Trading Risk: Mapping the Hidden Vulnerabilities in Global Energy Flows

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Abstract

Energy vulnerability indexes are scarce or rather non-existent. This work represents a first effort in this direction. Using bilateral trade energy flows and structural and institutional factors from the importer and exporter country, we generate a database through a deep learning-based methodology that exposes the intrinsic energy risks for natural gas, oil, and solid fossil fuels and the total economy between 1995 and 2023. These indices can provide valuable information regarding energy risks, which countries can consider reducing dependence on a single importer, diversify their exports, or even meet demand through domestic production. The analysis reveals clear temporal and country differences: in 1995, Central and Eastern Europe faced extreme natural gas vulnerability due to heavy reliance on Russian supply, while major oil importers such as Japan and Western Europe were highly exposed to foreign producers. Solid fossil fuel dependence primarily affected import-dependent European regions. By 2023, diversification strategies, improved institutional quality in exporting countries, and the expansion of renewable energy reduced exposure for several European nations, although significant risks persisted for some importers like Hong Kong, Bangladesh, the Netherlands, Turkey or Lithuania.

Introduction

The world is currently facing a polycrisis driven by the convergence of multiple geoeconomic factors, including wars, limited access to energy resources, and geopolitical tensions (WEF, 2025). These developments have increased volatility in global energy markets, driving up the prices of oil, solid fossil fuels, and gas, and consequently affecting both industrial competitiveness and household consumption. In particular, the conflict between Russia and Ukraine marked a critical turning point, leading to a sharp rise in gas prices and intensifying the challenges of the energy trilemma—balancing sustainability, security, and affordability (WEC, 2024).

In response to these risks, countries have diversified their energy sources, investing in renewable energies, and broadened their range of import partners, often aligning with states that share similar governance and ideological profiles, phenomena known as *powershoring* (Arbache, 2022). For example, *REPowerEU* Plan aims to reduce dependence on fossil-fuel imports and accelerate the green transition in the EU (European Commission, 2022). Similarly, the *Inflation Reduction Act* (U.S. Congress, 2022) and subsequent Executive Orders (The White House, 2025) promote domestic energy production with the goal of securing energy supply. Also, in China the *14th Five-Year Plan* (2021–2025) (NDRC, 2022) pursues energy security through centralized planning and technological innovation.

Despite energy security being in the centre of national policy agendas, the academic literature on this topic scarce or rather non-existent (Aiyar, Presbitero, & Ruta, 2023). Consequently, this paper is the first effort to tackle the topic of energy vulnerability. Energy security be defined as the uninterrupted availability of energy sources at an affordable price (IEA, 2014). Considering this, a novel methodology is proposed that leverages a deep learning approach to calculate an index of energy vulnerability for the total economy and the three most critical energy raw materials—oil, solid fossil fuels and gas—across 65 countries from 1995 to 2023. The model integrates structural country-level features (e.g., production-consumption ratios, supplier diversification) and institutional factors (e.g., exporter political alignment, institutional quality) to provide an evaluation of the country risk exposure to geopolitical threats

Between 1995 and 2023, global energy vulnerability has experienced significant shifts due to changes in production, consumption, and supply diversification. Natural gas vulnerability increased overall, largely driven

by price volatility, although LNG imports and institutional improvements have reduced risks for some countries. In 1995, gas risk affected importers like Belgium, Portugal, and Hong Kong, while self-sufficient producers remained relatively safe. By 2023, diversification and stronger institutions lowered exposure in several countries, yet key importers such as Portugal, Turkey, and Hong Kong still face medium to high vulnerability. Oil vulnerability was high particularly for Japan, Europe, and Hong Kong, due to reliance on politically unstable supplies. Some countries reduced their risk through domestic production or secure imports, while others, including Switzerland, the Philippines, and China, saw vulnerability rise. Vulnerability to solid fossil fuels has increased moderately, remaining lower than oil or gas due to stable supply patterns. Some countries reduced their exposure through lower consumption or diversified imports, while others still face rising risks.

Overall, total energy vulnerability has declined thanks to greater domestic production and the growth of renewables. However, import-dependent countries, including Hong Kong, Turkey, and Lithuania, continue to face medium to high risks, reflecting uneven progress in global energy security.

This paper is divided into 6 sections. Section 2 outlines the theoretical and conceptual framework, research hypothesis, data and explain the deep learning approach. Section 3 presents the results. Section 4 offers conclusions and discussion while Section 5 proposes policy recommendations.

2. State of the art (expand but it will not be included in Nature version)

To date, the World Energy Council (WEC) index is the only temporal and cross-country measure of energy security. Although widely used, it has been criticized for methodological limitations and for failing to capture the multidimensional nature of energy security (Šprajc, Bjegović, & Vasić, 2019). Several alternative indices have been proposed. Gnansounou (2008) developed a composite index assessing energy demand vulnerabilities based on energy intensity, oil and gas import dependence, CO_2 content of primary energy supply, electricity supply weaknesses, and the lack of diversity in transport fuels. Gatto and Busato (2020) proposed an index including electricity access, energy intensity, energy imports, and fuel exports. Similarly, Gatto and Drago (2020) introduced a composite indicator based on three pillars—energy access, energy efficiency, and renewable energy—using interval-based methods to capture uncertainty. Other attempts include Gupta (2008), who applied factor analysis to weight dimensions, and Kim et al. (2025), who used a Herfindahl–Hirschman Index (HHI)–based approach to measure energy market concentration, integrating political risk adjustments to assess vulnerability to supply disruptions. While informative, these approaches tend to oversimplify a multidimensional problem without considering non-linear relationships among variables, assumptions in weighting variables, importing and exporting characteristics, or providing data across years, countries, and products.

2. Theoretical framework

As a theoretical framework we develop a modified version of the trade model proposed by Antràs (2016). Our model consists of a world with J consumer countries that consume w goods [1]— in our case energy products such as oil, solid fossil fuels and gas. Preferences are identical everywhere in the world and given by:

$$U_j = \sum_{i=1}^{I} \sum\nolimits_{w \in \Omega_{ij}} \beta_{ij} \log q_{ij,w}, \qquad \sum_{i=1}^{I} \beta_{ij} = 1 \qquad (1)$$

Each consumer countries is represented by j, whereas imported countries by i. β represents the share of country j's expenditure on energy originating from i. The $q_{ij,w}$ represents the demand of good w, while Ω_{ij} denotes the set of all products considered for country j originating from country i. These goods can either be imported $(i \neq j)$ or produced domestically $(i = j)$.

The total demand of energy goods from consumption country j is given by Q. In equation 2, consumption shares are additive of goods w. Since energy goods w are largely independent and not easily substitutable (Serletis et al., 2010a; 2010b), their cross-price elasticities are zero.

[1] We will use the terms 'goods' and 'energy goods' interchangeably, but this model focuses on energy goods trade.

$$Q_j = \sum_{i=1}^{I} \sum_{w \in \Omega_{ij}} q_{ij,w} \quad (2)$$

Based on equation (2), the share of each country's consumption from each origin can be defined as:

$$s_{ij} = \frac{\sum_{w \in \Omega_{ij}} q_{ij,w}}{Q_j} \quad (3)$$

In our model, individual demand is given by equation (4), where E_j represents the total expenditure of country j; β_{jj} denotes the consumption proportion of domestic production; $p_{jj}(w)$ is the domestic price of good w; β_{ij} is the proportion of imported consumption, $p_i(w)$ is the external price of good w from country i. τ_{ij} captures the institutional quality of the exporting country, γ_{ij} represents inherent transport costs between i and j, $f(d_{ij})$ denotes the effect of country political distance.

$$q_{ij,w} = \begin{cases} \beta_{jj} E_j \dfrac{1}{p_{jj}(w) + \varepsilon} & i = j \\ \beta_{ij} E_j \dfrac{f(\tau_{ij})}{p_i(w) + \gamma_{ij} + f(d_{ij})} & i \neq j \end{cases} \quad (4)$$

Where E_j is given by (5):

$$E_j = \sum_{i=1}^{I} \sum_{w \in \Omega_{ij}} p_{ij,w} q_{ij,w} \quad (5)$$

The level of domestic production is limited by available energy reserves, such that $q_{jj,w} \leq R_{j,w}^{res}$, where $R_{j,w}^{res}$ represents the reserves or capacity available in country j to produce good w. If reserves are insufficient, domestic production falls and the demand is met through imports. From this, we can obtain the total domestic production for each country given by (6).

$$Y_j^{dom} = \sum_{w \in \Omega_{jj}} q_{jj,w} \quad (6)$$

The importing country may diversify its providers to reduce import risk (Cohen, Joutz, & Loungani, 2011). This is given by (7).

$$D_j = \sum_i \theta_{ij}^2 \quad (7)$$

When $D_j \to 1$, there is concentration in a few suppliers, and when $D_j \to 0$, there is high diversification. From this, we can obtain the level of exposure to risk of country j from equation 8.

$$R_{wj} = \bar{R} \quad - \propto Y_j^{dom} - \delta \sum_{i \neq j} f(\tau_{ij}) \quad + \Gamma \sum_{i \neq j} f(d_{ij}) + \theta D_j + \varepsilon_j \quad (8)$$

The risk of country j for energy product w, R_{wj}, depends on an average level of risk on the global landscape ($\bar{R}$). Higher domestic production Y_j^{dom} reduces risk, while reliance on foreign suppliers, adjusted for institutional quality τ_{ij}, and greater political distance d_{ij} reduce (δ) and increase (Γ) it respectively. Also, lower diversification of suppliers D_j increases risk (θ), and ε_j captures idiosyncratic shocks.

3.1 Conceptual framework and research hypothesis

The conceptual framework introduces a novel model in which countries face two main sources of energy risks. Structural factors create vulnerabilities when countries lack sufficient domestic resources to be self-sufficient

or rely heavily on a single foreign supplier (Cohen, Joutz, & Loungani, 2011), increasing their exposure to geopolitical disruptions. Institutional factors further amplify risk when imports come from countries with weaker levels of governance (Antràs, 2016; Kim et al., 2025) or significantly different political and ideological orientations (Bailey et al., 2017; Kim et al., 2025). See Figure 1 for a conceptual framework.

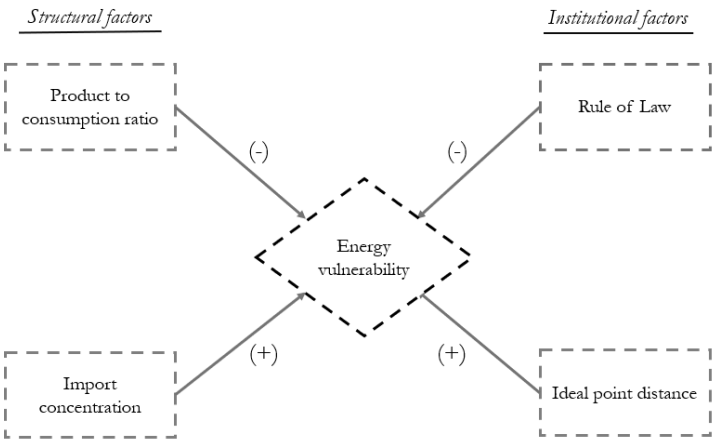


Fig. 1. A conceptual framework about the country energy vulnerability given by structural and institutional factors.
Source: Own elaboration
We investigate three main hypotheses in this paper:

- H_1: Countries exhibit energy vulnerabilities in their energy supply due to import dependence from risk countries
- H_2: Energy-producing countries may still be exposed to risk despite having domestic resources, due to imports dependence.
- H_3: Some countries are more resilient than others to economic and geopolitical shocks in the energy sector.

3.2 Data

A panel dataset of international trade flows was constructed covering 65 importing countries[2], for the raw materials most relevant to energy vulnerability (IEA, 2025) – namely gas, solid fossil fuels, and oil. These commodities accounted for approximately 81.3% of global energy consumption in 2024, with gas representing 23.6%, solid fossil fuels 26.2%, and oil 31.6%. The dataset spans the period 1995–2023 and is based on BACI for oil and solid fossil fuels, which provides bilateral trade flow data for 200 countries at the HS 6-digit product level code while for gas is provided by the International Energy Agency.

As import features, production-to-consumption ratio[3] is considered since countries with a higher ratio are expected to have lower energy vulnerability (Gatto and Drago, 2020). This variable is calculated for, oil, solid fossil fuels and gas using data from Our World in data (OWID). Moreover, the Herfindahl-Hirschman index (HHI) is included representing the import concentration, as higher diversification of providers is expected to reduce vulnerability (Cohen, Joutz, & Loungani, 2011).

Regarding the exporting countries, two features are included. First, Rule of Law: importing from countries with lower Rule of Law is expected to increase a country's energy vulnerability (Antràs, 2016). Second, to capture differences in political alignment, which represents the divergence in positions on United Nations issues (Bailey

[2] Importing countries were selected due to data availability restrictions.

[3] Production is used instead of reserves because, in some countries, reserves are not immediately available for extraction (Welsby et al., 2021). Moreover, countries with higher reserves are expected to produce more, leading to a higher production-to-consumption ratio and, consequently, lower energy vulnerability.

et al., 2017). This accounts for the fact that for some countries (e.g., Japan) importing from one country (e.g., Australia) may be more secure than importing from another (e.g., Saudi Arabia), and for others (e.g., Venezuela) importing from one country (e.g., Russia) may be more secure than importing from another (e.g., United States). Since our objective was to include the actual dependence of the importer country on others, the share of a country consumption that relies on foreign sources is calculated. We use, oil, solid fossil fuel and gas data from OWID, reported in TWh, and convert BACI trade data for oil and solid fossil fuels[4] from tons to TWh using calorific values from the United Nations (2016).[5] All features were standardized to ensure comparability across countries and years.

3.3. Networks & Deep Learning

Let $X^{(t,w)} \in \mathbb{R}^{DxN}$ be the input feature matrix for year t and product w, where D is the total number of nodes (countries) and N is the total number of features. This matrix can be partitioned into importer and exporter features as

$$X^{(t,w)}{}_{\text{importer}} \in \mathbb{R}^{N_{\text{imp}} \times F_{\text{imp}}} \quad \text{and} \quad X^{(t,w)}{}_{\text{exporter}} \in \mathbb{R}^{N_{\text{exp}} \times F_{\text{exp}}}$$

where $N_{\text{imp}} + N_{\text{exp}} = D$ and $F_{\text{imp}} + F_{\text{exp}} = N$. Here, N_{imp} and N_{exp} denote the number of importers and exporters, respectively, while F_{imp} and F_{exp} represent the number of features for importers and exporters.

Further, let $H_i \in \mathbb{R}^{D\ x\ h_i}$ be the output matrix of the hidden layer i, being $W_i \in \mathbb{R}^{D\ x\ h_i}$ the weight of each hidden layer and $b_i \in \mathbb{R}^{D\ x\ h_i}$ be the corresponding bias where h_i is the number of neurons in the i hidden layer with $h_o = N$ and thus $H_o = X$. Moreover, we denote $z_i\ (.)$ as the activation function, in our case a Gaussian Error Linear Unit (GELU)[6] function (Hendrycks and Gimpel, 2016). Then, we calculate the output layer $L \in \mathbb{R}^{D\ x\ S}$, where s is the number of modelled features (see equation 9.). See Figure 2 for a graphical representation of the network. In the output layer the subscripts o, s and g refer to oil, solid fossil fuels and gas respectively.

$$L = H_i W_{I+1} + b_{I+1} \quad (9)$$

[4] Gas data were reported in TWh by the IEA.

[5] For 0.05% of the sample, the import share exceeds consumption. In some cases, we assume this occurs to increase the proportion of reserves; in others, we imagine the country is acting as storage to later send goods to other countries. However, most of these cases are considered measurement errors in the BACI trade data. Therefore, when imports exceed consumption, we cap the value at 1. That is, a country cannot import more than it consumes.

[6] GELU is selected over traditional approaches like Rectified Linear Unit (ReLU) since due to its desirable attributes, including its smoothness and differentiability (Lee, 2023).

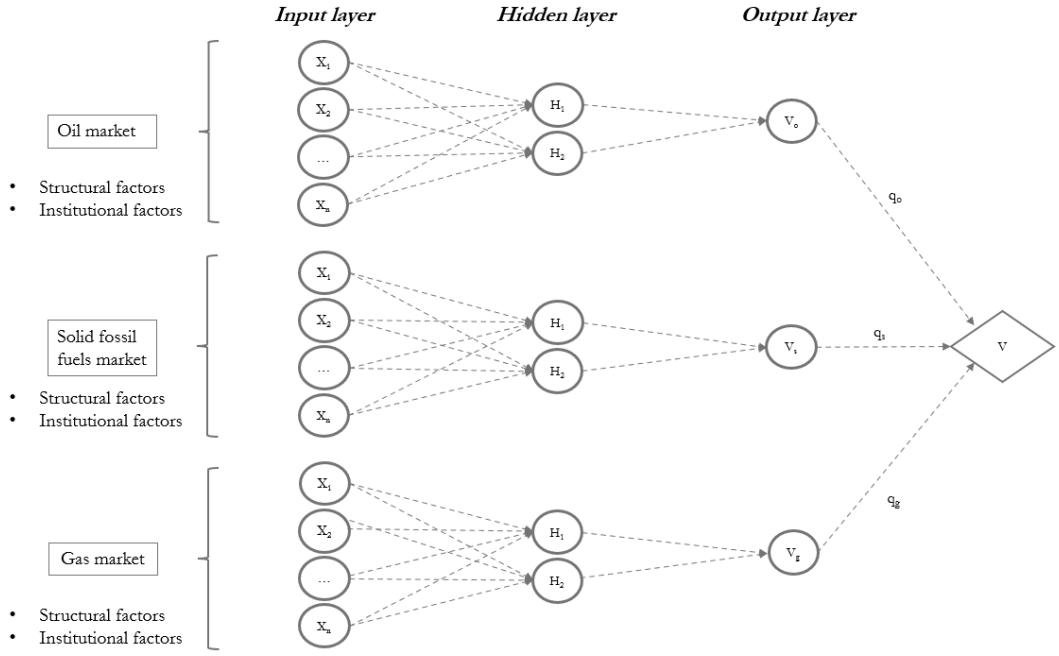


Fig. 2. A conceptual framework about the deep learning approach developed.

Since we do not have a dependent variable to compare against for minimizing the error, so we generate it using inductive methods. A self-supervised loss function is defined that guides the model (Bardes, Ponce and LeCun; 2021)

$$\mathcal{L} = \alpha\,\mathcal{L}_{\text{var}} + \beta\,\mathcal{L}_{\text{corr}} + \gamma\,\mathcal{L}_{\text{sign}} \quad (10)$$

$\mathcal{L}$ refers to the total loss that the network tries to minimize (equation 10). The variance per node ($\mathcal{L}_{\text{var}}$): maximizes the dispersion of the scores to avoid flat values. α is associated with how much we want to maximize the variance of the scores (equation 11).

$$\mathcal{L}_{\text{var}} = -\text{Var}(\hat{v}) \quad (11)$$

$\mathcal{L}_{\text{corr}}$ guarantee that the model is correlated with the features described in Section 3.1 and β represents how much we want that the calculated index follows the directions of the features (equation 12). In our case, $\hat{v}$ represents the vulnerability score for each importer, product and year, k is the feature and s_k is the expected direction that are based on Sections 3.1 and 3.2. So, what we want is to maximize the correlation between the index and the feature.

$$\mathcal{L}_{\text{corr}} = -\frac{1}{K}\sum_{k=1}^{K} \text{corr}(\hat{v}, X^{(k)}_{\text{importer}} \cdot s_k) \quad (12)$$

Correlation sign ($\mathcal{L}_{\text{sign}}$): It penalizes correlations that are contrary to economic theory, for both importers and aggregated exporters (equation 13).

$$\mathcal{L}_{\text{sign}} = \sum_{k=1}^{K_{\text{imp}}} \text{GELU}(-s_k \cdot \text{Cov}(\hat{v}, X^{(k)}_{\text{importer}})) + \sum_{l=1}^{K_{\text{exp}}} \text{GELU}(-s_l \cdot \text{Cov}(\hat{v}, X^{(l)}_{\text{exporter-agg}})) \quad (13)$$

Where s_k, s_l indicates the expected direction. $s_k, s_l \in \{-1,1\}$

$\mathcal{L}_{\text{corr}}$ guides the model to align predictions with the trend and magnitude of the features, penalizing deviations from the expected direction and smoothing the learning process, while $\mathcal{L}_{\text{sign}}$ ensures that the scores maintain the correct sign regardless of slope. Together, these losses are complementary. $\mathcal{L}_{\text{corr}}$ aligns predictions with known relationships, and $\mathcal{L}_{\text{sign}}$ prevents sign inversions, allowing the model to capture complex non-linear interactions among features.

Each model is trained separately for each country, year and energy product. Inference is then performed year by year using the trained model, producing vulnerability scores for each importer. The model weights are optimized through backpropagation using the Adam optimizer (Kingma and Ba, 2015) and a dropout (Srivastava et al. 2014) to avoid overfitting. Each model produces a scalar vulnerability score through a final sigmoid activation (Narayan, 1997), which maps the output of the linear layer into the [0,1] range, representing the model's estimated vulnerability probability. Finally, vulnerability embeddings were first scaled to a fixed (0,100) range using the 2nd and 98th percentiles of the distribution across all years, thereby reducing the influence of outliers. Then, embeddings were aligned to a common reference frame using Orthogonal Procrustes (Maystre et al. 2025) to make them comparable across years

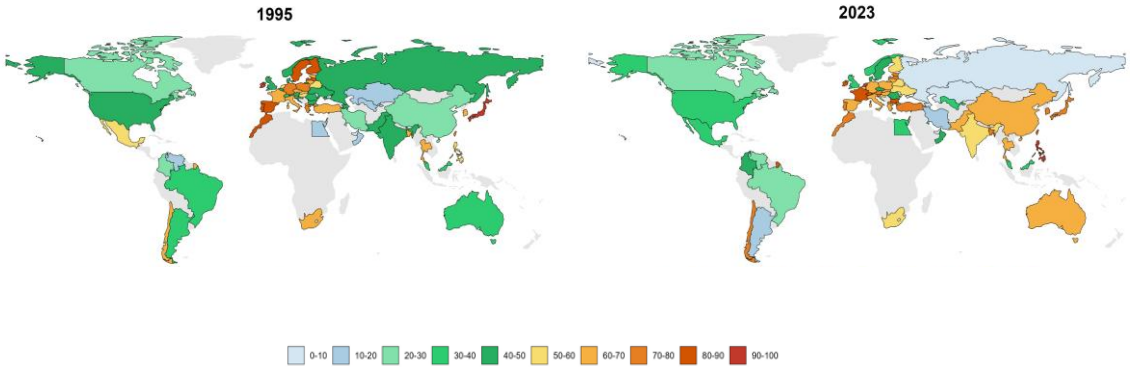
Finally, vulnerability indexes for each product are weighted by the proportion of total final consumption q_w to calculate the total actual vulnerability for each country (V) (see equation 14). Since we quantify each product consumption relative to total consumption, if countries produce more renewable energies[7] will exhibit lower vulnerability, as these sources are assumed to be domestically produced.

$$V = V_o q_o + V_s q_s + V_g q_g \quad (14)$$

4. Results

Before discussing the observed results, it is important to emphasize that the data specifically reflect the risk associated with the product itself. A reduction in consumption does not necessarily translate into a lower risk. Even if a country decreases its reliance on a particular product, it may remain highly exposed if it lacks domestic production capacity or continues to depend on imports from countries with elevated risk or from states with which it has limited political alignment. For example, a country whose gas consumption represents only 5% of its total energy needs may still face significant vulnerability if that 5% is imported from a nation experiencing civil unrest.

Figure 3: Energy vulnerability for oil. Left panel represents 1995, and right panel represents 2023



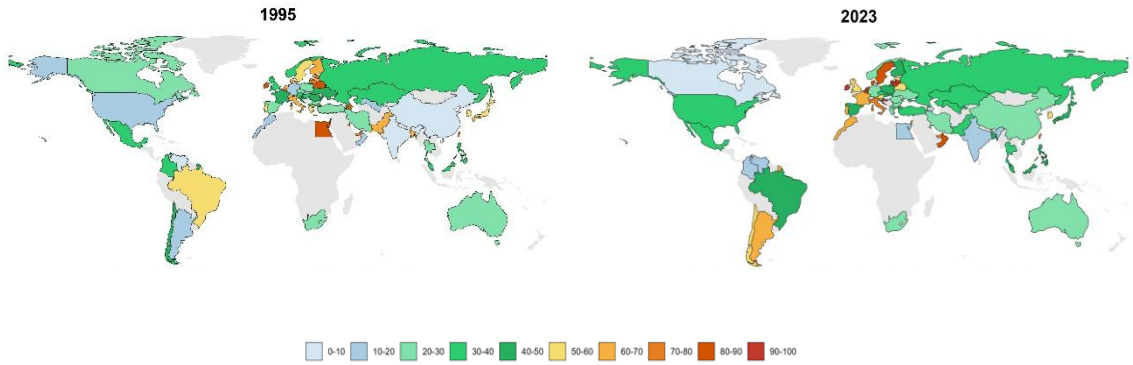
Oil results are presented in Figure 3. Overall, oil risk is increasing over time with volatility. In 1995, oil-related vulnerability was high and widespread, particularly among major importers such as Japan, most of Europe, Marruecos, South Africa, Taiwan, Hong Kong or Singapore where values ranged between 70 and 100. In 1995, the main oil exporters were Saudi Arabia (15.2%), Norway (6.7%), and Russia (5.8%). For many years, it has

[7] In this group, we include solar, wind, biofuels, hydro, nuclear, and other renewable sources.

been considered the highest-risk resource, as a large portion of its production comes from countries experiencing deteriorating institutional quality due to political and economic instability, such as Iran, Saudi Arabia, Iraq, Nigeria, Angola, Venezuela or Russia. By the end of the series, Saudi Arabia accounted for 12.13% of exports, the United Arab Emirates for 11.7%, Russia for 7.8%, and the United States 9.3%. Several significant changes occurred between 1995 and 2023. In 2023, on average, the risk was higher in all the world, where we highlight countries like Hong Kong, Netherlands, Philippines, Switzerland, France, Bulgaria, Taiwan, Ireland, Estonia or Chile.

Regarding changes in position, we can highlight that vulnerability declined in Azerbaijan and Russia because of increased domestic production. In Western Europe, countries such as Sweden (-43.7 percentage points (pp.)) and Finland (-26.0 pp.) experienced reductions in vulnerability due to their near-exclusive reliance on Norway, a secure supplier. The Czech Republic (-25.3 pp.) benefited from decreased dependence on Russian imports and increased sourcing from Germany. Similarly, Spain (-24.9 pp.) reduced its vulnerability by shifting imports toward politically aligned and secure partners, including the United States, while reducing exposure from Nigeria, Libya, and Iran. Conversely, some countries experienced an increase in vulnerability over the same period. Switzerland (52.3 pp.) saw a rise due to a more concentrated import structure, while the Philippines (40.7 pp.)[8]. Also, China (34.9 pp.) registered higher vulnerability driven by increased imports from Russia, Iraq, and Oman.

Figure 4: Energy vulnerability for solid fossil fuels. Left panel represents 1995, and right panel represents 2023

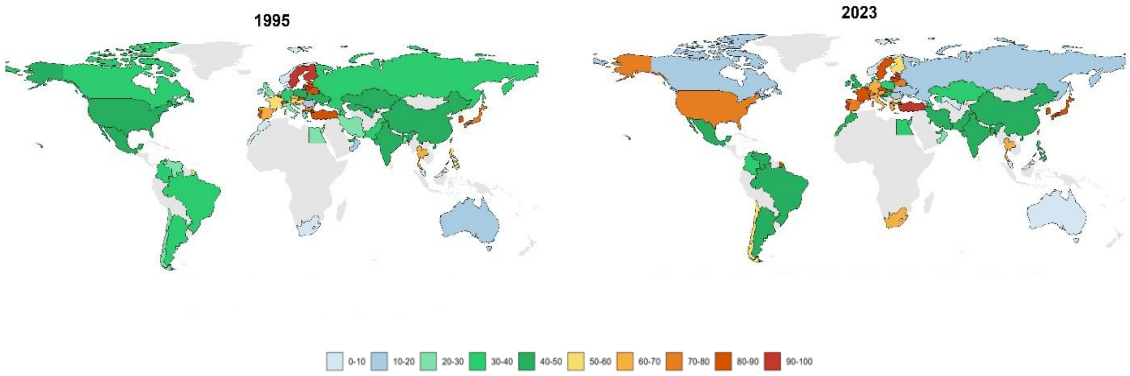


Results for solid fossil fuels are presented in Figure 4. Overall, solid fossil fuels risk is increasing over time with volatility. In this case, vulnerability is lower compared to oil or gas, since the main producing countries are more politically stable. In 1995, Australia accounted for 32.6% of exports and the United States for 17%, acting as the primary exporters. Major producer–consumer countries, including Venezuela, China, the United States, Australia, India, exhibited low vulnerability levels (0–20). In contrast, import-related risks were mainly concentrated in Western and Central Europe—such as Lithuania, Netherlands, Latvia, Croatia, Ireland, Sweden, Denmark, Oman, Singapore and Belgium—where vulnerability levels were substantially higher (80–100). By the end of the period, Indonesia (32.4%), Australia (25.5%) and Russia (10.3%) had become the main suppliers of solid fossil fuels, which explains the high vulnerability observed in some countries in 2023. Several countries decreased their vulnerability compared to 1995; for example, Azerbaijan (-80.8 pp), due to its practically non-existent consumption; Switzerland (-64.8 pp), thanks to higher imports from countries such as Australia and Germany instead of China, Venezuela, or South Africa; Egypt (-61.2 pp), also due to lower consumption; and Pakistan (-32.8 pp), owing to diversification and imports from politically aligned suppliers. Conversely, vulnerability levels increased in other countries. Oman (+72.0 pp) experienced higher exposure due to increased import dependence, particularly from Russia. Croatia (+60.9 pp) recorded greater vulnerability, mainly driven by solid fuel consumption sourced from Kazakhstan, Colombia, and Indonesia. Argentina (+48.0 pp) saw an increase in vulnerability due to declining domestic reserves and growing import dependence,

[8] We consider that the import data for the Philippines in the current year are likely overestimated since they import a 691% more than the previous year.

primarily from Indonesia. Finally, Morocco (+45.3 pp) became more vulnerable as imports expanded from suppliers such as the United States, Colombia, and Russia.

Figure 5: Energy vulnerability for gas. Left panel represents 1995, and right panel represents 2023



Results for gas are presented in Figure 5. Overall, gas risk is increasing over time with volatility experiencing the highest risk increase in all the three products considered. In 2023 the mean risk across all countries is 55.20. Natural gas vulnerability exhibited a geopolitical concentration in 1995 since most production was concentrated on Russia (39%) and Canada (16.9%). The most critical conditions were Belgium, Finland, Sweden, North Macedonia, Lithuania, Portugal, Switzerland, Singapore, South Korea and Hong Kong, Conversely, large producers and self-sufficient regions such Canada, Russia, Malasia or Denmark maintained low vulnerability levels (0–20). Between 1995 to 2023, there is a diversification of supply sources, including LNG imports from Norway, Qatar, and improvements in regional institutional in some exporting countries such as Indonesia, Malasia or Argelia. In 2023, the main global suppliers of natural gas were the United States (16.0%), Qatar (11.3%), and Russia (10.85%).

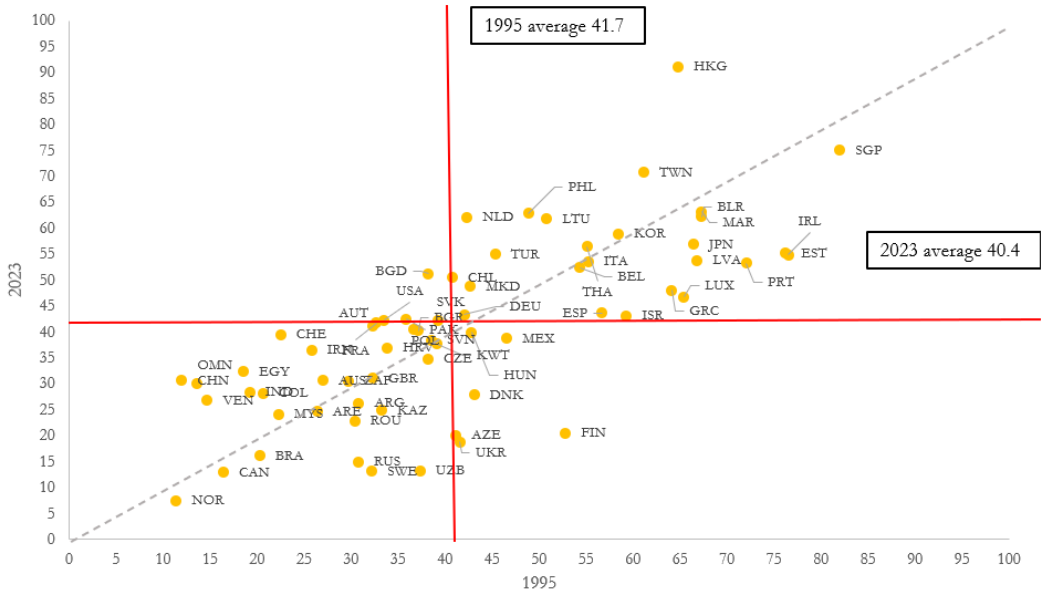
Nevertheless, vulnerability remained medium to high for key importing countries, reflecting structural dependencies. The countries exhibiting the highest energy risk are Portugal, Latvia, Estonia, Luxembourg, Slovenia, Belgium, North Macedonia, Turkey, Lithuania, and Hong Kong. In this regard, the United States can be highlighted as a risky case, since despite having domestic gas production, it exports part of its output while simultaneously importing from Russia—a politically non-aligned supplier associated with elevated geopolitical risk.

The main decreases in vulnerability during the period were observed in Finland (-46.9 pp), due to increased imports from the United States and Australia and reduced reliance on Russia; Israel (-44.8 pp), driven by the availability of domestic reserves; Ukraine (-37.4 pp), thanks to diversification toward suppliers such as the United States, Poland, Australia, and Colombia; and Uzbekistan (-36.5 pp), following diversification and a shift toward politically aligned partners. In contrast, some countries experienced significant increases in vulnerability. South Africa (+61.4 pp) or Taiwan (+44.6 pp).

Results for the total vulnerability are presented in Figure 6. Overall, risk is decreasing over time mainly due to country self-dependence of energy. The Total Energy Vulnerability Index integrates the combined risks associated with natural gas, oil, and solid fossil fuels, since we quantify each product consumption relative to total consumption, if countries produce more renewable energies will exhibit lower vulnerability, as these sources are assumed to be domestically produced (see equation 14). High vulnerability levels persisted in Belarus, Estonia, Hong Kong, Ireland, Japan, Luxembourg, Lithuania, Morocco, Portugal and Singapore in 1995, reflecting high consumption intensity and strong exposure to external supply risks. In contrast, self-sufficient countries consistently maintained low risk levels, with North America, China, Norway, Oman,

Venezuela, Russia and Brazil. Some notable changes occurred between 1995 and 2023. Several European countries reduced their risk exposure through the increased penetration of renewable energy—such as Spain, Finland, Denmark, Sweden, Estonia, Ireland, Portugal, Luxembourg—while other countries experienced higher risk levels, notably Hong Kong, Bangladesh, the Netherlands, Turkey, Philippines, Egypt or Lithuania.

Figure 6: Total vulnerability. X axis represents 1995, and Y axis represents 2023



Conclusions and discussion

In this article, we propose a new methodology based on deep learning to estimate the intrinsic energy risks in energy flows—natural gas, oil, and solid fossil fuels—as well as the total vulnerability from 1995 to 2023, considering structural and institutional factors. The analysis of energy vulnerability highlights distinct patterns for natural gas, oil, solid fossil fuels and total vulnerability.

Natural gas vulnerability has increased overall, with volatility showing the largest risk rise. In 1995, risk was concentrated in Russia and Canada, affecting countries like Belgium, Portugal, and Hong Kong, while self-sufficient producers remained low. By 2023, supply diversification through LNG imports and institutional improvements in exporters reduced exposure for some countries. Despite this, key importers—including Portugal, Turkey, and Hong Kong—still face medium to high vulnerability, while countries like Finland, Israel,

and Ukraine managed to lower their risk. Oil vulnerability has increased over time, with major importers like Japan, Europe, and Hong Kong facing high risk due to reliance on politically unstable exporters. In 1995, Saudi Arabia, Norway, and Russia were the main suppliers. Between 1995 and 2023, some countries—such as Azerbaijan, Russia, Sweden, and Finland—reduced risk through domestic production or secure imports, while others, including Switzerland, the Philippines, and China, saw vulnerability rise. Solid fossil fuel vulnerability has generally increased, though it remains lower than oil or gas due to stable producers. In 1995, Australia and the United States dominated exports, while import-dependent countries in Europe faced the highest risk. By 2023, Indonesia, Australia, and Russia became key suppliers, raising vulnerability in countries like Oman, Croatia, Argentina, and Morocco. Some countries, such as Azerbaijan, Switzerland, Egypt, and Pakistan, reduced their risk through lower consumption or diversified imports.

Overall, total energy vulnerability has decreased over time, mainly thanks to greater domestic energy production and the growth of renewables. Back in 1995, countries with high imports and energy-intensive consumption, like Belarus, Hong Kong, and Portugal, faced the highest risks. Self-sufficient regions such as North America, China, and Russia stayed relatively safe. Between 1995 and 2023, many European countries lowered their vulnerability through renewables, while some import-dependent countries, including Hong Kong, Turkey, and Lithuania, saw their risk increase.

Regarding policy recommendations to enhance energy security and reduce vulnerability, policymakers should pursue both short-term strategic measures and long-term structural actions. In the short term, diversifying supply sources diversifying providers with high institutional quality and politically aligned is important, also promoting alternative routes avoiding geopolitical attacks, flexible contracts is essential, storage facilities, regional interconnections and promoting local self-sufficiency. For the long term, coordinated strategies at regional and multilateral levels are critical. Accelerating the energy transition through renewable deployment and energy efficiency improvements will reduce dependency on imports of fossil fuels. Finally, during the transition is relevant to monitor energy vulnerability to adapt policies in response to evolving global conditions.

Although the index is constructed using the most reliable database currently available, there are certain limitations arising from reporting gaps. Some countries do not provide natural gas data for 2023, and in these cases the model assigns approximate values, placing them in mid-distribution positions. Additionally, other countries, such as have not updated their reports since 2015, which may introduce uncertainty in the final estimation. Moreover, this study does not account for "dark trade," or unrecorded exports, which may mask actual energy risks in countries like Iran, Venezuela, and Russia. Future research should aim to estimate the scale and impact of this hidden trade to better assess global vulnerability.

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Appendix

Appendix A. List of imported countries included.

Iso code	Country name	Iso code	Country name
ARE	United Arab Emirates	JPN	Japan
ARG	Argentina	KAZ	Kazakhstan
AUS	Australia	KOR	South Korea
AUT	Austria	KWT	Kuwait
AZE	Azerbaijan	LTU	Lithuania
BEL	Belgium	LUX	Luxembourg
BGD	Bangladesh	LVA	Latvia
BGR	Bulgaria	MAR	Morocco
BLR	Belarus	MEX	Mexico
BRA	Brazil	MKD	North Macedonia
CAN	Canada	MYS	Malaysia
CHE	Switzerland	NLD	Netherlands
CHL	Chile	NOR	Norway
CHN	China	OMN	Oman
COL	Colombia	PAK	Pakistan
CZE	Czech Republic	PHL	Philippines
DEU	Germany	POL	Poland
DNK	Denmark	PRT	Portugal
EGY	Egypt	ROU	Romania
ESP	Spain	RUS	Russia
EST	Estonia	SGP	Singapore
FIN	Finland	SVK	Slovakia
FRA	France	SVN	Slovenia
GBR	United Kingdom	SWE	Sweden
GRC	Greece	THA	Thailand
HKG	Hong Kong	TUR	Turkey
HRV	Croatia	TWN	Taiwan
HUN	Hungary	UKR	Ukraine
IND	India	USA	United States
IRL	Ireland	UZB	Uzbekistan
IRN	Iran	VEN	Venezuela
ISR	Israel	ZAF	South Africa
ITA	Italy		

Appendix B. Product Categories with Included Items

Group	HS2007 Code	Product name
Oil	270820	Pitch coke
	270900	Crude oil
	271000	Oil products
	271011	Petroleum oils; crude, not elsewhere specified
	271019	Other petroleum oils, n.e.s.
	271112	LPG propane
	271113	LPG butanes
	271114	LPG ethylene/etc.
	271119	Other LPG
	271129	Gaseous hydrocarbons
	271210	Petroleum jelly
	271220	Paraffin wax
	271311	Petroleum coke
	271312	Calcined petroleum coke
	271320	Petroleum bitumen
	271390	Petroleum residues
Solid fossil fuels	270111	Anthracite coal
	270112	Bituminous coal
	270119	Other coal
	270120	Coal briquettes
	270210	Lignite
	270300	Peat
	270400	Coke
Gas	271111	LNG
	271121	Natural Gas

Source: Own elaboration.