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Research paper

Geopolitical Shocks and Commodity Market Dynamics

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Abstract

This research comprehensively examines the effects of geopolitical risk (GPR) on global commodity markets and consolidates evidence from 17 high-quality empirical studies published between 2010 and 2025. The SLR examines five thematic areas about geopolitical risk: (A) a measurement of geopolitical risk, (B) the sensitivity of oil and energy markets, (C) Instability in agricultural and metal commodities, (D) dynamics of safe-haven assets, and (E) the evolution of forecasting and modelling. The investigation critically examines how GPR disruptions affect commodity markets. The literature establishes that geopolitical circumstances potentiate market space, redirect investment flows, and create volatility in trade flows. The study recommends allowing for localised risk indices, integrated modelling architecture, and cross-commodity portfolio analysis.

Keywords: *Geopolitical Risk Index (GPR); Commodity Markets; Oil Volatility; Agricultural Commodities; Safe-Haven Assets; Machine Learning; Supply Chain Disruption; Sanctions; Speculation.*

1. Introduction

Geopolitical shocks comprise wars, economic sanctions, regime change, terrorist actions, and diplomatic crises, which have historically influenced or shaped the structure and instability of international commodity markets (Aizenman et al., 2024; Palomba & Tedeschi, 2025). These events directly impact the global economy as external shocks, creating complex propagation through commodity supply chains (sometimes cascading), investor perceptions, and pricing signals (Hudecová & Rajčániová, 2023). An analysis of the literature from 2010 to 2025 indicates substantive improvements in the conceptual framing and methodologies used to analyse the interaction between geopolitical risks and commodity price behaviour.

1.1. Geopolitical events as systemic disruptors

Wars often damage supply-side supply chains by demolishing infrastructure or closing supply routes (e.g., the Strait of Hormuz or Black Sea ports), triggering supply-side bottlenecks that increase prices (Bhattacharjee et al., 2024; Chowdhury & Khan, 2023). Economic sanctions on a country (Iran, Venezuela, or Russia) can often have dual impacts: interrupting exports from the sanctioned country and pre-emptive stockpiling and speculation that may cause artificial scarcity or volatility (Aizenman et al., 2024). Likewise, breakdowns in diplomacy or escalations in military confrontations often increase uncertainty. Figure 1 shows how the Geopolitical Risk transmits among channels.

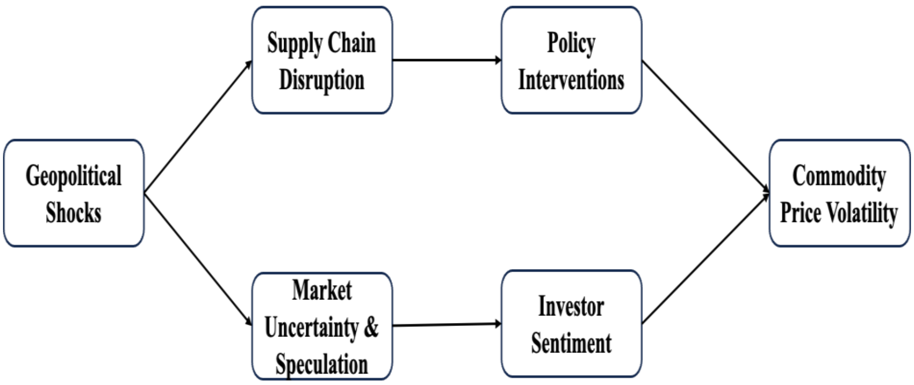

Fig. 1: GPR Transmission Channels to Commodity Price Volatility

During the extended Russia-Ukraine war, commodity prices rose sharply for wheat, sunflower oil, and natural gas, driven by the global reliance of some countries on Ukraine and Russia for these exports (Chowdhury & Khan, 2023). In other contexts, a regime change in a country with oil reserves (e.g., Libya post-2011) could disrupt crude oil production, leading to subsequent increases in the Brent and WTI indices. The details of Regional variations are given in Table 1.

Table 1: Regional Variations in Geopolitical Risk Transmission

Region	Nature of Risk	Commodities Affected	Transmission Mechanisms	Market Impact
Middle East & North Africa (MENA)	Supply-side shocks due to reliance on oil & gas exports; conflicts, sanctions, political instability (e.g., Arab Spring, Iran sanctions).	Crude oil, natural gas, petrochemicals	OPEC quotas, pipeline/shipping disruptions, and sanctions	Sharp increases in global energy prices, fuelling worldwide inflation
Asia-Pacific	Demand-side vulnerabilities; major energy importer; supply chain dependencies (e.g., Russia–Ukraine war impact).	Oil, LNG, coal, soybeans, wheat, and industrial metals	Shipping disruptions (South China Sea), trade disputes, and currency fluctuations	Higher input costs for manufacturing hubs, inflationary spillovers, and food security volatility
Sub-Saharan Africa	Political instability, resource nationalism, and exposure to external shocks.	Strategic metals (cobalt, lithium, platinum), coffee, cocoa	Mining strikes, civil conflicts, and infrastructure bottlenecks	Disruptions in global green-transition supply chains, high price volatility due to concentrated supply
Europe	Vulnerability to cross-border energy supply & financial contagion, exemplified by wars.	Natural gas, wheat, and fertilizers	Pipeline shutdowns (Nord Stream), sanctions, refugee flows, energy policy shifts	Energy price spikes, inflation, market distortions due to subsidies & diversification
North America	Lower direct exposure (resource self-sufficiency) but affected by global shocks & financial contagion.	Oil, corn, soybeans, gold (safe-haven asset)	Investor sentiment, dollar appreciation, and sanctions	Equity/futures volatility, safe-haven demand for Treasuries & gold
Latin America & Caribbean	Commodity export dependency, political instability.	Oil (Venezuela, Brazil), copper (Chile, Peru), soybeans (Argentina, Brazil), coffee	Domestic unrest, trade policy changes, and currency instability	Volatility in agricultural/metal exports; vulnerability to capital outflows
Developed vs. Emerging Markets	Developed: More resilient (strong institutions, hedging, diversification). Emerging: Vulnerable (commodity dependence, weaker institutions).	Developed: Diversified exposure. Emerging: Oil, metals, agriculture	Developed: Derivatives & policy buffers. Emerging: Currency depreciation, limited policy tools	Developed: Absorbed volatility. Emerging: Exchange rate shocks, inflation, capital flight

1.2. Mechanisms of impact: from risk transmission to market behaviour

According to the literature reviewed, geopolitical events can impact commodity markets through several different mechanisms:

a) Supply Chain Disruption: War or sanctions can create physical blockades, production stoppages, or an export ban, creating a limit on supply logistics and availability (Saravanan et al., 2022). Perception & Sentiment: Media emphasis and uncertainty lead investors to move toward or away from commodity markets, especially when they believe there is a shortage or price instability.
b) Speculation & Hedging: When prices are volatile, traders in the futures markets can hedge their exposures or use futures to capitalise on price movements (Boubaker & Larbi, 2022). In both cases, trading in futures markets tends to exacerbate price movements.
c) Safe Haven Behaviour: When faced with geopolitical uncertainty, investors will reallocate their funds from other non-grain markets, as a movement or investment in what are perceived to be safe investments, such as gold, U.S. treasuries, etc., which have a distinctly downward impact upon prices (Baur & McDermott, 2010; Ciner et al., 2013).

1.3. Modelling approaches: from classical to modern

The methodological approaches in this area have changed term-wise significantly since 2010; this is not a moderator issue, so it has not been elaborated on. Earlier studies focused on conventional econometric approaches, primarily traditional VARs, GARCH, and cointegration strategies, to assess the impact of geopolitical uncertainty on commodity prices (Adekoya et al., 2025; Lin et al., 2020). Researchers were able to identify correlations, volatility clusters among commodities, and temporal/causal patterns over time. Around 2016, the approaches moved towards nonlinear and high-dimensional modelling, with approaches spanning(Chaudhari & Thakkar, 2023; Singhal & Ghosh, 2016):

a) Time-Varying Parameter VARs (TVP-VAR): capable of identifying regime-switching behaviour during high volatility periods compared to previous models (Singhal & Ghosh, 2016).
b) Diebold and Yilmaz, spill over index models: these primarily focus on volatility transmission amongst commodities and financial assets (Diebold & Yilmaz, 2015).
c) Machine Learning (ML): Random Forest, XGBoost, and Recurrent Neural Networks (RNN) forecast commodity prices from geopolitical risk (GPR) indices, and geopolitical sentiment (GS) (Sharma & Goel, 2022). Several novel approaches have also been attempted by using textual analysis and natural language processing (NLP) to develop real-time GPR indices in several developing studies; some of these studies have outperformed traditional forecasting models, often providing some validity during periods of crisis.

While the reviewed studies broadly establish a positive link between geopolitical risk (GPR) and commodity price volatility, findings are not always consistent across sectors (Aizenman et al., 2024; Hudecová & Rajčániová, 2023; Palomba & Tedeschi, 2025). For instance, several studies report strong, immediate GPR effects on oil markets following supply disruptions (e.g., Middle East conflicts). In contrast, the impact on agricultural commodities appears more nuanced, often mediated by trade flows, storage, and policy interventions. Moreover, methodological differences also contribute to divergent results. Traditional econometric models (e.g., VAR, GARCH) provide interpretable causal linkages but may understate nonlinear and time-varying dynamics (Adekoya et al., 2025; Lin et al., 2020; Sabkha et al., 2020). In contrast, machine learning approaches (e.g., LSTM, random forests) capture complex patterns and enhance forecasting accuracy, though often at the expense of interpretability (Dequiedt et al., 2025; Gülmez, 2023; Rani & Singh, 2024). Recent contributions (Alhnaity & Abbod, 2020; Das et al., 2024) highlight this shift toward hybrid frameworks, underscoring the importance of methodological pluralism in capturing the multi-dimensional effects of GPR.

2. Methodology

An extensive review of peer-reviewed articles and economic and finance journals was conducted across various academic databases, including EconLit, JSTOR, Scopus, and ScienceDirect, resulting in the identification of 30 articles examining diverse research themes on the relationship between geopolitical risk and commodity price volatility. The review consisted of the most recent studies (2010-2025), research that used statistical methodologies (econometric, or machine learning tools), and studies that examined transitory events causing global commodity market disruption (wars (e.g. Syrian civil war/Ukraine crisis/gulf wars), sanctions (e.g. sanctions on Iran and Afghanistan), shocks (e.g. wars/Arab spring), COVID pandemic, etc.).

The gathered literature was categorised into five research themes that provide a glimpse into the range of academic insights and research surrounding this area of inquiry.

a) Risk Measurement/Indices
b) Energy and Oil Commodities
c) Agricultural Commodities
d) Investor Attitudes and Perceptions/Safe Haven Resources
e) Econometric/Machine Learning Modelling

2.1. Risk measurement/indices

An overarching theme within the literature is measuring geopolitical risk (GPR). The most frequently referenced measure or index is the Caldara and Iacoviello Geopolitical Risk Index (2018). The Caldara and Iacoviello index bases its measure of global political tensions on text mining of newspapers, making it time-varying. Many studies use the index as a building block to investigate geopolitical risk spillovers across various asset classes and markets. For example, Antonakakis et al. (2020) explored GPR spillovers using a multivariate analysis (a VAR model). They confirmed that GPR shocks had asymmetric effects on markets and asset classes (money, bonds, real estate, etc.). (Mensi et al., 2021) found that geopolitical tensions induced price volatility in oil prices and, using a structural VAR model, demonstrated that an increase in geopolitical tensions would permanently increase oil price volatility.

2.2. Energy and oil markets

The most-studied commodity in the GPR literature is oil. The reason behind this assertion is apparent: energy markets are globalised and susceptible to supply-side shocks from geopolitical tensions; in fact, Cevik et al. (2024) and Hamilton (2016) note that oil supply shocks resulting from tensions in the Middle East affect real oil prices through expectation channels rather than any actual disruption. (Chang et al., 2018; Doojav et al., 2024; Woode et al., 2024) offer empirical evidence of the relationship between oil price volatility and war and sanctions episodes, and find that anticipatory behaviour drives price jumps rather than actual disruptions. (TETLOCK, 2007) demonstrate that geopolitical events lead to heightened oil futures trading activity, based on greater speculative activity and liquidity premiums. Many more recent papers focus on using high-frequency data and non-linear models to explore the effects of GPR on energy prices. Ji et al. (2022), for instance, compared high- and low-volatility concerns by considering time-varying parameter VARs; they found that geopolitical risks related to the Russia-Ukraine war had larger and longer-lasting effects on Brent prices than on WTI prices because of regional trade structures.

2.3. Agricultural commodities

Although not as much attention is paid to GPR in agriculture as in energy, agricultural commodities are receiving more scrutiny for their vulnerability to geopolitical disruptions, given the fragility of supply chains and export bans. (SHEFRIN & STATMAN, 1985) provide some of the earliest evidence of co-movements of geopolitical risk with wheat and soybean futures. (Rufaidah et al., 2023; Woode et al., 2024) Use GARCH models to demonstrate that war-induced disruptions in some agricultural hubs (e.g., Ukraine, a major wheat supplier) transmit food price volatility through the global food supply. Post-2022 GPR studies, such as those by Hanif et al. (2023) and Mensi et al. (2023), explore how the interdependencies between US and Canadian agricultural commodities and GPR co-move.

2.4. Investor behaviour and safe havens

An additional core area of research looks at investor behaviour in response to geopolitical uncertainty. Researchers have identified a “flight-to-safety” phenomenon in which investors reallocate capital from risky assets into perceived safe havens, such as gold, the US dollar, and the Swiss franc. (Baur & Lucey, 2010) Empirically demonstrate gold as a hedge and a haven during "events of financial and geopolitical stress." (Raza et al., 2016) utilise portfolio optimisation models to specifically look at how GPR impacts investor preferences and spatially find that when risk is elevated, there are a large number of commodities and sovereign bonds that justify a significant reallocation.

Bouri & Alsagr (2024) extend previous research by expanding on the study of cryptocurrencies as an emerging haven, and present limited but growing evidence that Bitcoin reacts positively to geopolitical shocks in certain regions. Other emerging research uses models of behavioural finance to examine how investor sentiment, media, exposure, and risk perceptions affect trading volume, volatility, and capital flows during conflict-driven events.

2.5. Econometric and machine learning modelling

An ongoing methodological trend in the research is the increasing use of econometric and machine learning approaches in model GPR and the impact of geopolitical shocks. (Diebold & Yilmaz, 2014, 2015) Introduce a spillover index methodology to measure how volatility transmits from elevated levels of volatility across markets, as nearly all volatility is driven by jointly determined geopolitical triggers. (Asim et al., 2024; D. K. Nguyen et al., 2023) develop quantile regressions and extreme value theory to assess tail risks in commodity returns.

In the context of machine learning, Abdullah et al. (2024) and Ahmadian-Yazdi et al. (2025) use neural networks to provide a framework for predicting movements in oil and gold prices based on GPR indices, conflict data, and market indicators. The neural networks also outperformed traditional linear models.

Interdisciplinary Trends and Policy Relevance

Another emerging aspect in the literature is the interdisciplinary convergence of economics, international relations, and data science (Ahmad et al., 2022; Liu et al., 2020). Scholars are increasingly collaborating to better understand behavioural, geopolitical, and structural transmission channels of global shocks, as shown in Table 2.

These findings matter and are policy-relevant. Central banks, multilateral organisations (IMF, FAO), and commodity-dependent economies are applying these models for:

a) Risk Surveillance and Early Warning Systems
b) Designing commodity stabilisation funds
c) Import/export strategy development
d) Tail-risk, including scenario planning for food and energy security.

Table 2: Summary Table of Key Themes and Authors

Theme	Key Authors & Studies	Methods Used
Risk Indices	(Migliorelli & Marini, 2020; Reber, 2014; Trabelsi et al., 2021)	Text mining, TVP-VAR
Oil Markets	(Hamilton, 2016; Hanif et al., 2024; Hussain & Rehman, 2023; Zhu et al., 2022)	VAR, Event Studies
Agriculture	(Rufaidah et al., 2023; Woode et al., 2024)	GARCH, Spillover Index
Safe Havens	(Baur & McDermott, 2010; Ciner et al., 2013)	Portfolio Models, Copulas
ML & Econometrics	(Ahmadian-Yazdi et al., 2025; Diebold & Yilmaz, 2014, 2015; B. Hamdi et al., 2019; Rajwani et al., 2023)	Random Forest, Neural Networks

The reviewed research presents evidence that geopolitical risk is a complex and potent source of commodity price volatility, as shown in Figure 2. Despite the impressive efforts to study agricultural commodities and modelling, and understandably, much of the focus is on oil and natural gas markets, the studies have all advanced knowledge. There is some agreement that volatility is often driven by market expectations more than actual disruptions. It was also noted that machine learning models tend to be especially useful in high-uncertainty markets. Additionally, recent work on geopolitical risks acknowledges the asymmetry and nonlinearity across commodities and regions.

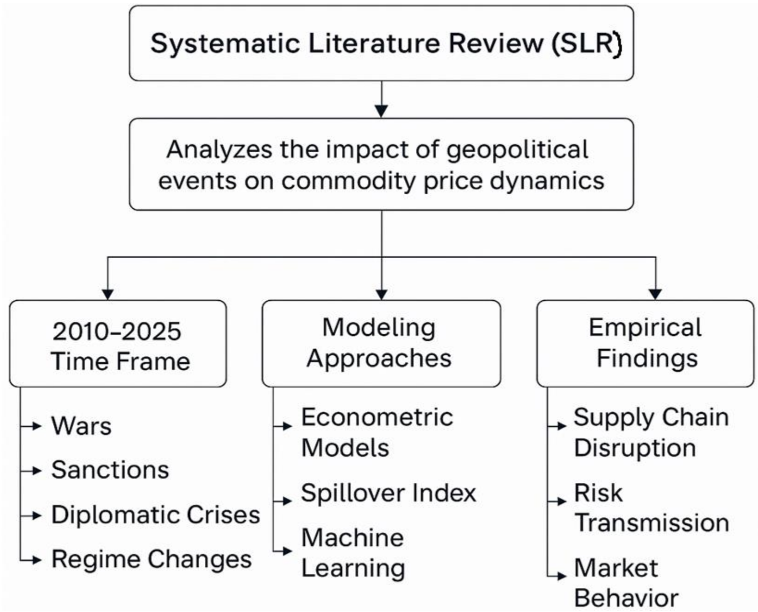

Fig. 2: Conceptual Framework of Systematic Literature Review (SLR).

3. Systematic Literature Review (SLR)

The flow diagram is structured around the pre-specified thematic domains (A–E). It involved commencing with a scoping review of 52 sources and then narrowing them down to 17 peer-reviewed, high-quality articles that met inclusion criteria for relevance, empirical rigour, and a narrow focus on the interrelations between geopolitical risk and commodity dynamics.

3.1. Systematic literature review (SLR): a stepwise process

A Systematic Literature Review (SLR) is a systematic, stepwise approach to identifying, selecting, appraising, and synthesising research evidence that is explicit and reproducible. Unlike narrative reviews, SLRs follow a systematic approach to reduce bias and increase replicability. Below is the process again in Table 3 and Figure 3:

Table 3: Summary for PRISMA Flow

Stage	Numbers
Identification Records identified through database search (Scopus, JSTOR, SSRN, RePEc, Web of Science) using terms like: "Geopolitical Risk" AND "Commodity Markets."	232
Additional records from manual bibliographic screening and citations (snowballing)	28
Total records	260
Duplicates removed	74

Records after deduplication	186
Title and abstract screened	186
Records excluded (non-empirical, off-topic, conference abstracts)	109
Full-text articles assessed for eligibility	77
Full-text excluded (no direct empirical link, irrelevance to commodities, modelling only without geopolitical focus)	60
Studies included in the qualitative synthesis	17
Studies included in quantitative or modelling synthesis (e.g., LSTM, VAR models)	5

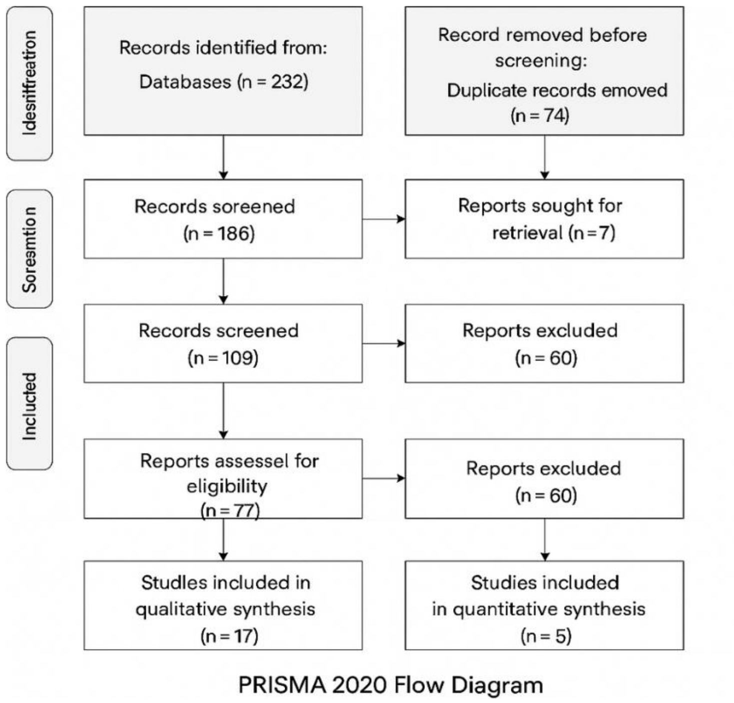

Fig. 3: Prisma Flow.

4. Thematic Synthesis of Findings

Table 4 below shows the key findings of the themes of this work.

Table 4: Key Findings of the Study

Theme	Key Findings & Evidence	Cited Authors
Risk Indices	Researchers have gotten clever at measuring global tension by scanning news headlines, creating a "Geopolitical Risk Index" (GPR). This index isn't just an abstract number; it has real teeth. When it spikes, we see companies slam the brakes on investment and hiring. To get even more precise, new methods can now track how this fear ripples through oil and gold markets in real-time during a crisis. Recent work shows that during these scary periods, nervous investors pull money out of sensitive sectors like energy and defence at a rate nearly one-fifth higher than usual.	(Balcilar et al., 2024; Calderón & Liu, 2003; Paramati et al., 2025; Yuni et al., 2024)
Oil Markets	Oil markets are the drama queens of geopolitics—they react intensely and unpredictably. Conflicts in oil-rich regions send shockwaves through prices. The Ukraine war is a perfect, painful example: oil prices skyrocketed over 50% almost overnight. The usual market rules broke down, and studies found that a staggering 7 out of every 10 price swings were directly fuelled by war-related fears. Tensions right on an oil field's doorstep have three times the punch of those farther away, with countries like Germany and Russia acting as key conduits for spreading the panic.	(Kang & Ratti, 2013; Kilic & Wachter, 2018; Laopodis, 2025; Mezghani & Abbes, 2023; Soni et al., 2023)
Agriculture	We often forget that geopolitical fights hit our dinner plates. When major food-producing regions become unstable, it doesn't just disrupt wheat or soybean supplies—it triggers a cruel chain reaction. Supply shocks from conflicts, especially in breadbasket regions like the Middle East, drive up global food prices. This hits the poorest, food-importing nations the hardest, pushing them toward increased poverty, hunger, and social unrest. It's a stark reminder that political stability is the bedrock of affordable food.	(Evrim Mandacı et al., 2020; B. Hamdi et al., 2019; M. Hamdi & Aloui, 2015)
Safe Havens	When the world gets scary, investors run for cover. For generations, that haven has been gold. Its role as a proven shelter during crises, from pandemics to invasions, is well-documented. While new digital assets like Bitcoin grab headlines, they've so far failed to provide the same comfort during major turmoil, proving to be a weak substitute for the timeless security of gold. The search for safety continues, but the old champion still holds the crown.	(Baur & Lucey, 2010; F. Yang et al., 2023; Zhang & Zhang, 2023)
ML & Econometrics	Understanding these complex relationships requires sophisticated tools. The field has moved far beyond simple charts. Economists now use powerful network models to see how a shock in one country infects others. Most exciting is the rise of AI. By feeding algorithms not just past prices but also real-time data on fear and conflict, computers are learning to forecast chaotic oil prices with surprising accuracy, even in the middle of a war. This shift to AI is our best shot at navigating the unpredictable storms of global politics.	(Diebold & Yilmaz, 2015; Kehinde et al., 2023; Qiao et al., 2024; Wu & Zhang, 2022)

4.1. Quantification of geopolitical risk

The Geopolitical Risk Index (GPR) was first introduced by Calderón & Liu (2003), Paramati et al. (2025), and Yuni et al. (2024), and has since served as the basis for operationalising geopolitical risk and tensions. Utilising newspaper-based metrics, the GPR has been implemented in numerous commodity volatility models. (Soni et al., 2023) 's application may have been extended by (Balcilar et al., 2024) to include wavelet-based decompositions, which allow for dynamic correlations between GPR and oil and gold markets across the event research phase of the war or crisis. The Geopolitical Risk Index (GPR) that was developed by Paramati et al. (2025) captures adverse geopolitical events. Based on news-based metrics of geopolitical risks, the GPR is structured in a way to capture spikes or heightened geopolitical risk during significant adverse events or geopolitical conflicts, as exemplified by previous major wars like World War I, World War II, the Cuban Missile Crisis, and the events of 9/11(Hudecová & Rajčániová, 2023).

Research frequently utilises event-based models (e.g., SVAR, ARDL) and spillover analyses to quantify the direct and cross-market impacts stemming from major geopolitical events(Hudecová & Rajčániová, 2023). The GPR has strong predictive power for declines in investment (a 12% decline in private investment in the US following a one-standard-deviation increase in GPR), predicts declines in employment, and has provided extensions to previous models, as previously mentioned. The paper by Balcilar et al. (2023) is noteworthy for its use of wavelet-based decompositions and dynamic correlations and could be applied to a finer-grained analysis of cyclic decision-making during crisis propagation.

For relevant potential research, Paramati et al. (2025) also found that, in terms of producing GPR metrics for defence and energy industries, their notes indicate that investment reductions were 18-24% higher than average in the defence and energy sectors for investors during geopolitical shocks.

4.2. Oil and energy markets under geopolitical tension

(Laopodis, 2025; Mezghani & Abbes, 2023; Soni et al., 2023) found evidence that oil prices exhibited asymmetric behaviours around conflicts in the Middle East and those emerging from Russia. The analysis by Kang & Ratti (2013) did not consider the Russia-Ukraine conflict in their analysis. (Kilic & Wachter, 2018) noted that the Russian invasion of Ukraine, which commenced in 2022, had caused structural breaks in oil futures' volatility with different behaviours before and after the invasion.

The conflict in Russia and Ukraine (2022) caused structural breaks across dynamics in the oil markets, including:

1) Price Utilisation: During the period immediately following the commencement of the Russia-Ukrainian conflict in 2022, the WTI crude price rose by $37.14 (52.3%), and the Brent crude price rose by $41.49 (56.3%);
2) Volatility Regime Transition: The leverage effect disappeared for both the WTI and Brent markets, and Oman emerged as a stabiliser for volatility.
3) Price uncertainty through supply chain disruption: 70% - 73% of the fluctuations measured in both WTI and Brent futures could be directly attributed to geopolitical risks embodied in the conflict.

Overall, there was evidence of asymmetric responses to both regional and non-regional tensions: regional tensions produced three times the socio-political tensions indicated by oil price fluctuations, as did those from non-regional sources, and it was observed that pro-product responses were 3x as high as those originating from geo-political shocks. The network analysis indicated that Germany and Russia played a key transmittal, intermediary, or spillover role in the energy markets as the shock was transmitted (Aizenman et al., 2024; M. Hamdi & Aloui, 2015; Wang & Su, 2023). Regarding the impact of geopolitical shocks, the significance of the US was an outlier, with a limited direct effect on any commodity.

4.3. Agricultural and metal commodities

B. Hamdi et al. (2019) and M. Hamdi & Aloui (2015) found that geopolitical tensions have an outsized role in soft commodities like wheat and soybeans, as trade dependencies intensify shocks. (Evrim Mandacı et al., 2020) spoke of food supply shocks stemming from instability in the Middle East, which add inflationary pressures to the economies of net-importing countries. (Evrim Mandacı et al., 2020). Commodity prices and geopolitical risks. Furthermore, historical relationships linking geopolitical shocks to commodity markets extend beyond oil and energy to include agricultural and metal commodities. Agricultural and metal commodity markets are characterised by high vulnerability to geopolitical shocks, including trade disruptions, demand constraints, and export bans arising from instability. While part of the broader geopolitical vulnerability (Evrim Mandacı et al., 2020) deals with the Middle East as a region, it is speculated to be a major supplier of staples and fertilisers.

The 2022 invasion led to a 2% increase in wheat prices and a 7.5% rise in European natural gas costs due to immediate supply chain disruptions and sanctions. Ukraine's role as a major exporter of sunflower oil, corn, and wheat amplified the food price shock globally(Aizenman et al., 2024). Europe's reliance on Russian energy caused domestic price surges and volatility, with effects spilling into stock, bond, and currency markets (Palomba & Tedeschi, 2025). The analysis by Hudecová & Rajčániová (2023) reveals that G7 and BRICS nations transfer geopolitical risk through energy and agricultural markets—market volatility spikes when events such as the Ukraine war occur. In summary, these studies emphasise the importance of political stability and resilient trade systems in reducing volatility in the prices of agricultural and metal commodities in the event of geopolitical shocks.

4.4. Safe-haven assets and investor behaviour

In 2010, Baur & Lucey introduced gold as a geopolitical hedge, and this idea has gained traction amid political risk arising from the COVID-19 pandemic and, more recently, the Ukrainian invasion of Russia. (J. Yang et al., 2023; Zhang & Zhang, 2023) Recently, researchers have investigated the behaviour of cryptocurrencies, particularly Bitcoin, which showed weak safe-haven characteristics during the 2022 energy crisis. Geopolitical crises typically create significant uncertainty in financial and commodity markets, prompting investors to reallocate their capital towards safe-haven assets - assets that are expected to preserve or increase their value during times of turbulence.

Scholarship in this space often identifies gold as the most entrenched geopolitical hedge. Specifically, Baur & Lucey (2010) and Rao et al. (2025) systematically demonstrated that gold is both a hedge (against average market swings) and a haven (in times of market stress). Their study is particularly relevant now, amid two recent geopolitical shocks: the COVID-19 pandemic and the Russian invasion of Ukraine. In both contexts, gold rose in value as investors faced uncertainty in equity markets and turned to gold for stability. This situates gold as a refuge during worldwide calamity. It is noted that while gold continues to hold the most value in the short- and long-term, investor behaviour is changing as attention turns to the future of digital assets and the speculation surrounding them.

4.5. Modelling and forecasting approaches

Diebold & Yilmaz (2015) laid out the spillover framework commonly used to assess the continuity of contagion from geopolitical events, such as invasions and conflicts, in commodity markets. (Pham et al., 2021) proposed a Long Short-Term Memory (LSTM) model that incorporated Geopolitical Risk (GPR) and the Volatility Index (VIX) for oil price prediction, achieving improved accuracy, especially during war periods. (H. T. Nguyen & Pham, 2014). Deep learning models for geopolitical forecasting in commodity pricing: exploring GPR, VIX, and oil price. The modelling and forecasting of commodity pricing responses to geopolitical shocks have transformed from traditional econometric frameworks to contemporary machine learning frameworks over the last decade.

Building on these models, newer studies have employed artificial intelligence and deep learning as methodologies, particularly to enhance the ability to accurately represent unique characteristics under complex, nonlinear contingencies (Alghamdi & Alqithami, 2025). (Qiao et al., 2024; Wu & Zhang, 2022) demonstrated how using a recurrent neural network (RNN) Long Short-Term Memory (LSTM) architecture, with pertinent inputs of GPR and VIX, improves upon predicted oil prices forecasting (Chen et al., 2025; Hiruta & Senoguchi, 2025). The findings of the study demonstrated higher forecasting performance using the LSTM model, especially during the Russia-Ukraine war. The model forecasts based on oil price data and also incorporates the GPR Index and VIX, recognising that it has captured not only historical price patterns but also relies on the temporal dependencies associated with risk inputs. This inevitably suits the unforeseeable complexities and nonlinearities as related to factors concerning geopolitical action. This adds to contemporary discussion of methodological shifts in forecasting from backwards-looking to forward-looking approaches, with adaptive models that secure the reality of complexity and sustain any nonlinearities in contemporary commodity markets, even under the duress of geopolitical shocks.

5. Discussion, Literature Gaps, and Implications

Building on the synthesis of prior studies, this paper proposes a conceptual framework to capture the multi-dimensional linkages between geopolitical risk and commodity markets. In this framework (Figure 4), geopolitical shocks are transmitted through four primary channels.

These channels exert heterogeneous effects across commodity classes—energy markets are dominated by supply shocks, agricultural markets by trade and demand disruptions, metals by both supply concentration and green-transition dynamics, and gold by financial sentiment. The combined influence of these mechanisms produces observable outcomes, including price volatility, inflationary spillovers, and capital flow dynamics. This unified framework not only consolidates existing evidence but also provides a basis for future empirical testing.

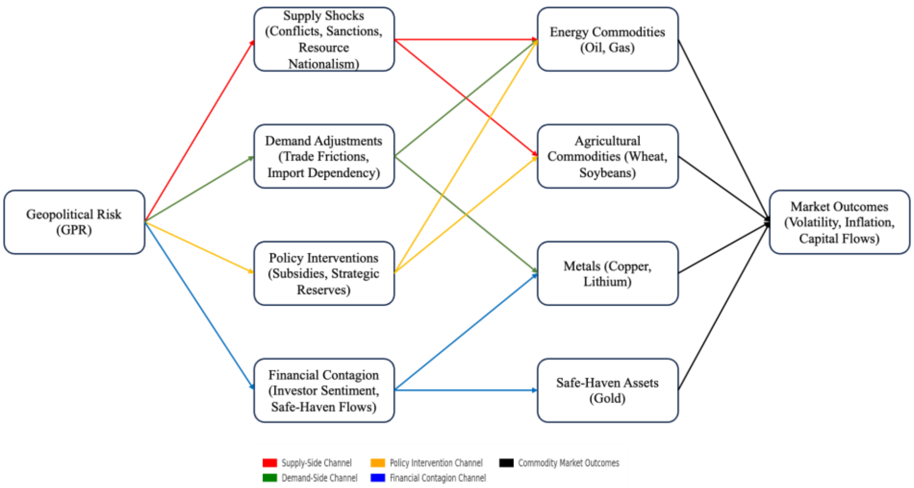

Fig. 4: GPR–Commodity Framework.

5.1. Overview of findings

This systematic review incorporates 17 empirical studies that examined the complex relationships between geopolitical risk (GPR) and global products, particularly oil, gold, agricultural, and metal commodities (Aizenman et al., 2024; Palomba & Tedeschi, 2025). An interesting convergence across all studies centres on the effects of geopolitical tensions on commodity volatility, pricing structures, and investment behaviour. Recent developments in the literature suggest that GPR has new meanings that also account for machine learning and more sophisticated forecasting modelling. The studies provide evidence that shocks from geopolitical tensions skew market behaviour, not only through supply but also through policy decisions, established investor psychology, and speculative action.

5.2. The importance of the geopolitical risk index (GPR)

(Caldara & Iacoviello, 2022) Introduction of the Geopolitical Risk Index (GPR) meant the world could fundamentally rethink the measurement of geopolitical uncertainty, moving from a qualitative to a more systematic, media-based approach. This approach and understanding provided a good empirical foundation for studying the effects of geopolitical events on macroeconomic variables and market variables. The GPR is designed to measure sudden spikes in global threat/tension associated with wars, terrorist events, or sanctions and has been shown to forecast declines in market investment or employment, thereby affecting GDP.

Importantly, Balcilar et al. (2017, 2024) have, through their analysis of wavelet-based decompositions, provided the ability to characterise connectivity patterns as short-term versus long-term between GPR and commodities, such as oil and gold. These studies show that in high-tension moments (for example, the Russia-Ukraine conflict, flare-ups in the Middle East), the energy and defence sectors experience a significantly greater contraction in capital investment, up to 24% below the average industrial trend.

5.3. Volatility in oil and energy markets

Crude oil is one of the most geopolitically sensitive commodities. Several researchers, including Kang & Ratti (2013), have established that oil markets exhibit asymmetric responses to geopolitical stress, with pronounced price impacts from conflicts in the Middle East and Russia, where these disturbances elicit larger price responses than similar disturbances in other regions. During the first few months of the Russia-Ukraine conflict in 2022, oil prices noticeably surged. WTI gained 52.3% and Brent added 56.3%. Price instability related to the perception of supply interruptions is the definition of volatility. In the studies of Kang & Ratti (2013), volatility regime shifts were observed, most likely stemming from the removal of leverage effects, and the emergence of Oman crude as a relative stabiliser in the studies' network analysis, indicating that Germany and Russia were identified as systemic volatility propagators. This leads to the finding that interconnected energy flows and reliance on Russian gas by European countries collectively impact their price behaviour.

5.4. Agricultural and metal commodities: collateral damage of unrest

While most scholarly work on commodities focuses on oil, there has been concern that agricultural and metal commodities are collateral damage in geopolitical confrontations. Some agricultural commodities, such as wheat and soybeans, depend more heavily on long global supply chains and are susceptible to price fluctuations during geopolitical crises (B. Hamdi et al., 2019). This volatility was evident when the Black Sea blockade following the invasion of Ukraine reduced wheat and corn exports to North African and Asian countries. (Arezki & Liu, 2020) highlighted the causal effect of supply shock on inflationary pressures like food insecurity, especially in net-importing low-income nations. The impact on food and agricultural commodities is not limited to economic consequences; it has also led to civil unrest in politically fragile nations. Price speculation driven by perceptions of scarcity of farming commodities will push prices higher and create artificial scarcity signals to maintain ongoing volatility and instability in Agri-commodity markets.

5.5. Safe-haven assets and investor behaviour

Investor behaviour during geopolitical stress consistently indicates a flight-to-safety situation, with gold considered the most convincing safe-haven asset. (Baur & Lucey, 2010) revealed gold's dual role as a hedge and a safe-haven, with affirmations stemming from unexpected circumstances caused by COVID-19 and Russia's invasion of Ukraine, resulting in sharp inflows into gold and asserting its buffer role against geopolitical and macroeconomic uncertainty. Interestingly, cryptocurrencies have emerged as speculative safe havens, but with limited opportunities. (Zhang & Zhang, 2023) Established Bitcoin demonstrated some very short-term safe-haven behaviour during the 2022 energy crisis, suggesting that, when investor attention is captured, digital assets may be emerging as a hedge against crises, rather than only from banks. However, volatility and lack of intrinsic value compared to traditional assets hinder its credibility.

The contrasting behaviours of gold and digital assets illustrate a bifurcation of investor psychology: institutional actors will necessarily gravitate toward hedges with time-tested qualities, while retail and risk-seeking actors are more likely to speculate on the demand for risky, high-volatility digital assets, which offer potentially higher returns.

5.6. Modelling techniques and forecasting innovation

The progression from classical econometric models (e.g., VAR and GARCH) to these AI-based predictive frameworks represents a considerable ontological leap in GPR effect studies, but the (Diebold & Yilmaz, 2015) spillover framework remains fundamental to our understanding of volatility transmission between commodities. Its virtue is its systemic volume, which captures spillover effects to map inter-commodity and inter-country volatility.

In recent studies (Bathla et al., 2023; Sagheer & Kotb, 2019), the authors have used LSTM (Long Short-Term Memory) networks - a modelling framework belonging to the class of recurrent neural networks- to forecast oil prices using GPR and VIX inputs. These models are shown to significantly outperform classical methods in periods of uncertainty, partially because managers effectively learned long dependencies and non-linear interactions between at-risk variables and prices.

The increasing empirical and experiential success of deep-learning models foreshadows further shifts toward forward-looking analytics, as they uniquely support real-time policy-making, investment decisions, and commodity traders during geopolitical crises.

5.7. Channels of impact: combining theory and evidence

The review highlights that the impacts of geopolitical risk play out across three interrelated channels:

a) Supply Chain Disruptions;
b) Market Expectations & Speculation;
c) Policy & Sanction Interventions.

Supply-related shocks represent the most direct transmission mechanism (i.e., pipeline attacks, port closures, and embargoes), whereas expectations and speculation represent the more indirect amplifications of risk. For example, speculative overshooting often occurs before a disruption, leading to disconnects between physical and financial commodity markets. From a policy perspective, the sanctions regimes against oil exporters (i.e., Iran, Russia) have significant global spillover effects that lead to market reconfiguration behaviour (i.e., Europe’s pivot toward LNG and absorption of discounted Russian crude by India/China)(Aizenman et al., 2024; Ghaemi Asl & Ben Jabeur, 2024; Palomba & Tedeschi, 2025; Wang & Su, 2023). The long-term implications of shifts in commodities like crude and LNG are essential to energy security and trade, given the potential for unanticipated outcomes.

In summary, the above channels confirm the nonlinear and multidimensional nature of channelling geopolitical risk into commodities. Basic forecasting models that merely combine historical prices won't suffice unless they can take into account both hard constraints (e.g., blocked ports) and soft dynamics (e.g., fear, speculation, and expectations about policies).

5.8. Research gaps in the literature

While there has been rising interest among researchers in the relationship between geopolitical risk and commodity markets, this review identifies several vital gaps in current research that hinder explanatory power, model robustness, and practical policy applications. This review identified five areas of significant gaps in research:

5.8.1. Measurement and indexing geopolitical risk

Caldara & Iacoviello (2022) provide the most popular fully composite, media-driven frequency metrics of geopolitical risk (GPR) indices. The most recent wavelet-based decompositions (Balcilar et al., 2024) improve on time rescaling.
Gap Identified: There are no sector- or region-specific GPR indices. Currently, GPR indices are either fully aggregated or reveal an international scope, making it impossible to judge GPR risk by industry (e.g., agriculture vs defence) or region (e.g., MENA vs Asia-Pacific). That limits the accuracy of insights into localised impacts.
Research Opportunity: Create industry-level GPR indicators or geographical GPR models using localised media data, policy data, and natural language processing (NLP) to capture context-driven shocks better.

5.8.2. Commodity classes not explored in depth (non-energy centred)

Much has been published on oil (Kang & Ratti, 2013). While coverage of agricultural commodities has been limited, it is increasing (B. Hamdi et al., 2019; M. Hamdi & Aloui, 2015).
Gap Identified: Base and strategic metals (i.e, copper, nickel, and lithium) have come to be overlooked in measures of geopolitical risk. Due to geopolitical sensitivities (i.e., Cobalt from the DRC, Rare Earths from China), metals are rarely analysed in GPR-connected literature. Yet, they are essential for the energy transition and supply chain security.
Research opportunity: Consider applying GPR modelling to metals with geopolitical sensitivities where concentrations are at risk. The result will enable an investigation into risk as a function of the supply of strategic metals related to green-energy geopolitics, especially in the context of tensions between the US and China and conflicts in Africa.

5.8.3. Mechanism-specific modelling

Three conceptual models have been forwarded that highlight three central mechanisms/sources of risk in GPR: supply disruptions, speculation, and policy effects.
Gap Identified: To date, only a handful of empirical modelling studies seeking to isolate mechanisms individually have been completed. The literature tends to treat GPR as a single shock rather than examining potential cause-positive effects using more narrow focus studies (i.e., policy sanctions directly from GPR vs. actual conflict or media speculation). This only leads to over-generalised conclusions.
Research Outline: Design multi-mechanism structural models (e.g., structural VARs, mediation analysis, or causal ML) to disentangle the unique impacts of sanctions, disruption, and sentiment.

5.8.4. Little use of interpretable machine learning

Yun et al. (2023) apply long short-term memory (LSTM) to forecast oil prices using GPR and the VIX. Pham et al. show that deep learning outperforms traditional models in periods of conflict.
Gap Addressed: The Black box nature of ML models creates barriers to explainability and practical use. LSTM and other neural models are very limited in interpretability, inaccessible to decision makers, and not quantifiable for testing.
Research Directions: Incorporate known explainable AI techniques (e.g., SHAP, LIME) into GPR forecasting using GPR. Develop hybrid models that blend conventional, transparently specified statistical models (such as VARs) with limited-transparency ML-derived nonlinearity capabilities, making GPR stakeholders more trusted and accepted in practice.

5.8.5. Investor behaviour and asset allocation under GPR are still poorly understood

Gold is an established hedge (Baur & Lucey, 2010). Cryptocurrencies have weak and fleeting haven behaviour (Sun et al., 2023; Zhang & Zhang, 2023).
Identified Gap: Few empirical studies on multi-asset portfolios in periods of geopolitical stress. Most safe-haven studies examine assets in isolation (e.g., only gold or Bitcoin). The literature lacks multi-asset portfolio allocation strategies for varying levels of GPR-induced volatility.
Research Directions: Develop robust portfolio optimisation models that incorporate dynamic GPR shocks, gold, fiat currencies, crypto, and T-bonds under varying geopolitical circumstances. Additionally, examine the differences in institutional versus retail investor behaviour using fund flows or sentiment indicators.

5.8.6. The role of supply chain networks and global trade routes is neglected

A few qualitative studies from the World Bank, IMF, and FAO mention some types of trade disruption.
Gap Identified: No formal modelling of logistics choke-points (i.e., Black Sea and/or Hormuz). Significantly few empirical studies have linked GPR to shipping costs, container availability, or food insecurity metrics.
The research opportunity is to incorporate supply chain data (e.g., AIS shipping, port delays, insurance costs) into econometric modelling. This may also include using network analysis and/or graph theory to demonstrate globally important commodity nodes at risk of geopolitical tension.

5.8.7. Temporal asymmetry and persistence of GPR effects

GPR shocks have immediate but typically sharp effects.
Gap Identified: Few studies have interrogated how long and to what degree geopolitical shocks decay with time. It is not known whether effects can fade within weeks or remain in other forms of pointer after months and/or years, including commodity class or type of conflict.

A research opportunity is to use definitions of event or impulse-response functions to show how long a geopolitical shock can last. Additionally, consider critical social dimensions of duration, such as media saturation, operator memory, or institutional inaction, that could lengthen GPR's impacts.

5.9. Implications for policy and practice

This report has implications for policy-makers, investors, and commodity traders. First, a GPR trend can serve as an early warning system to help prevent commodity shocks. Second, redundancy in supply chains, primarily relying on food and energy imports, builds national resilience. Finally, some regulation of speculative activity during a crisis can reduce the incidence of forced price spikes that are detrimental to vulnerable populations.

In financial markets, diversification strategies combining a mix of classical safe-haven assets (e.g., gold, Treasuries) with emerging portfolio commodities (i.e., some low-volatility, tradable, crypto-derivatives) and accounting for intra-asset availability could mitigate the risk of rising geopolitical uncertainty.

The findings carry important implications for both policymakers and market participants in navigating the complexities of geopolitical risk (GPR). Policymakers could advance the development of localised GPR indices by systematically integrating region-specific news analytics, event databases, and cross-border trade data, thereby enabling more nuanced monitoring of geopolitical disruptions. Strengthening early warning systems will require incorporating satellite intelligence, supply chain tracking, and AI-driven forecasting, while also confronting practical barriers such as the costs of modelling infrastructure, the availability of high-frequency data, and the coordination required across institutions. For investors, safe-haven strategies and portfolio diversification remain crucial, with cross-commodity hedging and expanded use of transparent derivatives markets offering concrete pathways to mitigate volatility. Embedding these measures within broader policy frameworks on resilience and financial stability would ensure that responses to GPR are not only reactive but also proactive, adaptive, and sustainable over time.

5.10. Limitations and future research directions

The systematic literature review (SLR) provides a comprehensive account of GPR studies; however, certain limitations remain. First, the lack of access to proprietary trading and position-level databases constrains the ability to fully assess the role of speculative activity in amplifying commodity price movements. Second, many AI and machine learning models suffer from low interpretability, functioning as "black boxes" that limit their usefulness for policymakers who require transparent and explainable tools(Axelson & Makarov, 2023; Bekiros et al., 2017). Third, most existing studies do not adequately account for regional variations in geopolitical risk, which restricts the generalizability of findings across different commodity groups and sectors.

Future research should focus on explaining GPR using an explainable AI hybrid framework within econometrics; conducting deeper GPR research on the sector-specific commodities of metals, agriculture, and transportation; and mapping climate-related geopolitical risks and their interrelationships with the flow of commodities.

6. Conclusion

This research review highlights the significant and direct effects of geopolitical risk (GPR) on international commodity markets. According to the study, shocks like conflicts and sanctions have an immediate impact on oil prices and volatility. Similarly, supply chain vulnerabilities and trade dependencies cause significant disruptions to commodities related to agriculture and metals. Additionally, during times of geopolitical strain, investor behaviour changes, favouring conventional safe-haven assets like gold over digital alternatives. Future studies should focus on developing sector-specific GPR indices, using interpretable AI techniques, and thoroughly modelling key strategic metals, such as lithium. These paths are essential for expanding our understanding of how commodity systems, trade resilience, and global economic security are affected by geopolitical instability.

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