Economic Statecraft and Country Risk:

Managing the Increasing Use of Economic Policy Tools to Achieve Foreign Policy Goals

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Table of Contents

I. Introduction

Increasing fragmentation of the global economic landscape is driven by major blocs—such as the West and China—and non-aligned nations have emerged as pivotal yet unpredictable players. As the U.S. and other major powers **target national security objectives in their economic policies**, globalization is increasingly re-defined through the lens of “friend-shoring”, “decoupling”, and “de-risking”. These shifts create systemic risks for multinational institutions navigating an economic environment characterized by growing polarization and politicization.

This report seeks to support **Goldman Sachs' Sovereign and Economic Risk Group (SERG)** in assessing the frequency and impact severity of economic statecraft tools on country risk through a comprehensive literature review and quantitative modeling.

To examine the relationship between economic statecraft tools and country risk, the team conducted an in-depth **literature review** to develop a comprehensive “flow framework” of economic statecraft tools as well as five key “Rules of Thumb” assessing the relationship of each, both standalone and in relation to the tools and each other. This initial research suggested that **no single modeling approach can provide a definitive answer** to the question of how impactful are such economic policy tools in achieving foreign policy goals.

Starting with the rules of thumb as a guide, we further conducted several **deep-dives** on both general market reactions following the implementation of economic statecraft tools and a sectoral analysis of key industries important to Goldman Sachs. Finally, we developed a complementary set of **three quantitative approaches** to analyze the effects of economic statecraft tools: an econometrics approach using a two-way fixed effects regression and two machine learning approaches — one through ChatGPT-assisted textual analysis and another through a supervised random forest regression approach.

The **two-way fixed effects regression** tried to establish causality by assessing the effect of economic statecraft tools on country risk, as proxied by sovereign credit ratings and Credit Default Swap (CDS) spreads. Meanwhile, the **text analysis** employs prompt engineering with ChatGPT-4o-mini on a 10-year Moody’s database of rating action reports to retroactively map historical changes in sovereign credit ratings to specific economic statecraft actions, such as sanctions, export controls, or tariffs. And supportingly, the **decision tree** approach seeks to identify which factors most contribute to ratings changes.

II. Framework of Economic Statecraft Tools

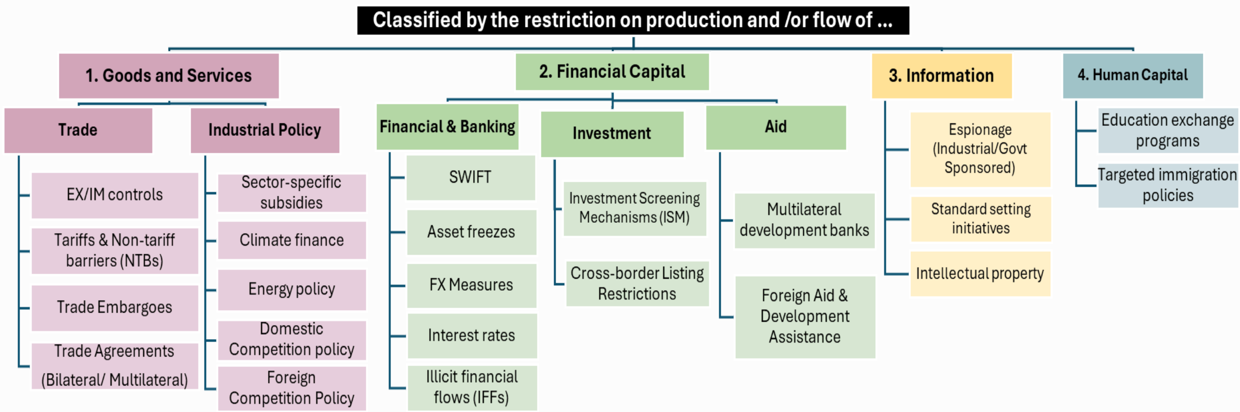
Economics statecraft (ES), as defined by the current literature[1], refers to **an attempt by a sender state to influence a target state** — either to do something it would not ordinarily do or to forgo an action that it would otherwise engage in by the manipulation of the market in a manner that provides economic **benefit** to states that comply and/or imposes economic **penalties** on those who fail to or choose not to do so (Blanchard & Ripsman, 2013).

In light of this definition, we constructed a comprehensive model — dubbed the **"Flow Framework"** — that clusters all identified ES tools according to their effects on the production and/or the flow of a specific underlying value. Roughly speaking, all economic statecraft tools fall, non-exclusively, into one of four categories of economic activity:

1) **The flow of goods and services,**
2) **The flow of financial capital,**
3) **The flow of information,**
4) **And the flow of human capital.**

By restricting the production and/or the flow of goods and services, ES tools affect behavioral change either through the trade channel or through industrial policies. Similarly, in respect to the flow of financial capital, ES tools cluster into categories of financial and banking tools, investment tools, and aid.

Flow Framework



*Twenty-three specific tools of economic statecraft can be grouped into four broad categories of economic activity.

[1] A complete summary of the literature review will be attached to this report.

III. Derived Rules of Thumb

From our literature review, we derived five key rules of thumb to serve as a guideline in the evaluation of some of these statecraft tools as they relate to country risk.[2]

Rule 1: Multilateral sanctions cause deeper and more lasting output losses than unilateral sanctions

While assessing the impact of sanctions over time and across countries, one consistent observation from previous research on this topic has been that **multilateral (coordinated) sanctions tend to inflict greater and more sustained economic damage** than do unilateral sanctions. This applies as well to sanctions that, despite being announced unilaterally by a single state, are subsequently enforced multilaterally and/or in a unified way by a number of states, as unified enforcement of these sanctions is what ultimately counts in delivering detrimental economic impact. The following empirical estimates from research are based on all U.N and U.S sanctions from 1976-2012, and they shed light on the difference in economic impact for both types of sanctions:

> “On average, the imposition of UN sanctions (multilateral) decreases the target state's annual real per capita GDP growth rate by more than 2 percentage points. These adverse effects last for a period of 10 years and lead to an aggregate decline in the target country's GDP per capita of 25.5%. Secondly, the effect of US sanctions (unilateral) is smaller and less distinct considering that enforcement under UN sanctions is mandated to all member states, while U.S sanctions are ‘bought in’ by differing levels of coalitions, and are sometimes also completely unilateral in enforcement. This contrasts in impact which is supported by empirical work, that concludes the imposition of US sanctions decreases the target state's GDP growth by 0.75-1 pp, with this detrimental impact on growth persisting for seven years and accounting for an aggregate decline in GDP of 13.4%” (Neuenkirch and Neumeier, 2015).

[2] *Note: full citations for the experts referenced in the derived rules of thumb can be found at the end of this report*

This is significantly less than U.N sanctions, which are multilateral in nature. Furthermore, the two main reasons why multilateral sanctions are more effective are:

1) **<u>Coalition Size and Unity</u>**: the number & economic weight of partners with a shared willingness to bear costs and act together. Itskhoki & Ribakova (2024) show that the welfare hit to the target rises with the GDP ratio of the coalition to the target, and then collapses when partners move away or fail to stop leaks.
2) **<u>Effective Enforcement</u>**: (concrete actions that police leaks and punish violators) through monitoring, secondary sanctions, and behaviors that deter "black-knight" effects from trade diversion. Studies confirm that this rigorous enforcement is essential and is the actual key, because multilateral legal mandates do not automatically translate into across the board unity or enforcement, effectiveness depends on the coalition's willingness and capacity to police leaks, because when monitoring is weak, even the UN coalition can have leaks, and not be as impactful.

Ultimately, these are both key variables that ensure **constraint on a target's ability to divert trade or investment to alternative markets** — effectively preventing circumvention of sanctions (Joshi & Mahmud, 2020). These broad coalitions are able to close evasion routes, sustain pressure, and reduce "black-knight" leakages, with unity and enforcement levels usually higher than unilateral when a multilateral body provides credible monitoring and secondary sanction tools. On the flip side weak or unilateral enforcement erodes this impact, ultimately having a lower economic impact as seen in the aforementioned comparison (Hufbauer et al. 2008, Giumelli 2024).

Two pivotal channels (Variables)	
Coalition Size and Unity	• Bigger, united bloc multiplies pressure and spreads sender costs • Losses to target rise with coalition size; collapse if partners peel away • The welfare hit rises with coalition-to-target GDP ratio (Itskhoki & Ribakova 2024)
Enforcement	• Closes diversion routes, sustaining pressure • Turns legal unity into real trade & finance cut-offs; weak enforcement → leakage, lower impact

In short, multilateral sanctions outperform unilateral ones because **a united, well policed coalition simultaneously blocks substitution channels and spreads enforcement costs thinly among many senders**— as captured by Neuenkirch & Neumeier's cross-country panel that demonstrates the larger, longer-lasting GDP effects of this approach and quantifies this rule of thumb in terms of both the magnitude and duration of it. This observation is further supported by theoretical models such as the one by Joshi & Mahmud that demonstrates why multilateral efforts constrain a target's economy more effectively compared to unilateral sanctions. Finally, Itskhoki & Ribakova's assessment of the sanctions imposed on Russia provides a further case study that corroborates this assessment as well as detailing the variables for assessment of sanctions in the process.

Rule 2: More comprehensive sanctions impose larger economic damages – though absolute magnitudes remain case specific

While our first rule of thumb highlights the impact of sanctions as they relate to multilateral versus unilateral enactment, this second one distinguishes between levels of severity, defined by the comprehensiveness and scope of the measures, as research has found that the use of extensive sanction measures is positively associated with macroeconomic disruptions. Empirical research on these tools lends credence to the idea of there being a tiered structure of severity, with broader, and thus more severe sanctions being correlated with inflicting greater economic damage as opposed to limited measures (Hufbauer et al. 2008; Neuenkirch & Neumeier 2015; see also Alhassan et al. 2023).

The structure outlined below is drawn directly from the literature review and econometric analysis done by Neuenkirch and Neumeier in 2015. It gives us estimates of comprehensive sanction regimes correlating with greater economic disruptions, making them more severe.

Level	**Sanction Measures (Framed with U.N as example initiator)**	**Avg. annual GDP Impact (U.N & U.S Sanctions) on Target**
Mild/ Limited	Aid suspension, arms embargoes, travel bans, bans on grants, loans, or credits, or restrictions on the sale of specific products or technologies; not including primary commodities embargoes	-1.36 p.p (statistically weak) -1.20 p.p (U.S Only sanctions statistically significant)
Moderate	Import or export restrictions, sectoral financial sanctions, investment bans	-3.22 p.p (Statistically significant)
Severe/ Extensive	Comprehensive economic sanctions such as embargoes on all or most economic activity	-5.08 p.p (Statistically significant)

*Neuenkirch and Neumeier (2015), covers all U.S and U.N sanctions from 1976-2012

It is important to note that this tiered structure of severity based on comprehensiveness holds up with statistically significant results, and serves as credible evidence of the relationship holding. However, at the same time deeper research indicates that the actual magnitude of economic impact remains highly context- and case-specific, with the same level of severity of sanctions producing different macroeconomic outcomes and magnitudes for the sender/target state but generally following these parameters. These differing contexts and cases are due to differences in economic and political factors of countries as well as sanction regimes, for example a country with diversified trade partners, deep financial reserves, or the ability to reroute trade through third parties (i.e “black knights”) often mitigate the intended disruption (Itskhoki & Ribakova, 2024; Giumelli, 2024).

Additionally, with support from the first rule, the literature identifies **five key variables which ultimately decide the effectiveness**, and thus the potential magnitude of impact of these sanctions upon a target country's GDP and the wider economy:

1) Economic size
2) Bilateral trade exposure (sender-target) and global trade centrality (key resource)
3) Degree of financial integration
4) Elasticity of goods substitution
5) Unity of the coalition and degree of enforcement

These variables are identified across both empirical and theoretical work, including gravity model extensions (Neuenkirch & Neumeier (2015); Hufbauer et al. (2008); Itskhoki & Ribakova (2024)).

To further the understanding of various magnitudes for specific cases and also bidirectional macroeconomic impacts, particularly transmission channels through which severity translates into economic disruption from trade and financial tools, an extension of the gravity model of trade is identified from the literature, whose theoretical underpinnings consistently show up in our review.

This framework, as developed in Itskhoki & Ribakova (2024), models sanctions through trade frictions and welfare losses, showing how trade sanctions not only reduce bilateral trade flows and payment connectivity for the target, but also impose welfare and efficiency costs on the “sender” as well when global value chains are involved. The model quantifies these losses using:

Figure 1: Welfare Loss from Sanctions: ACR Gravity Model Extension

$$\text{Welfare Loss} \approx -\frac{1}{\varepsilon} \cdot \Delta \log(\lambda_{ii})$$

- λ_{ii} = domestic expenditure share
- ε = trade elasticity (i.e., ease of substitution)
- The full ACR extension adds $\Delta \log \lambda_{i\square}$ (share of spending on imports from the sanctioning partner); high $\lambda_{i\square}$ magnifies the welfare loss for both target and sender.

A higher elasticity implies that countries can more easily substitute away from sanctioned trade flows towards domestic production or to third party countries, hence welfare losses from trade shocks (sanctions) are smaller. Conversely, when substitution is difficult which may be due to supply chain bottlenecks, unique input dependencies, inability to substitute away or financial choke points, the welfare cost of sanctions increases.

In addition, the model also quantifies spillover costs to the sender state, especially when sanctions disrupt globally integrated supply chains or when third-party countries are not part of the enforcement coalition. For example, firms may face rising input costs or retaliatory barriers.

In summary, while greater severity generally correlates with deeper economic impact, its actual magnitude within those parameters depends on a host of context-specific variables, with sanctions frequently imposing reciprocal costs on sender economies particularly when poorly coordinated or lightly enforced. The Itskhoki-Ribakova model finally helps illuminate these trade-offs and provides a useful framework for assessment of these contexts.

Table 1. Variables That Shape Magnitude and Effectiveness

Variable	What it means	Proxy for assessment	What it entails about magnitude on target
1. Economic size	How big the target economy is compared with the total GDP of the sanctioning coalition.	- Coalition-to-target GDP ratio	Large gap ⇒ senders absorb costs the target cannot; welfare loss scales with the ratio and shrinks if a major sender defects (Itskhoki & Ribakova 2024, 4)
2. Bilateral trade exposure + global trade centrality (Key resources)	Size and share of the target's trade, especially critical inputs/exports-with the sanctioning bloc, plus how many alternative partners it has.	Bilateral import (and export) value and share λ_i□ - Trade-to-GDP; - Network-centrality score - Share of "key resource" flows (oil, semiconductors, fertiliser, etc.)	Gravity-model welfare loss ≈ $-(1/\varepsilon)\,\Delta \log \lambda$; a big or highly concentrated trade link (high value and share) means a larger $\Delta \log \lambda$, magnifying GDP loss for both target and, when λ_i□ is large, the sender (Itskhoki & Ribakova 2024, 12; Neuenkirch & Neumeier 2015).
3. Degree of financial integration	Degree to which the target relies on cross-border banking, reserve-currency funding, and global payment rails.	Cross-border bank claims FX-debt share SWIFT traffic share	When sanctions choke payment channels or dollar/euro funding, liquidity dries up and real-sector stress intensifies; shallow less integrated systems endure a smaller immediate hit (Hufbauer et al. 2008, ch. 4).
4. Elasticity of goods substitution ε	How easily producers and consumers inside the target can swap sanctioned inputs/markets for domestic or third-country alternatives	Sector-level trade-elasticity estimates (GTAP, WIOD)	Welfare loss rises with 1/ε: low-ε inputs (pipeline gas, specialised chips) lock the target into high costs, whereas high-ε goods reroute quickly (Itskhoki & Ribakova 2024, 12).
5. Coalition unity & enforcement	How cohesive the senders are and how forcefully they police leaks (monitoring, secondary sanctions, customs seizures).	GDP share of actively enforcing states Existence of secondary-sanction tools Leakage indexes (re-exports ÷ lost coalition exports)	Unity supplies potential pressure; credible enforcement converts it into real pain by closing diversion routes. Large, sustained leakage quickly erodes growth effects (Joshi & Mahmud 2020; Giumelli 2024).

Rule 3: Greater sanction severity does not necessarily guarantee policy success

Our third rule will highlight observations on the success and effectiveness of sanctions in achieving stated policy goals, especially the assumption that higher severity, as defined in rule two, would result in a higher compliance rate from a target state. This logic, that severe sanctions with greater economic damage would lead to higher distress thereby making it more likely for states to comply, seems straightforward. **However, our research of sanction studies finds mixed compliance despite high severity.** Hufbauer et al. (2007) find only a conditional link — that severity helps only when goals are modest and other enabling factors are in place. GAO-20-145 (2019) confirms the pain effect but offers no evidence that it converts into policy change. Meta-analysis of 37 studies (Demena & van Bergeijk, 2025) indicates that trade linkage, short duration, and friendly prior relations are the most robust predictors of political success, not breadth of sanctions. We thus concluded that there are ambiguous results on policy success when it comes to a linear relationship with severity of sanctions (as it was defined in our rule 2).

Ultimately sanction design and enforcement appear to matter more than scope. Thus **Itskhoki & Ribakova advocates for a "comprehensive, technocratic approach with clear, measurable objectives"** rather than indiscriminate pressure" (Itskhoki & Ribakova, 2024). Factors other than pure economic pressure matter to policy success. Across the literature review several factors were identified as contributing to impacting policy success in one way or another. As noted in this case, real-world outcomes are immensely contextual and a combination of economic, political, and strategic considerations can come into play. Together with some of the channels that dictate the magnitude and effectiveness of such efforts that we covered in rule 2, these other conditions hugely shape whether pressure can be effectively sustained and translated into political change.

The following table highlights factors that can add to or negate the probability of policy success:

Table 2. Factors that can add to or negate the probability of policy success:

Factor	Context	Association with Success / Source
Trade linkage	Depth of economic ties between	Strong trade ties raise success: sanctions work best

	sender and target (trade/dependence).	when sender-target trade is high (Demena & van Bergeijk, 2025).
Duration	Length and speed of sanctioning episode	Short, rapid sanctions are more likely to succeed (Demena & van Bergeijk, 2025)
Pre-sanction relations	Quality of diplomatic/political relationship before sanctions	Friendly prior relations (e.g., alliances) boost success (Demena & van Bergeijk, 2025; Psomopoulou, 2021)
Type	Targeted use of measures which include "severe ones" acc. to rule two definition (financial, travel bans) vs broad trade embargoes	Smart sanctions yield higher compliance than broad trade sanctions (Caetano et al., 2023)
Objective	Policy goal of sanctions (e.g., human rights, democracy, regime change)	Democratic reform goals have higher success, while bigger policy changes like regime change goals have a high likelihood of failure (Caetano et al., 2023; Psomopoulou, 2021)
Target regime type	Level of democracy/hybridization in target's government	Sanctions induce compliance most often in intermediate or mixed regimes; fully democratic or deeply autocratic targets are less responsive (Zarpli, 2023; Caetano et al., 2023)
Target social equality	Degree of egalitarian resource distribution (low inequality)	More-equal societies see higher compliance (Caetano et al., 2023)
Target political volatility	Instability (coups, leader turnover) during sanction period	High volatility (e.g., frequent coups) raises chances of compliance (Caetano et al., 2023)
Domestic institutions	Number of political "veto players" or decision-makers that must agree	More (and ideologically distant) veto players lower the probability of compliance (Corda, 2023)
Third-party support ("black knights")	Ties and presence of other states or firms that continue trade with and help the target	Active third-party trade severely undermines sanctions: "black knight" support offsets pressure and reduces success (Psomopoulou, 2021)

Key findings include those of Caetano et al. (2023) on regime and domestic factors, Demena & van Bergeijk (2025) on trade and duration, Zarpli (2023) on regime type, Corda (2023) on veto players, Psomopoulou (2021) on alliances/trade dependence, and Drezner (2000) on sanctioner coalitions. These studies isolate the political and diplomatic side of sanctions success, and how and whether sanctions will end up inducing compliance.

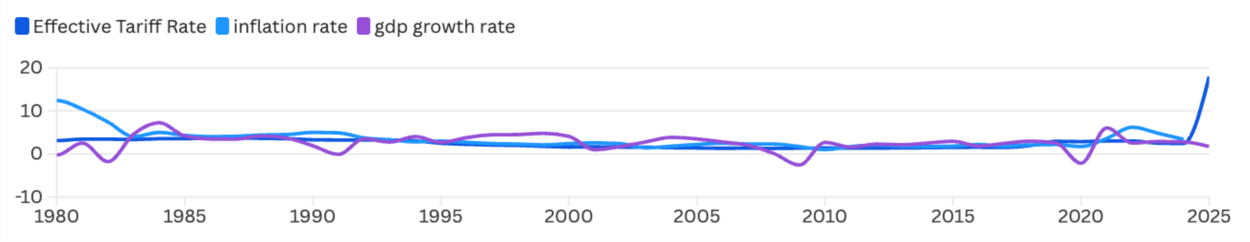
In conclusion, greater sanction severity alone does not guarantee political success. Instead, effective sanctions with the highest level of probability of success align with clear, achievable policy goals that target specific vulnerabilities. Amongst others, evidence from the research consistently highlights strong sender-target trade ties, swift enactment of sanctions, and friendly diplomatic relations before sanctions as important measures affecting the likelihood of success of such actions. Additionally, domestic political factors and situations make some countries more and some countries less vulnerable to coercion through the enactment of sanctions. This factors hugely into the likelihood of policy success, and variables related to this can serve as key predictors of potential compliance.

Rule 4: Tariffs historically result in higher inflation and lower economic growth

Recent tariff escalations under both of President Trump's administrations in 2018 and 2025 reflect increased economic interventionism. The effect of this shift has caused significant economic and geopolitical uncertainty.

Tariffs historically result in higher inflation and lower economic growth in the sender country. This section evaluates how tariffs influence inflation and GDP growth by examining historical precedents alongside detailed sector-specific forecasts. First, we synthesized three datasets to show the historical association between effective tariff rates (Yale Budget Lab, 2025), GDP growth rates (Bureau of Labor Statistics, 2025), and inflation rates (Bureau of Economic Analysis, 2025). For the GDP growth rates and inflation rates projection in 2025, we use benchmark estimates for 2025 on an inflation rate of 4.0% (Capital Economics, 2025) and GDP growth of 1.7% (Goldman Sachs, 2025). In Figure 1, the association between higher effective tariff rates and both higher inflation and lower GDP growth is minimal and relatively not significant in 2018—but becomes much more apparent in 2025.

Figure 2. Trends in effective tariff rates, inflation rates, and GDP growth rates (1980—2025)



**Source: Author's visualization based on data from Yale Budget Lab, Bureau of Economic Analysis, and Bureau of Labor Statistics.*

We want to highlight three historical cases which indicates the correlation between tariff hikes, inflation, and GDP outcomes:

1. **Smoot-Hawley Tariff Act (1930—1933):** Tariffs rose to approximately 18%, contributing to an average annual GDP contraction of -7.26%. Due to the lack of official data on its inflation rate, it is not concluded in the association visualization.
2. **Trump Tariffs (2018—2019):** Tariffs increased from 2.9% by an additional 1%, slightly raising inflation (+0.3% in 2018; +0.1% in 2019) and reducing GDP growth from +0.51% in 2018 to -0.38% in 2019.
3. **Projected Trump Tariffs (2025):** Tariffs expected to rise to nearly 18%, potentially driving inflation up by 0.4% and decreasing GDP growth by 1.1% if using benchmark estimates for 2025 on an inflation rate of 4.0% and GDP growth of 1.7%.

Further, we found support for the association between higher tariffs with increased inflation and reduced GDP growth, particularly during economic expansions (Mahajan & Tomar, 2020; Boudreaux, 2024; Furceri et al., 2019). Research further identifies multiple specific channels of the negative impact of tariffs on GDP growth, including reduced productive efficiency (Boudreaux, 2024), increased unemployment, and the one that section focuses on—elevated producer prices and therefore final production prices (Furceri et al., 2019). Wilding (2025) similarly emphasizes that tariffs undermine market demand due to rising input costs. Existing empirical studies further support this tariff pass-through mechanism, demonstrating significant increases in import prices (10%—30%), reduced import volumes (25%—30%), and elevated domestic production costs (Flaaen, Hortaçsu, & Tintelnot, 2020). These costs are shown to be predominantly borne by U.S. consumers and businesses (Nie, von Ende-Becker, & Yang, 2021). Yilmazkuday (2025) further quantifies this relationship, showing a 0.53% rise in core inflation for each 1% tariff increase. Therefore, this section will use the tariff pass-through mechanism to explore how higher tariffs lead to increased inflation and therefore reduced GDP growth.

This analysis focuses on agriculture as it accounts for a main trade commodity, sensitive to tariffs, and its specific significance in the U.S. and China trade relations. To understand how elevated input costs result in increased prices for agricultural final products, consequently lowering market demand, incentivizing buyers to seek alternative sources, and contracting agricultural output and GDP, we conceptualized two pathways: First, tariffs on imported agricultural inputs increase domestic costs, raising final product prices, reducing international demand, exports, and ultimately output and GDP. Second, retaliatory tariffs increase U.S. agricultural export prices, reducing foreign demand, exports, and U.S. output and GDP.

Given the complexity of estimating varying tariff increases across multiple countries, a weighted calculation methodology was implemented. This approach integrates each country's announced tariff rate by the Trump administration and its respective share of total U.S. agricultural exports. In Table 1, green cells indicate literature-based estimates, yellow cells reflect data from official sources, and blue cells represent the author's own calculations. For example, approximately 14% of U.S. agricultural production is exported to China, where it will face a tariff of 145%. The analysis similarly includes the other top four export partners, which are Mexico, Canada, Japan, and the EU. The remaining exports, covering approximately 39% of total agricultural trade, were assessed using an average assumed tariff rate of 15% to account for tariff heterogeneity that is hard to calculate one by one among smaller trade partners. Additionally, we consider a secondary scenario in which tariffs on China are halved (72.5%), a possibility mentioned by President Trump. We then used two estimation equations for our analysis:

- Output Shrinkage (%) = Tariff Increase (%) × Estimated Pass-Through Coefficient
- Estimated GDP Drag (%) = Output Shrinkage (%) × Sector GDP Share × Sectoral Multiplier

Using a pass-through coefficient (0.049) to estimate demand sensitivity and a sectoral multiplier (2.09) to gauge broader economic impacts (USDA, 2025; Abbas & Lan, 2020), the agricultural sector is projected to contract by approximately -1.85%, comparable to the -2.0% contraction during the 2008—2009 financial crisis. The estimated GDP drag is -0.2035% or around $60.47 billion, implying substantial recessionary risks given a modest 2.4% GDP growth rate for 2024.

Given these calculations summarized in Table 1, the outsized impact from tariffs on China emerges as particularly significant. Despite being the third-largest importer, China significantly influences the aggregated GDP drag outcomes, clearly illustrating how tariff magnitude heavily shapes economic consequences. This is also demonstrated by comparing the two scenarios (145% vs. 72.%) for China's tariffs.

Table 3. Estimated Output Shrinkage and GDP Drag in the U.S. Agricultural Sector under Scenario-Based 2025 Tariff Increases

Sector	Tariff Increase (%) (scenario based)	Pass-Through Coefficient	Output Shrinkage	Sectoral Multiplier	GDP Contribution	Estimated GDP Drag
Agriculture	37.73% (weighted)	0.049	**-1.85% vs. in -2.0% in 2008-9**	2.09	5.5%	–0.2035% (~$60.47B) vs. 2.4% 2024 US growth rate
Mexico	17.31%*25%=4.33%	0.049	-0.21%	2.09	0.102%	-0.00043%(–$127.81 M)
Canada	16.23% × 25%= 4.06%	0.049	-0.199%	2.09	0.096%	–0.00038% (–$113M)
China (scenario 1)	14.11%*145%=20.46 %	0.049	−1.00%	2.09	0.083%	–0.00166% (–$493.9 M)
China (scenario 2)	14.11%*72.5%=10.2 3%	0.049	-0.50%	2.09	0.083%	–0.00083% (–$247.1 M)
Japan	7.31%*24%=1.754%	0.049	-0.086%	2.09	0.048%	–0.000083% (–$24.7M)
EU	6.85%*20%=1.37%	0.049	-0.067%	2.09	0.045%	–0.0000603% (–$17.9M)

Note: Green cells indicate parameter values from literature; yellow cells reflect data from official sources (e.g., BEA, USDA, trade statistics); blue cells are the authors' own calculations Output shrinkage is calculated using a pass-through coefficient of 0.049 (Abbas & Lan, 2020), and estimated GDP drag is computed by multiplying sectoral output shrinkage by GDP contribution and a sectoral multiplier of 2.09 (USDA, 2025).

Rule 5: Tariffs appear to have a higher impact on certain demographic groups

While the previous section examined how tariffs contribute to higher inflation and lower GDP growth at the aggregate level, these broad trends can obscure important underlying differences—not all households share this burden equally. Drawing from a wide range of literature, we find that tariffs seem to disproportionately affect certain vulnerable groups due to differences in consumption patterns—particularly for products that are heavily targeted by tariffs. This section will therefore take a closer look at who is most affected and why that matters. Moreover, this section continues to apply the same underlying mechanism that indicates how tariffs raise final product prices; this analysis will now examine how those price increases disrupt the traditional consumption bundles of different demographic groups, resulting in unequal exposure to and volatility from tariff policies. Overall, existing literature has consistently shown that tariffs act like regressive taxes, placing a heavier burden on vulnerable demographic groups—especially lower-income households, Black communities, women, younger consumers, and single parents.

First, lower-income households bear a significantly greater relative burden from tariffs. Empirical evidence from Russ et al (2017) highlights that the lowest income decile experiences nearly five times the relative tariff burden compared to the highest decile. This disproportionate impact arises mainly because lower-income households allocate a larger share of their consumption budget to tariffed essential goods such as food, tobacco, and apparel. For example, tariff rates on low-priced goods like inexpensive shoes (valued below $3) are considerably higher at 48%, in contrast to 8.5% for higher-priced leather shoes (Ikenson, 2018). Similarly, Moran (2024) confirms the regressive nature of tariffs: households earning less than $10,000 annually face tariff impacts averaging approximately 13.95%, whereas households with incomes above $150,000 experience tariff impacts averaging only 5.24%. Fajgelbaum and Khandelwal (2016) also confirm that lower-income households benefit substantially more from trade because they spend a higher proportion of their income on tradable goods such as food and apparel.

Second, Black households exhibit the highest tariff exposure due to consumption patterns that concentrate on tariffed goods. Black households' tariff intensity, defined by the share of their consumption affected by tariffs, is higher (0.385) than that of White households (0.35) and Asian households (0.345), suggesting greater vulnerability to price hikes resulted from tariff imposition (Nievon, Ende, Becker, & Yang, 2021).

Third, the same research also suggests that younger consumers (ages 16—25) are more exposed to tariffs compared to older consumers (age above 75). Younger households have a higher tariff exposure rate (0.39 compared to 0.315), which largely results from their distinct consumption patterns, frequently involving clothing, electronics, and footwear, all of which are categories typically affected by high tariffs.

Fourth, tariffs disproportionately affect women due to the "pink tariff," a phenomenon where products frequently purchased by women are subject to higher tariffs. The tariff rates on women's apparel, such as suits (23% compared to 14% for men's suits) and sportswear (21% compared to 7% for men's sportswear), highlight the gender disparity clearly (Russ et al, 2017). In 2015, women’s clothing faced an average tariff of 14.9%, compared to 12.0% for men’s. Households also spent more on women’s apparel—1.2% of annual expenses versus 0.7% on men’s (Gailes, Gurevich, Shikher, & Tsigas, 2018). Women’s apparel alone accounted for roughly 66% of the total apparel tariff burden, amounting to $2.77 billion more in tariffs than men’s clothing (USITC, 2015).

Lastly, single-parent households disproportionately bear the tariff burden due to their higher spending proportion on tariffed goods. The tariff burden as a percentage of expenditure (excluding rent and mortgage) is substantially higher for single parents (0.69%) compared to married households without children (0.44%) (Russ et al, 2017). This heavier burden reflects the higher reliance of single-parent households on goods frequently subject to tariffs.

However, these statistics should be critically assessed. First, all findings are limited to descriptive statistics. Second, there might be confounding relationships between these demographic traits, and therefore a further multivariate or causal analysis is recommended. Finally, the statistics cited are drawn from the past decade but do not all correspond to the same tariff announcement periods, which may affect comparability.

The disparate demographic impact of Tariffs is especially acute in the Republican Party's electoral base. Tariff-induced price increases disproportionately affect voters in rural and economically undiversified regions—areas strongly overlapping with Trump's core support base. A recent study, summarized in Table 1 and based on Eckhardt, O'Brien, and Glasner (2024), finds that economically marginalized regions are precisely those that shifted to support Trump in 2024. The research categorizes U.S. counties into five quintiles according to the increase in Republican vote share from 2020 to 2024. It shows counties in Quintile 5—the counties with the largest shifts toward Trump—tend to be economically worse off, characterized by higher poverty rates (17.5%), higher rates of prime-age adults not in work (27.7%), lower median household incomes ($58,954), and fewer residents living in prosperous zip codes (7.5%). Regarding counties with the smallest shifts toward Trump (Quintile 1), they generally experience lower poverty (12.2%), lower unemployment among prime-age adults (21.8%), higher median incomes ($68,232), and more residents in prosperous areas (16.1%).

Table 4: Economic Distress and Shifts Toward the Republican Party (2020-2024)

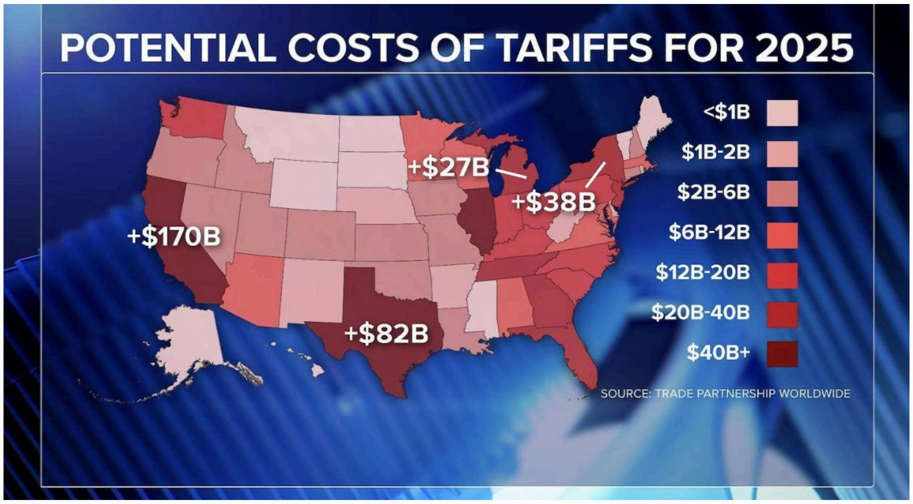
Republican Voting Share Increase Quintile	Average Poverty Rate	Average % of Prime Age Adults Not in Work	Average Median Household Income	Average % Population in Prosperous Zip Codes
1	12.2%	21.8%	$68,232	16.1%

2	13.4%	22.7%	$64,629	11.6%
3	14.2%	24.1%	$62,367	9.7%
4	15.0%	25.2%	$61,939	8.5%
5	17.5%	27.7%	$58,954	7.5%

**Source: Eckhardt, O'Brien, & Glasner, 2024*

This association is also demonstrated in Figure 3: besides traditional Democratic states like New York and California, both traditional Republican strongholds like Texas and Florida and 2024 swing states such as Georgia, Wisconsin, and Michigan are hit really hard. It is even more interesting that most of the states that are hit hard are Republican states or lean-Republican swing states. These regions often rely heavily on agriculture and manufacturing, sectors severely exposed to retaliatory tariffs and global supply chain disruptions stemming from Trump's tariffs.

Figure 3: Trade Partnership Worldwide, ABC News (2024)



**Note: This map illustrates the projected state-level cost burden of proposed 2025 tariffs. The shading reflects the estimated dollar impact by state, ranging from under $1 billion to over $170 billion, with darker colors indicating higher costs.*

Beyond geography, specific demographic backlash poses additional political threats. Women, a group disproportionately impacted by tariffs on apparel and household goods as we show, have already shown signs of eroding support. In the 2024 election, Harris led Trump among female voters by six percentage points (51% vs. 45%), narrower than Biden's ten-point advantage in 2020. Thus tariff-driven price hikes could wipe out that 4-point gender gain for Trump or the next Republican candidate. Similarly, Trump's gains in 2024 among young and Black voters, which have been often strongholds for Democrats, may prove fragile in light of the economic burden imposed by new tariffs. Among young men (ages 18—44), Trump led by 8 points against Harris (52% vs. 44%), a dramatic 16-point shift from Biden's 8-point lead in 2020. Similarly, Harris's lead among Black men narrowed to 47 points (71% vs. 24%), down from Biden's 82-point margin—a 35-point swing to Trump in 2024. These hard-won groups could be at risk of slipping away again if tariff impacts disproportionately affect young voters and Black households, who are vulnerable to rising living costs.

These trends from the 2024 election, which occurred before the full imposition of tariffs, indicate that continued tariff-driven economic strain, especially from rising living costs, may reverse these electoral shifts in future elections. Persistent dissatisfaction could particularly impact GOP support in critical swing districts during the 2026 midterms and the subsequent presidential election.

Based on political unpredictability shown above, for Goldman Sachs, two key implications stand out. First, political pressure from tariff and price hikes could force policy revisions and reversals which will definitely increase economic volatility and unpredictability. This section was initially constructed in early May 2025—but already on May 12th, Trump temporarily reversed his tariff policy by re-entering negotiations with China, rolling tariffs back to 10% on most goods (except fentanyl-related goods, which remain at 20%). Therefore, such politically motivated adjustments are likely to recur more frequently, especially as the 2026 midterms and 2028 presidential election approach, driven more by political rather than economic indicators.

Second, the growing entanglement of politics and economic policymaking has implications not just domestically but also internationally. If Trump maintains aggressive tariffs on China, Beijing may strategically exploit these U.S. domestic political vulnerabilities by targeting politically sensitive American exports, such as agriculture, to amplify internal political pressures. Similar to the way this tactic was employed during the 2018 trade disputes, targeted retaliatory tariffs by China would raise domestic political audience costs in the U.S., potentially weakening American leverage in trade negotiations. Such an approach can also be taken by other countries. Such politically driven economic retaliation and countermeasures are likely to become increasingly common, posing a new layer of strategic risk that risk observers should carefully monitor and gauge.

IV. Country Risk Impacts

In addition to analyses pulled from current literature and market and sector deep-dives, we prioritized finding methods to quantitatively analyze the effects that tools of economic statecraft have historically had on country risk. To compare results and address this question from multiple angles, we employed **three different quantitative models** - a regression analysis, an AI text analysis, and a random forest classifier model.

Data Sources

The following analyses utilize two primary data sources: Moody's Default & Recovery Database and the Global Sanctions Database (GSDB v.4.0).

Moody's Default & Recovery Database provides two key components: (1) a comprehensive history of sovereign credit ratings (excluding rating affirmations), comprising 2,107 observations from 1949 to the present, and (2) Sovereign Ratings Actions reports, which lay out the underlying rating rationale behind the ratings (including rating affirmations), available from 1994 to the present, that consists of 3,231 observations.

The Global Sanctions Database, GSDB v.4.0, is provided by Drexel University and covers sanctions imposed globally from 1950 to 2019. This dataset includes 1,547 cases of both bilateral and multilateral sanctions, detailing the year and types of sanctions imposed, the political goals behind them, and the success levels achieved. Version 4 includes 223 new cases. The GSDB is invaluable for examining the timing, type, and effectiveness of sanctions, offering critical insights into how these ES tools correlate with changes in sovereign credit ratings.

In total, **1,547 sanction episodes are recorded with 98 unique targets**, spanning 1946 to 2019. The mean duration is 5.49 years (SD = 7.99) with the shortest sanction being less than a year and the longest being over 73 years long. Of the outcomes, 368 failed, 871 are ongoing, 97 ended in negotiation or settlement. Of the ones that are successful, 106 achieved some but not all of its objectives, 105 achieved all of its intended goals.

The sovereign ratings data are a time-stamped assessment (at a point in time) of countries' creditworthiness, comprising both foreign currency and local currency debt. Outlook designations are also available (positive, stable, negative) to show the agency's view of the direction in which the country's risk rating is trending based on then available information. Actions span the period from 1990s to roughly 2023 and cover around 120 sovereign issuers with 5 to 30 observations per country. Foreign currency ratings matter most for cross-border investors. Local currency ratings mostly are restricted to domestic funding risks. The distribution of the ratings is skewed towards investment-grade. Several rapid downgrades into high-yield territories occurred during crises. Emerging markets often are updated annually. Advanced countries often receive quarterly or ad hoc reassessment if encountering stress.

Approach 1: Two-Way Fixed Effects Regression

*The two-way fixed effects regression shows **no statistically significant causal effect** of sanctions on country risk.*

Findings

The results from our regression approach examining the effect of sanctions on sovereign risk (measured by Sovereign Rating and Average CDS Spreads) show that **none of the sanctions—including trade, financial, arms, and travel sanctions—have a statistically significant impact on country risk** measures.

In the Sovereign Rating Model (see Table 2) the coefficients for each sanction type are not statistically significant at conventional levels ($p > 0.1$ for all sanction types). The R^2 values across all models (ranging from 0.505) suggest that the model explains about 50% of the variance in the data, but this does not reflect a meaningful causal relationship with the sanctions variable. AIC and BIC values suggest that the model fit is relatively similar across all sanction types, which is consistent with the lack of statistical significance in the coefficients.

Similar to the sovereign rating model, the coefficients for average CDS spreads also do not achieve statistical significance. The R^2, AIC, and BIC values are also similar across the different sanction types, further confirming that the sanctions do not have a strong or statistically significant effect on country risk as measured by CDS spreads.

While these findings suggest no significant impact of sanctions on sovereign risk, it is important to recognize that this is not conclusive proof of a lack of an effect as there are several limitations in the dataset and modeling approach that may affect the interpretation.

First, the Global Sanctions Database used in this study **only captures whether a country has received a sanction**, but it **does not reflect the intensity of sanctions**, such as the percentage of tariffs imposed or the scope of financial restrictions.

Second, the data **aggregates various sanction types** (e.g., trade, financial, arms) into broad categories. However, the impact of these sanctions on country risk might differ significantly depending on the specific type and implementation of the sanction. For example, a financial sanction could have a much larger impact than a minor travel ban, but this distinction is not captured by the current categorization.

Finally, despite the use of two-way fixed effects regression to control for unobserved heterogeneity, there may still be **omitted variables that affect the relationship between sanctions and sovereign risk**. For instance, geopolitical factors or domestic political events might influence both the likelihood of receiving sanctions and the perceived country risk, leading to a potential bias in the estimates. These are difficult to capture in a systematic way through data for 53 countries across 70 years.

Table 5. Regression Results for the Baseline Model | Outcome: Average CDS Spreads

	Trade Sanction	Financial Sanction	Arms Sanction	Travel Sanction
Average CDS Spread	-56.806	27.007	8.673	44.449
	(53.401)	(82.810)	(21.164)	(147.330)
Num.Obs.	1859	1859	1859	1859
R2	0.505	0.505	0.505	0.505
R2 Adj.	0.485	0.485	0.485	0.485
R2 Within	0.001	0.000	0.000	0.000
R2 Within Adj.	0.000	0.000	-0.001	0.000
AIC	30138.0	30139.4	30139.6	30138.7
BIC	30541.5	30542.9	30543.2	30542.3
RMSE	771.05	771.34	771.40	771.21
Std.Errors	by: sanctioned_state	by: sanctioned_state	by: sanctioned_state	by: sanctioned_state
FE: factor(sanctioned_state)	X	X	X	X
FE: factor(year)	X	X	X	X

p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 6. Regression Results for the Baseline Model | Outcome: Sovereign Rating

	Trade Sanction	Financial Sanction	Arms Sanction	Travel Sanction
Sovereign Rating	-56.806	27.007	8.673	44.449
	(53.401)	(82.810)	(21.164)	(147.330)
Num.Obs.	1859	1859	1859	1859
R2	0.505	0.505	0.505	0.505
R2 Adj.	0.485	0.485	0.485	0.485
R2 Within	0.001	0.000	0.000	0.000
R2 Within Adj.	0.000	0.000	-0.001	0.000
AIC	30138.0	30139.4	30139.6	30138.7
BIC	30541.5	30542.9	30543.2	30542.3
RMSE	771.05	771.34	771.40	771.21
Std.Errors	by: sanctioned_state	by: sanctioned_state	by: sanctioned_state	by: sanctioned_state
FE: factor(sanctioned_state)	X	X	X	X
FE: factor(year)	X	X	X	X

p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Methodology

We utilized a **panel dataset covering 2,052 observations from 1950 to 2023**, combining data from the ***Bloomberg Terminal*** *(country CDS spreads)*, ***Moody's Default and Recovery Database*** *(sovereign credit ratings)*, and the ***Global Sanctions Database***. Our outcome variables were average yearly country CDS spreads and yearly sovereign credit ratings, both of which serve as indicators of sovereign risk. The treatment variable, representing sanctions, is binary: 1 if a country receives a sanction during a given year, and 0 otherwise. We considered five types of sanctions: trade, financial, arms, military and travel.

To examine the causal impact of sanctions on sovereign risk, we utilized a two-way fixed effects regression model, which controls for both time-invariant country-specific factors and time-varying global effects. The baseline model specification is:

$$\text{Outcome Variable} = \beta_0 + \beta_1 \cdot \text{Treatment Variable} + \gamma_1 \cdot \text{Year Fixed Effects} + \gamma_2 \cdot \text{Country Fixed Effects} + \epsilon$$

Where:

- Outcome Variable: is either CDS spreads or sovereign credit ratings,
- Treatment Variable: indicates whether a specific type of sanction was imposed,
- Year Fixed Effects: capture time-invariant factors that vary between countries but remain constant across time. Year fixed effects account for global economic conditions, international trends, or events that may influence all countries in a given year (e.g., global financial crises, fluctuations in oil prices, etc.).
- Country Fixed Effects: capture time-varying factors that are shared across all countries in any given year. These include geopolitical and economic conditions unique to each country, such as political stability, historical conflicts, and long-term economic policies.

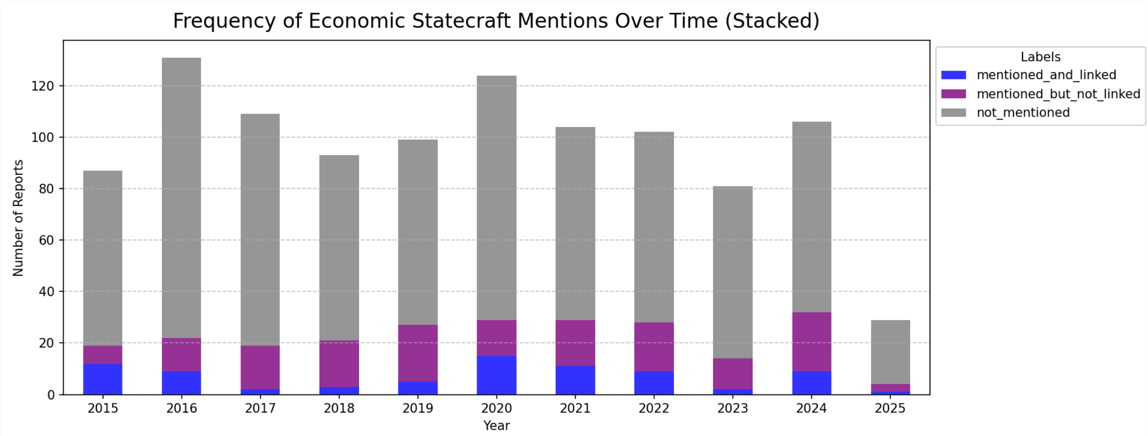
The baseline model was fit at least once for each sanction type. To enhance the robustness of our results, additional iterations were conducted, focusing on smaller regional samples to capture regional dynamics and the heterogeneity in the sanctions impact. These iterations involved transforming key variables to improve model fit and mitigate potential issues such as endogeneity and omitted variable bias. Furthermore, we imputed values for countries excluded from ratings by the agencies, treating these instances as a one-notch downgrade. We also tested the lagged impacts of sanctions, acknowledging that the effects on country risk may not be instantaneous.

Approach 2: Prompt Iteration & Text Analysis

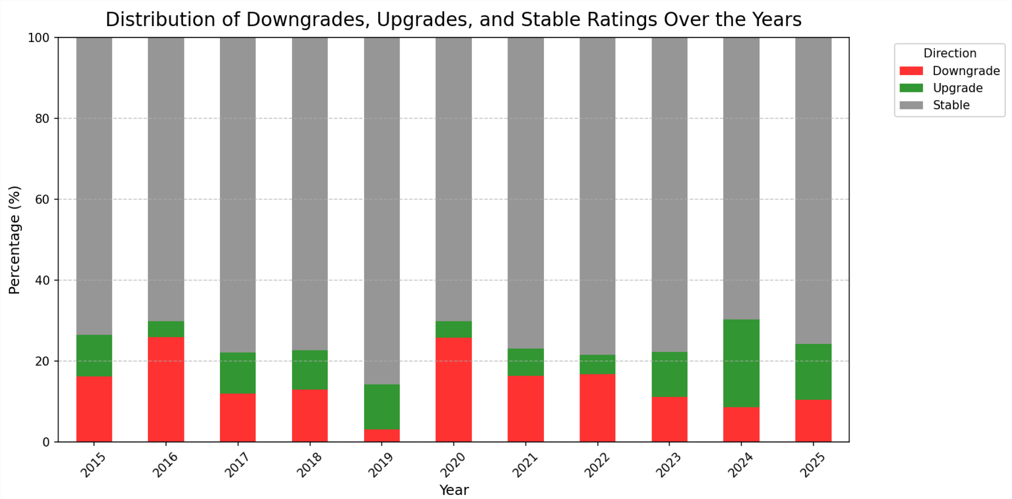
*Economic Sanctions are mentioned in ~30% of sovereign rating changes, of which **~70% are linked to a downgrade.***

Findings

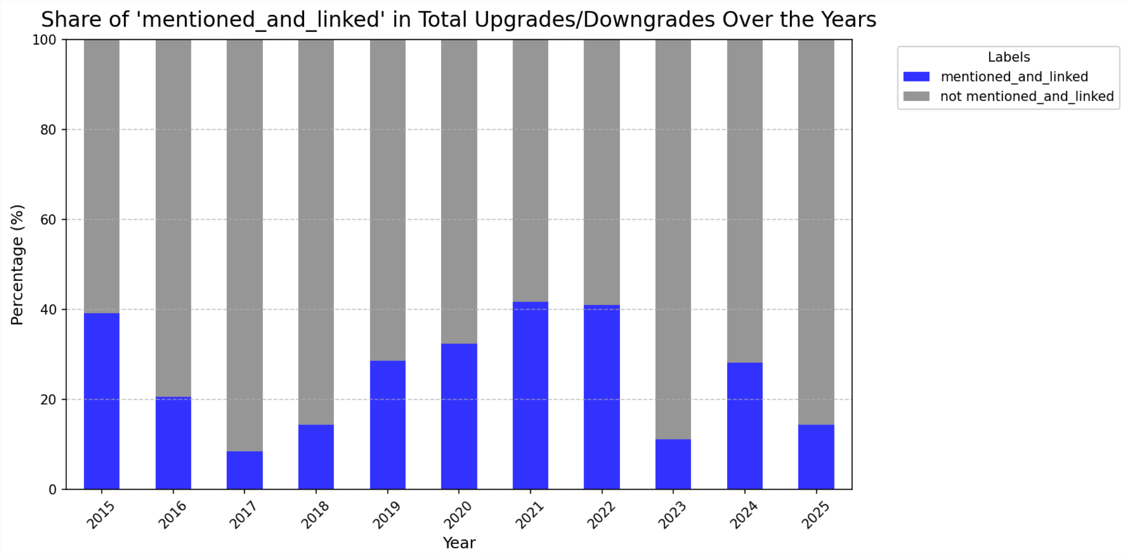
Prompt-iteration with ChatGPT-4o-mini on a 10-year database of Moody's rating action reports revealed that, on average, 23% of the reports from 2015 to 2025 mentioned Economic Statecraft (ES) tools, indicating a notable portion of reports discussed these tools in relation to sovereign credit ratings. Of these mentions, about 32% were classified as "mentioned_and_linked," meaning that ES tools were directly associated with a rating change, either an upgrade or downgrade. This results in approximately 7% of all reports in the period being both mentioned and linked to rating changes.



The results also highlight trends over time, providing a clearer picture of how the frequency of ES mentions have evolved across the dataset. The first bar chart illustrates the distribution of downgrades, upgrades, and stable ratings over the years, showing some fluctuation. It indicates varying levels of rating changes across different years, likely reflecting shifts in geopolitical events or other external factors.



The next chart visualizes the share of “mentioned_and_linked” ES tool mentions in total upgrades and downgrades. It shows **noticeable fluctuations in the proportion of “mentioned_and_linked” reports**. Such variations may reflect the heightened use of these tools and their impact on credit ratings during times of political or economic stress, or in response to specific global developments.



However, despite these fluctuations, the **overall trend suggests a relatively stable relationship between ES tool mentions and rating changes**, with no clear upward or downward trend observed over time. Averaging across the years, we find that about 29% of all rating changes were related to ES tools, which suggests a relatively high ratio of mentions in the context of upgrades and downgrades, despite the fact that some ratings get withdrawn in geopolitical crises (e.g., Russia, 2022). Notably, of the “mentioned_and_linked” instances, around 71% were downgrades, indicating that ES tools are more strongly associated with negative rating actions, likely reflecting the perceived negative impact of sanctions or other economic measures on the creditworthiness of sanctioned countries.

Methodology

Automated web scraping via Selenium was employed to extract key data, such as the country, rating change, and rating rationale, from sovereign credit rating action reports in ***Moody’s Default & Recovery Database***. The extracted data was then cleaned by removing non-ASCII characters, unnecessary symbols, and extra spaces from the “Ratings Change,” “Ratings Rationale,” and “Date” columns. In addition, missing values were handled, dates were standardized, and rows with incomplete or irrelevant information were removed. A total of 1,195 reports were used, covering a period from January 2015 to the present (10 years).

A fixed set of 30 rating actions was manually labeled to benchmark the accuracy of the prompt, ensuring a balanced sample that included edge cases. This approach is commonly used in pilot studies and exploratory text classification tasks. The prompts were iteratively refined using the validation set to achieve consistent 3-class labeling, supported by API credits. **After ten iterations, accuracy peaked at 83.33% using model version 9.2 (max_token response of 50, temperature of 0.8).** To prevent overfitting, no further refinements were made, and the final prompt was applied unchanged to the remaining dataset.

Each report was classified into one of the following three categories:

- **"Mentioned_and_linked"**: ES was mentioned and coincided with a rating change.
- **"Mentioned_but_not_linked"**: ES was mentioned but does not coincide with a rating change.
- **"Not_mentioned"**: No ES tool was mentioned.

Version	Accuracy	Notes
v1	66.67%	labels not well enough described; forgot FDI; too conservative
v2	56.67%	does still not understand up/downgrade logic; does not capture indirect mentions
v3	60.00%	sometimes problems with indirect/direct mention; might be too complex
v4	63.33%	still worse than v1; likely not enough ES examples
v5	66.67%	same accuracy as first model despite higher level of concreteness
v6	73.33%	slightly better as up/downgrade logic more specific; still too conservative
v7	76.67%	specified that no no causal link is needed, still more on the conservative side; does not fully understand up/downgrade logic
v8	73.33%	worse again; trying two step model
v9.1	83.33%	gets the ratings changes logic right not; still too conservative (too many not_mentioned) - trying increasing temperature
v9.2	83.33%	highest accuracy so far (as gave up to 86.67% in some runs); did not get better after despite increasing the temperature

To predict labels for the remaining sovereign credit rating reports, an attempt was made to scale the labeling process using FinBERT, training and testing it on a random sample of 300 reports with cross-validation. However, FinBERT's maximum token length of 512 tokens proved inadequate, as the average token size for our prompt inputs was around 1,000 tokens. Given this limitation, this model ultimately utilized API credits via ChatGPT-4o-mini.

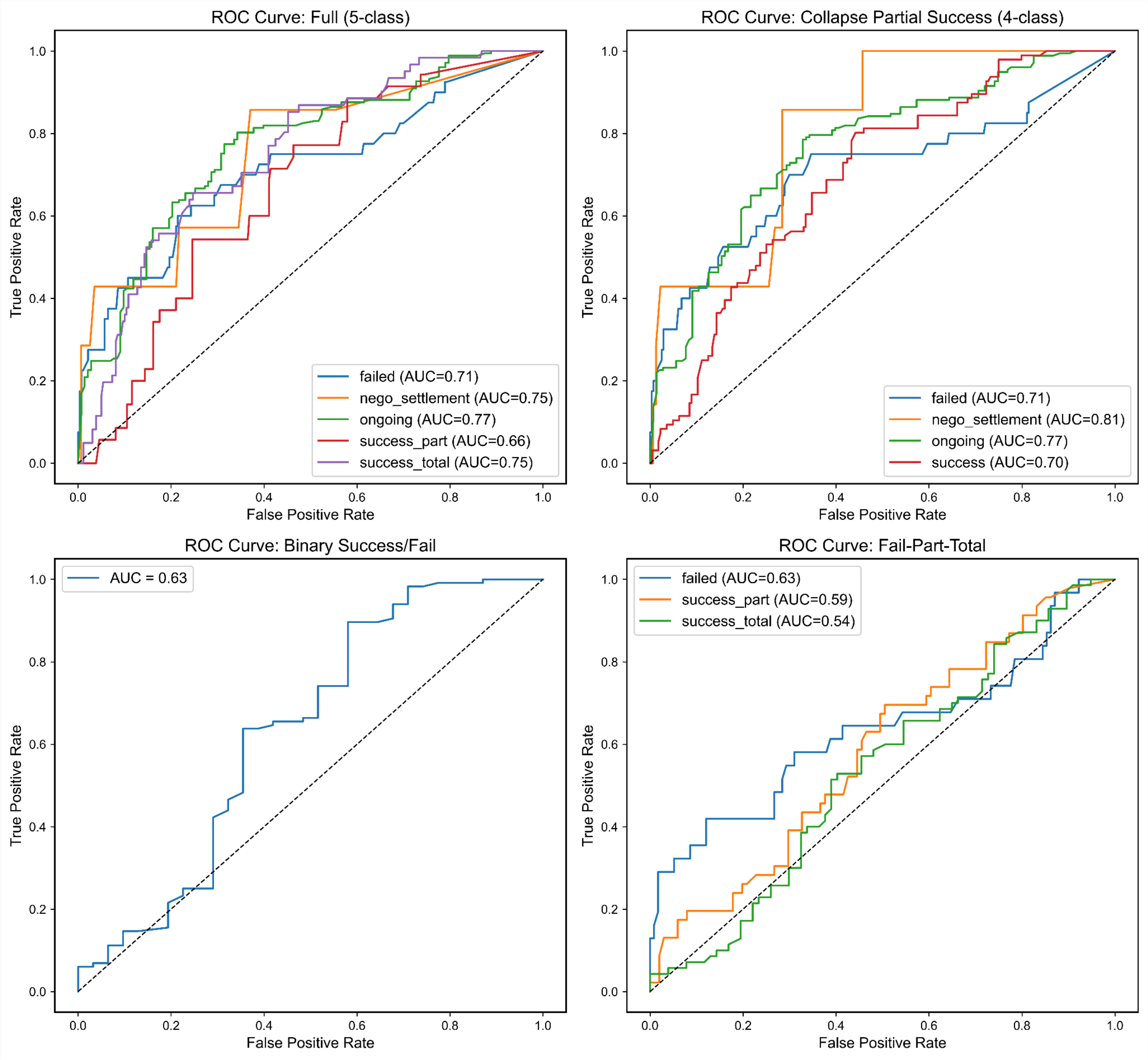
Finally, we merged the labeled datasets from the remaining and validation sets, both containing labels predicted by ChatGPT-4o-mini and examined the distribution of ES mentions across the dataset, analyzing the role of ES in sovereign rating reports and specifically focusing on its impact on rating changes.

Approach 3: Tree-based Modeling

*The tree-based approach indicates a ratings change is most associated with **duration of sanction, landlocked (Y/N), and hybrid target regime**.*

Findings

Here we report our model performance metrics. **Precision** measures how many cases predicted as a certain class were, in fact, correct. If the model labels 100 observations as successes and 80 of the 100 were truly successes, the precision would be 80%. High precision means few false positives (Type I errors). **Recall**, on the other hand, is how many actual instances of a class the model correctly identified. For instance, if there are 100 true failures and the model correctly catches 80 failures of 100 true failures, the recall for failure is 80%. High recall means few false negatives (Type II errors). Therefore we report the **harmonic mean of precision and recall (F1-score)**. As the balance of the two measurements, it is especially useful when classes are imbalanced (some outcomes are much rarer than others). Lastly, accuracy is the overall percentage of correct predictions across all classes. Two averages are taken. First macro average is the unweighted average of precision, recall, and F1 across all classes, treating all classes equally. Weighted averages give more weight to low support classes, providing a sense of how well the model performs overall.



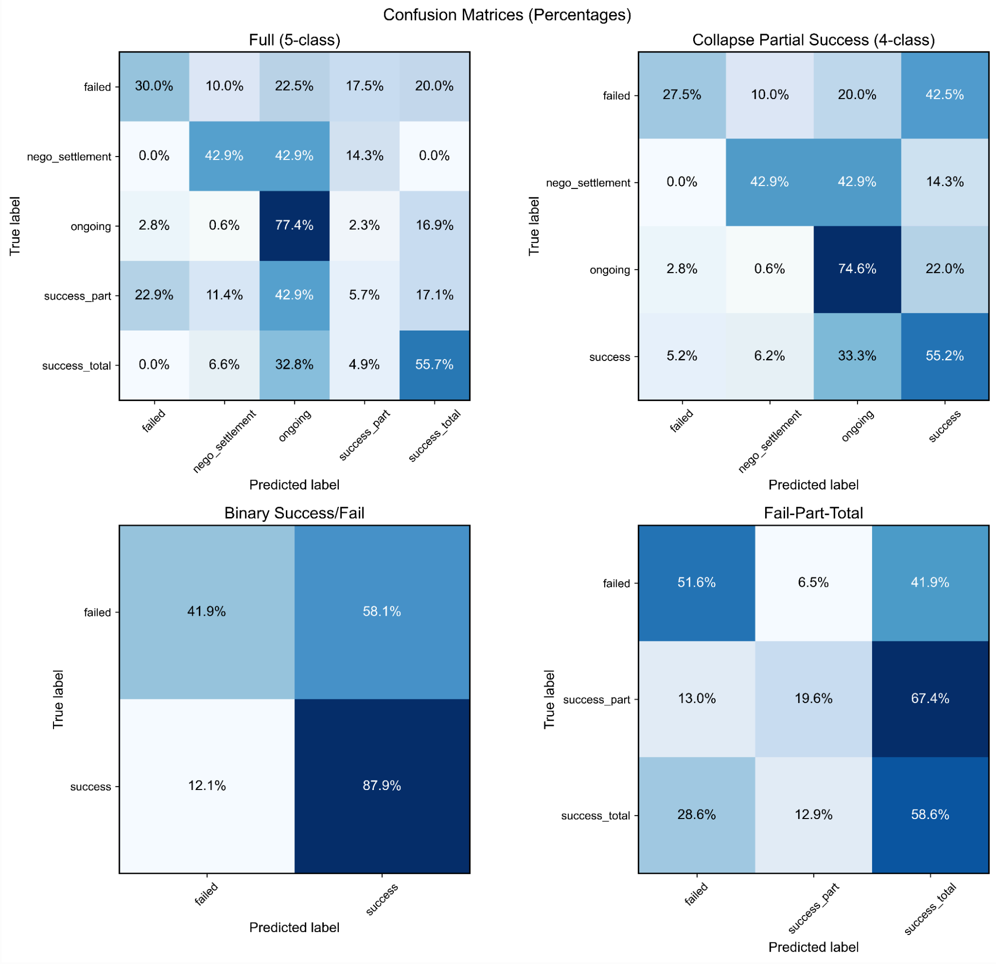
We report the **Receiver Operating Characteristic (ROC) curve** for the Random Forest Classification task. This curve visually presents the trade-off between true positive rate (sensitivity) and false positive rate (1 - specificity) for each outcome class of the sanctions success variable. The Area Under the Curve (AUC) measures the model's ability to distinguish each class from the others. We observe that our AUC is greater than 80% across all classes, which indicates strong discriminatory performance. Ongoing sanctions (AUC = 88%) is the most accurate category, largely due to the number of observations (support). All other classes are also predicted well.

In the context of our research, type I error (or a false positive case) refers to the situation where we predict success (or failure, etc.) but the sanction did not achieve that outcome.

Type II error then, would mean that we failed to predict success (or failure) when it actually occurred. ROC and AUC prioritize minimizing type II errors by evaluating true positives. However mislabelling success can be costly as both error types are important.

Outcome Specification Tests and Model Adjustments

The full Random Forest classifier using the original five-class outcome yielded modest performance (accuracy 59%, macro F1-score 0.39). It struggles to make nuanced distinctions across imbalanced and overlapping categories. To explore whether collapsing categories of outcomes can improve model performance, I experimented with various permutations and filtering of outcome class. In the *collapse_partial_success* model, I collapsed the partial and total success into a single success category. This modestly improved performance (accuracy 59% → 62%; macro F1 0.39→ 0.48). Then, I considered a *binary_success_fail* model, excluding ongoing and negotiated cases, retaining only failures versus a broad success category. This substantially improved performance (accuracy 59% → 78%, macro F1 0.39 → 0.66). Finally, I wanted to see if the model can pick up on the nuance between partial and full success. The *fail_part_total* model excludes ongoing and negotiated cases. Overall performance declined somewhat per expectation (accuracy 59% → 45%, macro F1 0.39→0.41).

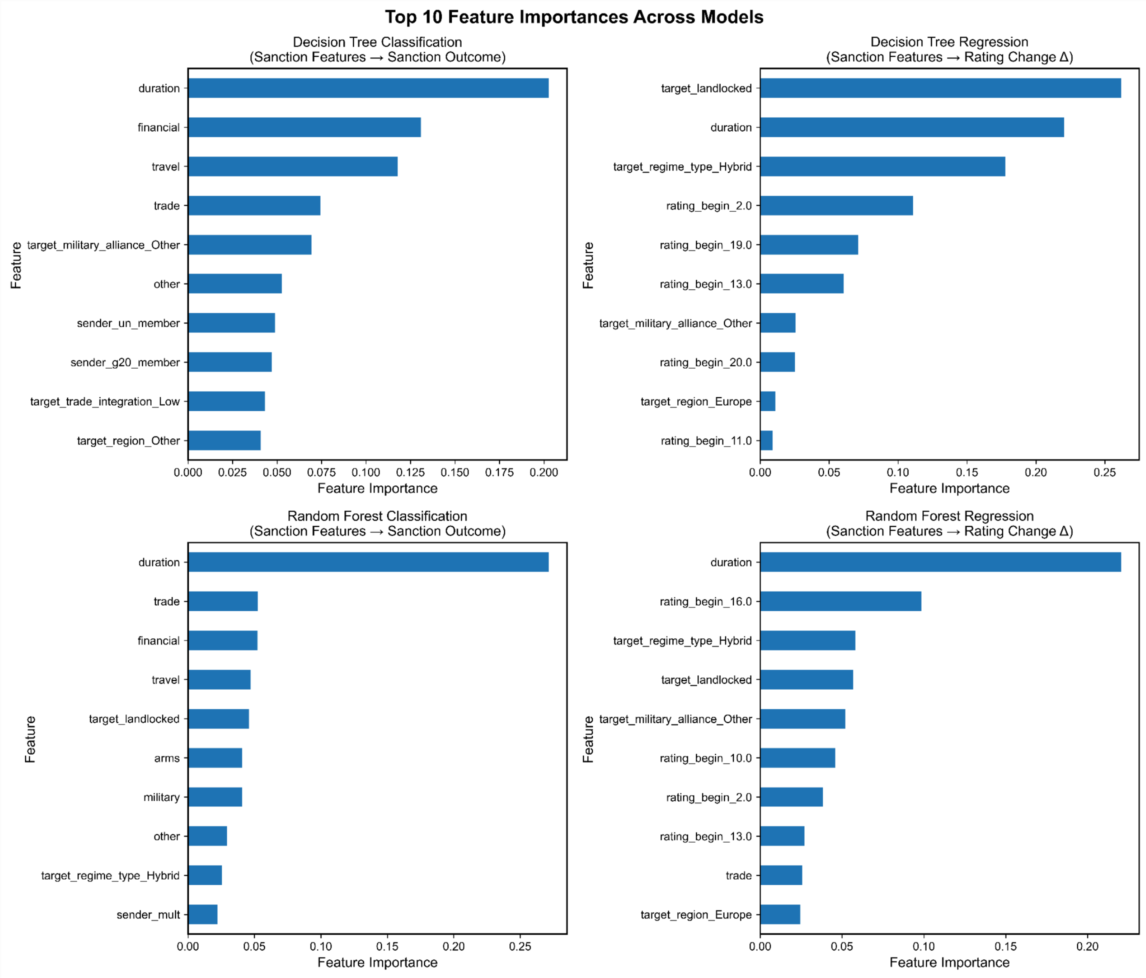


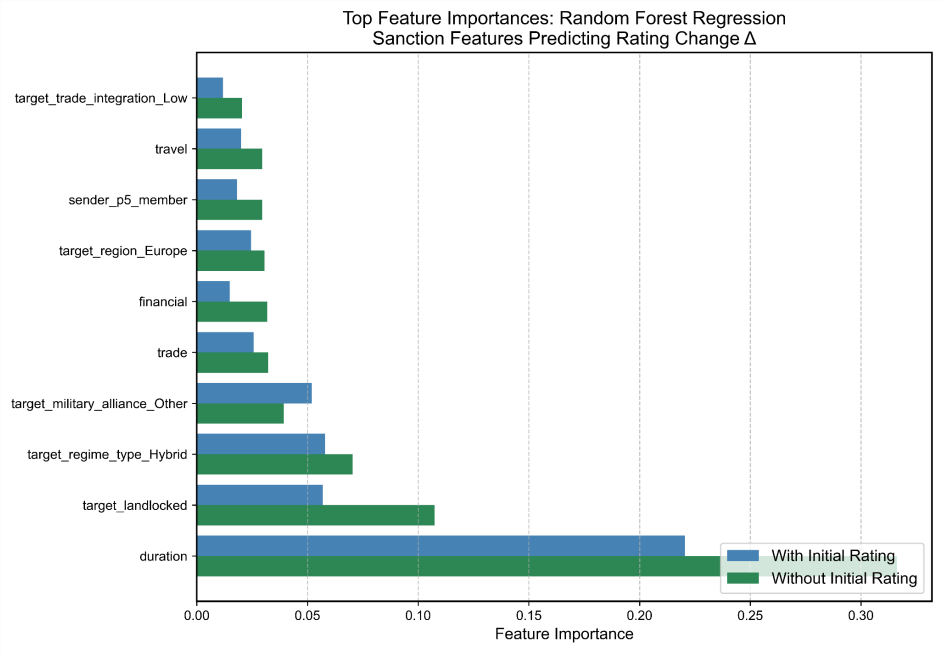
Trade-Offs

Simplifying the outcome classes seems to improve predictive accuracy, at the cost of losing nuanced distinctions important to political or policy interpretations. The binary model (bottom left) performed the best at minimizing type II errors (false negative) for success. The *fail_part_total* model (bottom right), despite being substantively appealing for distinguishing between different degrees of success, did not achieve meaningful predictive gains. The *collapse_partial_success* model (top right) is a compromise: it retains more granularity than the binary case but still better compared to the original five-class model. All tested models performed meaningfully better compared to random guessing, especially when outcome categories were consolidated.

Feature Importance

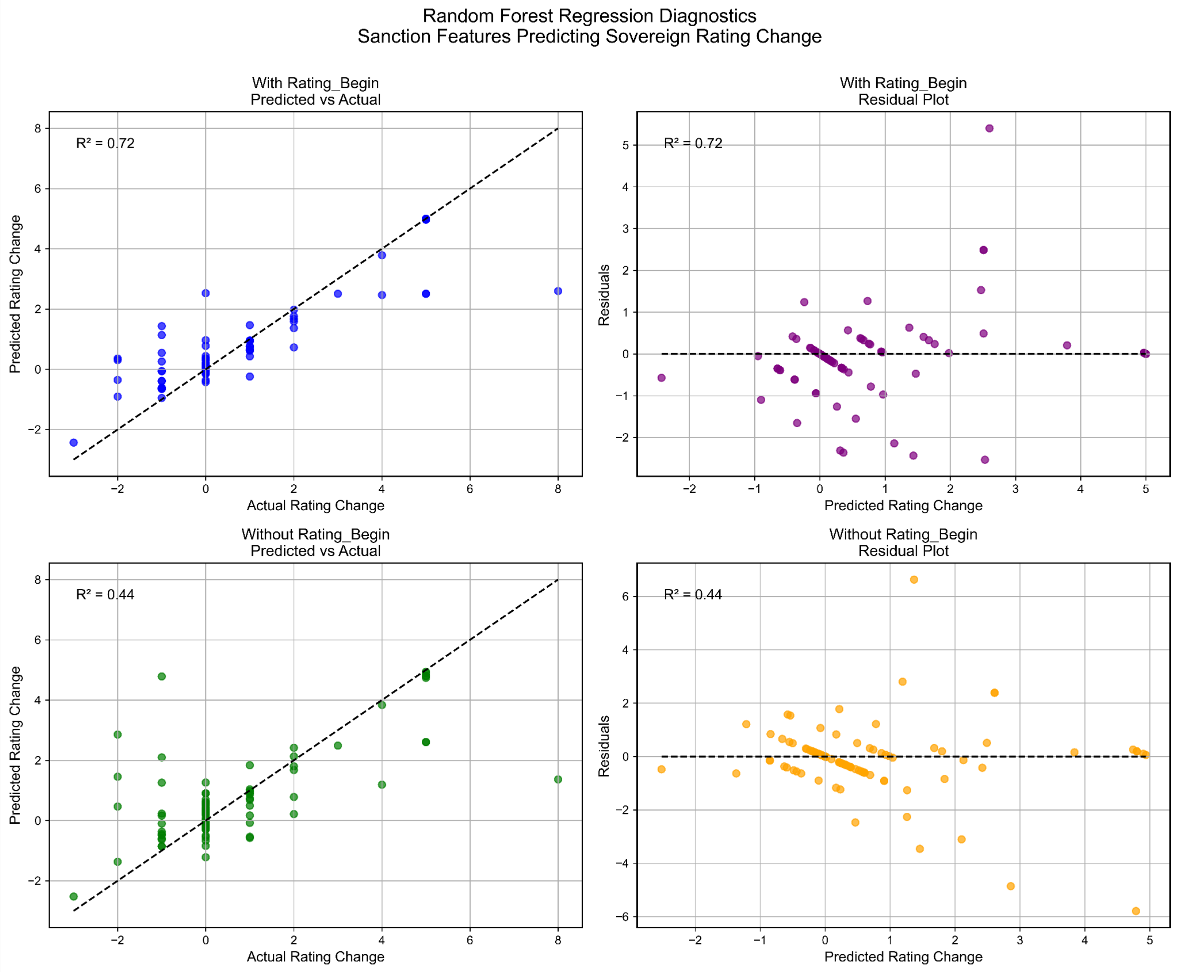
Sorting by level of importance, the most important features that contributed to the prediction accuracy of the classification tree are: the **duration of sanctions (longer sanctions linked to greater changes), target regime type (with hybrid target regimes most sensitive), regional factors, and the time period (era) of the sanction.**





When comparing the top features contributing to rating changes, we see that **initial rating dominates when included but, when removed, structural factors (duration, landlocked status, regime type) and design variables (trade, financial) remain key predictors**. Therefore, we can say that beyond baseline sovereign credit conditions, which seems to explain some of the ratings change, sanction characteristics maintain certain explanatory power.

Duration dominates as one of the top features across both pipelines. Longer sanctions correlate with greater rating changes. One potential point of confusion is w.r.t **rating_begin** variables appearing frequently in both feature charts for the regression task. From a machine learning perspective, the rating at the beginning of a sanction episode is a baseline predictor. The initial value often carries predictive power. From the political economics perspective, countries that start with a low credit rating may have limited downgrade potential (floor effects). Further, the low rating may capture pre-existing vulnerabilities — weaker economies may have some inherent characteristic that renders it more likely to be targeted and vulnerable to rating shifts.



We plot both the scatter of predicted and actual ratings change before and after controlling for rating_begin. We see that points follow the diagonal moderately well in both cases, albeit predictions are a bit weaker without initial rating.

Residuals in both models center around zero, signifying **low heteroscedasticity**. We see a slight funneling, wider residual at higher predictions for our residual plot with rating_begin (top right) and dispersion for the residual plot without rating_begin (bottom right) but both are expected.

The x-axis plots the actual ratings change, while the y-axis is the predicted ratings change by the model. The dashed diagonal is the perfect prediction line if predicted = actual. The 45 degree slope represents the perfect prediction scenario. It's important to note the distinction of the random forest from the traditional method of econometric regression that aims to estimate a slope coefficient. Since the random forest is a non-parametric model, it predicts without assuming a linear relationship, and thus does not provide a single slope or regression equation.

Table 7. Random Forest Regression performance with and without rating_begin

Model	R^2	MAE	Top Features (Random Forest Regression)
With rating_begin	0.719	0.506	duration, rating_begin, regime type, landlocked
Without rating_begin	0.436	0.749	duration, landlocked, regime type, trade, financial

Finally, as a robustness check, we tested our results by removing initial ratings characteristics, to examine if and by how much other sanctions features contribute to the predictive capabilities. **We see that our predictive power drops, with the R^2 fell from ~0.72 to ~0.44 and the MAE increased somewhat but within reasonable bounds.** This shows that other sanctions features retain substantial explanatory power despite removing the target's initial state.

Methodology

We standardized country names to match GSDB sanctioned_state, converted Moody's rating (Aaa to C) into numeric notches (20 = Aaa, 1 = C, etc.). Then we dropped non-rated cases (NR, Withdrawn) and aggregated so we kept one rating per country-year (typically the last available rating per year).

To measure the impact of sanctions on sovereign risk, we merged ***GSDB*** with ***Moody's sovereign credit rating actions***. First, we calculated rating_begin: Nearest rating before or at sanction start year and rating_end: Nearest rating after or at sanction end year, then computed fc_change = rating_end - rating_begin. If multiple ratings are available, we pick the closest year retained. Finally, sanctions starting before 1990 were excluded since Moody's ratings coverage was sparse.

Overall, we retained episodes with non-missing rating change data (fc_change) and cases with valid outcome labels (failed, ongoing, nego_settlement, success_part, success_total).

Next, to enrich the feature space, we used a custom **automated labeling system, assisted by ChatGPT**, to assign region and subregion (for both sender and target), military and economic alliance memberships (e.g., NATO, EU, IMF, WTO), political regime type (autocracy, democracy, hybrid) as well as other static attributes such as landlocked status and resource richness. We also engineered sanction duration (in years), target and sender multiplicity (whether multiple countries were involved) and era buckets to capture decade effects. Categorical variables were encoded using one-hot encoding (drop-first) to create a final feature matrix.

Our final dataset for tree-based methods consisted of 3,547 observations (representing 1,547 sanction episodes), with an **80/20 train-test split** (~2,800 training, ~700 testing episodes). Initial model testing used random train-test splits, while final models addressing outcome definitions used GroupShuffleSplit stratified by case ID to avoid leakage across country-years.
(*Note: For regression models, the sample size was slightly smaller due to missing rating change values.*)

Table 8. Variable used in each supervised machine learning step

Feature Group	Features	Classification	Regression
Sanction Design	trade, arms, military, financial, travel, other, target_mult, sender_mult	✓	✓
Temporal Variables	duration, era, duration_bucket	✓	✓
Structural Factors	target_trade_integration, sender_trade_integration, target_financial_integration, sender_financial_integration, target_landlocked, sender_landlocked, target_resource_rich, sender_resource_rich	✓	✓
Political / Institutional	target_regime_type, sender_regime_type, target_un_member, sender_un_member, target_imf_member, sender_imf_member, target_wto_member, sender_wto_member, target_wb_member, sender_wb_member, target_oecd_member, sender_oecd_member, target_g20_member, sender_g20_member, target_p5_member, sender_p5_member	✓	✓

Alliances & Regional Context	target_military_alliance, sender_military_alliance, target_economic_alliance, sender_economic_alliance, target_region, target_subregion, sender_region, sender_subregion	✓	✓
Baseline Creditworthiness	rating_begin	✗	✓ (excluded in robustness test)

We chose decision tree-based models (classification and regression trees) as the foundational algorithm due to their interpretability, ability to handle both categorical and numerical data ,and robustness to non-linear relationships. To reduce the possibility of overfitting from single-tree models, we adopted random forests for both tasks as a second stage. Random forest average across many trees to improve the stability and predictive performance while preserving the ability to estimate feature importance — important for our goal of finding which feature most influences outcome and sovereign creditworthiness.

We employed a random forest classifier for sanction outcomes since the target variable was categorical. Although the outcome variable was ordinal, we chose to specify our classifiers to treat outcomes as categorical. The forest model allows us to address class imbalance, complex interactions, and non-linear effects. To predict credit rating changes, we used a random forest regressor since the dependent variable (*fc_change*) is continuous.

To ensure the model was not overly reliant on the initial credit rating, we conducted a robustness test by retraining the regression model without the rating_begin feature. Although our R-squared dropped from 0.72 to 0.44, the model still retained meaningful explanatory power.

V. Market and Sectoral Analysis

To supplement the findings of our research and quantitative analyses, we conducted two deep-dives on the impacts that economic statecraft has on markets and specific industrial sectors. The market response to the Liberation Day tariff and the sectoral impacts of the ongoing U.S.—China trade war work as case studies and exemplify the tangible, fiscal, and political effects of ES tools in action.

Market Reaction Deep-Dive: Liberation Day Tariffs

Aside from the effects of economic statecraft tools on macroeconomic indicators and country risk, the effect on financial markets is also worth exploring. In recent years, rising political risk has become one of the primary concerns for global investors. Among the key promises of President Trump's 2nd term is the intent to use tariffs to address US trade imbalances, raise revenues, and protect national security. This section will focus on the latest tariff policy of the Trump administration, announced on Liberation Day, and its immediate impact on global markets; it will also be compared to the tariff implemented in 2018.

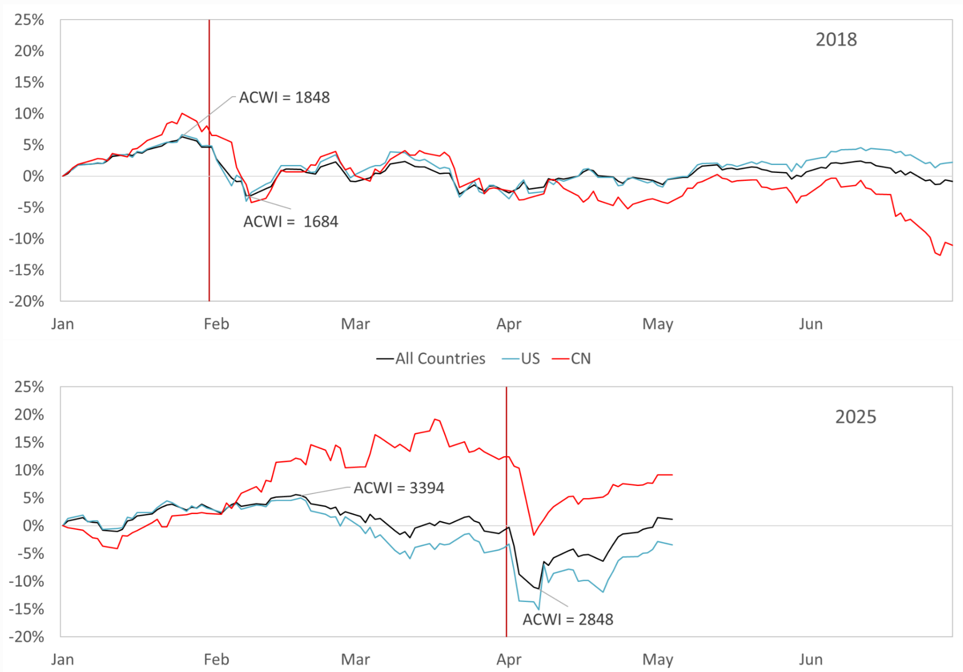
The situation is still evolving, however, we have found that the **current tariff has caused higher volatility in the financial markets** compared to the previous round of Trump tariffs. While the US appears to have backed off of the initial, more severe, tariffs that were announced, uncertainty remains high and there has been an uneven recovery of value across risky assets. The unpredictability of policies has raised investors' hesitation on holding US assets, including traditional safe haven options like treasuries, which has also faced erratic movement following the tariff.

Despite widespread expectations of higher tariffs following President Trump's election victory, the Liberation Day announcement still brought a **high level of uncertainty**. Many market participants' speculation pointed toward a more stagflation environment effect of the looming tariffs. However, the actual scope and scale of the "reciprocal tariffs" was not revealed until April 2nd which the Administration dubbed "Liberation Day". The Budget Lab analysis prior to the announcement modeled that the tariffs would result in a rise in the effective tariff rate of 13 %. However, after the actual announcement and the following tit-for-tat response from China, the effective tariff rate estimate was revised up to 16.1%

(after imports substitution). Consequently, economist surveys from Bloomberg generally revised down projected US GDP (1.9% YoY to 1.4%), revised up inflation (Core PCE 2.7% YoY to 3.1%) as well as increased the possibility of a recession from 30% to 45%.

The worsening economic outlook contributes to a shift in risk sentiment. **As a result, following the tariff announcement, there was a broad selloff in all risk assets**, while the VIX index sharply increased to 60, the highest intraday level since the 2020 Covid crisis. However, the selloff was not limited to just the US market as the global equity index also decreased. Compared to the impact of the 2018 tariff announcement on China, the Liberation Day tariff's impact has caused a higher reaction with the maximum drawdown of the MSCI All Countries World Index at 16.1%, compared to 8.9% in 1H 2018.

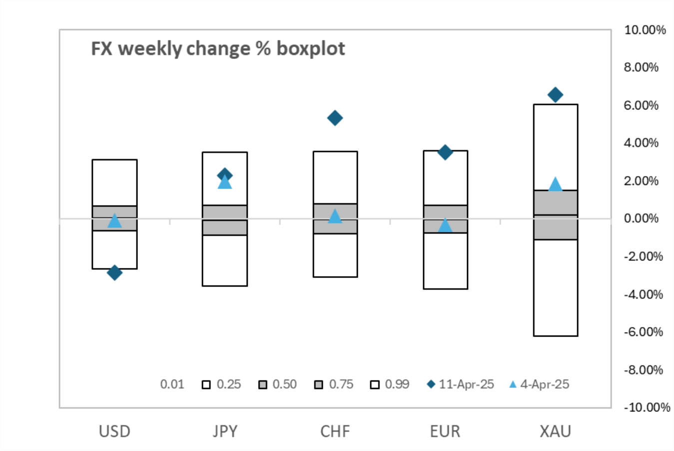
Region wise, another interesting note is the comparison between the US and China's equity performance. In 2018, the US outperformed both the World Index and China while in 2025 the Chinese markets, partly benefitting from a series of stimuli since September 2024, has shown significant outperformance.

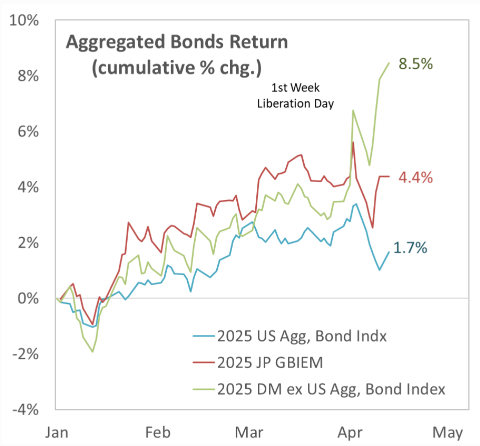


Following the initial reaction, the volatile trades continued until the pause announcement, which helped relieve the pressure on the markets. The policy reversal has signaled to investors that there is room for President Trump to backtrack on the announced measures.

As a result, the level of pessimism has decreased and risk assets have begun to recover. However, despite the pause, the pace of recovery was uneven between economies with some country indices have lagged behind. Going forward, policy uncertainty remains. The next key date will be July 8th, which will be the terminal date of the current tariff pause.

The USD and US Treasuries have underperformed other safe haven assets. The following boxplot is the distribution of weekly returns from 2008. In it, we can see that in the week following Liberation Day, the USD underperformed all other traditional safe assets. Returns of US Government Bonds also underperformed sovereign bonds of both developed and emerging markets. However, it is worth noting that while the tariffs are expected to be inflationary, the 5y5y inflation breakeven for the US has decreased (254 bps to 225 bps), from higher increases in TIPs yields, following the Liberation Day.





Sectoral Shifts Deep-Dive: Insights from the US-China Trade War

Methodology

This section analyzes the **sectoral** and **strategic impacts** of economic statecraft, using data from the U.S. Federal Reserve, Departments of Agriculture and Defense, and reports from Brookings, the Atlantic Council, MSCI, and industry sources. To assess the impact of economic statecraft tools, these sources were cross-referenced with contemporary news coverage and economic commentary to identify both first- and second-order effects. The first order effects can be defined as direct sectoral impacts on trade flows, prices, and output. To further assess the long-term impact of such actions, second-order effects defined as indirect disruptions, structural shifts, and geopolitical consequences, were included in the analysis. The goal of this section is to synthesise the analysis of these effects through the lens of economic statecraft, illustrating how tariffs and trade controls function not only as economic instruments, but also as levers to reshape industrial dynamics.

Sectoral Fallout of China's Soybean Tariffs on US Agriculture and Agribusiness

In 2018, in retaliation for US tariffs on Chinese goods, China imposed a 25% tariff on American soybeans, effectively halting most imports. China had previously been the largest buyer of US soybeans, accounting for more than 50% of total exports. With Chinese buyers shifting rapidly to Brazilian and Argentinian suppliers, US soybean exports to China plummeted by over 70% within the year. As global demand failed to absorb the surplus, soybean prices in the US dropped sharply, reaching their lowest level in over a decade. The price collapse placed immediate financial strain on US agricultural producers, particularly across the Midwest in states like Iowa, Illinois, and Minnesota, home to vertically integrated farm operations and high concentrations of commodity-processing infrastructure.

To stabilise the sector, the US government introduced a $29 billion emergency bailout package, accounting for 40% of income within the sector. **While this support offered temporary relief, it distorted normal market signals, prompting producers to base future planting decisions on subsidy patterns rather than pricing trends.** The knock-on effects were sector-wide: grain handlers, rail and barge transporters, farm equipment manufacturers, and agricultural lenders all reported lower revenues and increasing uncertainty within the sector. Storage capacity scaled for China-bound exports turned into stranded assets, while futures markets became more volatile amid shifting trade expectations.

Second-order effects cascaded across interconnected sectors. Farmers preemptively switched from soybeans to other grains, such as corn and wheat, leading to domestic oversupply and downward price pressure in adjacent commodity markets. Regional banks began reporting rising delinquency rates in farm-related loans, and capital investment in rural areas declined. In addition, agricultural supply chains, spanning seed technology, chemical inputs, and freight logistics, experienced reduced throughput, further dampening innovation and investment.

At the macro-industrial level, the soybean tariff episode contributed to an estimated 1% drag on US GDP growth over 2018—2019, primarily due to depressed income from farmers output, supply chain inefficiencies, and curtailed business investment in agriculture-adjacent sectors. The US also experienced Inflationary ripples in processed food and animal feed prices, both increasing amid the trade-war. Labor market impacts were also sector-specific: roughly 245,000 jobs cumulatively were lost across key sectors. The US witnessed long-lasting impacts as a result of poor equipment sales, canceled logistics contracts, and decline in productivity of regional supply clusters, especially in communities already facing economic vulnerability. In response, the US took ad hoc measures to preserve short-term viability, but the long-term crop allocation and patterns were fundamentally altered, with long-lasting impacts.

Rare Earth Export Controls and Their Cross-Sectoral Impact on US Strategic Industries

That was 2018. Since then, US—China tensions have moved beyond short-term trade disruptions and into **more structural, long-term vulnerabilities**. At the center of this shift are rare earth metals, now widely cited as one of the most strategically significant pressure points. China's dominance in rare earth element production has evolved from a latent risk into a strategic weapon. Since 2023, the Chinese government has introduced targeted **export controls on key rare earths**, particularly medium and heavy elements such as dysprosium and yttrium, critical to high-performance magnets, aerospace guidance systems, radar, and electric vehicle motors. By subjecting these materials to opaque and selectively enforced licensing rules, China has limited access for downstream users while simultaneously gaining insight into global supply chain dependencies. The resulting price volatility, such as the spike in dysprosium oxide costs, has created ripple effects across US industrial sectors.

These measures are a form of economic statecraft designed to exert pressure on **high-value segments of the US economy**. Affected sectors include aerospace and defense, as well as renewable energy, consumer electronics, and automotive manufacturing. Unlike agricultural shocks, where financial subsidies can offer partial relief, **disruptions in rare earth supply chains risk systemic functional delays**. An inability to produce specialized components on time can delay product rollouts, stall defense procurement schedules, and erode competitiveness in strategic export markets.

Stockpiling has emerged as a short-term risk mitigation measure. However, without significant downstream processing capacity, the US remains largely unable to transform raw rare earth ores into usable inputs. Currently, nearly 90% of global rare earth separation and refining occurs in China, reinforcing its position as a chokepoint in the global value chain.

Despite sizable domestic reserves, the **US lacks sectoral breadth in rare earth processing and recycling**. For industries such as defense and renewables, this means that even modest export controls from China can cause significant procurement challenges. Substituting materials or redesigning systems to use alternatives often entails high costs, regulatory approval delays, and performance compromises, making short-term diversification infeasible for many applications. For example, renewable energy firms remain exposed to Chinese upstream control of neodymium and praseodymium, both vital to high-efficiency turbines. Defense contractors continue to depend on Chinese-sourced elements for advanced munitions and satellite components. This concentrated exposure is compounded by the **long lead time** required to bring new refining and processing facilities online, typically 7 to 10 years from permitting to production.

Emerging government-backed investments and allied partnerships show promise, but scale remains insufficient. As does, joint development deals with allies such as Japan and Australia. On April 30, 2025, the United States announced a Joint Economic Investment with Ukraine, aimed primarily at securing rare earth metals. While Ukraine holds 5% of global reserves, its capacity to process and refine high-quality outputs at scale remains uncertain, highlighting persistent capability gaps.

In sum, China's rare earth strategy reveals how sectoral chokepoints can be exploited for strategic gain. The US response must transcend diversification and prioritize cohesive industrial policy, focused sectoral investment, and strategic stockpiling tailored to the distinct requirements of each industry. As with soybeans, overreliance on a fragile or adversarial supply source has resulted in structural disruptions whose effects will persist long after the immediate trade measures have passed.

VI. Conclusion

Overall, the consolidation of these analyses and case studies resulted in several final insights on how economic statecraft affects country risk. First, the use of economic statecraft tools has increased in frequency over time and measurably impacts global economics, which influences country risk. This can be seen through sovereign rating changes. However, the precise magnitude of this impact can vary considerably based on factors like sanction direction, initial credit rating, regime type, and country landlocking status. Moreover, while we were unable to establish a direct, causal link between the usage of economic statecraft tools and country risk, through a reverse analysis, we did determine that around 70% of ratings downgrades were associated with economic statecraft. Finally, limited data availability and granularity in this process of analysis constrained our ability to establish causality. But monitoring our recorded observations and rules of thumb should prove useful and potentially economically valuable in future pursuits to track how economic statecraft affects overall country risk.

References

1. Abbas, S. K., & Lan, H. (2020). Commodity price pass-through and inflation regimes. *Energy Economics, 92*, 104977. https://doi.org/10.1016/j.eneco.2020.104977

2. ABC News. (2024, April 29). New tariffs could cost US importers $700 billion by 2025. https://abcnews.go.com/Business/new-tariffs-cost-us-importers-700-billion-2025/story?id=120571745

3. Alhassan, Abukari, et al. 2023. Sanctions and Economic Growth: Do Sanction Diversity and Level of Development Matter? ResearchGate, https://www.researchgate.net/publication/373635478_Sanctions_and_economic_growth_Do_sanction_diversity_and_level_of_development_matter.

4. Boudreaux, D. (2024, April 10). *Letter: Tariffs act as a tax on an economy's production*. *Financial Times*.

5. Bureau of Economic Analysis. (2025, April 30). Gross Domestic Product, 1st Quarter 2025 (Advance Estimate). https://www.bea.gov/news/2025/gross-domestic-product-1st-quarter-2025-advance-estimate

6. Caetano, J., Galego, A. & Caleiro, A. (2023) 'On the Determinants of Sanctions Effectiveness: An Empirical Analysis by Using Duration Models', *Economies*, 11(5), p.136. Available at: https://doi.org/10.3390/economies11050136

7. Capital Economics. (2025, April 10). US Consumer Prices (Mar. 2025). https://www.capitaleconomics.com/publications/us-rapid-response/us-consumer-prices-mar-2025

8. Corda, T. (2023) 'Constraining Compliance? Reconsidering the Effect of Veto Players on Sanctions Success', *Defence & Peace Economics*, 34(7), pp.880—892. Available at: https://doi.org/10.1080/10242694.2022.2158288

9. Cousens, M. (2024, December 11). *2024 post-election survey: Racial analysis of 2024 election results*. Navigator Research.

10. Demena, B.A. & van Bergeijk, P.A.G. (2025) *"A Meta-Analysis of Determinants of Success and Failure of Economic Sanctions."* **Econometrics** 13(2):16. https://doi.org/10.3390/econometrics13020016

11. Demena, B.A. & van Bergeijk, P.A.G. (2025) 'A Meta-Analysis of Determinants of Success and Failure of Economic Sanctions', *Econometrics*, 13(2), p.16. Available at: https://doi.org/10.3390/econometrics13020016

12. Demir, B., & Javorcik, B. S. (2020). *Trade policy and firm boundaries* (NBER Working Paper No. 27114). *National Bureau of Economic Research*. https://doi.org/10.3386/w27114

13. Drezner, D.W. (2000) 'Bargaining, Enforcement, and Multilateral Sanctions: When Is Cooperation Counterproductive?', *International Organization*, 54(1), pp.73—102. Available at: https://web.stanford.edu/class/ips216/Readings/drezner_00.pdf

14. Early, Bryan R., and Robert Spice. "Economic Sanctions, International Institutions, and Sanctions Busters: When Does Institutionalized Cooperation Help Sanctioning Efforts?" *Foreign Policy Analysis* 11, no. 3 (2015): 339—360. https://www.jstor.org/stable/24910807.

15. Eckhardt, S., O'Brien, C., & Glasner, B. (2024). *Economic geography of the 2024 election*. Economic Innovation Group. https://eig.org/economic-geography-2024/

16. Fajgelbaum, P. D., & Khandelwal, A. K. (2016). *Measuring the unequal gains from trade*. *The Quarterly Journal of Economics, 131*(3), 1113—1180. https://doi.org/10.1093/qje/qjw013

17. Flaaen, A., Hortaçsu, A., & Tintelnot, F. (2020). *The production relocation and price effects of US trade policy: The case of washing machines*. *American Economic Review, 110*(7), 2103—2127. https://doi.org/10.1257/aer.20190611

18. Flaaen, A., & Pierce, J. (2019). *Disentangling the effects of the 2018—2019 tariffs on a globally connected U.S. manufacturing sector* (FEDS Working Paper No. 2019-086). *Board of Governors of the Federal Reserve System*. https://doi.org/10.17016/FEDS.2019.086

19. Furceri, D., Hannan, S. A., Ostry, J. D., & Rose, A. K. (2019). *Macroeconomic consequences of tariffs*. *International Monetary Fund*. https://www.imf.org/en/Publications/WP/Issues/2019/01/09/Macroeconomic-Consequences-of-Tariffs-46566

20. Furman, J., & Powell, W. (2019). *US tariffs: An illustrative history*. *Journal of Economic Perspectives, 33*(4), 187—206. https://doi.org/10.1257/jep.33.4.187

21. Gailes, A., Gurevich, T., Shikher, S., & Tsigas, M. (2018). *Gender and income inequality in United States tariff burden*(Economics Working Paper Series No. 2018–08–B). U.S.

International Trade Commission.
https://www.usitc.gov/publications/332/working_papers/gender_tariff_1.html

22. Giumelli, Francesco. “A Comprehensive Approach to Sanctions Effectiveness: Lessons Learned from Sanctions on Russia.” *European Journal on Criminal Policy and Research* 30 (2024): 211—228. https://www.researchgate.net/publication/382194450_A_Comprehensive_Approach_to_Sanctions_Effectiveness_Lessons_Learned_from_Sanctions_on_Russia.

23. Goldman Sachs. (2025, March 10). Why the US economy may grow more slowly than expected. https://www.goldmansachs.com/insights/articles/why-the-us-economy-may-grow-more-slowly-than-expected

24. Hufbauer, Gary Clyde, Jeffrey J. Schott, Kimberly Ann Elliott, and Barbara Oegg. *Economic Sanctions Reconsidered*, 3rd ed. Washington, DC: Peterson Institute for International Economics, https://www.piie.com/bookstore/economic-sanctions-reconsidered-3rd-edition-paper

25. Ikenson, D. (2018). Separating tariff facts from tariff fictions. Cato Institute. https://www.cato.org/publications/separating-tariff-facts-tariff-fictions#who-actually-pays-tariffs

26. Itskhoki, Oleg, and Elina Ribakova. “The Economics of Sanctions: From Theory Into Practice.” *Brookings Papers on Economic Activity*, https://www.brookings.edu/wp-content/uploads/2024/09/6_ItskhokiRibakova.pdf.

27. Joshi, Sumit, and Ahmed Saber Mahmud. “Sanctions in Networks.” *European Economic Review* 130 (2020). https://www.sciencedirect.com/science/article/pii/S0014292120302361.

28. Mahajan, A., & Tomar, S. (2020). COVID-19 and supply chain disruption: Evidence from food markets in India. American Journal of Agricultural Economics, 103(1), 35—52. https://doi.org/10.1111/ajae.12158

29. Moran, T. (2014). *American consumers pay steep hidden tariffs on everyday goods*. Peterson Institute for International Economics. https://www.piie.com/publications/commentary/american-consumers-pay-steep-hidden-tariffs-everyday-goods

30. Neuenkirch, Matthias, and Florian Neumeier. “The Impact of UN and US Economic Sanctions on GDP Growth.” *European Journal of Political Economy* 40 (2015): 110—125. https://www.researchgate.net/publication/271512626_The_impact_of_UN_and_US_economic_sanctions_on_GDP_growth.

31. Nievon, M., Ende, S., Becker, D., & Yang, M. (2021). *How tariffs affect U.S. consumers*. *Federal Reserve Bank of Kansas City, Economic Review, 106*(4), 5—28. https://www.kansascityfed.org/documents/8408/EconomicReviewV106N4NievonEndeBeckerYang.pdf

32. Nova, A. (2025, April 10). Here's the inflation breakdown for March 2025 — in one chart. CNBC. https://www.cnbc.com/2025/04/10/heres-the-inflation-breakdown-for-march-2025-in-one-chart.html

33. Pape (1997), “Why Economic Sanctions Do Not Work”, *International Security, Volume 22, Issue 2,* Available at: https://web.stanford.edu/class/ips216/Readings/pape_97%20(jstor).pdf

34. Psomopoulou, K. (2021) 'Financial Sanctions Effectiveness as a Foreign Policy Tool on Crises Management', *HAPSc Working Paper 20/2021*, Hellenic Observatory (LSE). Available at: https://www.hapsc.org/wp-content/uploads/2021/12/HAPSc-Working-Paper-20.2021-Psomopoulou.pdf

35. Russ, K. N., Shambaugh, J., & Furman, J. (2017, January 12). *US tariffs are an arbitrary and regressive tax*. VoxEU.org. https://cepr.org/voxeu/columns/us-tariffs-are-arbitrary-and-regressive-tax

36. U.S. Bureau of Labor Statistics. (2025). Gross domestic product (GDP): All industry total. https://data.bls.gov/pdq/SurveyOutputServlet

37. U.S. Department of Agriculture, Economic Research Service. (2025). Agricultural trade multipliers. https://www.ers.usda.gov/data-products/agricultural-trade-multipliers

38. U.S. Government Accountability Office (2019) Economic Sanctions: Agencies Assess Impacts on Targets, and Studies Suggest Several Factors Contribute to Sanctions' Effectiveness. GAO-20-145. Available at: https://www.gao.gov/assets/gao-20-145.pdf

39. U.S. International Trade Commission. (2015). *The economic effects of significant U.S. import restraints: Ninth update 2015*. https://www.usitc.gov/publications/332/pub4535.pdf

40. Wilding, T. (2025, April 9). The U.S. economy's trajectory amid higher tariffs. PIMCO. https://www.pimco.com/us/en/insights/the-us-economys-trajectory-amid-higher-tariffs

41. Yale Budget Lab. (2024). *Fiscal, macroeconomic, and price estimates of tariffs under both non-retaliation and retaliation*. *Yale University*.

42. Yilmazkuday, H. (2025). *Unequal inflationary effects of tariffs across socio-demographic groups*. *Florida International University, Department of Economics*. SSRN. https://ssrn.com/abstract=5158840

43. Zarpli, O. (2023) 'When Do Imposed Sanctions Work? The Role of Target Regime Type', *Journal of Conflict Resolution*, 67(7-8), pp.1482—1509. Available at: https://doi.org/10.1177/00220027221139809

Appendix A - Market Reaction Dashboard

The following data supplements the market reaction section regarding the Liberation Day tariffs: data shown in the table include market movement starting from February 1st, and a snapshot of cumulative change after 1 month, 2 month, and 3 month. The box plot is a distribution of weekly returns since 2008.

FROM 30-Jan-25

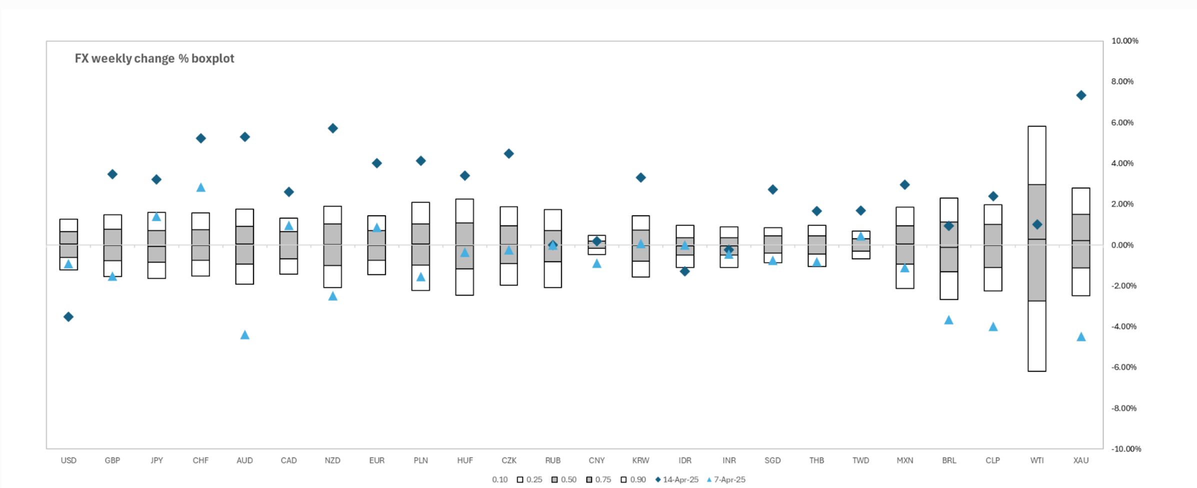
(grey) =DATA UNAVAILABLE

				Safe Haven		High Beta			EU Core		EU Peripheral				CEE			APAC							LatAm		
% chg.	T+	USD	GBP	JPY	CHF	AUD	CAD	NZD	EUR	DEM	FRF	ITL	ESP	GRD	PLN	HUF	CZK	CNY	KRW	IDR	INR	SGD	THB	TWD	MXN	BRL	CLP
Spot FX	1M	0%	1%	3%	0%	0%	0%	-1%	0%						0%	1%	0%	0%	-2%	-3%	-1%	0%	-1%	0%	0%	0%	3%
	2M	-4%	4%	3%	2%	0%	0%	0%	4%						4%	5%	4%	0%	-3%	-2%	1%	0%	-1%	-2%	0%	3%	4%
	3M	-8%	7%	8%	9%	2%	4%	5%	8%						6%	9%	9%	0%	0%	-3%	2%	3%	1%	2%	4%	3%	4%

				Safe Haven		High Beta			EU Core		EU Peripheral				CEE			APAC							LatAm		
% chg.	T+	USD	GBP	JPY	CHF	AUD	CAD	NZD	EUR	DEM	FRF	ITL	ESP	GRD	PLN	HUF	CZK	CNY	KRW	IDR	INR	SGD	THB	TWD	MXN	BRL	CLP
EQ Index	1M	-1%	3%	-6%	4%	-3%	0%	-3%	4%	4%	3%	6%	8%	4%	7%	3%	5%	2%	0%	-13%	-5%	2%	-11%	-2%	2%	0%	3%
	2M	-7%	0%	-10%	1%	-7%	-2%	-6%	1%	3%	-1%	4%	7%	9%	11%	5%	12%	2%	-2%	-9%	2%	4%	-15%	-12%	2%	6%	8%
	3M	-7%	0%	-7%	-3%	-3%	-2%	-9%	-1%	5%	-3%	4%	9%	10%	15%	9%	8%	-1%	2%	-5%	5%	1%	-11%	-13%	9%	9%	13%

				Safe Haven		High Beta			EU Core		EU Peripheral				CEE			APAC							LatAm		
% chg.	T+	USD	GBP	JPY	CHF	AUD	CAD	NZD	EUR	DEM	FRF	ITL	ESP	GRD	PLN	HUF	CZK	CNY	KRW	IDR	INR	SGD	THB	TWD	MXN	BRL	CLP
CDS	1M	(2.32)	(3.28)	(2.57)		(0.26)				(1.23)	(8.04)	(8.78)	(4.63)					(15.21)	(9.90)	(9.53)			(3.40)	(3.20)	(12.05)	(27.47)	(10.77)
	2M	4.38	(4.59)	(3.30)		2.29				(0.82)	(7.93)	(10.88)	(5.61)					(12.14)	(8.90)	0.21			0.71	17.80	(3.29)	(17.52)	(6.51)
	3M	4.19	(0.69)	1.41		6.26				(0.39)	(0.95)	(1.69)	1.87					8.81	(4.99)	26.87			16.79	45.67	15.84	(1.70)	10.55

				Safe Haven		High Beta			EU Core		EU Peripheral				CEE			APAC							LatAm		
% chg.	T+	USD	GBP	JPY	CHF	AUD	CAD	NZD	EUR	DEM	FRF	ITL	ESP	GRD	PLN	HUF	CZK	CNY	KRW	IDR	INR	SGD	THB	TWD	MXN	BRL	CLP
2Y10Y Spread	1M	(0.18)	0.02	0.01	(0.05)	0.02	0.01	(0.06)	0.01	0.01	(0.08)	(0.02)	(0.11)	(0.20)	(0.29)	(0.00)	(0.11)	(0.07)	0.04	0.01	0.02	(0.06)	(0.12)		0.04	0.12	0.36
	2M	(0.10)	0.20	0.13	0.14	0.06	0.13	(0.01)	0.37	0.37	0.26	0.38	0.28	0.23	(0.32)	(0.01)	(0.02)	(0.11)	(0.04)	0.18	0.05	0.01	(0.12)		0.06	0.50	0.12
	3M	0.13	0.36	0.19	0.10	0.50	0.18	0.50	0.43	0.43	0.35	0.42	0.37	0.09	(0.06)	0.11	(0.04)	(0.16)	0.09	0.05	0.21	0.15	0.01		0.49	0.72	(0.07)



Appendix B - Two-Way Fixed Effects Regression

Code in Google Drive Folder

Appendix C - Prompt Iteration & Text Analysis

Code in Google Drive Folder

Appendix D - Tree-Based Modeling

Code in Google Drive Folder