

Bilateral Conflict Risk and Trade: Military Wars, Trade Wars, and Diplomatic Noise

JADT 2026 Conference – S06 Text Analysis in Economics

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Aula 9, University of Palermo

Chair: Davide Furceri

Conference venue: Complesso Didattico – Building 19, University of Palermo

Military war

Missile strikes, invasion,
battlefield destruction

Immediate disruption

Trade war

Tariffs, sanctions, export
controls, coercive diplomacy

**Policy uncertainty +
retaliation**

War of words

Protests, accusations,
diplomatic friction

Potentially just noise

How damaging is a “trade war” relative to a military war or diplomatic noise?

Where the paper sits in the literature

Conflict, sanctions and trade

- ▶ **War and trade:** Martin, Mayer and Thoenig (2008); Glick and Taylor (2010).
- ▶ **Political frictions and sanctions:** Fuchs and Klann (2013); Heilmann (2016); Felbermayr et al. (2020); Crozet and Hinz (2020).
- ▶ **This paper:** continuous directed hostility, split into kinetic and trade-context layers.

Text-as-data indicators

- ▶ Baker, Bloom and Davis (2016); Mueller and Rauh (2018); Caldara and Iacoviello (2022).
- ▶ Closest dyadic benchmark: Chevalier et al. (2026) and IntenSE.
- ▶ **This paper:** severity weights, media salience, ICEWS calibration, directionality, and sanctions-context reclassification.

Fragmentation and gravity

- ▶ Geoeconomic fragmentation: Gopinath et al. (2025); Mohr and Trebesch (2025).
- ▶ Structural gravity: Santos Silva and Tenreyro (2006).
- ▶ **This paper:** layer-specific PPML trade effects, delayed retaliation, and aggregate trade at risk.

Contribution

The paper links **preprocessed event data** to **dyadic geopolitical measurement** and then to **gravity-based trade losses**.

Contributions to the literature(s)

Substantive literatures

- ▶ **War and trade / sanctions:** continuous directed hostility, not only binary wars, sanctions, or single episodes.
- ▶ **Geoeconomic fragmentation:** bilateral hostility is measured directly, rather than proxied by blocs or voting distance.

Text-as-data contribution

- ▶ Raw event data are preprocessed through severity weights, media salience, ICEWS calibration, directionality, and sanctions context.
- ▶ In horse races against IntenSE, the preprocessed indicator wins: it remains significant when IntenSE controls are added.

Econometric payoff

Only **military wars** and **trade-context conflicts** measurably reduce trade; baseline diplomatic noise is close to zero in the long run.

A simple example: why preprocessing matters

The problem

News-based indicators can mix three objects: actual conflict, media visibility, and negative language. This is especially problematic when the same underlying GDELT source is transformed through article tone and frequency.

Example: military exercises

- ▶ Joint military exercises may contain militarized vocabulary.
- ▶ They may receive intense press coverage.
- ▶ But they can reflect strategic cooperation, not bilateral conflict.

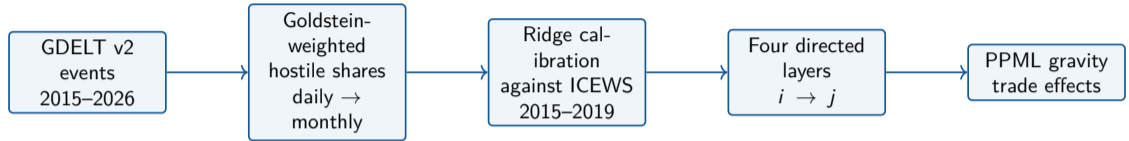
Example: economic coercion

- ▶ Technical sanctions or export controls may receive little coverage.
- ▶ Highly publicized diplomatic announcements may be overweighted.
- ▶ The economically relevant object is trade-context hostility.

Our contribution

We preprocess raw events using severity and salience weights, supervised calibration on ICEWS, directionality, and sanctions-context reclassification. This turns news events into an economically interpretable bilateral conflict indicator.

Measurement pipeline



Daily hostile share

$$r_{ij,d} = \frac{\sum_{e \in C_{ij,d}} |G_e| M_e}{\sum_{e \in C_{ij,d}} |G_e| M_e + \sum_{e \in K_{ij,d}} G_e M_e}$$

Monthly directed score

$$r_{ij,t} = \frac{1}{|D_t|} \sum_{d \in D_t} r_{ij,d}$$

- ▶ Direction $i \rightarrow j$ is retained.
- ▶ Calibration corrects automated-coding noise.
- ▶ The layer split is imposed after preprocessing.

Goldstein score G_e captures conflict/cooperation intensity; NumMentions M_e weights media salience.

Four layers of bilateral hostility

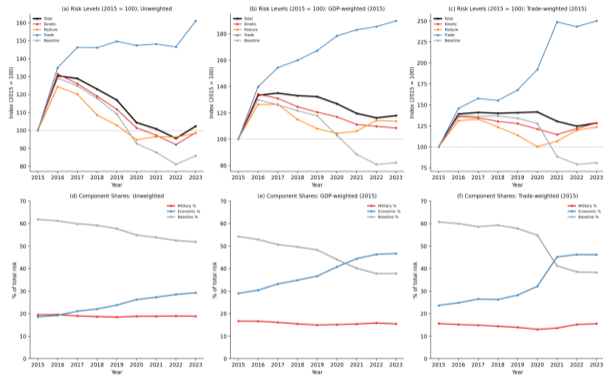
Pair	L^{kin}	L^{pos}	L^{trd}	L^{base}	Pattern
ISR→PSE	0.300	0.007	0.004	0.095	Kinetic war
USA→CHN	0.003	0.003	0.154	0.000	Trade war
RUS→UKR	0.254	0.035	0.158	0.000	Kinetic + sanctions
USA→IRN	0.023	0.001	0.204	0.000	Sanctions
FRA→DEU	0.008	0.002	0.001	0.044	Baseline diplomacy

Interpretation

The same aggregate score can hide very different mechanisms: **USA→CHN** is overwhelmingly economic, **ISR→PSE** is kinetic, and **FRA→DEU** is mostly baseline diplomacy.

Values are 2015–2023 means of calibrated hostility components. Components sum to aggregate calibrated risk.

Descriptive result: the economisation of conflict



Key pattern

- ▶ Aggregate risk is comparatively stable.
- ▶ Trade-context hostility rises sharply.
- ▶ Trade-weighted economic hostility approaches one-half of total bilateral hostility.

Conflict is increasingly economic.

Figure 1 from the manuscript: global conflict risk, 2015–2023.

Case studies: same label, different mechanisms

USA→CHN

Trade-context conflict

$$L^{trd} = 0.154$$

$$L^{kin} = 0.003$$

Tariffs, sanctions context, export controls, and coercive economic diplomacy.

RUS→UKR

Kinetic + sanctions

$$L^{kin} = 0.254$$

$$L^{trd} = 0.158$$

Military escalation combines with economic confrontation after 2022.

FRA→DEU

Baseline diplomacy

$$L^{base} = 0.044$$

$$L^{trd} = 0.001$$

Low-level political friction without a trade-relevant conflict channel.

Why the decomposition matters

The same aggregate label can describe distinct mechanisms. A single conflict coefficient would misread both the US–China trade confrontation and the Russia–Ukraine war.

Values are 2015–2023 means of calibrated hostility components.

$$x_{ij,t} = \exp \left(\sum_s \beta_s Risk_{ij,t-s} + \alpha_{ij,m} + \gamma_{i,t} + \delta_{j,t} \right) + \varepsilon_{ij,t}$$

Outcome and estimator

- ▶ Monthly bilateral trade from UN COMTRADE.
- ▶ PPML-HDFE gravity estimator.
- ▶ Standard errors clustered by directed pair.

Fixed effects and lags

- ▶ Pair \times calendar-month FE.
- ▶ Exporter \times year-month FE.
- ▶ Importer \times year-month FE.
- ▶ Lags: $\bar{L}_1, \bar{L}_{2-4}, \bar{L}_{5-7}$.

Identifying variation

Bilateral escalation or de-escalation within a directed pair, net of country-specific time shocks and pair seasonality.

Main result: only two layers reduce trade

Channel	Cumulated effect	SE
Kinetic conflict, L_{ij}^{kin}	-4.544***	(0.614)
Trade-context hostility, L_{ij}^{trd}	-1.400***	(0.251)
Retaliation, L_{ji}^{trd}	-0.527***	(0.130)
Total trade-context, $ij + ji$	-1.927***	(0.303)

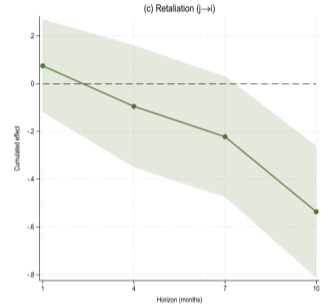
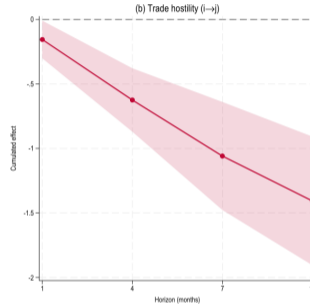
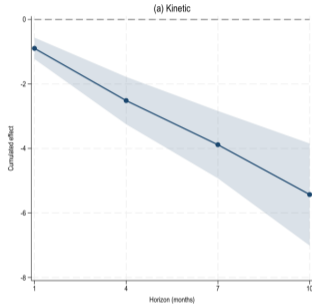
Preferred specification; cumulated effects over seven months. *** $p < 0.01$.

Interpretation

- ▶ Kinetic conflict has the largest effect.
- ▶ Trade-context hostility is large and precisely estimated.
- ▶ Retaliation adds about **27%** to the direct trade-context effect.
- ▶ Posture and baseline diplomacy are not retained in the parsimonious model.

Military wars and trade wars matter; diplomatic noise does not drive the long-run trade loss.

Dynamics distinguish mechanisms



Kinetic
immediate and monotonic

Trade-context
gradual adjustment

Retaliation
delayed response

Figure 9 from the manuscript: cumulated PPML effects with 95% confidence intervals.

Economic magnitude: trade at risk

Pair	Trade at risk	Dominant channel
CHN→USA	\$136.6B	trade-context hostility
USA→CHN	\$32.7B	trade-context hostility
USA→MEX	\$24.0B	sender hostility
MEX→USA	\$16.7B	retaliation channel
RUS→UKR	\$6.3B	kinetic conflict
All pairs	\$334B	68% trade, 29% retaliation, 3% kinetic

2015 trade weights; changes measured between 2015 and 2023.

Global decomposition

- ▶ Total bilateral trade at risk: **\$334B**.
- ▶ US–China accounts for roughly half.
- ▶ Channel shares: **68%** trade-context, **29%** retaliation, **3%** kinetic.

Policy reading

The largest aggregate losses come from economic coercion, not battlefield destruction.

What could go wrong?

- ▶ Slow bilateral drift.
- ▶ Lagged trade dependence.
- ▶ Firms anticipating future conflict.
- ▶ Reverse causality from trade to conflict.

What the paper checks

- ▶ ✓ Pair trends and lagged trade controls.
- ▶ ✓ Leads: trade-context passes; kinetic leads reflect anticipation.
- ▶ ✓ Reverse-causality test: past trade does not predict future conflict.
- ▶ ✓ Same-month feedback is unlikely at monthly frequency.

The causal reading is most persuasive for the **kinetic** and **trade-context** channels.

Against IntenSE

- ▶ Monthly gravity: our calibrated indicator remains significant with IntenSE controls.
- ▶ Decomposed gravity: kinetic, trade-context, and retaliation remain significant; IntenSE is jointly insignificant.
- ▶ HS4 product-level replications deliver the same pattern.

Why preprocessing matters

- ▶ Raw automated event data overcode routine interactions.
- ▶ ICEWS calibration compresses systematic noise.
- ▶ Directionality identifies retaliation.
- ▶ Sanctions context assigns trade-relevant diplomacy to the trade layer.

Other robustness checks

Sanctions dummies, route risk, zero-filled panels, product-level aggregation, and UNGA alignment controls do not overturn the kinetic and trade-context results.

IntenSE comparison: Chevalier et al. (2026).

Takeaways for a text-analysis audience

1. **Raw event data require preprocessing.** Automated event coders overstate hostility in routine, high-media relationships unless calibrated.
2. **Context matters.** Diplomatic events during sanctions episodes are part of economic coercion, not generic political noise.
3. **Direction matters.** Retaliation is identified from asymmetric month-to-month movements within dyads.

Broader message

Text-as-data is most useful for economics when it is linked to a clear measurement target, external validation, and an outcome model.

Substantive conclusion

Geopolitical deterioration since 2015 has placed roughly **\$334B** of bilateral trade at risk, mostly through **economic coercion** and **retaliation**.

Measurement conclusion

Aggregate conflict indices obscure the channels that matter. A directed four-layer decomposition distinguishes military wars, trade wars, and diplomatic noise.

Thank you

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Backup slides

Additional figures and details

Backup: early warning example, RUS→UKR

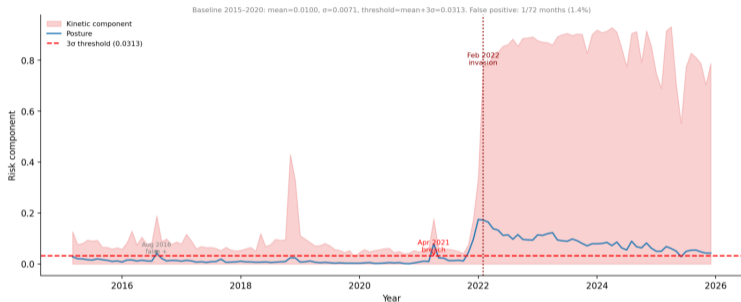
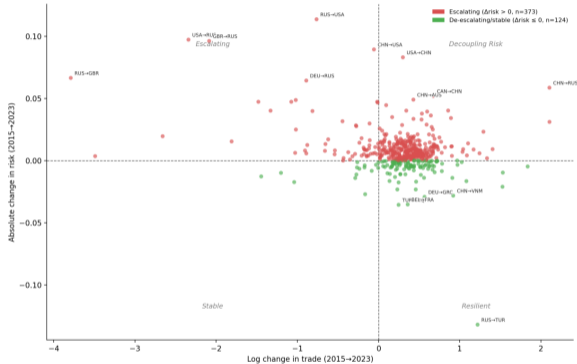


Figure 7 from the manuscript.

Posture signal

- ▶ Posture component breaches a 3-sigma threshold in April 2021.
- ▶ Kinetic escalation follows in February 2022.
- ▶ Baseline diplomacy would miss the preparation signal.

Backup: decoupling risk among top trading pairs



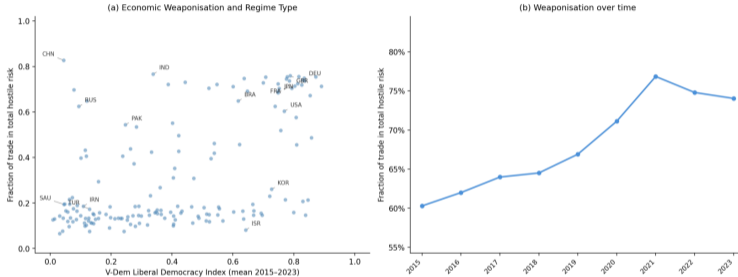
Sample: top-500 bilateral pairs by 2015 trade. Pairs with zero trade or zero risk in either year excluded (3 dropped).
373 of 497 pairs show escalating risk 2015–2023. RUS–UKR war outlier excluded; RUS–UKR (Arisk=0.715, Δln trade=-7.27).
X-axis: lntrade_2023/trade_2015; Y-axis: risk_2023 - risk_2015. Dashed lines at x = 0 and y = 0.

Figure 8 from the manuscript.

Reading

- ▶ Extreme escalation is concentrated in a few pairs.
- ▶ Many top trading pairs show stable or declining conflict risk.
- ▶ The global system is resilient but exposed to specific chokepoints in bilateral relations.

Backup: economic weaponisation



Weaponisation index: $W_i = \sum_j L_{ij}^{(2015)} / (\sum_j L_{ij}^{(2015)} + L_{ij}^{(2016)} + L_{ij}^{(2017)})$ = fraction of trade in total hostile risk. Countries with < 100 outgoing events excluded. Panel (b) uses 2015 bilateral trade weights.

Figure 5 from the manuscript.

Interpretation

- ▶ Some countries channel a large share of actionable hostility through economic instruments.
- ▶ Trade-weighted weaponisation rises over 2015–2023.

Backup: layer mapping

Layer	Event content	Interpretation
L^{kin}	CAMEO 18–20	Armed violence and fighting
L^{pos}	CAMEO 15 subset	Threats, force displays, military posture
L^{trd}	CAMEO 16–17 + sanctions context	Economic sanctions and coercion
L^{base}	Political/diplomatic residual	Diplomatic friction outside sanctions context

Sanctions-context reclassification

When trade or financial sanctions are active, diplomatic hostility is reassigned to the trade-context layer because demands, accusations, and threats become instruments of economic coercion.

Aggregate indicator






$$\hat{r}_{ij,t}^{cal} = L_{ij,t}^{kin} + L_{ij,t}^{pos} + L_{ij,t}^{trd} + L_{ij,t}^{base}$$

Trade-context layer

$$L_{ij,t}^{trd} = \hat{r}_{trd,ij,t}^{cal} + D_{ij,t}^{sanc} \hat{r}_{dip,ij,t}^{cal}$$

Why additivity matters

The four layers exactly sum to the calibrated aggregate. The decomposition changes interpretation, not the total amount of measured hostility.

-  Baker, Bloom, and Davis (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*.
-  Caldara and Iacoviello (2022). Measuring geopolitical risk. *American Economic Review*.
-  Chevalier et al. (2026). Trade under tensions: insights from media-reported bilateral events. CEPII Working Paper 2026-02.
-  Crozet and Hinz (2020). Friendly fire: the trade impact of the Russia sanctions and counter-sanctions. *Economic Policy*.
-  Glick and Taylor (2010). Collateral damage: trade disruption and the economic impact of war. *Review of Economics and Statistics*.
-  Santos Silva and Tenreyro (2006). The log of gravity. *Review of Economics and Statistics*.