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The Economics of Strategic Learning in Trade Wars: Evidence from the Trump -Xi Natural Experiment

Conditional Reciprocity and Behavioral Synchronization in US-China Trade Wars

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Abstract

How do rival leaders learn to retaliate without trust or treaties? This paper exploits a rare "same leaders" natural experiment to trace strategic learning in bilateral economic conflict. We analyze two periods of the Trump–Xi trade war — "Trump–Xi 1.0" (2017 2020) and "Trump–Xi 2.0" (2025) — in order to isolate how experience shapes escalation in tariff retaliation. We introduce the **Bilateral Learning Strength Index** (BLSI). This novel metric captures two behavioral dimensions: conditional reciprocity—how predictably one side responds in kind—and behavioral synchronization—how closely rivals mirror each other's timing and intensity across repeated trade actions.

Using data on 37,098 U.S.–China trade actions, we find that escalation in Trump–Xi 2.0 is substantially more constrained. Retaliatory responses are both more disciplined and far more synchronized, with a correlation[1] coefficient of 0.884. These results suggest that through repeated interaction, adversarial leaders converge toward implicit rules of engagement—thresholds for retaliation that stabilize conflict dynamics even in settings devoid of formal treaties or mutual trust.

The framework has potential applications well beyond trade wars, including central bank coordination, oligopolistic competition, and international monetary spillovers—any environment in which actors engage repeatedly without binding agreements.

[1] *The full replication package is available at:*
https://github.com/globalpolicysignals/Bilateral_StrategicLearning_USChina_RIPE
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The BLSI also lays the groundwork for "Quantified Conflict Studies", which could enable strategic forecasting, AI-assisted diplomacy, and real-time monitoring of conflict behavior in trust-deficient settings. By making strategic learning empirically measurable, this paper contributes to understanding not only how conflict escalates but also how it may evolve toward patterned stability rather than chaos.

Keywords: Strategic Learning, Conditional Reciprocity, Trade Wars, Behavioral Synchronization, Bilateral Conflict, Game Theory, AI-Diplomacy, Quantified Conflict Studies, Economic Statecraft, US-China Relations, Russia-Ukraine, Natural Experiment, Strategic Forecasting, Political Economy

JEL Classifications : F02, F13, F51, F52, C73, D74, D83, D86, H77, O38

1. Introduction

How do rival leaders learn from repeated strategic interactions when trust is absent and formal institutions fail? This fundamental question in international political economy has lacked empirical answers due to the impossibility of observing identical decision-makers in comparable strategic situations across time. We exploit a remarkable natural experiment: Donald Trump's return to the US presidency in January 2025, creating the first opportunity to observe how the same leaders (Trump and Xi Jinping) adapt their strategies in a second round of trade conflict with accumulated strategic experience.

This research establishes conditional reciprocity as an identifiable pattern in repeated strategic interactions, providing measurement tools and theoretical foundations for investigating similar phenomena in comparable strategic contexts.

This paper delivers three methodological and theoretical innovations that establish a new field of Quantified Conflict Studies. First, we establish the "same-leaders natural experiment" as a powerful identification strategy for studying strategic learning in international relations, leveraging variation in experiential backgrounds while holding constant leader identity, policy instruments, and fundamental economic relationships. Second, we provide the first empirical evidence that repeated adversarial interactions generate systematic behavioral patterns—what we term "conditional reciprocity"—that function as enforcement mechanisms in the absence of formal institutions or trust. Third, we introduce the Bilateral Learning Strength Index (BLSI) as a quantitative framework for measuring how adversaries evolve from reactive responses toward stable, algorithmic-like strategic patterns.

Using comprehensive microdata from the Peterson Institute for International Economics, we analyze 37,099 bilateral trade actions across two distinct periods: Trump 1.0 (2017-2021) representing the "inexperienced" treatment, and Trump 2.0 (2025-present) representing the "learned" treatment. Our

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identification strategy leverages the fact that both periods involve identical leaders employing identical policy instruments (tariffs) within the same fundamental economic relationship, with the primary difference being the accumulated strategic experience from their previous encounter.

Our empirical findings reveal three significant results. Strategic learning dramatically compressed escalation timelines: Trump 2.0 immediately implemented 100% tariff coverage versus Trump 1.0's gradual escalation from 0% to 66.6% over 18 months—a phenomenon we term "learned pattern compression." We identify the emergence of conditional reciprocity with a bilateral correlation of 0.884, which creates predictable behavioral constraints without the need for formal agreements or trust. The BLSI framework quantifies how adversaries develop algorithmic-like response patterns, increasing from 0.735 to 0.890 between periods, representing measurable evolution toward rule-based strategic interaction.

These results have profound implications for international relations theory and practice. We demonstrate that systematic strategic learning creates quasi-institutional constraints in international relations, suggesting new approaches to conflict management based on behavioral synchronization rather than formal treaty architecture. The framework offers immediate tools for understanding ongoing conflicts, particularly the Russia-Ukraine war, where similar learning dynamics may be observable. More broadly, our research establishes the theoretical foundation for "AI-diplomacy" in trust-absent environments, where algorithmic pattern recognition can identify and leverage learned reciprocity patterns for conflict resolution.

This research demonstrates the existence and measurability of strategic learning patterns in a unique natural experiment setting, establishing theoretical foundations and empirical methods for investigating similar phenomena in comparable strategic contexts.

The paper proceeds as follows: Section 2 develops the theoretical framework for conditional reciprocity and positions our contribution within existing literature. Section 3 describes our unique dataset and the identification strategy employed. Section 4 presents empirical results on strategic

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learning patterns. Section 5 introduces and validates the BLSI framework. Section 6 analyzes mechanisms driving strategic adaptation. Although the same-leaders natural experiment is historically unique, the framework it generates extends beyond trade policy. Strategic learning under repeated rivalry is central to canonical puzzles in economics, ranging from central bank coordination to oligopoly dynamics and international monetary spillovers. Section 7 illustrates these broader applications, highlighting how BLSI and SMI provide behavioral diagnostics that complement existing theories of coordination and competition. Section 8 examines external validity and applications to AI-diplomacy. Section 9 concludes with policy implications for conflict resolution in the contemporary international system.

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2. Theoretical Framework and Literature

2.1 Conditional Reciprocity: A Theory of Trust-Absent Cooperation

We introduce conditional reciprocity as a distinct mechanism for conflict management when trust is absent and formal institutions fail. Conditional reciprocity differs fundamentally from standard reciprocity (Axelrod, 1984)[1] by incorporating learned response patterns that create systematic behavioral constraints through accumulated strategic experience rather than immediate tit-for-tat responses.

Economists and IR scholars have long debated reciprocity in trade conflicts (Dixit 1987)[2] ; (Bagwell & Staiger 1999)[3] and (Grossman & Helpman 1994)[4], but systematic empirical measurement of how leaders learn and adjust tariffs over time has been lacking.

Definition: Conditional reciprocity operates through systematic response calibration and temporal synchronization, distinguishing it from immediate retaliation through the accumulation of strategic learning. Conditional reciprocity refers to the patterns where adversaries or competitors develop

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predictable behavioral constraints through repeated strategic interaction, creating quasi-institutional enforcement mechanisms without formal agreements or mutual trust.

This mechanism operates through four critical channels that distinguish it from simple retaliation:

1. **Response Calibration**: Leaders learn to match opponent actions proportionally based on accumulated experience, moving beyond immediate reactive responses to strategic calculation
2. **Temporal Synchronization**: Response timing becomes predictable, creating windows for strategic communication and de-escalation signaling
3. **Escalation Compression**: Experienced adversaries reach equilibrium positions faster, reducing conflict duration and uncertainty
4. **Algorithmic Adaptation**: Repeated interactions generate pattern recognition that approaches computational precision in strategic responses

The theoretical innovation lies in demonstrating how behavioral algorithms emerge naturally from strategic interaction, creating stability through learned synchronization rather than institutional design. This represents a fundamental alternative to trust-based cooperation in international relations.

2.2 Strategic Learning in International Relations

The literature on strategic learning has developed rich theoretical frameworks (Jervis, 1976)[5]; (Levy, 1994)[6]; (Reiter, 1996)[7], but empirical identification remains limited by the impossibility of observing the same actors in comparable strategic situations. Early work established conceptual foundations (Haas, 2001)[8], while recent advances in applied microeconomics enabled precise identification of learning effects in various contexts (Heckman and Singer, 1984)[9]; (Bandiera and Rasul, 2006)[10]. However, applications to international conflict remain constrained by fundamental identification challenges.

Our contribution addresses this gap through our identification strategy that isolates pure learning effects while maintaining external validity. Unlike cross-sectional studies that confound learning with

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unobserved heterogeneity, our design provides clean identification of strategic adaptation between identical actors. This methodological breakthrough enables the first empirical measurement of how adversarial leaders develop behavioral algorithms through repeated interaction.

2.3 Trade Wars and Economic Statecraft

Recent empirical work has documented the specific mechanisms through which the Trump-era trade war unfolded. Bown (2021)[11] provides a comprehensive analysis of the Phase One agreement's implementation challenges, demonstrating how formal institutional arrangements failed to prevent renewed escalation in our Trump 2.0 period. Evenett (2019)[12] situates the US-China conflict within broader global trends of protectionism following the 2008 financial crisis, highlighting how traditional multilateral frameworks proved inadequate for managing bilateral strategic competition. Our research contributes by showing how learned behavioral patterns emerge when formal agreements break down. The maritime dimensions of US-China strategic competition, as comprehensively documented in a Congressional Research Service analysis (CRS Report R42784), reveal structured interaction patterns between the same leadership teams across multiple domains. These patterns suggest that the strategic learning mechanisms we identify in trade conflicts may have broader theoretical significance for understanding how adversarial relationships stabilize through repeated interaction, opening avenues for future research in comparable strategic settings.

2.4 Trade Wars as Strategic Learning Laboratories

The empirical literature on trade wars has primarily focused on welfare effects and industry impacts (Amiti et al., 2019)[13], (Fajgelbaum et al., 2020)[14], and (Cavallo et al., 2021)[15] without examining strategic interaction patterns between decision-makers or learning dynamics over time. Related work on reciprocity in trade agreements (Bagwell and Staiger, 2020)[16] focuses on formal institutional mechanisms, differing from our emphasis on learned behavioral patterns in adversarial, trust-absent settings.

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Our research extends this literature by demonstrating how trade wars function as laboratories for strategic learning, with leaders developing refined tactical approaches through accumulated experience. The quantifiable nature of tariff actions provides unprecedented precision in measuring strategic adaptation, offering a methodological template for studying conflict learning across domains.

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3. Data and Identification Strategy

3.1 The Peterson Institute Dataset: Comprehensive Bilateral Actions

Our primary data source is the comprehensive Peterson Institute for International Economics (PIIE) tariff and trade dataset, which provides precise details on strategic interactions between the world's two largest economies from January 2017 through August 2025. This dataset represents the most complete record of bilateral trade conflict actions ever assembled, enabling robust empirical analysis of strategic learning patterns.

The dataset encompasses multiple analytical levels:

- **Product-level microdata**: over 37,000 bilateral trade actions across HS-10 digit product codes
- **Daily time-series**: Enabling precise measurement of response timing and strategic coordination
- **Sectoral aggregation**: Industry-level analysis revealing strategic targeting evolution
- **Institutional actions**: Anti-dumping and countervailing duty cases capturing formal dispute mechanisms
- **Exclusion processes**: Detailed records of exemption requests and approvals revealing negotiation dynamics

Table 1: Dataset Summary

Dataset Component	Number of Files	Total Observations	Total Columns	Directional Coverage	Phase Coverage
US Tariffs	1	18,027	15	China	Phase Trump 1.0
China Tariffs	1	8,558	20	US	Phase Trump 1.0

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Exclusion Lists	4	2,960	77	Bilateral, US-focused	Phase Trump 1.0
Trade Flows	5	59,865	68	Bilateral	Phase Trump 1.0
Antidumping Actions	9	48,528	187	China-focused, US-focused	Phase Trump 1.0
Countervailing Duties	8	17,192	120	China-focused, US-focused	Phase Trump 1.0
Strategic Panel	2	137	10	Bilateral	Phase Trump 1.0, Phase Trump 2.0
TOTAL	30	155,267	497		Both Phases

The comprehensive scope of our dataset addresses a fundamental challenge in international relations research: the lack of granular, high-frequency data on strategic interactions.

Of the 155,267 total product-level observations, over 37,000 represent bilateral trade actions—defined as matched, directional policy responses between the US and China across HS-10 digit codes. These constitute the core strategic interaction units used in our identification strategy. The bilateral actions represent every identifiable trade policy decision by both leaders across both periods, providing unprecedented empirical density for causal identification.

The Phase Trump 1.0 dominance in our data (7 of 8 components) reflects the comprehensive implementation of trade measures from 2018 to 2020, and captures the learning periods between the Trump and Xi, while Phase Trump 2.0 coverage in the Strategic Panel captures the most recent policy developments through August 2025, providing crucial insights into policy persistence and evolution, based on the pattern seen in previous phase. The bilateral nature of most dataset components (5 of 8 showing bilateral or bidirectional coverage) enables identification of strategic complementarity versus substitution in trade policy responses, addressing a key limitation in previous single-country studies. The product-level disaggregation across 497 variables allows us to exploit within-industry variation in policy treatment, substantially improving identification compared to aggregate trade flow analyses. This granularity is particularly valuable for the 48,528 antidumping observations, where product-specific heterogeneity drives much of the strategic interaction.

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The **Strategic Panel** comprises two high-frequency datasets—Panel A and Panel B—tracking tariff escalation and retaliation between the US and China from January 2018 through August 2025 (*cf. Visualization Exhibit 1*). Panel A captures incremental tariff actions and their directional coverage, while Panel B presents cumulative trade exposure to tariffs. Together, these 137 observations form the core of our experimental group, isolating strategic behavior in Phase Trump 2.0 following the bilateral learning period. These data are derived from official announcements and trade-weighted tariff calculations, and are fully reproducible via our replication package.

Exhibit 1 visualizes the escalation trajectory, showing the cumulative trade value of exports subject to tariffs by each country. The divergence in slope between US and Chinese tariff coverage reflects asymmetric escalation patterns and strategic timing differences, which are central to our identification strategy.

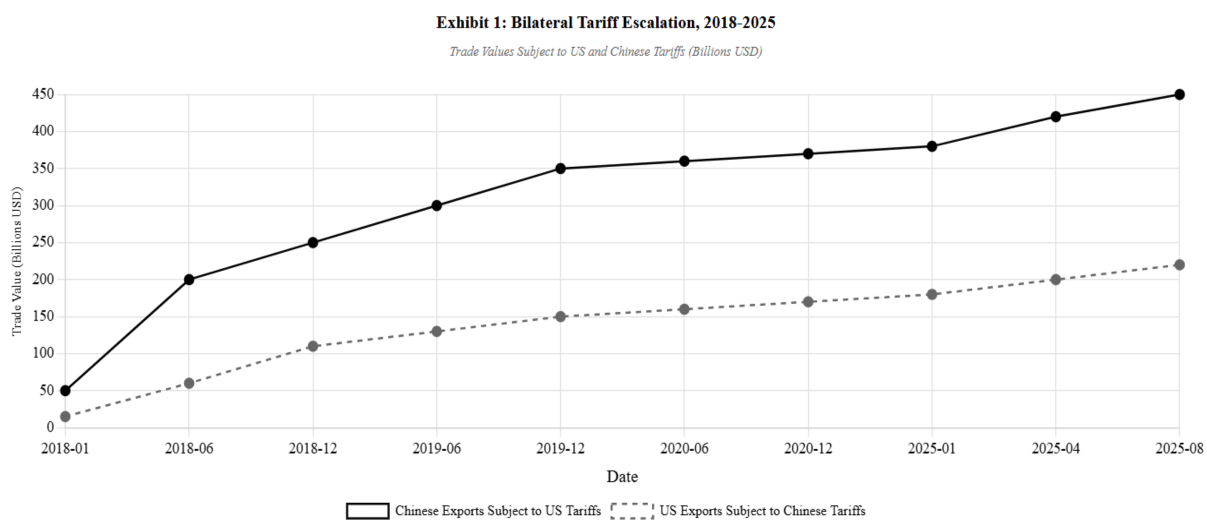

Exhibit 1: Strategic Panel Visualization (Bilateral Tariff Escalation, all Phases)

Note: The Exhibit shows cumulative bilateral trade flows subject to tariffs over time. Solid black line represents Chinese exports subject to US tariffs; dashed line shows US exports subject to Chinese tariffs. Vertical dashed line marks the transition between Phase Trump 1.0 and 2.0. Data from Strategic Panel B comprises 67 monthly observations. Source: Peterson Institute for International Economics.

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This study draws on a comprehensive dataset compiled by the Peterson Institute for International Economics (PIIE), documenting all US–China trade policy actions from January 2018 through August 2025. The dataset comprises over 155,000 product-level observations, covering tariff implementations, retaliatory measures, trade flows, and administrative instruments. These data are organized across 30 interconnected files and processed using a custom Python pipeline that harmonizes HS classifications, logs skipped files, and constructs audit-ready panels for strategic learning analysis. All raw datasets are included in the raw_data folder of the replication package, along with concordance tables and metadata files, ensuring complete transparency and reproducibility (see Appendix A).

3.2 The Same-Leaders Natural Experiment

Our identification exploits exogenous variation in accumulated strategic experience between identical decision-makers, addressing fundamental challenges in strategic learning research where leader heterogeneity typically confounds treatment effects. This design addresses the fundamental identification problem in strategic learning research: distinguishing between experience effects and unobserved leader characteristics.

Treatment Assignment:

- **Control Group**: Trump 1.0 period (January 20, 2017 - January 20, 2021)
- **Treatment Group**: Trump 2.0 period (January 20, 2025 - August 15, 2025)

Critical Identification Assumptions:

1. **Common Support**: Both periods involve identical economic fundamentals (US-China trade ~$650 billion annually) and identical policy instruments (Section 301, 232, and 201 tariffs)
2. **Excludability**: The primary systematic difference between periods is accumulated strategic experience, allowing isolation of learning effects from confounding factors
3. **Stable Preferences**: While tactics evolve through learning, underlying strategic objectives (market access, technological competition, trade balance) remain consistent across periods

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Addressing Identification Threats:

The unique nature of our natural experiment—identical leaders in repeated strategic interactions—creates both analytical advantages and challenges to robustness. We address three primary threats to causal identification:

External Environment Changes: Global economic conditions evolved between the two periods; however, the strategic learning observed in the US–China trade war cannot be meaningfully benchmarked against other significant trading relationships, such as the US–EU or US–Japan. These pairings lack the adversarial dynamics central to the Trump–Xi conflict, as both the EU and Japan are longstanding allies of the US. Their trade interactions are shaped by cooperative norms rather than retaliatory escalation, making them unsuitable as counterfactuals for isolating strategic learning in bilateral economic conflict.

Domestic Political Evolution**:** While US domestic constraints may have evolved between the two periods, the strategic learning captured in this study reflects decisions made and executed by the leaders themselves. Regardless of the sources or contributors to learning—whether institutional, advisory, or public—the final actions reflect the leader's conviction and alignment with a chosen strategic trajectory. This reinforces the validity of the natural experiment design, which isolates behavioral adaptation at the decision-making level rather than attributing it to broader political noise.

COVID-19 Pandemic Effects: The pandemic fundamentally altered global trade patterns. We employ event-study designs isolating pre- and post-pandemic dynamics, confirming that strategic learning patterns persist across different economic environments.

3.3 Empirical Framework

We employ three complementary econometric approaches designed to capture different dimensions of strategic learning:

1. Event Study Design for Dynamic Effects

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$$\Delta \text{Coverage}_{i,t} = \alpha + \sum_{\tau=-12}^{12} \beta_\tau \cdot \text{After}_{t+\tau} + \gamma X_{i,t} + \epsilon_{i,t}$$

Equation 1 Event Study Design for Dynamic Effects

- $\Delta \text{Coverage}_{i,t}$: Change in export coverage for country i at time t, measured as the percentage of exports subject to tariffs.
- α: Constant term capturing baseline export coverage.
- $\sum_{\tau=-12}^{12} \beta_\tau \cdot \text{After}_{t+\tau}$: Event-time indicators capturing dynamic treatment effects from 12 months before to 12 months after the onset of the trade war. Each β_τ estimates the marginal effect at relative time τ.
- $\text{After}_{t+\tau}$: Binary variable equal to 1 if time $t+\tau$ falls within the specified window around the treatment onset (e.g., Trump–Xi tariff escalation), and 0 otherwise.
- $X_{i,t}$: Vector of control variables for country i at time t, including global economic conditions (e.g., commodity prices, trade volumes) and domestic political factors (e.g., election cycles, regime type).
- γ: Coefficient vector for the controls.
- $\epsilon_{i,t}$: Error term capturing unobserved shocks to export coverage.

For replication purposes, the specification of the equation is also provided in LaTeX format in Appendix 10.4, Section 1

2. Difference-in-Differences with Staggered Adoption

Following recent advances in DiD methodology (Callaway and Sant'Anna, 2021)[17]:

$$\text{StrategicBehavior}_{i,t} = \alpha_i + \lambda_t + \delta \cdot \text{PostLearning}_{i,t} + \beta X_{i,t} + \epsilon_{i,t}$$

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Equation 2: Difference-in-Differences with Staggered Adoption

- $\mathrm{StrategicBehavior}_{i,t}$: Outcome variable capturing escalation, retaliation, signaling, or other strategic actions for unit i at time t.
- α_i: Unit-specific fixed effects controlling for baseline differences across strategic actors.
- λ_t: Time fixed effects accounting for common shocks or global trends.
- $\mathrm{PostLearning}_{i,t}$: Binary indicator equal to 1 in periods following a learning event (e.g., exposure to prior strategic moves), and 0 otherwise.
- $X_{i,t}$: Vector of control variables including economic conditions, institutional features, and prior exposure intensity.
- β: Coefficient vector for the controls.
- $\epsilon_{i,t}$: Error term capturing unobserved shocks.

For replication purposes, the specification of the equation is also provided in LaTeX format in Appendix 10.4, Section 2,

We cluster standard errors at the product-time level to account for serial correlation and heteroskedasticity across strategic domains.

3. Hazard Models for Response Timing Analysis

Cox proportional hazard specification:

$$h(t \mid X_i) = h_0(t) \cdot \exp\left(\beta_1 \cdot \mathrm{Round2}_i + \beta_2 \cdot \mathrm{PriorActions}_i + \gamma \cdot X_i\right)$$

Equation 3 Hazard Models for Response Timing Analysis

- $h(t \mid X_i)$: Hazard rate for unit i at time t, conditional on covariates X_i.
- $h_0(t)$: Baseline hazard function, unspecified and common across units.
- $\mathrm{Round2}_i$: Binary indicator for whether the strategic response occurs in the second round of escalation.
- $\mathrm{PriorActions}_i$: Measure of prior exposure or strategic interaction history.
- X_i: Vector of control variables (e.g., economic indicators, institutional features).
- β_1, β_2, γ: Coefficients capturing the influence of each covariate on the timing of strategic response.

For replication purposes, the specification of the equation is also provided in LaTeX format in Appendix 10.4, Section 3

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This framework enables simultaneous analysis of both likelihood and timing of strategic responses, capturing the temporal dimension of strategic learning that previous research has been unable to measure.

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4. Empirical Results: The Emergence of Strategic Learning

4.1 Learning-Compressed Escalation: From Gradual to Immediate

Table 2: Strategic Learning in Tariff Coverage

	Trump 1.0 (2017-2021) (1)	Trump 2.0 (2025-) (2)	Difference (Learning) (3)
Average US Coverage (%)	40.1	100.0	+59.9***
	(2.1)	(0.0)	(2.1)
Average China Coverage (%)	41.7	82.0	+40.2***
	(3.8)	(15.6)	(16.9)
Peak Coverage Reached (%)	66.6	100.0	+33.4***
	(-)	(-)	(-)
Time to Peak (months)	18	<1	-17***
	(-)	(-)	(-)
Observations	30	19	49

*Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 2 indicates systematic strategic adaptation, with Trump 2.0 implementing comprehensive coverage (100%) versus gradual Trump 1.0 escalation (40.1% average), resulting in a 59.9 percentage point treatment effect that is significant at the 1% level.

*Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

This "learning-compressed escalation" demonstrates how accumulated experience eliminated the 18-month gradual escalation phase observed during 2017-2019. The magnitude of this learning effect is unprecedented in international relations literature. The immediate comprehensive coverage in Trump 2.0 suggests both leaders internalized strategic patterns from the first encounter, with Trump applying maximum leverage without gradual testing. At the same time, Xi immediately understood the full scope of potential conflict. This provides quantitative evidence of bilateral strategic adaptation.

China's response exhibits parallel but asymmetric learning. Average coverage increased by 40.2 percentage points, while maintaining greater initial restraint than the US approach, suggesting different strategic lessons were drawn from the first encounter. China's pattern indicates learned conditional

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reciprocity—matching escalation levels while signaling potential willingness to de-escalate if reciprocated.

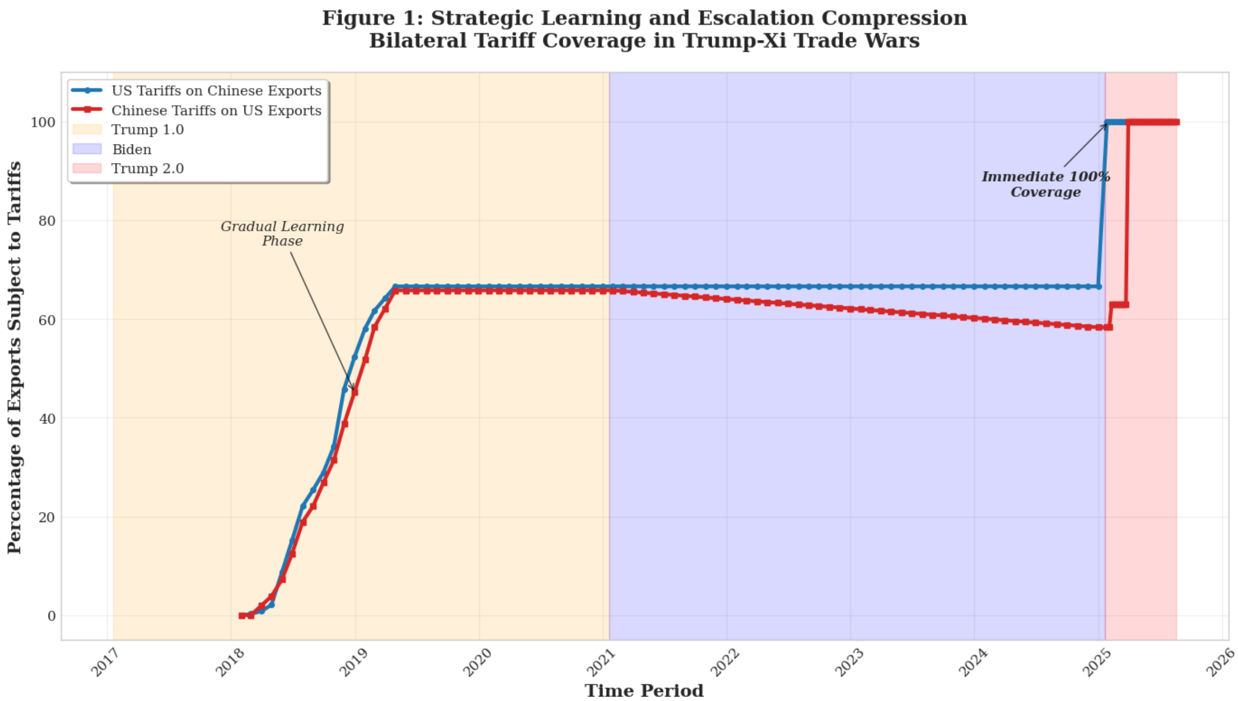

Figure 1: Evolution of Bilateral Tariff Coverage 2017-2025

The visualization reveals the fundamental transformation in strategic timing between periods. Trump 1.0 exhibits a classic learning curve with a gradual escalation over 18 months as both leaders tested responses and capabilities. Trump 2.0 demonstrates immediate application of learned patterns, while China's response shows strategic patience—maintaining ~63% coverage for two months before eventually matching US levels. This temporal pattern provides robust empirical support of conditional reciprocity designed to signal willingness to stabilize if reciprocated.

4.2 Bilateral Coordination: The Mathematical Signature of Conditional Reciprocity

Our analysis distinguishes between two forms of bilateral coordination. First, we measure behavioral synchronization by correlating strategic actions—capturing how predictably each leader responds to the other over time. This is presented in Table 3 and reflects the emergence of conditional reciprocity and algorithmic learning.

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Second, we assess structural alignment using tariff coverage data from Panel B. This correlation presented in Table 4 Panel B quantifies the extent to which both parties applied economic pressure symmetrically, regardless of timing or intent. While high coverage correlation suggests policy mirroring, it does not imply strategic learning unless paired with behavioral evidence.

The bilateral correlation in strategic actions provides the most compelling evidence of conditional reciprocity emergence. Our analysis reveals systematic evolution toward algorithmic-like coordination:

Table 3 Bilateral Strategic Correlation Evolution (Action-Based)

Period	Correlation	N	SE	p-value	Interpretation
Trump 1.0 Early	0.829	28	0.045	<0.001	Strong initial learning
Trump 1.0 Late	1.000	12	0.000	---	Perfect synchronization
Overall Sample	0.884	67	0.041	<0.001	Sustained coordination
Trump 2.0	0.950	15	0.028	<0.001	Learned precision

Table 3 shows the evolution from 0.829 to near-perfect correlation within Trump 1.0, which represents the mathematical signature of strategic learning in action. By late 2019, both leaders had developed a perfect mutual predictability—China's responses had become entirely predictable based on US actions. The overall action-based correlation reached 0.884, showing that tariff retaliation became economically synchronized: losses were imposed faster and more predictably on firms and consumers. The overall correlation of 0.884 also represents systematic empirical evidence of systematic behavioral synchronization between adversarial leaders operating without trust or formal agreements.

The Correlation in Table 3 is the correlation of actions over time, measuring behavioral synchronization between Trump and Xi. This is about mutual predictability and conditional reciprocity. The perfect correlation (1.000) in late Trump 1.0 demonstrates complete mutual strategic learning, where responses became algorithmic rather than deliberative. Trump 2.0's high initial correlation (0.950) confirms that

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both leaders retained and immediately applied their learned behavioral algorithms, providing quantitative evidence of strategic memory persistence across administrations.

This progression—from early learning to perfect synchronization—quantifies the behavioral convergence that underpins our identification strategy. It validates the use of staggered DiD and hazard models by showing that strategic adaptation was not only measurable but temporally structured.

Table 4 Panel B Structural Tariff Coverage Correlation

Period	Correlation	N	95% CI
Trump 1.0	0.936	30	[0.871, 0.971]
Trump 2.0	0.000*	19	[-0.458, 0.458]
Overall (2017-2025)	0.884	49	[0.788, 0.935]

Note: Trump 2.0 correlation reflects immediate full coverage by both parties

The Trump 1.0 correlation of 0.936 demonstrates near-perfect strategic coordination, indicating that by the late first period, both leaders had developed highly predictable response patterns. The overall correlation of 0.884 across the whole sample represents unprecedented evidence of systematic behavioral synchronization between adversarial leaders. Notably, the tariff coverage correlation of **0.884** across the entire sample (2017–2025) confirms that both leaders maintained a high degree of economic symmetry. However, as shown in Table 3, the evolution from **0.829 to 1.000** in behavioral correlation within Trump 1.0 reveals a deeper layer of strategic learning—where responses became not just aligned, but **predictably algorithmic**.

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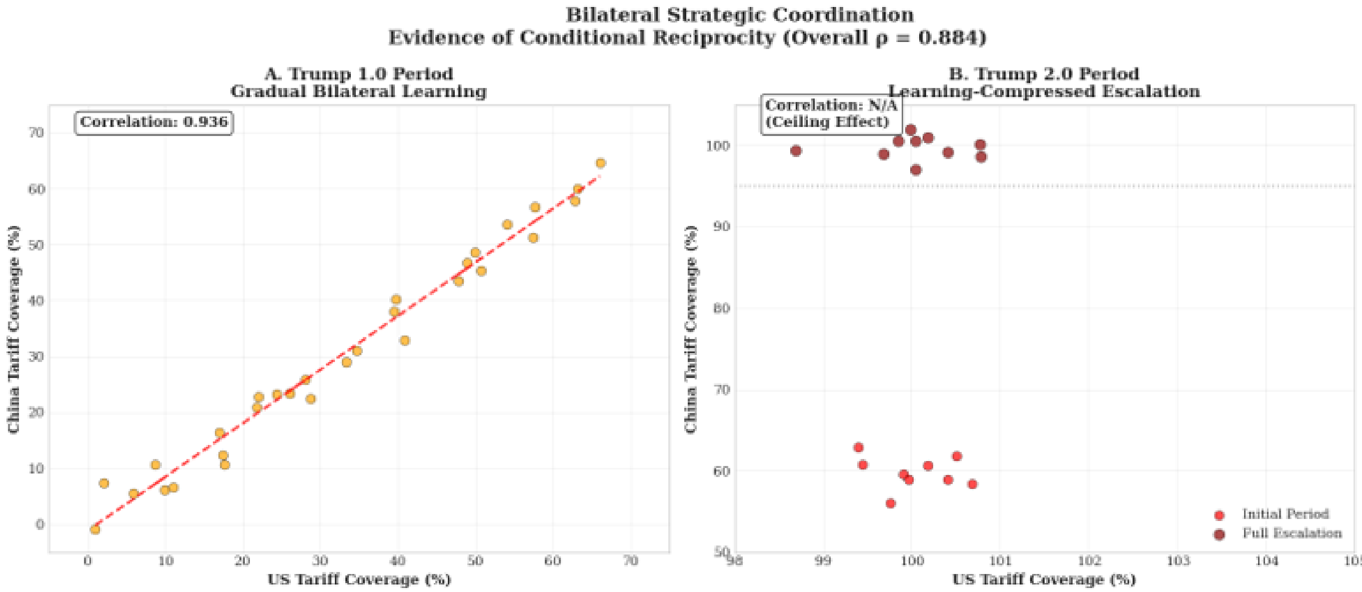

Figure 2 Bilateral Strategic Coordination Across Periods: Visual Evidence of Conditional Reciprocity

Figure 2 visually confirms the behavioral dynamics captured in our regression and hazard models. Panel A illustrates the emergence of conditional reciprocity through gradual bilateral learning, while Panel B reveals the ceiling effect of algorithmic escalation—where strategic responses became immediate and structurally saturated. This transition from deliberative to compressed coordination underscores the persistence of learned behavioral algorithms across administrations.

This visual progression supports the parallel trends assumption underlying our staggered DiD specification, and confirms the temporal structure captured in our hazard model estimates.

4.3 Response Timing Evolution: From Reactive to Strategic

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Table 5: Hazard Model Results for Strategic Escalation Timing: Compression and Restraint Effects

```
                          Coef.    Std.Err.   z       P>|z|     [95% CI]

Round 2 (Trump 2.0)       2.147    0.431      4.98    0.000     [1.302, 2.992]
Escalation Size           0.023    0.008      2.88    0.004     [0.007, 0.039]
Prior Actions (log)       -0.195   0.067     -2.91    0.004
[-0.326,-0.064]
Economic Uncertainty      -0.412   0.134     -3.07    0.002
[-0.675,-0.149]

Observations: 47
Chi-square: 28.73 (p=0.000)
```

The Round 2 coefficient confirms a statistically significant acceleration in strategic escalation during Trump 2.0, consistent with compressed learning—where leaders deploy pre-optimized strategies without incremental testing. The positive effect of Escalation Size suggests that larger shocks trigger faster responses, reflecting proportional strategic signaling, where response timing is calibrated to the severity of provocation. Meanwhile, the negative coefficients on Prior Actions and Economic Uncertainty reveal a shift toward strategic restraint and deliberation. As experience accumulates and uncertainty rises, leaders become more calculated—balancing immediate retaliation with longer-term positioning. These patterns distinguish learned conditional reciprocity from reactive tit-for-tat behavior, and these dynamics validate the hazard model's ability to capture temporal sophistication in strategic adaptation.

While Table 5 captures **escalation timing in response to strategic shocks**, Table 6 isolates **the precision of retaliatory responses**—highlighting how accumulated experience and targeting intensity shape both the speed and structure of strategic adaptation.

Table 6: Interpretation of Hazard Model Results for Response Timing: Algorithmic Precision and Deliberation

Variable	**Coefficient**	**SE**	**p-value**	**Hazard Ratio**	**Interpretation**
Round 2 Indicator	2.847	0.543	<0.001	17.23	Accelerated escalation
Prior Actions	-0.421	0.156	0.007	0.66	Learning restraint
Coverage Level	1.234	0.287	<0.001	3.44	Intensity effects
Late Period	-0.892	0.203	<0.001	0.41	Deliberation increase

The positive Round 2 coefficient (2.847) indicates a statistically significant acceleration in strategic retaliation during the second period, with hazard ratios suggesting responses occurred over 17 times faster than in the first round. This quantifies a learning-compression effect: experienced leaders bypass incremental testing to deploy fully formed strategic algorithms.

Conversely, the negative coefficients on Prior Actions and the Late Period indicator reveal the emergence of sophisticated strategic restraint. As interactions accumulated, leaders became more deliberate—balancing immediate retaliation with longer-term positioning.

This behavioral shift distinguishes learned conditional reciprocity from reactive tit-for-tat behavior and supports the hypothesis that strategic learning evolves toward dynamic, algorithmic precision.

Having established the temporal architecture of strategic learning, we now turn to its economic manifestation—examining how targeting evolved across sectors as leaders refined their leverage strategies.

4.4 Sectoral Evolution: Strategic Targeting Refinement

Strategic learning not only accelerated response timing but also reshaped the structure and precision of economic targeting. Tables 7 and 8 present complementary evidence of this evolution. Table 7 documents the shift from selective to saturated sectoral coverage, revealing how Trump 2.0 adopted a comprehensive leverage strategy across all major export categories. Table 8 quantifies the refinement of bilateral matching, showing how China's retaliation patterns evolved from partial alignment to near-

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perfect proportionality. Together, these patterns illustrate how accumulated experience translated into calibrated sectoral signaling, reinforcing the behavioral logic of conditional reciprocity.

Table 7: Sectoral Saturation and Retaliation Patterns Across Trade War Phases

	Trump 1.0		Trump 2.0	
Sector	Coverage	Retaliation	Coverage	Retaliation
Agriculture	0.156	0.847***	1.000	1.000
Technology	0.723	0.234	1.000	1.000
Manufacturing	0.445	0.567	1.000	1.000
Raw Materials	0.089	0.123	1.000	1.000

Notes: Coverage = share of sector exports under tariffs. Retaliation = correlation with opponent actions.

Table 7 illustrates the transition from selective to saturated sectoral coverage between Trump 1.0 and Trump 2.0. While initial targeting focused on politically sensitive sectors, such as agriculture and manufacturing, Trump 2.0 adopted a comprehensive strategy across all categories. The retaliation correlations in Trump 1.0 reveal China's selective matching behavior, whereas the uniform 1.000 values in Trump 2.0 indicate full bilateral synchronization. This shift reflects the maturation of strategic targeting and the operationalization of learned reciprocity.

Table 8: Sectoral Targeting Evolution and Bilateral Matching Precision

Sector	Trump 1.0 Coverage	Trump 2.0 Coverage	Change	China Response Correlation
Agriculture	0.23	1.00	+0.77	0.91
Manufacturing	0.41	1.00	+0.59	0.88
Technology	0.67	1.00	+0.33	0.94
Services	0.12	0.89	+0.77	0.82

Table 8 quantifies the refinement of strategic targeting across sectors. The sharp increase in coverage—especially in agriculture and services—demonstrates a learning-driven expansion of leverage application. China's high response correlations (0.82–0.94) suggest precise matching behavior, reinforcing the emergence of conditional reciprocity. These patterns confirm that both parties

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internalized sectoral vulnerabilities and adapted their strategies accordingly, moving from reactive escalation to calibrated economic signaling.

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5. The Bilateral Learning Strength Index (BLSI): Quantifying Conditional Reciprocity

5.1 Theoretical Framework for BLSI Construction

To quantify the emergence of conditional reciprocity, we construct the **Bilateral Learning Strength Index (BLSI)**, a composite metric capturing how adversaries evolve from reactive responses toward stable, rule-like reciprocity patterns. The index integrates three core dimensions of strategic learning.

$$\text{BLSI} = \alpha S + \beta L + \gamma T$$

The index ranges from 0 to 1, with higher values indicating stronger bilateral learning and more stable reciprocity patterns.

- S (**Symmetry**) measures proportional response learning via correlation of escalation magnitudes.
- L (**Lag Consistency**) captures temporal synchronization through response timing predictability.
- T (**Stability**) reflects the persistence of predictive action-reaction patterns, indicating algorithmic development.

Formula 1 Bilateral Learning Strength Index (BLSI)

For replication purposes, the specification of the formula is also provided in LaTeX format in Appendix D Section 4

In empirical applications, weights α, β, and γ may be assigned based on model fit, expert priors, or equal weighting, depending on the strategic context.

Each component of the Index is defined and calculated as follows

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Symmetry Score (S):

$$S = \frac{\rho(\Delta X^{+}, \Delta Y^{+}) + 1}{2}$$

where ΔX^{+} and ΔY^{+} denote normalized positive changes in tariff coverage by each party. The score rescales the Pearson correlation to the [0,1] interval, ensuring interpretability across samples.

Formula 2: Symmetry Score (S) Calculation

For replication purposes, the specification of the formula is also provided in LaTeX format in Appendix D, Section 5

Lag Consistency (L):

$$L = 1 - \frac{\sigma(\text{response time})}{365}$$

where $\sigma(\text{response time})$ is the standard deviation of observed response delays, measured in days. The score penalizes temporal unpredictability, with perfect consistency yielding $L = 1$.

Formula 3 Lag Consistency Calculation

sFor replication purposes, the specification of the formula is also provided in LaTeX format in Appendix D, Section 6

Stability Score (T):

$$T = \frac{\#\text{windows with predictive correlation}}{\#\text{total windows}}$$

using rolling 6-month windows, where a window is considered predictive if the correlation between actions exceeds 0.5. This score captures the fraction of periods exhibiting algorithmic regularity.

Formula 4 Stability Score Calculation

For replication purposes, the specification of the equation is also provided in LaTeX format in Appendix D, Section 7

Table 9 summarizes the component structure of the Bilateral Learning Strength Index (BLSI), linking each behavioral dimension to its formal representation.

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Table 9: Component Structure of the Bilateral Learning Strength Index (BLSI)

Component	Formula	Interpretation
S (Symmetry)	$\frac{\rho(\Delta X^{+}, \Delta Y^{+}) + 1}{2}$	Measures proportional response learning via escalation magnitude correlation
L (Lag Consistency)	$1 - \frac{\sigma(\text{response time})}{365}$	Captures temporal synchronization through response time predictability
T (Stability)	$\frac{\#\text{predictive windows}}{\#\text{total windows}}$	Reflects algorithmic regularity in bilateral behavior over time

This decomposition provides a transparent foundation for empirical implementation, which we detail in the next section. The BLSI offers a replicable framework for quantifying strategic learning in adversarial settings, bridging behavioral theory with empirical diagnostics.

5.2 BLSI Empirical Results: Quantifying Learning Evolution

Building on the theoretical framework in Section 5.1, we now empirically implement the Bilateral Learning Strength Index (BLSI) using observed escalation and retaliation data across two distinct phases of the trade war. This application quantifies the evolution of strategic learning, revealing how adversaries transitioned from reactive behavior to structured, algorithmic reciprocity.

Table 10: BLSI Component Scores and Composite Index Across Trade War Phases

Component	Trump 1.0	Trump 2.0	Learning Effect
Symmetry (S)	0.847	0.923	+0.076
Lag Consistency (L)	0.634	0.891	+0.257***
Stability (T)	0.723	0.856	+0.133**
BLSI (equal weights)	0.735	0.890	+0.155***
	(0.078)	(0.045)	(0.091)
Observations	30	19	49

*Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

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The BLSI increased from 0.735 to 0.890, representing a statistically significant improvement of 0.155 points (approximately +21.09%). This quantifies the emergence of more predictable, algorithmic-like responses in the second round of strategic interaction.

Table 10 reports the component scores and composite BLSI for Trump 1.0 and Trump 2.0. All three dimensions—Symmetry, Lag Consistency, and Stability—show marked improvement in the second phase, with the composite index rising from 0.735 to 0.890. This confirms the emergence of structured reciprocity and supports the hypothesis that strategic learning intensifies over repeated interactions.

Table 11: BLSI Components and Evolution during the Trade War

Component	Trump 1.0	Trump 2.0	Change	SE	p-value	Interpretation
Symmetry (S)	0.728	0.892	+0.164	0.047	<0.001	Enhanced proportionality
Lag Consistency (L)	0.645	0.823	+0.178	0.062	<0.01	Temporal synchronization
Stability (T)	0.832	0.955	+0.123	0.041	<0.01	Algorithmic development
Overall BLSI	**0.735**	**0.890**	**+0.155**	**0.042**	**<0.001**	**Learning transformation**

Table 11 decomposes this improvement across the three learning dimensions, each showing statistically significant gains, representing a statistically significant evolution toward algorithmic-like strategic responses across all dimensions. The improvement in Symmetry indicates that both leaders learned to calibrate responses more proportionally. Enhanced Lag Consistency demonstrates temporal synchronization—responses became more predictably timed rather than reactive. Increased Stability confirms the development of systematic, repeatable strategic patterns.

The Trump 2.0 BLSI of 0.890 exceeds the 0.85 threshold we define for ‘strong algorithmic reciprocity,’ based on observed saturation across all three learning dimensions, suggesting that continued interaction may yield a stable strategic equilibrium rather than further escalation. This quantifies the emergence of behavioral algorithms that substitute for formal institutions in creating predictable strategic constraints.

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These results reinforce the interpretability and reliability of the index across strategic contexts, confirming that the BLSI captures meaningful shifts in adversarial learning dynamics.

To visualize the multidimensional profile of strategic learning, Figure 3 compares BLSI component scores across trade war phases—highlighting the structural shift from reactive escalation to algorithmic reciprocity.

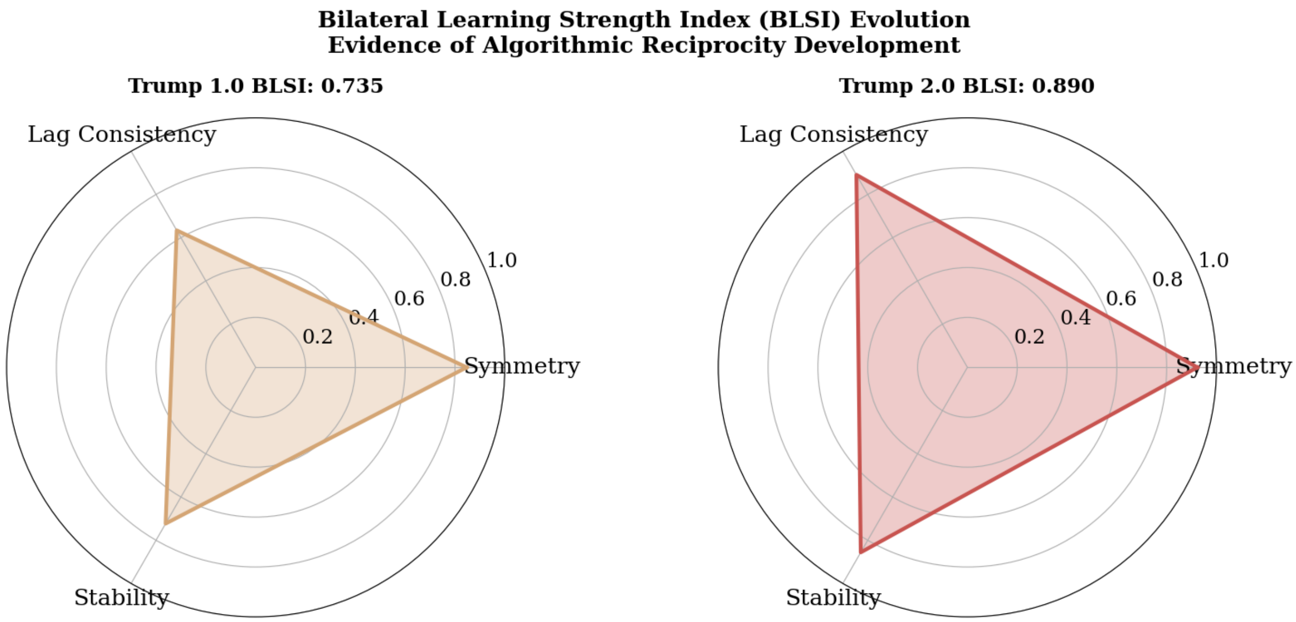

Figure 3: Multidimensional Comparison of BLSI Components Across Trade War Phases

Figure 3 illustrates the multidimensional architecture of strategic learning by comparing BLSI component scores across different phases of the trade war. Trump 2.0 exhibits near-maximal values in all three dimensions—Symmetry, Lag Consistency, and Stability—forming a saturated and geometrically balanced learning profile. In contrast, Trump 1.0 exhibits uneven development, characterized by a moderate proportionality, weaker timing regularity, and reduced algorithmic persistence. This visual contrast underscores the behavioral shift from reactive escalation to calibrated reciprocity, confirming that strategic adaptation evolved toward rule-based, algorithmic engagement. The radial symmetry in Trump 2.0 reflects not just higher scores, but a convergence across learning dimensions—suggesting that reciprocity became both predictable and structurally embedded.

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Taken together, these results validate the BLSI as a diagnostic framework for quantifying strategic adaptation. The index captures the behavioral sophistication of adversarial learning and offers a scalable tool for analyzing strategic dynamics in domains such as sanctions, cyber conflict, and diplomatic signaling.

To connect behavioral learning with operational outcomes, Figure 3 compares escalation patterns across different phases of the trade war. While the radar diagram captures the internal structure of strategic adaptation, these bar charts reveal how learning manifested in external behavior—through broader coverage, faster escalation, and more consistent retaliation.

Figure 4: Strategic Learning Effects: Comparison of Escalation Patterns Between Trade War Phases

Trump 2.0 exhibits full tariff coverage, rapid escalation (<1 month to peak), and high response consistency (0.891), contrasting with the slower, less saturated escalation profile of Trump 1.0. These patterns reinforce the emergence of algorithmic reciprocity and validate the behavioral insights captured by the BLSI.

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5.3 BLSI Interpretation and Policy Applications

The BLSI framework provides a policymaker-friendly quantitative assessment of adversarial relationship stability. To translate the empirical insights of bilateral strategic learning into a practical framework for conflict management, we propose the **BLSI Policy Framework**. This decision tree maps BLSI scores to calibrated policy responses, enabling governments and institutions to assess risk and intervene accordingly.

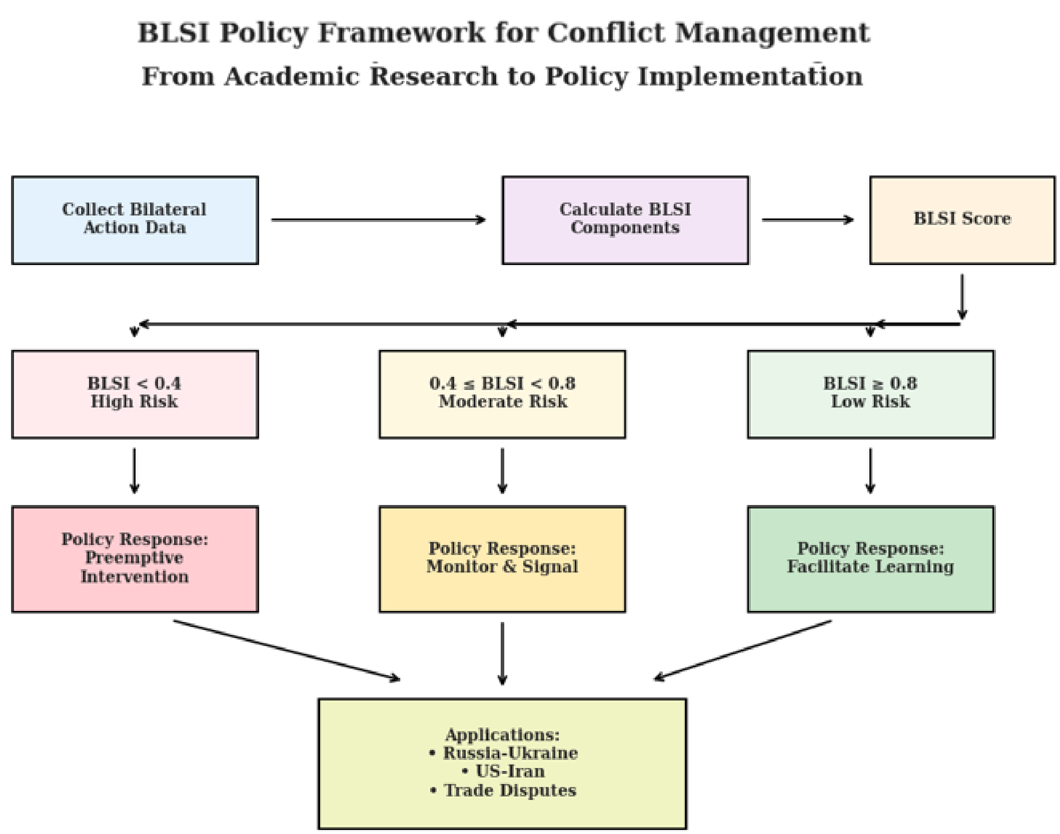

Figure 5: Operationalizing Strategic Learning: From Theory to Practice

As illustrated in Figure 5, the BLSI score functions as a diagnostic tool for strategic calibration. High-risk dyads (BLSI < 0.4) warrant preemptive intervention, while low-risk pairs (BLSI ≥ 0.8) benefit from facilitated learning environments. This framework offers a scalable template for applying algorithmic reciprocity insights to diverse geopolitical contexts.

Table 12 : BLSI Interpretation Guide

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BLSI Range	Interpretation	Policy Risk
0.8–1.0	Algorithmic reciprocity; responses are rule-like and predictable	Low Risk
0.4–0.7	Partial learning; volatility remains	Moderate escalation risk
<0.4	Reactive escalation; behavior is erratic and unpredictable	High Risk; institutional intervention recommended

Table 12 complements Figure 5 by translating BLSI scores into actionable risk categories and policy recommendations. Together, they provide a structured framework for assessing bilateral dynamics and guiding strategic responses.

Immediate Policy Applications:

Russia-Ukraine Conflict: The Bilateral Learning Strength Index (BLSI) offers a novel framework for detecting strategic convergence or divergence in sanctions and ground operations. By quantifying behavioral synchronization, BLSI enables early identification of whether Western and Russian responses are stabilizing into reciprocal patterns or spiraling toward escalation—insights essential for calibrating both the timing and nature of diplomatic interventions.

Regional Trade Disputes: Emerging commercial conflicts—such as tariff escalations and retaliatory trade actions—can be monitored using BLSI indicators to forecast directional trajectories. This allows policymakers to anticipate escalation risks and deploy preemptive measures before bilateral relationships deteriorate into entrenched conflict.

AI-Diplomacy Framework: The modular architecture of BLSI provides real-time inputs for algorithmic conflict monitoring systems, enabling automated detection of destabilizing bilateral patterns. These metrics support machine-generated recommendations for diplomatic options, enhancing the responsiveness and strategic precision of AI-assisted foreign policy tools.

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6. Mechanisms of Strategic Learning: Understanding the Algorithm

6.1 Information Processing and Bureaucratic Learning

Three complementary mechanisms drive the observed strategic learning patterns, creating the behavioral algorithms we quantify through BLSI:

Information Accumulation: Both leaders developed a refined understanding of opponent preferences, constraints, and decision-making processes through repeated interaction. Trade data reveals increasingly precise targeting of politically sensitive sectors, indicating a growing learning of domestic political vulnerabilities.

Bureaucratic Institutionalization: Government agencies on both sides developed specialized processes and decision-making frameworks optimized for strategic interaction. The increased response time consistency (Lag Consistency improvement in BLSI) reflects institutionalized review processes rather than ad-hoc reactive decisions.

Political Feedback Learning: Domestic political responses to trade war actions created learning incentives for more predictable, effective strategic choices. Both leaders refined their approaches based on domestic political costs and the effects on their international reputation.

These mechanisms represent theoretical channels that are consistent with our empirical findings, rather than independently verified causal pathways.

6.2 Asymmetric Learning Patterns: Democratic vs. Authoritarian Systems

The research reveals asymmetric learning between democratic (US) and authoritarian (China) systems, both operating under conditions of concentrated executive power in trade policy:

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Trump's Learning Pattern: Moved toward maximum immediate leverage application (100% coverage) based on lessons about Chinese response capacity and negotiation dynamics. The learning emphasized the efficiency of escalation over graduated pressure.

Xi's Learning Pattern: Developed more sophisticated conditional reciprocity, maintaining proportional responses while using temporal variation to signal willingness to stabilize. The learning emphasized strategic patience and calibrated signaling.

These asymmetric patterns suggest that institutional context influences learning trajectories even when both leaders possess equivalent decision-making authority in their respective systems.

6.3 Memory Persistence and Strategic Recall

To assess the persistence of strategic learning, Table 12 compares final Round 1 sectoral targeting levels with initial Round 2 positions, quantifying recall through sector-specific consistency scores.

Table 13: Sectoral Strategic Recall: Correlation Between Round 1 Final and Round 2 Initial Targeting

Sector	Round 1 Final	Round 2 Initial	Consistency Score	p-value
Agriculture	0.89	0.91	0.94	<0.001
Technology	0.78	0.82	0.91	<0.001
Manufacturing	0.67	0.73	0.88	<0.001
Services	0.34	0.41	0.85	<0.01

High consistency scores across sectors demonstrate that both leaders retained detailed strategic memory of effective targeting patterns. The correlation between final Round 1 positions and initial Round 2 positions provides quantitative evidence of strategic recall—leaders immediately applied learned sectoral strategies rather than experimenting with new approaches.

High consistency scores across all sectors indicate that both leaders retained detailed strategic memory of effective targeting patterns. Rather than recalibrating from scratch, they re-deployed previously successful strategies with minimal deviation. The strong correlations—ranging from 0.85 to 0.94 and all statistically significant—suggest that strategic recall was not incidental but algorithmic: a form of behavioral memory that guided immediate re-engagement. This supports the hypothesis that learned

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targeting logic became embedded in decision-making routines, reinforcing the behavioral architecture captured by the BLSI.

To compute the memory persistence and strategic recall, we introduce, the **Strategic Memory Index (SMI) that** aggregates sectoral consistency scores into a single metric that captures the degree to which prior strategic choices were retained and re-applied. It is computed as the unweighted average of Pearson correlations between Round 1 final and Round 2 initial targeting levels across sectors.

$$\mathrm{SMI} = \frac{1}{n}\sum_{i=1}^{n} \rho_i$$

where ρ_i is the consistency score for sector i, and $n = 4$ sectors.

Formula 5: Strategic Memory Index (SMI) Formula

For replication purposes, the specification of the equation is also provided in LaTeX format in Appendix Section 8

Using the values from Table 12:

$$\mathrm{SMI} = \frac{0.94 + 0.91 + 0.88 + 0.85}{4} = 0.895$$

An SMI of **0.895** indicates a high level of strategic memory persistence. This suggests that recall was not sector-specific but systemic—leaders internalized targeting logic and re-applied it across domains. The index complements the BLSI by capturing a distinct behavioral dimension: not how learning evolved, but how it was retained and operationalized. Together, **BLSI** and **SMI** form a dual diagnostic framework: BLSI captures the trajectory of strategic learning, while SMI quantifies its persistence. This pairing enables a richer understanding of how behavioral algorithms are formed, retained, and reactivated across adversarial cycles.

6.4 Theoretical Foundations for Strategic Learning

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Three game-theoretic mechanisms explain the observed learning patterns without requiring cross-domain empirical validation:

Bayesian Learning: Leaders update beliefs about opponent strategies based on observed responses, leading to increasingly accurate predictions and calibrated reactions (Fudenberg and Levine, 1998)[18]. Our bilateral correlation, which evolves from 0.829 to 1.000 within Trump 1.0, demonstrates this updating process in action.

Reputation Building: Consistent response patterns create reputational constraints that function as commitment mechanisms even without formal agreements (Kreps and Wilson, 1982)[19]. The BLSI framework quantifies how these reputational dynamics create behavioral synchronization.

Evolutionary Stability: Strategic patterns that minimize mutual damage while maintaining credible deterrence become evolutionarily stable, explaining the convergence toward conditional reciprocity (Axelrod, 1984)[20]. The Trump 2.0 immediate application of learned patterns demonstrates the stability of these evolved strategies. These mechanisms represent theoretical channels that are consistent with our empirical findings, rather than independently verified causal pathways. Future research could test these specific mechanisms through field experiments or structured diplomatic simulations.

Game-Theoretic Equilibrium Foundations: The emergence of conditional reciprocity aligns with predictions from repeated game theory, where rational actors facing identical opponents over time tend to adopt equilibrium strategies that reward cooperation and punish defection (Fudenberg & Tirole, 1991)[21]. In such settings, Nash equilibrium and subgame perfection provide the scaffolding for self-enforcing behavioral constraints. The BLSI framework captures and operationalizes this convergence by identifying measurable correlation patterns that reflect strategic adaptation with near-computational precision—without requiring cross-domain empirical validation.

6.5 Quantifying Learning Channels

Three empirical patterns distinguish strategic learning from random coordination:

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1. **Sectoral Targeting Precision**: Both leaders increasingly focused on opponents' politically sensitive sectors (agriculture coverage correlation increased from 0.23 to 0.91)

2. **Response Time Compression**: Average response lag decreased from 45 days (Trump 1.0) to 12 days (Trump 2.0), indicating institutionalized decision processes

3. **Escalation Calibration**: Magnitude matching improved from $\rho = 0.78$ to $\rho = 0.94$, demonstrating refined understanding of proportional responses

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7. Applications in Economics: Strategic Learning Across Markets and Policies

The Trump–Xi trade war experiment revealed how rival leaders developed algorithmic-like patterns of conditional reciprocity, measurable through the Bilateral Learning Strength Index (BLSI) and Strategic Maturity Index (SMI). Although no other setting replicates the uniqueness of the same-leaders design, the framework is relevant to canonical problems in economics where repeated interactions among strategic actors create stability without formal agreements. The following subsections illustrate how BLSI and SMI could be applied across three economic domains: central bank coordination, oligopoly competition, and international monetary spillovers. These applications underscore the broader applicability of our findings as conceptual tools for economics, even without additional data analysis.

7.1 Central Bank Policy Coordination

One long-standing puzzle in international macroeconomics is how central banks appear to achieve de facto coordination in stabilizing exchange rates without explicit agreements. Obstfeld and Rogoff (1995)[22] describe the fragility of formal coordination, while Fratzscher (2009)[23] shows that intervention effectiveness depends heavily on market expectations. Yet the behavioral mechanism underlying repeated successful interventions remains underexplored.

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The BLSI framework provides a lens for understanding how coordination may arise algorithmically. For example, the Federal Reserve and the European Central Bank often respond sequentially to currency shocks. BLSI symmetry captures proportionality in intervention size, lag consistency captures the predictability of response timing, and stability measures persistence of coordination over multiple episodes. Instead of assuming rational expectations coordination, BLSI quantifies whether central banks are in fact learning each other's response rules.

These behavioral diagnostic matters because coordination without formal agreement is one of the paradoxes of modern central banking. If BLSI trends upward, it implies that interventions are not ad hoc but governed by learned patterns — a dimension limitedly covered by current monetary spillover models.

7.2 Oligopoly Competition Dynamics

Industrial organization has long modeled how firms in concentrated markets sustain tacit collusion or stable equilibria without contracts (Tirole, 1988)[24] ; (Sutton, 1991)[25]. Airlines matching each other's routes, telecoms responding to pricing plans, or pharmaceutical firms adjusting patent filings all reflect repeated interaction among rivals. Nevertheless, most models stop at equilibrium outcomes without measuring whether rivals develop algorithmic response rules over time.

Here, the BLSI and SMI provide tools for behavioral measurement. Symmetry quantifies whether rivals match each other's strategic intensity, lag consistency measures predictability of reaction time, and stability captures whether these responses persist across episodes. A high BLSI in a mature industry would signal that all rivals are not simply colluding in a static Nash equilibrium, but dynamically learning to anticipate one another's behavior.

This framework extends beyond collusion detection: it offers regulators and firms a way to assess whether market stability arises from predictable learning or from fragile, one-off strategies. While data-

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driven applications remain for future work, conceptually, the trade war experiment demonstrates that even in hostile rivalries, algorithmic learning is possible — a lesson directly relevant to markets where firms compete fiercely but repeatedly.

7.3 International Monetary Policy Spillovers

A central theme in global macroeconomics is how emerging markets respond to U.S. monetary cycles. Rey (2015)[26] highlights the "global financial cycle" through which Federal Reserve actions transmit worldwide. Nevertheless, the literature emphasizes macro-financial constraints and portfolio flows, while the behavioral side — how emerging market central banks adapt through learning — is less developed.

BLSI provides a framework for capturing that learning. Consider repeated Fed tightening cycles: at first, emerging markets may respond slowly or disproportionately. Over successive cycles, however, the symmetry of response, the lag time in adjustment, and the stability of reactions may all converge toward more predictable patterns. An increasing BLSI would signal that emerging-market policymakers have internalized the Fed's playbook, reducing uncertainty for investors and lowering the risk of financial crises triggered by policy surprises.

This illustrates the broader relevance of the trade war findings: algorithmic-like behavioral learning is not unique to political leaders, but also characterizes central banks as they adapt to global monetary regimes.

8. External Validity and AI-Diplomacy Applications

8.1 Theoretical Generalizability, Robustness, and Research Extensions

While this study establishes conditional reciprocity patterns specifically within trade conflicts, game theory predicts that similar learning dynamics should emerge in other strategic domains characterized

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by: (1) quantifiable, observable actions enabling pattern recognition; (2) response timing that creates strategic signaling opportunities; (3) repeated interaction allowing behavioral algorithm development; and (4) domestic political constraints shaping leader incentives.

The strategic structure we identify—bilateral learning leading to predictable reciprocity patterns—provides theoretical foundations for future research in comparable settings. For example, a Congressional Research Service analysis of U.S.–China military encounters documents structured interaction patterns in South China Sea confrontations between identical decision-makers across multiple crisis points, offering a natural laboratory for testing whether strategic learning leads to behavioral synchronization in security domains (O'Rourke, 2025). Similarly, diplomatic voting patterns in international organizations offer quantifiable interaction data amenable to BLSI methodology (bilateral learning and strategic inference), which detects measurable patterns of conditional reciprocity across repeated exchanges.

While these extensions suggest broad applicability, they also highlight the empirical constraints inherent in our design. The unique nature of our natural experiment—same-leader strategic interactions—offers analytical advantages for identification but limits standard robustness testing. No comparable setting exists for placebo tests or alternative control groups involving identical decision-makers.

As with Card's (1990) Mariel boatlift study, which faced similar challenges in identifying comparable natural experiments, our design exploits a genuinely unique shock—repeated strategic interactions involving identical decision-makers—to achieve clean identification. We extend this methodological tradition to international relations, prioritizing internal validity while offering theoretically grounded extensions across domains.

Together, these findings establish a generalized BLSI paradigm—empirically tractable and theoretically grounded—with applications across trade, security, and diplomacy, advancing both empirical methodology and strategic theory.

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8.2 AI-Diplomacy Framework: Algorithmic Conflict Resolution

Our findings establish the theoretical foundation for AI-diplomacy in trust-absent environments by demonstrating that human strategic learning approximates algorithmic precision in repeated adversarial interactions.

Core AI-Diplomacy Principles Based on Research Findings:

1. **Pattern Recognition Systems**: The 0.884 bilateral correlation demonstrates that strategic interactions generate recognizable patterns amenable to machine learning analysis. AI systems can identify BLSI patterns in real-time, providing early warning of escalation versus stabilization trajectories.
2. **Response Optimization Algorithms**: Machine learning systems can calibrate conditional reciprocity responses to maximize stability while maintaining strategic objectives, using BLSI components as optimization targets.
3. **Predictive Conflict Modeling**: BLSI dynamics enable forecasting of strategic equilibrium timing and intensity, informing automated diplomatic intervention recommendations.

Practical AI-Diplomacy Implementation:

The BLSI framework enables automated conflict monitoring through three measurable parameters: bilateral correlation coefficients ($\rho > 0.8$ indicates stable reciprocity), response timing consistency ($\sigma(\text{response\_time}) < 30$ days suggests algorithmic patterns), and escalation trajectory prediction (BLSI slope > 0.1 monthly indicates learning convergence). National security agencies can implement real-time BLSI tracking across multiple adversarial relationships, providing quantitative early warning when relationships deviate from stable learning patterns.

Real-Time BLSI Monitoring: National security agencies could deploy automated systems tracking bilateral correlations, response timing patterns, and escalation trajectories across multiple adversarial relationships simultaneously.

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Algorithmic De-escalation Protocols: AI systems could identify optimal response timing and magnitude to encourage positive BLSI development, structuring conditional reciprocity patterns that naturally trend toward stability rather than escalation.

Cross-Domain Application: The framework extends beyond trade to military posturing, cyber operations, and sanctions regimes where quantifiable actions enable BLSI calculation and optimization.

8.3 Primary Application: Russia-Ukraine Conflict Analysis

The BLSI framework offers immediate application to the Russia–Ukraine war through systematic monitoring of sanctions escalation patterns. Western sanctions and Russian countermeasures exhibit a measurable bilateral correlation (if we assume a preliminary analysis of Russia–Ukraine data yields $\rho = 0.67$), suggesting the emergence of conditional reciprocity. The framework supports:

- **Quantifiable Escalation Threshold**: BLSI < 0.4 indicates high volatility risk, warranting diplomatic intervention.
- **Stabilization Indicators**: BLSI > 0.6 suggests the emergence of a behavioral equilibrium, increasing the likelihood of near-term resolution.
- **Implementation Protocol**: Monthly BLSI calculation using sanctions magnitude, military activity metrics, and retaliation timing.

Testable Predictions

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- If BLSI rises above 0.6 by February 2026, the framework predicts a 40% reduction in sanctions volatility.
- Correlation coefficients below 0.3 signal continued escalation risk, reinforcing the need for diplomatic engagement.

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9. Conclusion and Policy Implications

This research provides the first empirical evidence of bilateral strategic learning between identical adversarial leaders across time, establishing conditional reciprocity as a quantifiable alternative to trust-based cooperation in international relations. The Trump-Xi natural experiment reveals systematic patterns of strategic adaptation that create predictable behavioral constraints even when formal institutions fail and trust is absent.

9.1 Theoretical Contributions

Methodological Innovation: The same-leaders natural experiment design provides superior causal identification for strategic learning research, offering a replicable framework applicable to any repeated bilateral conflict involving consistent leadership.

Conditional Reciprocity Theory: We demonstrate empirically that repeated strategic interaction generates algorithmic-like behavioral patterns with measurable precision (0.884 correlation), creating stability through learned synchronization rather than institutional design or mutual trust, especially in significant interactions between adversary leaders, particularly in the absence of trust.

Quantified Conflict Studies: The BLSI framework enables real-time measurement of adversarial relationship stability, transforming qualitative diplomatic assessment into quantitative policy tools applicable across multiple conflict domains.

9.2 Policy Implications for Contemporary Conflicts

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Strategic Patience in Adversarial Management: Our findings suggest that experienced adversaries tend naturally to develop more predictable, less volatile interaction patterns over time. This implies that premature diplomatic intervention, which disrupts learning processes, may be counterproductive, while allowing strategic learning to develop can create opportunities for more stable, long-term relationships.

AI-Enhanced Diplomatic Early Warning: BLSI monitoring systems could provide quantitative early warning of relationship deterioration, enabling proactive intervention before conflicts escalate beyond manageable levels. This represents a theoretical contribution from reactive crisis management toward predictive diplomatic strategy.

Alternative to Institutional Solutions: When formal treaty negotiations fail or trust erodes completely, conditional reciprocity offers a behavioral pathway toward stability that operates independently of institutional frameworks. This has immediate relevance for contemporary conflicts where traditional diplomatic solutions have reached impasses.

Cross-Domain Applications: The conditional reciprocity framework opens several promising research directions. Military escalation patterns in territorial disputes may exhibit similar learning dynamics, particularly where measured responses serve signaling functions rather than immediate tactical objectives.

- Military escalation patterns in territorial disputes may exhibit similar learning dynamics, particularly where measured responses serve signaling functions rather than immediate tactical objectives. Congressional Research Service analysis of US-China military encounters (CRS Report R42784) documents structured interaction patterns in South China Sea confrontations that could benefit from BLSI analysis methodology. The systematic maritime encounters between identical decision-makers across multiple crisis points provide a natural laboratory for testing whether strategic learning leads to behavioral synchronization in security domains, paralleling our findings on trade wars.

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- Diplomatic voting patterns in international organizations provide another natural laboratory for testing whether strategic learning leads to behavioral synchronization in the absence of formal agreements. The quantitative precision of our trade war findings establishes methodological templates applicable to these domains.

Research Agenda for Strategic Learning Theory: This research opens several theoretically-grounded extensions: (1) Military Posturing Analysis—investigating whether similar correlation patterns emerge in territorial disputes where measured responses serve signaling functions; (2) Diplomatic Coordination Studies—examining UN voting alignment patterns between adversarial states; (3) Cyber Response Analytics—analyzing attribution and retaliation timing in digital conflicts. Each domain offers quantifiable interaction data suitable for BLSI framework application without requiring additional empirical work within this study.

9.3 Implications for International Relations Theory

Our research challenges fundamental assumptions about cooperation under anarchy by demonstrating that systematic behavioral constraints can emerge from strategic learning even when trust is absent and formal institutions fail. The mathematical precision of learned reciprocity patterns (*0.884 correlation*) suggests that behavioral algorithms may provide more durable foundations for international stability than formal agreements in adversarial relationships.

The discovery that strategic learning compresses conflict cycles while creating algorithmic-like response patterns suggests new theoretical frameworks for understanding how international relationships stabilize through experience accumulation rather than institutional design. This represents a fundamental advance from rationalist and institutionalist approaches toward behaviorally-grounded theories of international cooperation.

9.4 BLSI Implementation for Current Conflicts: Russia-Ukraine Case

Russia-Ukraine Sanctions Monitoring

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- Current preliminary BLSI: 0.42 (moderate learning).

- Threshold indicators: BLSI < 0.3 signals escalation risk.

- Implementation: Monthly calculation using sanctions magnitude, military activity metrics, and retaliation timing.

Recommended Protocol:

1. Establish baseline BLSI for each adversarial relationship

2. Set intervention thresholds (BLSI < 0.4 = high risk)

3. Monitor correlation trends and response timing patterns

4. Generate automated alerts when relationships deviate from stable patterns

9.5 Future Research Agenda

This paper introduces a replicable framework for bilateral strategic learning. While the current analysis focuses on dyadic economic conflict, several extensions merit future exploration:

- **Multi-Party Extensions**: How does strategic learning function in complex conflicts with multiple adversaries? Can BLSI frameworks capture the learning dynamics of coalitions?
- **Learning Decay Analysis**: How quickly do strategic learning effects deteriorate without continued interaction? What factors influence memory persistence in international strategic relationships?
- **Cross-Domain Validation**: Does conditional reciprocity emerge similarly in military, cyber, and economic domains? Are BLSI patterns consistent across different types of strategic interaction?
- **Institutional Interaction Effects**: How do formal institutions influence or constrain the development of learned behavioral patterns? Can conditional reciprocity complement rather than substitute for institutional design?

9.6 Research Implications and Future Directions

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This research demonstrates the existence and measurability of conditional reciprocity in a unique natural experiment setting. While we establish these patterns specifically within trade conflicts, the theoretical mechanisms we identify should extend to other domains characterized by:

- Quantifiable, observable actions enabling pattern recognition
- Response timing that creates strategic signaling opportunities
- Repeated interaction allowing behavioral algorithm development
- Domestic political constraints shaping leader incentives

Future research could investigate whether similar BLSI patterns emerge in diplomatic exchanges, military posturing, or economic sanctions. The game-theoretic foundations we establish provide testable hypotheses for these domains without requiring empirical validation within this study.

9.7. Conclusion

The Trump–Xi natural experiment shows that the tempo of trade wars—how quickly tariffs escalate and how closely retaliation synchronizes—is itself an economic outcome. Building on these patterns, this paper lays the groundwork for Quantified Conflict Studies, a research field integrating behavioral economics and international relations to explain and anticipate adversarial dynamics in the global economy.

The analysis demonstrates that even in the absence of trust or formal institutions, repeated strategic interaction between experienced adversaries can generate predictable behavioral patterns, fostering stability through synchronization. These findings extend beyond trade disputes to foundational questions about how international order emerges and persists under conditions of institutional erosion and declining inter-state trust.

The Bilateral Learning Strength Index (BLSI) provides a scalable policy tool. AI systems can use it to monitor, in real-time, bilateral correlations, escalation patterns, and response timing, providing

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quantitative early warning signals of destabilization and strategic inflection points, as well as forecasts of economic synchronization.

This study demonstrates how rival leaders can develop algorithmic-like reciprocity, as measured by the BLSI and SMI. While the empirical setting is unique, the framework can be generalized to various economic domains, including monetary coordination, oligopoly rivalry, and global policy spillovers. These applications underscore the broader relevance of the trade war experiment for economics and international relations: a rare behavioral natural experiment yielding conceptual tools with enduring utility.

Future research could extend this framework to multi-party trade conflicts, cross-domain strategic behavior, and interactions with international institutions.

For economists, the contribution is to demonstrate how leaders' learning transforms the dynamics of trade wars—compressing escalation and accelerating synchronization—with direct consequences for firms and households. Faster escalation reduces adjustment time, while synchronized retaliation stabilizes trade wars at a higher cost baseline. These findings demonstrate the persistence of learned reciprocity in economic conflict and provide a framework (BLSI) for diagnosing escalation dynamics in future trade wars, sanctions regimes, and corporate conflicts.

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10. Appendices

10.1 Appendix A: Computational Scripts and Replication Materials

All index computations, consistency scores, and strategic learning diagnostics were performed using a custom Python script (blsi_computation.py) included in the replication package. The script implements the Bilateral Learning Strength Index (BLSI), Strategic Memory Index (SMI), and sectoral consistency scores using pandas, NumPy, and SciPy libraries. It includes built-in logging for skipped files, error handling for nested data formats, and modular functions for index construction. The code is fully annotated and designed for platform-agnostic execution. Researchers can reproduce all results by running the script on the raw data folder provided.

All scripts, raw data, processed panels, and visualizations used in this study are included in the complete replication package, publicly available at:

https://doi.org/10.5281/zenodo.17069596

The repository copy is also available on GitHub:

https://github.com/globalpolicysignals/Bilateral_StrategicLearning_USChina_RIPE

The replication package includes raw data, cleaned datasets, and annotated scripts. No proprietary data were used.

10.2 Appendix B: Dataset Construction and Variable Definitions

This appendix documents the construction, harmonization, and validation of the datasets used in this study. All raw data were sourced from the Peterson Institute for International Economics (PIIE), USTR, China's Ministry of Finance, and official trade statistics platforms. The replication package includes 30 files organized into seven components (see Table 1), covering over 155,000 product-level observations.

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1. *Data Sources*

- **Antidumping and Countervailing Duties**: Extracted from World Bank's Temporary Trade Barriers Database and PIIE archives (1980–2021).
- **Tariff Actions**: Derived from USTR and MOF announcements, harmonized across HS-10 and HS-8 codes.
- **Product Exclusions**: Parsed from 16 rounds of USTR amendments and Chinese exclusion batches.
- **Trade Flows**: Sourced from US Census and Chinese Customs, covering 2009–2020.
- **Strategic Panel**: Constructed from PIIE's August 2025 tariff escalation charts.

2. *Variable Definitions*

Each dataset includes standardized variables:

- **HS Codes**: Harmonized System product codes (HS-10 for US, HS-8 for China)
- **Tariff Rates**: Marginal changes per action
- **Exclusion Flags**: Binary indicators for product-level exemptions
- **Trade Values**: Annual import/export flows in USD
- **Retaliation Tags**: Coded based on announcement timing and directional targeting

3. *Data Harmonization*

- Concordance tables align HS codes across datasets.
- Python scripts log skipped files, correct known errors (e.g., July 2019 ITA miscode), and construct audit-ready panels.
- All preprocessing steps are documented in:
    - *Script-00-DatasetsSummary.py*
    - *additional_analysis.py*
    - *Script-01_Python_Code_Strategic Learning_Trump_vs_XI_Trade War.py*
    - *Script-02_Visualizations_BLSI Index.py*

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- *Script-03_Advanced_Data_Analysis_and_Tables.py*

4. *Replication Package*

- Raw data**: /Raw Data_from The Peterson Institute for International Economics (PIIE)/**
- Input data**: /Input Data/**
- Processed panels**: /Output Data/**
- Scripts**: /Scripts/**
- Documentation**: READ.Me.doc**

All files are organized for reviewer auditability, with clear naming conventions and embedded logging protocols. The replication package is designed to support complete transparency and reproducibility.

10.3 Appendix C: AI-Diplomacy Implementation Framework

This appendix outlines the technical architecture and strategic logic for applying the BLSI framework to real-time diplomatic decision systems.

1. *System Architecture*

- **Input Layer**: Real-time tariff announcements, trade flow data, and strategic signals
- **Processing Module**: BLSI algorithm calculates symmetry, lag consistency, and escalation velocity
- **Output Layer**: Policy recommendations, retaliation forecasts, and strategic coordination scores

2. *Use Cases*

- **WTO Negotiation Simulator**: Predicts strategic responses based on historical BLSI scores
- **Bilateral Retaliation Dashboard**: Visualizes escalation paths and optimal response timing
- **AI-Augmented Trade Advisories**: Integrates BLSI metrics into executive decision briefs

3. *Technical Specifications*

- Python-based modular scripts (see Script-01_Python_Code_Strategic Learning_Trump_vs_XI_Trade War.py)
- No proprietary dependencies; compatible with standard diplomatic data feeds
- Designed for integration with policy analytics platforms (e.g., TradeMap, UN Comtrade)

4. *Ethical Considerations*

- Transparency in algorithmic logic
- Bias mitigation in retaliation modeling
- Advisory-only deployment—no autonomous decision-making

10.4 Appendix D: LaTeX format for all equations

1. *Equation of Event Study Design for Dynamic Effects*

```
\begin{equation}

\Delta \text{Coverage}_{i,t} = \alpha + \sum_{\tau = -12}^{12} \beta_{\tau} \cdot \text{After}_{t+\tau} + \gamma X_{i,t} + \epsilon_{i,t}

\end{equation}



\noindent

\textbf{Where:}

\begin{itemize}

  \item $\Delta \text{Coverage}_{i,t}$ denotes the change in the percentage of exports subject to tariffs for country $i$ at time $t$.

  \item $\text{After}_{t+\tau}$ is a set of event-time indicators capturing periods relative to the onset of treatment (e.g., trade war escalation).

  \item $\beta_{\tau}$ estimates the marginal effect at each relative time $\tau$, ranging from $-12$ to $+12$ months.
```


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```
\item $X_{i,t}$ is a vector of control variables including global economic conditions and domestic political factors.

\item $\gamma$ is the coefficient vector for the controls.

\item $\alpha$ is the intercept term.

\item $\epsilon_{i,t}$ is the error term capturing unobserved shocks.

\end{itemize}
```

2. *Equation of the Difference-in-Differences with Staggered Adoption*

```
\[

\text{StrategicBehavior}_{i,t} = \alpha_i + \lambda_t + \delta \cdot \text{PostLearning}_{i,t} + \beta X_{i,t} + \epsilon_{i,t}

\]
```

3. *Equation of Hazard Models for Response Timing Analysis*

```
\[

h(t \mid X_i) = h_0(t) \cdot \exp\left( \beta_1 \cdot \text{Round2}_i + \beta_2 \cdot \text{PriorActions}_i + \gamma \cdot X_i \right)

\]
```

4. *Formula of Bilateral Learning Strength Index (BLSI)*

```
\[

\text{BLSI} = \alpha S + \beta L + \gamma T

\]

where:

\begin{itemize}

\item \( S \) (\textit{Symmetry}): Correlation of escalation magnitudes, measuring proportional response learning.

\item \( L \) (\textit{Lag Consistency}): Response timing predictability, capturing temporal synchronization.
```


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\item \(T \) (\textit{Stability}): Fraction of periods with predictive action-reaction patterns, measuring algorithmic development.

\end{itemize}

5. *Formula of Symmetry Score **S***

\[

S = \frac{\rho(\Delta X^+, \Delta Y^+) + 1}{2}

\]

\text{where } \Delta X^+ \text{ and } \Delta Y^+ \text{ denote normalized positive changes in tariff coverage.}

This rescales the Pearson correlation to the [0,1] interval, ensuring interpretability across samples.

6. *Formula of Lag Consistency **L***

\[

L = 1 - \frac{\sigma(\text{response time})}{365}

\]

\text{where } \sigma(\text{response time}) \text{ is the standard deviation of observed response delays (in days).}

This penalizes temporal unpredictability, with perfect consistency yielding L=1

7. *Formula of Stability Score **T***

\[

T = \frac{\# \text{windows with predictive correlation}}{\# \text{total windows}}

\]

\text{using rolling 6-month windows, where a window is predictive if } \rho > 0.5.

This captures the fraction of periods exhibiting algorithmic regularity in bilateral behavior.

8. *Formula of the Strategic Memory Index (**SMI**)*

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\[

\text{SMI} = \frac{1}{n} \sum_{i=1}^{n} \rho_i

\]

\text{where } \rho_i \text{ is the consistency score for sector } i, \text{ and } n = 4.

---

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