-0.0659***	-0.3240**			
	(0.0213)	(0.0181)	(0.1262)			
Shade Non-Violence$_{ijt}$	-0.0953***	-0.0344**	-0.2146***			
	(0.0146)	(0.0151)	(0.0741)			
Shade Violence$_{ijt}$ $\times\mathbb{1}_{\{Low\ \mathbb{I}_{ij}\}}$				-0.1105***	-0.0548***	-0.2643**
				(0.0198)	(0.0212)	(0.1255)
Shade Violence$_{ijt}$ $\times\mathbb{1}_{\{High\ \mathbb{I}_{ij}\}}$				-0.2789***	-0.1010***	-0.4387*
				(0.0476)	(0.0320)	(0.2354)
Shade Non-Violence$_{ijt}$ $\times\mathbb{1}_{\{Low\ \mathbb{I}_{ij}\}}$				-0.0366***	-0.0082	-0.1079*
				(0.0132)	(0.0162)	(0.0595)
Shade Non-Violence$_{ijt}$ $\times\mathbb{1}_{\{High\ \mathbb{I}_{ij}\}}$				-0.2389***	-0.1115***	-0.3888***
				(0.0319)	(0.0294)	(0.1415)
Observations	2,853,556	1,706,087	596,201	2,853,556	1,706,087	596,201
Pseudo R^2	0.43	0.44	0.42	0.43	0.44	0.42

Note: PPML estimations. Trade flows are from the ITPD-E database. All specifications include exporter-product-year, importer-product-year, and exporter-importer-product fixed effects. Standard errors clustered at the exporter-importer-year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 33: ITPD-E Sector-Specific Regressions

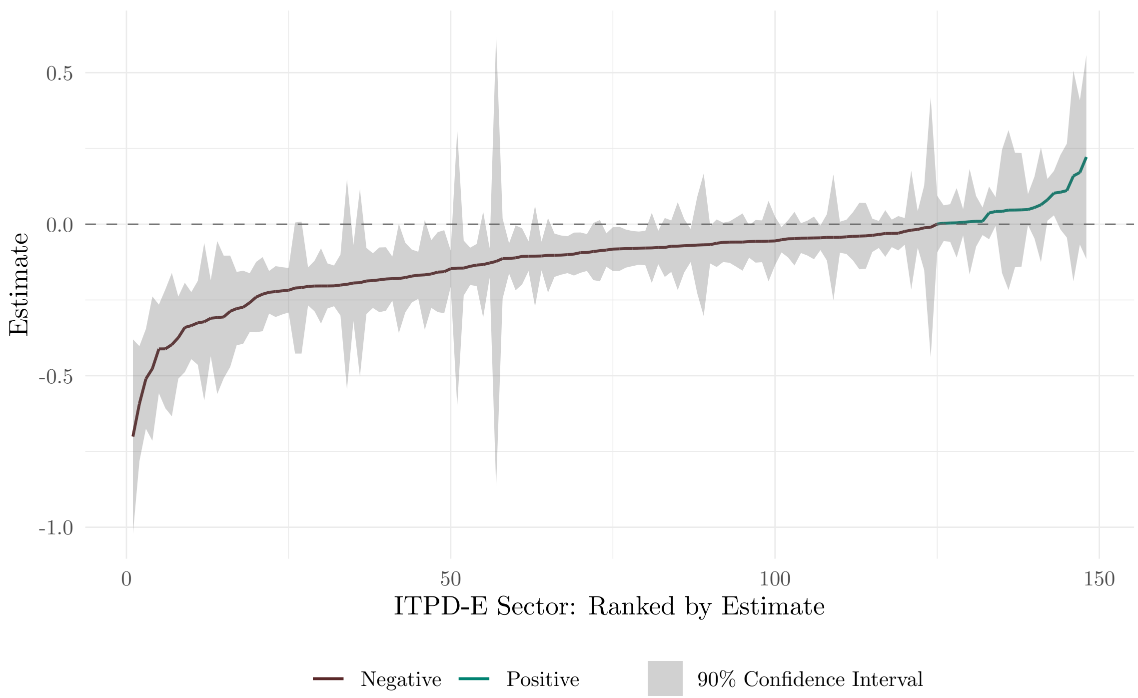


Figure 33 estimates Equation 7 for each ITPD-E sector.[51] A large majority of them (83.55%)

[51] Sector 75 (Publishing of recorded media) is not included since displaying transactions only for 2016. Sectors 9 (Raw and refined sugar and sugar crops, estimate=-1.29), 30 (Mining of lignite, estimate=1.02), 34 (Electricity production, collection, and distribution, estimate=-3.24), and 35 (Gas production and distribution, estimate=-0.29, standard error=11.47) are removed from the graph, clearly representing outliers.

is negative, and close to half (48.67%) is negative and significant, showing that our estimates are not solely driven by a small group of sectors. Only 1.97% are significantly positive, among which sectors 8 (Animal feed ingredients and pet food), 30 (Mining of lignite), and 136 (Optical instruments and photographic equipment).