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ORIGINAL ARTICLE

Transfer pricing, tariff-induced risk, and artificial intelligence supervision: a networked compliance model for banks and regulators

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Abstract
This article develops a simulation-based framework linking tariff shocks, transfer pricing (TP) distortions, AI-supported compliance capacity, and the network structure of multinational enterprises. Stylised simulations indicate three consistent patterns: tariff exposure is associated with greater deviation from arm's-length pricing and wider profit misallocation; stronger AI compliance capacity reduces these distortions; and mitigation effects are stronger when compliance capabilities are deployed at structurally central entities within the network. The framework has indirect prudential relevance. Indicators derived from tariff exposure, pricing deviation, and network centrality may serve as informational overlays for monitoring large cross-border corporate borrowers, helping identify cases where intra-group opacity warrants closer supervisory or credit risk review. The study is exploratory: results derive from stylised simulations rather than observed firm-level data and should be interpreted as indicative patterns within an assumed system.

Keywords Credit risk · Counterparty risk · Regulatory risk · Geopolitical risk · AI-driven compliance · Banking supervision

JEL Classification F23 · H25 · C63 · L86 · O33

Introduction

Rising tariff barriers and expanding algorithmic oversight have made transfer pricing (TP) increasingly relevant for regulatory, supervisory, and financial-stability discussions. While TP is traditionally viewed as a tax compliance function, tariff-induced pricing distortions can affect the transparency of intra-group cash flows, segment profitability, and legal-entity performance—information routinely used by banks and supervisors when assessing large cross-border borrowers.

This paper develops a simulation-based framework linking tariff shocks, pricing misalignment, AI-supported compliance capacity, and the network structure of multinational enterprises (MNEs). The central premise is that tariff shocks weaken comparability conditions and introduce structural pricing strain, while AI-based compliance tools may help restore benchmarking consistency, anomaly detection, and documentation reliability. These effects are shaped by organisational topology: AI deployed at structurally central subsidiaries, where transaction flows and information influence are concentrated, is expected to produce stronger system-wide mitigation.

The contribution is explicitly RegTech/SupTech-oriented. The goal is not to estimate realised impacts on bank balance sheets or capital requirements, but to develop an architectural framework for supervisory monitoring of large multinational borrowers and TP-related risk. Indicators derived from tariff exposure, pricing deviation, and network centrality can help identify borrower groups where informational opacity or structural concentration warrant closer supervisory or credit risk review.

The paper addresses a gap at the intersection of four literatures. First, prior work shows that tariffs can distort intra-group pricing and weaken the comparability conditions on which TP analysis depends. Second, a growing body of literature suggests that AI can support compliance by improving benchmarking, anomaly detection, and digital documentation. Third, network research shows that

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risk does not spread evenly across complex organisational systems, but tends to concentrate at structurally influential nodes. Fourth, banking-regulation scholarship increasingly highlights the value of technologically enhanced supervision when information is fragmented, opaque, or difficult to verify. What remains underdeveloped is an integrated framework connecting these insights: one that explains how tariff-induced TP distortions may propagate through MNE networks, why AI may be more effective when deployed at central subsidiaries, and how the resulting indicators may be relevant to supervisory prudential monitoring.

To address that gap, the paper develops a stylised multilayer simulation for 150 MNE groups over 2015–2023, using Orbis-inspired corporate structures as a calibration benchmark rather than as a source of directly observed firm-level estimates. The framework studies three main outcomes: deviation from arm's-length pricing, profit misallocation, and synthetic audit-risk signals. It then examines whether tariff shocks are associated with greater pricing misalignment, whether AI-supported compliance capacity mitigates that effect, and whether mitigation is stronger at structurally central subsidiaries.

The remainder of the paper is organised as follows. Sect. "Model" reviews the relevant literature on tariffs and TP, AI-supported compliance, network analysis, and supervisory technology. Sect. "Model 3 – Audit Exposure (Logistic Regression):" presents the simulation design and modelling framework. Sect. "Tariff-induced disruptions and AI moderation" reports the main simulation results. Sect. "Discussion" discusses the implications of tariff-induced disruptions for TP governance. Sect. "Conclusion" considers the regulatory and supervisory implications of the proposed architecture. Section concludes.

Large MNEs are core borrowers and counterparties for internationally active banks. In this context, the value of the proposed model lies not in recalibrating PD or LGD parameters, but in supporting supervisory judgement by identifying informational opacity within complex borrower structures. Tariff shocks, pricing misalignment, and uneven documentation quality can reduce the interpretability of segment profitability and intra-group cash-flow allocations—two elements routinely used in credit assessment, early-warning systems, and concentration-risk review.

The framework provides three types of indicators that can complement existing supervisory dashboards:

- Tariff-exposure metrics, highlighting subsidiaries whose financial statements may be more sensitive to fragmented trade conditions.
- Pricing-coherence indicators (DL, ΔR), which signal when intra-group profitability deviates from benchmark conditions and may warrant deeper credit-monitoring review.
- Network-centrality measures, identifying subsidiaries whose behaviour disproportionately affects the accuracy of group-level financial information.

In practice, such indicators could serve as supervisory overlays in large-exposure reviews, as early-warning indicators for multinational borrowers, and as a basis for supervisory scrutiny of segment profitability and legal-entity opacity. These indicators are not substitutes for internal risk models or Pillar 1 metrics. Rather, they serve as an overlay to existing supervisory processes, helping banks and regulators identify borrower groups in which informational opacity, tariff-sensitive business models, and structural concentration coincide. In practice, the framework can aid supervisory teams in prioritising analytical reviews, focusing engagement, and integrating TP-related signals into broader assessments of large cross-border exposures. Its role is therefore supportive: to enhance the coherence, transparency, and interpretability of borrower information in contexts where trade fragmentation increases the risk of structural mispricing.

Literature review

Recent research on TP increasingly shows that cross-border compliance cannot be analysed in isolation from trade frictions, digital monitoring, and evolving supervisory technologies. However, these strands of literature are still often treated separately. Studies on tariffs and TP focus mainly on sourcing, internal price adjustments, and tax-planning responses by MNEs, while research on artificial intelligence (AI) tends to examine anomaly detection, reporting, or disclosure quality. At the same time, network-based approaches to governance and systemic risk have become central in banking and regulatory studies, but they are only rarely extended to TP. This paper contributes by bringing these literatures together within a single framework, linking tariff-induced pricing distortions, AI-supported compliance, and network-based supervisory relevance for banks and regulators.

A first stream of literature examines how tariffs affect TP and intra-group behaviour. Bernard et al. (2018), Liu and Weller [1], and Mukunoki and Okoshi [2] show that trade barriers alter sourcing incentives, internal pricing choices, and the allocation of production across jurisdictions. Carroll and Hur [3] further highlight the distributive effects of tariffs, while Rokot and Nadi [4] show that exchange-rate pressures and fiscal incentives can amplify pricing distortions. Kohlhase and Wielhouwer [5] explicitly analyse the interaction between tax and tariff planning through transfer prices, with attention to intra-firm coordination between head office and operating units. More broadly, Bhattacharya [6] places tariff policy within a politically fragmented global environment, suggesting that pricing decisions are increasingly exposed to unilateral trade measures rather than stable multilateral disciplines. Taken together, this literature shows that tariffs can disrupt comparability and increase uncertainty in TP, but it generally stops short of examining how such distortions propagate through multilayered corporate structures or how they may become relevant for financial supervision.

A second stream concerns AI and digital compliance. Basharat [7], Khalil [8], and Mayer [9] all emphasise AI's capacity to improve TP accuracy, anomaly detection, and administrative efficiency. Belahouaoui and Attak [10] connect digital taxation, AI, and Tax Administration 3.0, showing that technological monitoring systems increasingly shape compliance behaviour. Boshnak, Al-Okaily, and Al-Ali [11], as well as Lehner and Knoll [12], situate AI within a broader transformation of accounting, control, and disclosure practices. These contributions are important because they show that AI is no longer merely an automation device,it is becoming part of the institutional infrastructure of compliance. At the same time, most of this literature addresses AI at the level of tax administration or accounting practice, without fully specifying how its effectiveness may depend on the entity's structural role in which it is deployed.

This gap is particularly important in a regulatory environment where AI cannot be evaluated only by predictive performance. Explainability, auditability, and governance have become central to the use of AI in compliance-sensitive settings.[1] This dimension is crucial for the present paper because it clarifies that the value of AI in TP is not simply technical. It also depends on whether its outputs can be used in a way that is legally suitable, proportionate, and compatible with supervisory review.

A third strand of literature concerns network theory and its application to complex economic systems. Barabási [13] and Bianconi [14] provide the foundational logic for understanding how influence and vulnerability are distributed across networks rather than uniformly across nodes. Nakamoto and Ikeda [15] apply network science to international tax avoidance, showing that relational structures matter for cross-border fiscal behaviour. Christensen [16] similarly highlights the strategic power embedded in networked interdependence. These contributions are highly relevant for TP because MNEs are not flat organisations: they are structured systems in which a limited number of subsidiaries often play outsized roles in coordinating flows of goods, services, intangibles, and financing. A network perspective, therefore, helps explain why a distortion arising in a central entity may have broader effects than a similar distortion arising in a peripheral entity.

This systemic perspective also strengthens the paper's connection to banking regulation. Research published in the Journal of Banking Regulation and related outlets has shown that disclosure quality, informational asymmetry, and supervisory technology are central to effective risk monitoring. Scannella and Polizzi [17] examine market risk disclosure in large European banks, while Polizzi and Scannella [18] and Scannella and Polizzi [19] analyse how risk disclosure can be measured and improved. Polizzi and Scannella [20] then extend this discussion to continuous auditing in public-sector and central-bank settings, and Polizzi and Scannella [21] explore how regulatory environments shape disclosure outcomes. More recently, Polizzi and Scannella [22] review distributed ledger technology in banking and finance, further illustrating the movement toward technologically enabled supervision. Jalan and Vaidyanathan [23] reinforce this broader governance concern by showing how tax-haven structures facilitate regulatory arbitrage and corporate opacity. In parallel, Gambacorta, Polizzi, Reghezza, and Scannella [24] demonstrate that disclosure inconsistencies matter in environmentally sensitive banking contexts. Although these studies do not focus on TP, they are directly relevant to the present article because they establish a broader supervisory logic: when information becomes more opaque, fragmented, or difficult to verify, regulatory risk increases, and technologically assisted monitoring becomes more valuable.

That insight matters for multinational corporate clients as well as for banks themselves. Large MNEs are major borrowers, counterparties, and users of cross-border financial services. Persistent TP distortions may therefore affect the informational quality of internal profitability, cash-flow allocation, and legal-entity performance used by banks in credit and concentration-risk assessment. From this perspective, TP ceases to be only a tax matter; it also becomes relevant to prudential monitoring when distortions affect the transparency and interpretability of large corporate exposures. The present paper extends this insight by suggesting that tariff shocks may exacerbate such opacity and that AI-supported, network-aware compliance tools may help mitigate it. Moro-Visconti [25] examines natural and artificial intelligence interactions that matter in this paper's framework.

[1] See OECD (2023), "OECD Framework for the Classification of AI Systems," and FATF (2023), "Opportunities and Challenges of New Technologies for AML/CFT," which stress explainability, auditability, and human oversight in AI-supported tax compliance systems. The integration of anomaly detection tools into TP audit processes must meet emerging transparency and explainability standards set by the EU AI Act and FATF (2023), ensuring that algorithmic decisions can be interpreted and challenged by human auditors.

The literature, therefore, points to an unresolved gap. We know that tariffs can distort intra-group pricing. We know that AI can support anomaly detection, benchmarking, and digital compliance. We also know that network structures shape the propagation of risk and that banking supervision increasingly relies on technologically enhanced monitoring tools. What is still missing is an integrated framework that connects these elements: one that explains how tariff-induced TP distortions may spread through MNE networks, why AI may be more effective when deployed at structurally central subsidiaries, and how the resulting indicators may be relevant not only for tax authorities but also for banks and prudential supervisors monitoring large cross-border corporate groups.

This paper addresses that gap by proposing a simulation-based, networked compliance model. Its contribution is not to claim direct empirical measurement of realised banking losses from TP disputes. Rather, it offers a structured conceptual framework showing how tariff shocks, AI deployment, and network centrality may interact to shape pricing misalignment, compliance exposure, and supervisory relevance. In doing so, it positions TP risk within a broader RegTech and SupTech agenda that is increasingly central to banking regulation in fragmented and data-intensive global markets.

Model

This study develops a simulation-based multilayer network model for 150 MNEs over 2015–2023, using Orbis-inspired corporate structures as a calibration benchmark rather than as a source of directly observed firm-level estimates. The framework integrates three core elements: (1) tariff-induced pricing pressure, (2) structural positioning within corporate networks, captured primarily through eigenvector centrality, and (3) subsidiary-level AI-supported compliance capacity. Eigenvector centrality is particularly suitable in this setting because it captures both the number of a node's connections and the importance of the nodes to which it is connected, allowing the model to represent subsidiaries that coordinate flows across multiple parts of the corporate network. Tariff shocks are introduced exogenously to simulate pricing stress under different trade conditions, both with and without AI deployment. Pricing misalignment and profit misallocation are then generated within the model relative to arm's-length benchmarks, and the simulation is repeated across 1000 Monte Carlo iterations to assess the consistency of directional patterns.

Alongside the quantitative simulation, the paper includes a focused doctrinal discussion of the regulatory compatibility of AI-based compliance mechanisms, concentrating on explainability, auditability, proportionality, and human oversight in the supervisory settings most directly relevant to the proposed model. The aim is not to test legal outcomes empirically, but to assess whether the proposed compliance architecture is conceptually compatible with emerging supervisory expectations regarding explainability, auditability, and human oversight.

The modelling framework addresses how tariff escalation may impair TP comparability and documentation integrity through three linked channels. First, tariff shocks are treated as external disruptions that weaken comparability between intra-group and benchmark prices, consistent with prior findings on the TP effects of trade barriers [1]. Second, AI is modelled as a compliance-enhancing capability operating through improved benchmarking, anomaly detection, and documentation support, in line with the literature on AI-assisted TP governance [7]. Third, network structure matters because central subsidiaries can amplify both distortions and corrective responses: when pricing decisions originate or pass through highly connected entities, shocks can spread more widely, but mitigation may also be more effective if AI is deployed at those nodes [14].

Mechanistically, the model assumes that expected deviation from arm's-length pricing depends on tariff pressure, transaction complexity, data quality, and AI-supported compliance capacity. AI does not eliminate tariff-induced distortions, but it may reduce their magnitude by improving the selection of comparables, identifying anomalous pricing patterns, and enhancing internal consistency in documentation. This makes AI especially relevant in networked MNE structures where local pricing choices can have system-wide implications.

In this framework, AI tools affect transfer-pricing compliance through three primary channels: improved benchmarking and comparables selection, anomaly detection across intra-group transactions, and enhanced consistency in transfer-pricing documentation. AI is therefore modelled as a compliance-support mechanism rather than an autonomous pricing system.

This integrated framework provides a structured framework for examining how MNEs may respond to trade-induced tax distortions through AI-supported, network-aware compliance strategies. The contribution is therefore conceptual and simulation-based: it does not estimate real-world magnitudes from proprietary firm data, but instead illustrates plausible structural interactions among tariffs, AI deployment, and organizational topology.

The research evaluates three hypotheses concerning the joint effects of trade frictions and network positioning:

H1 *Tariff Distortion Hypothesis.The presence of tariffs increases deviations from arm's-length pricing. The* *variable DL measures the absolute proportional deviation between the simulated intra-group transfer price and the arm's-length benchmark price derived from the model's comparable-transaction distribution. Values above 1.0 indicate upward TP distortions relative to the benchmark.*

H2 *AI Mitigation Hypothesis. The adoption of AI-based TP compliance systems reduces DL**DL** and **ΔR**, improving comparability and internal consistency, particularly under tariff conditions.*

H3 *Centrality Amplification Hypothesis. AI's mitigating effects on DL and ΔR are stronger when AI is implemented in structurally central subsidiaries within the MNE network, where pricing decisions and transaction flows have broader influence.*

Formally, ΔR represents the difference between the simulated group profit distribution under distorted prices and the counterfactual allocation under arm's-length prices, scaled by total group profits. Both DL and ΔR are model-generated indicators and should be interpreted as simulation outputs rather than as observed firm-level variables.

Simulation design and empirical architecture

To examine the model's implications, we construct a simulation-based panel of approximately 1200 firm-year observations for 150 stylised MNEs over 2015–2023. The objective is not to recover real-world econometric parameters, but to generate structured quantitative outputs under transparent assumptions about tariff shocks, AI_Use, and network topology. The simulated MNEs are represented as multilayer corporate systems spanning goods, services, and intangible transactions, with sectoral classifications and product flows broadly aligned with harmonized system (HS) tariff categories.

The empirical analysis relies on a stylised Monte-Carlo simulation calibrated to typical MNE structures observed in Orbis-type datasets. Each simulated network represents an MNE group composed of parent and subsidiary entities connected through intra-group trade relationships. Tariff shocks are assigned to a subset of cross-border transactions within a bounded range reflecting typical applied tariff rates in international trade (0–25%). AI_Use is modelled as a continuous compliance-capacity parameter capturing the degree to which firms deploy automated benchmarking, anomaly detection, and documentation tools in TP oversight. Network structure is represented using eigenvector centrality to capture the relative systemic importance of subsidiaries within the group.[2] The simulation generates synthetic observations of pricing deviations, profit misallocation, and audit-risk indicators under varying tariff and AI scenarios; regression estimates, therefore, illustrate directional relationships implied by the model rather than empirical magnitudes observed in real data.

The data-generating process is intentionally stylised. Tariff shocks are assigned exogenously within a bounded range reflecting heterogeneous exposure across sectors and jurisdictions. AI_Use is represented as a compliance-capacity variable rather than as a directly observed technology investment. Network centrality is computed from the simulated topology, with eigenvector centrality used as the main indicator of structural influence because it captures not only the number of a subsidiary's direct connections but also the importance of the nodes to which it is connected. This makes it especially suitable for TP networks in which a small number of entities may shape pricing coherence across the wider group. Degree centrality is also considered descriptively, but eigenvector centrality remains the primary measure used in the core specifications.

The framework generates three main compliance outcomes: deviation from arm's-length pricing (DL)**,** profit misallocation (ΔR)**,** and an audit-risk flag (Audit_Flag).[3] More specifically, tariff shocks are drawn exogenously in the model, AI compliance capacity is scaled to 0–1, and network centrality is normalised within each simulated group. DL is computed as the ratio of simulated intra-group prices to benchmark prices, with values above 1 indicating upward deviation from the benchmark:

$$DL_i = P_i^{IG} / P_i^{BM} \tag{1}$$

Values above 1 indicate upward deviation from the benchmark price.

ΔR captures the simulated profit-allocation gap between controlled and benchmark outcomes and is scaled by firm revenue:

$$\Delta R_i = \mid \Pi_i^{IG} - \Pi_i^{BM} \mid / Revenue_i \tag{2}$$

[2] Eigenvector centrality is used because it captures structural influence within the network, weighting not only the number of connections a subsidiary has but also the importance of the nodes to which it is connected.

[3] The binary variable *Audit_Flag* represents a stylised indicator of regulatory scrutiny. It is generated within the simulation as a probabilistic function of DL, ΔR, tariff exposure, and network centrality, reflecting the stylised assumption that larger pricing deviations and higher systemic relevance increase the likelihood of supervisory review. The indicator therefore serves only as an illustrative signal of potential audit attention rather than an estimate of actual audit probabilities.

DL therefore reflects pricing deviation at the transaction level, while ΔR captures the resulting profit-allocation distortion across entities within the simulated network.

Audit_Flag is activated when simulated pricing strain, tariff exposure, and structural salience jointly exceed a model-defined threshold. These choices are intended to generate transparent comparative scenarios rather than to calibrate real-world magnitudes empirically.

Audit_Flag is a synthetic supervisory-attention proxy generated from model conditions associated with pricing strain and structural salience, and should not be interpreted as an observed audit outcome. None of these variables should be interpreted as direct observations from actual firms; they are synthetic outputs used to compare scenarios across the simulated panel.

The regression models are used as compact summaries of the simulated system. They do not identify causal effects in the econometric sense; rather, they indicate whether the model generates directional relationships consistent with the theoretical hypotheses.

The Regression Models are the following:

Model 1 – Tariff Effects and AI Mitigation (DL):

$$\begin{aligned} DL_i = \beta_0 + \beta_1 Tarrif_i + \beta_2 AI\_Use_i + \beta_3 Tarrif_i \\ \times AI\_Use_i + \beta_4 \log\left(Assets_i\right) + \gamma industry + \delta counry + \varepsilon_i \end{aligned} \tag{3}$$

Model 2 – Profit Misallocation with Network Centrality (ΔR):

$$\begin{aligned} \Delta R_i = \beta_i + \beta_1 AI\_Use_i + \beta_2 Centrality_i + \beta_3 AI\_Use_i \\ \times Centrality_i + \beta_4 \left(Assets_i\right) + \gamma industry + \delta counry + \varepsilon_i \end{aligned} \tag{4}$$

Centrality is computed using degree and eigenvector measures across simulated MNE networks. Central organizations are subject to heightened regulatory scrutiny (producing TP master files), making them significant focal points for enhancing compliance through AI interventions.

Model 3 – Audit Exposure (Logistic Regression):

$$\begin{aligned} &\Pr\left(Audit\_Flag_i = 1\right) \\ &\quad = \log it^{-1}(\beta_0 + \beta_1 Tarrif_i + \beta_2 AI\_Use_i \\ &\qquad + \beta_3 Centrality_i + \beta_4 \log\left(Assets_i\right) + \gamma industry + \varepsilon_i) \end{aligned} \tag{5}$$

Model 3 is retained as an exploratory signalling device rather than as a fully reliable inferential model. Its function is to capture whether structurally central and tariff-exposed entities are more likely, within the simulation, to trigger supervisory attention. Because the audit-risk flag is synthetic and the resulting estimates may be unstable, this specification is interpreted more cautiously than Models 1 and 2.

Tariff shocks are calibrated using product-level customs categories, while AI_Use is simulated using a composite compliance-capacity proxy inspired by disclosure-based and innovation-based indicators. AI_Use represents an index (0–1), capturing the degree of AI-enabled compliance monitoring within the multinational network. These inputs are used to structure the synthetic data; they are not treated as direct observations from firm-specific ESG text mining or patent-level measurements in the empirical sense.

Parameter ranges for tariff levels, AI_Use intensity, and pricing noise are chosen to approximate plausible magnitudes observed in international trade and TP studies, ensuring that simulated DL and ΔR values fall within ranges commonly discussed in the empirical literature while maintaining the stylised nature of the modelling exercise.

To ensure transparency, the simulation framework is intentionally stylised and designed to generate internally consistent scenarios rather than empirical estimates of real-world magnitudes. The objective is to illustrate how tariff shocks, AI-supported compliance capacity, and network topology may interact within complex multinational structures. The resulting coefficients should therefore be interpreted as summaries of model-implied relationships within the simulated system rather than causal estimates derived from observed firm-level data. Future empirical work using firm-level or supervisory datasets could test whether the directional relationships generated by the model also arise in observed multinational networks.

Understanding network layers: how markets evolve under tariffs and AI

This section illustrates the structural evolution of TP complexity through visual modelling, beginning with a baseline representation in Fig. 1 and continuing with the AI-integrated scenarios shown in Fig. 2A and B. The purpose of

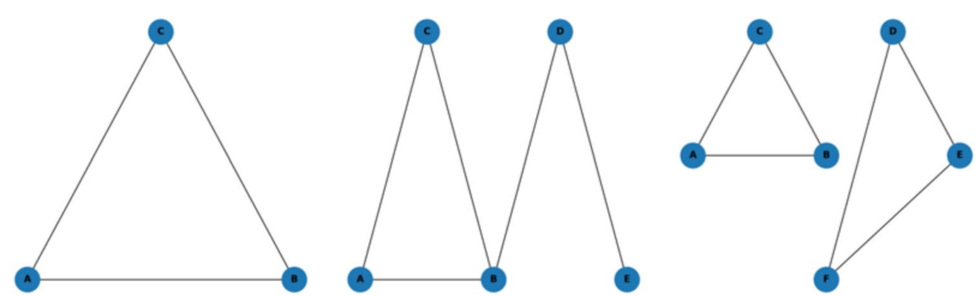

Fig. 1 Arm's Length Transactions and TP without or with Tariffs

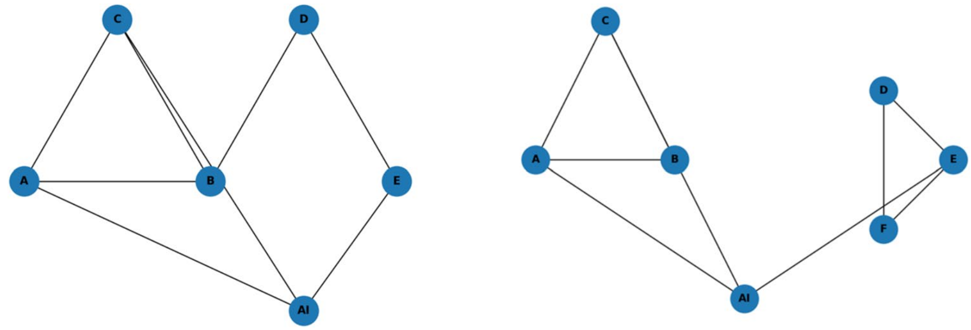

Fig. 2 **A** AI in a Fully Connected Network. AI improves benchmarking and data symmetry in a non-fragmented MNE structure. **B** AI in a Fragmented Network AI bridges tariff-induced clusters, restoring pricing coherence and audit robustness

these visuals is not to provide empirical proof, but to clarify the model's logic: how tariffs may fragment intra-group comparability and how AI may help restore pricing coherence under regulatory pressure.

Figure 1 provides the conceptual starting point. It shows how pricing networks can evolve from a comparatively open benchmark structure toward a more fragmented system shaped by tariffs and centralization. Panel A depicts a stylised arm's-length setting in which pricing information flows relatively freely between independent and affiliated parties. Panel B introduces the concept of structural centrality, showing how high-volume intra-group transactions can reduce reliance on third-party comparables. Panel C then represents tariff-induced distortion, in which comparability is weakened, and documentation becomes more difficult to defend.

Figures 2A and B extend this logic by illustrating how AI may mitigate TP distortions in simulated MNE networks. In Fig. 2A, a tariff-free, fully connected structure shows that centrally deployed AI improves benchmarking consistency by better information processing. Figure 2B introduces tariff-driven dislocation, isolating subsidiaries into clusters; AI positioned at a bridging node partially restores coherence by reconnecting fragmented pricing information and improving anomaly detection.

Taken together, these figures are part of the model-building exercise. They illustrate how network science can be used to simulate pressure scenarios, test the directional effects of technological intervention, and reveal structural vulnerabilities in pricing governance. In that sense, they are consistent with the three hypotheses of the paper: tariff shocks are expected to worsen pricing deviations and misallocation; AI is expected to mitigate some of these effects; and the mitigation is expected to be stronger when AI is deployed at central nodes.

The visualisations also clarify an important methodological point. Compliance outcomes depend not only on tariff exposure or AI_Use in isolation, but also on where technology is placed within the MNE structure. In fragmented trade environments, AI-supported systems may enhance resilience by improving comparability and reducing information asymmetries, but those benefits are likely to vary with organizational topology.

Incorporating these structural simulations into the model has three implications. First, tariff presence is treated as an external shock that degrades TP comparability. Second, the interaction between AI_Use and network centrality becomes a key driver of compliance recovery. Third, the multilayer network structure provides a scalable way to simulate pricing dynamics in high-friction environments, offering a conceptually replicable framework for firms and regulators. The resulting architecture allows the paper to capture both first-order effects (AI and tariffs separately) and second-order effects (AI × Tariff and AI × Centrality) without overstating the empirical status of the suggested simulations.

Structural disruptions and compliance diagnostics

The quantitative analysis examines DL**,** ΔR, and Audit_Flag as dependent variables, using Tariff_Presence**,** AI_Use, and Centrality_Score as the main predictors. These variables represent, respectively, trade shocks, compliance technology, and network positioning, in line with the model's structural hypotheses.

The purpose of the regression framework is to examine whether the simulation generates directional patterns consistent with the paper's conceptual expectations: whether tariffs are associated with higher pricing deviation, whether AI is associated with lower misalignment, and whether this mitigating effect is stronger at structurally central subsidiaries. Because all quantitative outputs are simulation-derived, the coefficients should be interpreted as model-implied relationships under stated assumptions, not as empirical estimates of real-world magnitudes.

A compact summary specification can be written as:

$$\begin{aligned} TPRisk\_it = {} & \beta_0 + \beta_1 TariffShock\_it + \beta_2 AIMaturity\_it \\ & + \beta_3 \left(TariffShock\_it \times AIMaturity\_it \right) \\ & + \beta_4 NetCentrality\_it + \gamma X\_it + \delta\_c + \tau\_t + \varepsilon\_it \end{aligned} \tag{6}$$

In this synthetic specification, TariffShock captures simulated tariff exposure, AIMaturity captures simulated AI-supported compliance capacity, and NetCentrality captures structural prominence within the simulated MNE network. These variables are scenario-design inputs rather than directly observed proprietary measures.

Equation (6) is intended as a synthetic representation of the model's logic rather than as a stand-alone empirical specification estimated on observed proprietary data. For that reason, the analysis focuses primarily on coefficient direction, interaction patterns, and internal coherence across simulated scenarios. Robustness checks in this setting should be understood as sensitivity exercises within the simulation, not as external empirical validation. The study is therefore exploratory and modelling-oriented, and future work using proprietary firm-level and supervisory data remains necessary to determine whether the same relationships hold in observed practice.

Results

This section presents the outputs of the simulation exercise based on 150 MNE groups over 2015–2023, corresponding to approximately 1200 firm-year observations. Because the dataset is generated through stylised simulation, regression coefficients should be interpreted as illustrating directional relationships implied by the model rather than empirical estimates of real-world magnitudes.

The analysis should be read as an exploration of model behaviour rather than as empirical testing on observed firm-level data. For the same reason, the simulations should not be read as direct estimates of bank-level credit losses, provisioning effects, or prudential capital impacts; rather, they illustrate how TP distortions may enter supervisory monitoring logic for complex multinational borrowers. The purpose is to examine whether the simulated system generates directional patterns consistent with the paper's hypotheses: namely, whether tariff shocks increase pricing deviation, whether AI-supported compliance reduces misalignment, and whether mitigation is stronger at structurally central nodes.

The simulated panel is calibrated to broad Orbis-type financial structures, sectoral trade characteristics, and network relationships, but the resulting variables remain synthetic. Accordingly, the regressions reported below are used as compact summaries of the model rather than as evidence of real-world effect magnitudes. In this setting, coefficient signs, interaction patterns, and coherence across specifications are more informative than precise point estimates.

Before turning to the regressions, the descriptive patterns already indicate that the simulated system behaves in a theoretically coherent way. Firms exposed to tariff shocks tend to show higher DL and wider ΔR than firms operating in less distorted settings, whereas scenarios with stronger AI-supported compliance generally display lower misalignment, especially when AI is deployed at structurally central subsidiaries.

Deviation from arm's-length pricing (DL)

Model 1 evaluates how tariff exposure and AI use relate to the simulated deviation from arm's-length pricing. In the simulation, the presence of a tariff is associated with higher DL values, consistent with Hypothesis 1. Within the simulation's logic, this pattern reflects the idea that tariffs weaken comparability between intra-group and benchmark prices, thereby increasing pricing strain within the network.

AI use is associated with lower simulated deviation, consistent with Hypothesis 2. Within the model, this reflects the assumption that AI improves benchmarking, anomaly detection, and documentation consistency. The interaction between tariffs and AI is negative in sign, suggesting that AI may partially mitigate the distortion caused by tariff exposure, even if it does not eliminate it. The substantive implication is that AI functions, in the simulation, as a compliance-stabilising mechanism under trade stress.

These simulations should nevertheless be interpreted with caution. Because the data are synthetic, the coefficients are informative primarily as indicators of the internal model's behaviour. They show that the model behaves in line with the theoretical expectations, but they do not establish the size of tariff or AI effects in observed firm populations.

Profit misallocation (ΔR)

Model 2 focuses on the simulated profit-allocation gap (ΔR) and examines whether AI is more effective when deployed at structurally central subsidiaries. The simulations provide directional support for Hypothesis 3. AI-supported compliance capacity is associated with lower simulated misallocation, and the interaction between AI and centrality suggests that mitigation is stronger where the entity occupies a more influential position in the network.

This pattern is consistent with the model's architecture. When a subsidiary is structurally central, its pricing decisions and informational role affect a broader portion of the MNE system. Improvements in benchmarking or anomaly detection at that node, therefore, have wider consequences for internal pricing coherence. Conversely, distortions originating in such nodes can also propagate more broadly if compliance capacity is weak.

For this reason, the centrality result is less about the statistical significance of a single coefficient than about the structural logic of the framework. The simulation suggests that the placement of compliance technology matters: the same AI capability can yield different outcomes depending on where it is embedded in the network.

Audit-risk signal (Audit_Flag)

Model 3 examines the simulated audit-risk flag through a logistic specification. This component should be interpreted more cautiously than the previous two models. Because the audit indicator is synthetic and because the resulting estimates are numerically unstable for some predictors, the model is better understood as an exploratory signalling device than as a reliable inferential specification.

Within these limits, the audit-risk exercise remains conceptually useful. It suggests that tariff exposure and structural centrality may contribute to supervisory salience within the simulated system, while AI-supported compliance may, in principle, reduce that exposure by improving internal consistency and documentation quality. However, given the instability of the estimates, the paper does not rely on Model 3 to make strong quantitative claims (Table 1).

Table 2 summarises the regression outputs generated by the simulation. Across the simulated specifications, the coefficient signs are consistent with the conceptual framework: tariff exposure is associated with greater pricing deviation, while AI use is associated with lower deviation and, in interaction terms, partial mitigation of tariff-related strain.

Figure 3 depicts compliance distortions across AI and tariff exposure categories, illustrating that firms without AI and facing tariffs exhibit the highest DL and ΔR. AI helps restore pricing symmetry under distortionary conditions.

Visual summary of simulation patterns

Figures 3 and 4 complement the regression summaries by showing how simulated compliance outcomes vary across tariff and AI conditions. Figure 3 compares the distribution of **DL** and **ΔR** across scenarios with and without tariff exposure and AI-supported compliance. The descriptive pattern is intuitive: firms facing tariffs without AI tend to display the highest simulated misalignment, while firms combining AI with less fragmented trade conditions tend to show lower deviation and lower profit-allocation gaps.

Figure 4 presents the average DL across the same scenarios and illustrates the same directional pattern in a more compact form. The figures do not independently support the hypotheses, but they provide a transparent visual representation of the model's internal behaviour. In this sense, they help connect the paper's theoretical structure with the quantitative outputs generated by the simulation.

Interim interpretation

Taken together, the simulation results provide coherent directional support for the paper's three hypotheses. Tariff shocks tend to worsen pricing alignment; AI-supported compliance tends to mitigate part of that effect, and mitigation appears stronger when AI is deployed at structurally central subsidiaries. These conclusions should be understood as model-based insights rather than as empirical estimates of realised market behaviour.

The value of the simulation lies precisely in clarifying these structural relationships. It shows how tariffs, compliance technology, and network topology may interact within a stylised MNE system and provides a foundation for the policy discussion that follows. At the same time, the synthetic nature of the data requires interpretive restraint: future work using proprietary firm-level and supervisory data would be needed to determine whether these relationships hold in observed practice.

Tariff-induced disruptions and AI moderation

This section briefly interprets the simulation patterns reported in the previous Section and links them to the supervisory discussion that follows. The main pattern is that tariff exposure tends to weaken TP comparability, increasing deviations from arm's-length pricing and widening simulated profit-allocation gaps. Within the model's logic, tariffs therefore operate not only as external trade costs but also as structural sources of compliance strain. As comparability deteriorates, documentation becomes harder to defend, and maintaining pricing coherence across the group becomes more difficult.

Against this background, AI appears in the simulation as a moderating compliance mechanism. Higher AI-supported capacity is associated with lower pricing misalignment and greater internal consistency, particularly where tariff stress is present. The model suggests that these gains arise from better benchmarking, anomaly detection, and documentation support, rather than from eliminating the underlying trade shock itself.

Network structure further shapes these effects. The simulation indicates that AI is more consequential when deployed at structurally central subsidiaries, because those entities influence a larger share of pricing and information flows across the MNE system. Centrality, therefore, matters both as a source of exposure and as a guide to where compliance interventions may have the greatest effect.

The patterns described in this section are consistent with the simulation outcomes reported in Table 2, which

Table 1 TP Traditional and emerging risks and regulatory challenge mitigation

Risk type	TP implications	Tariff complications	Implications for supervisory prudential monitoring and credit-risk assessment	AI + network mitigation
Credit, market, operational, and liquidity risks	Profit misallocation undermines cash flows and intercompany financing	Tariffs distort cost bases and profitability, stressing liquidity	Possible opacity in cash-flow allocation and legal-entity performance; relevant for borrower monitoring and concentration review	AI restores comparability through dynamic benchmarking; network analytics identify and monitor liquidity pressure points
Legal and compliance risks	Non-arm's length pricing triggers audits and penalties	Tariff-induced discrepancies amplify red flags	Heightened audit risk and cross-border legal complexity	Machine learning enhances risk scoring and APA strength; network centrality analysis reveals audit exposure zones
Investment risk	Mispriced transactions mislead capital allocation	Tariffs change expected returns across borders	Greater uncertainty in interpreting cross-border profitability and internal capital allocation within large borrower groups	AI optimizes capital deployment strategies; network insights map risk-adjusted return zones
Counterparty risk	Misaligned intercompany terms elevate settlement risk	Tariffs introduce renegotiation uncertainty	Stress on counterparty evaluation and payment reliability	AI forecasts counterparty fragility; network topologies help pre-empt settlement disruptions
Sovereign risk	Profit shifting may conflict with national tax priorities	Tariffs politicize cross-border pricing	Balancing national tax interests with cross-border compliance	Scenario modeling with AI projects sovereign conflict zones; networks track capital flight risk
Systemic risk	TP misalignment spreads through value chains and financing	Tariffs create cascading trade imbalances	Monitoring systemic contagion from TP-tariff feedback loops	Network-based contagion mapping supports macroprudential alerts; AI smoothens shock propagation
Environmental, social, and governance (ESG) risks	Opaque pricing undermines ESG traceability	Tariffs interrupt green supply chains	Tracking ESG-linked financial risks amid opaque pricing and disruptions	AI-powered traceability tools monitor ESG performance; networks track compliance across supply layers
Geopolitical risk	TP disputes align with national interests	Tariffs signal geopolitical stress	Assessing geopolitical exposure in corporate pricing decisions	AI evaluates geopolitical stress markers; network simulations flag potential economic bifurcations
Strategic risk	Inaccurate pricing distorts strategic planning	Tariffs shift supply chain priorities	Recalibrating strategic risk assessments in fluid trade environments	AI-driven simulations inform strategic decisions; networks visualize alternative supply and pricing paths
Regulatory risk	TP decisions trigger multi-jurisdictional reviews	Tariffs reflect regulatory fragmentation	Ensuring regulatory coherence in fragmented tariff landscapes	Regulatory tech ensures cross-border documentation integrity; AI automates reporting compliance
Model risk	Traditional TP models fail under volatility	Tariffs make static models obsolete	Adapting supervisory models to account for algorithmic risk management	AI adapts pricing models under real-time volatility; networks support decentralized stress testing

Table 2 Descriptive statistics and regression simulations

Panel A – Descriptive simulation patterns by industry

Industry	N Firms	Avg DL	Avg ΔR	AI Use (%)	Audit flag rate (%)
Manufacturing	48	1.12	0.31	0.42	0.28
Services	56	0.98	0.22	0.51	0.19
Technology	46	0.88	0.18	0.66	0.14

Panel B – Direction of main simulation relationships

Variable	DL (Model 1)	ΔR (Model 2)	Audit flag (Model 3)
Tariff shock	Positive	–	Positive
AI Use	Negative	Negative	Negative
Centrality	–	Negative	Mixed/Cautious
Tariff × AI	Negative	–	–
AI × centrality	–	Negative	–
Log assets	Controlled	Controlled	Controlled

Panel C – Interpretation of the main simulation patterns

Dimension	Interpretation
Tariff exposure	Associated with higher simulated pricing deviation and greater compliance strain
AI-enabled compliance	Associated with lower simulated misalignment and better internal consistency
Network centrality	Increases the structural relevance of both distortions and mitigation effects
Audit-risk signal	Interpreted cautiously because the indicator is synthetic and the logit estimates are unstable

Impact of Tariffs and AI_Use on Deviation from Arm's Length Pricing presents OLS estimates measuring the impact of tariffs and AI on pricing deviations (DL). It validates the hypothesis that tariffs inflate DL while AI mitigates these distortions. The Effect of AI and Network Centrality on Profit Misallocation Across Subsidiaries shows how AI_Use and network centrality interact to affect profit misallocation (ΔR). Though the effects are not statistically strong, the model supports the directional logic of H3.Audit Risk as a Function of Trade Fragmentation, AI Deployment, and Structural Network Position explores audit exposure with a logistic regression. Centrality Score emerges as the only significant predictor, affirming the importance of structural network position in compliance strategy

summarises the directional relationships between tariff exposure, AI deployment, and deviations from arm's-length pricing.

Discussion

The simulation framework[4] suggests that tariff shocks, AI-supported compliance capacity, and corporate network structure should be analysed together rather than in isolation. Although the model is based on stylised data and does not estimate real-world magnitudes, it helps clarify how trade fragmentation may generate TP strain and how digitally supported compliance tools may mitigate part of that strain within complex MNE systems.

A first implication concerns the effect of tariffs on TP coherence. In the simulated scenarios, tariff exposure tends to weaken comparability between intra-group and benchmark prices, increasing deviations from arm's-length pricing and widening profit-allocation gaps. This matters because the arm's-length principle depends on relatively stable reference conditions. When tariff barriers alter cost structures, sourcing patterns, and internal pricing incentives across jurisdictions, comparability becomes harder to maintain, and documentation becomes more fragile. The model therefore supports the view that tariffs act not merely as external trade costs, but as structural sources of compliance strain within MNE networks.

[4] This study is based on simulated data, with no field validation. Thresholds for AI synchronization scores are calibrated heuristically and may vary across real-world applications. Future empirical work should validate structural simulations with proprietary data and assess sensitivity to sectoral differences.

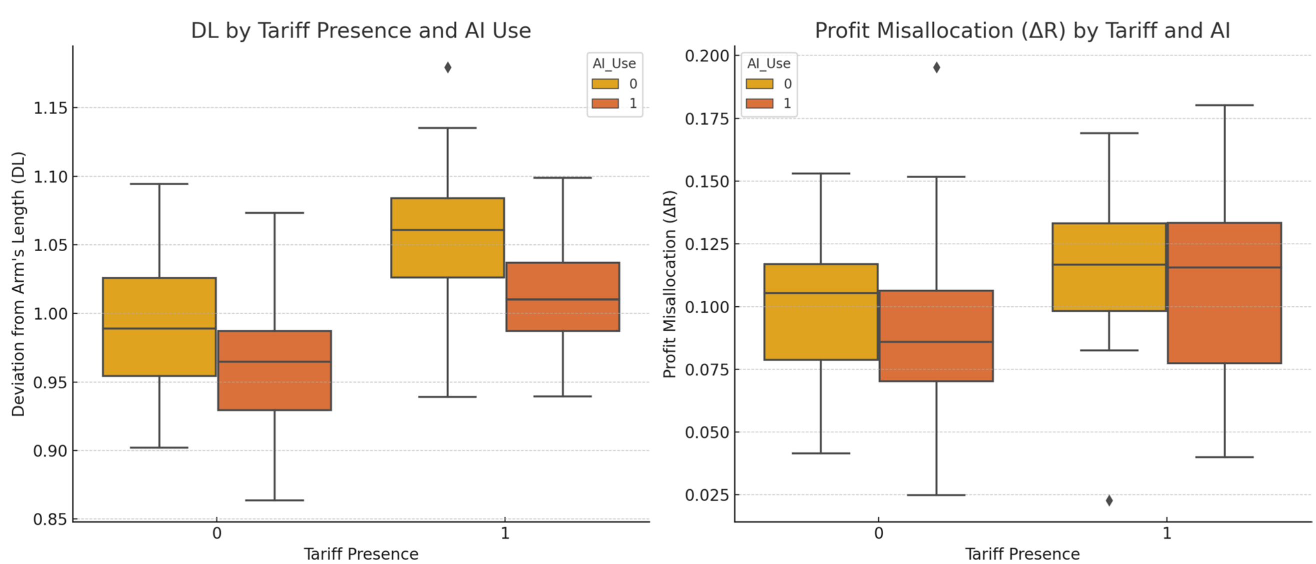

Fig. 3 Distributions of DL and ΔR by Tariff and AI Status

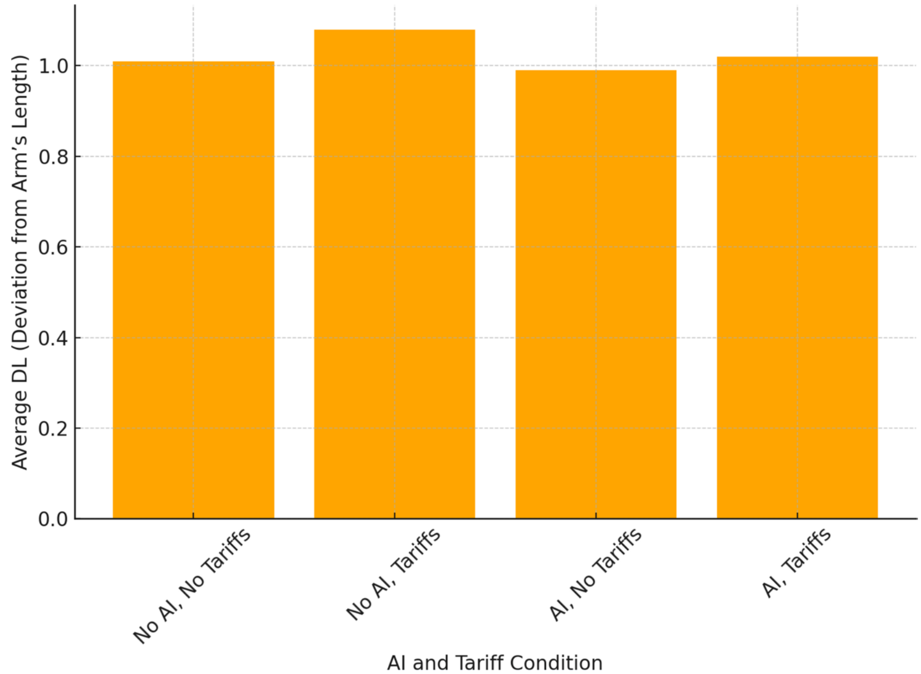

Fig. 4 Average Deviation From arm's-length Pricing (DL): With vs. Without Tariffs and AI use

A second implication concerns the role of AI. In the framework proposed here, AI is not treated as a generic technological upgrade, but as a compliance mechanism that may improve benchmarking, anomaly detection, and documentation quality.

A third implication concerns organisational topology. The model indicates that mitigation effects are stronger when AI-supported compliance is deployed at structurally central subsidiaries. This is consistent with the idea that not all affiliates have equal influence over the coherence of TP systems. Subsidiaries occupying central positions in transaction and information networks can transmit both distortions and corrective effects more widely across the group. For that reason, network centrality is relevant not only as a marker of exposure but also as a guide to where compliance investment may have the greatest marginal effect (Table 3).

This Table is consistent with OECD TP guidelines [26], AI governance challenges [27] and digital issues [28].These points also have supervisory relevance, although not as substitutes for internal bank models or Pillar 1 capital metrics. From a banking regulatory perspective, the framework is best understood as a decision-support overlay on existing monitoring processes. For large multinational borrowers, a dashboard could combine tariff exposure, DL, ΔR, network centrality, and AI-compliance capacity as supplementary indicators of informational opacity and structural concentration.

In operational terms, escalation would be triggered not by a single signal, but by a combination of conditions such as rising DL and ΔR at a structurally central entity, higher tariff exposure accompanied by weaker documentation coherence, or similar strain signals appearing across several subsidiaries in the same borrower network.

Such indicators would not automatically alter credit-risk parameters. Rather, they would prompt enhanced analytical review of intra-group cash-flow allocation, the enforceability of collateral across jurisdictions, the consistency of TP documentation with financial reporting, and the role of central entities in coordinating group-level transactions.

Used in this way, the framework can support horizontal screening of complex cross-border exposures and help supervisors prioritise cases where opacity, structural concentration, and tariff-sensitive business models overlap.

The framework is therefore best understood as a supervisory overlay for monitoring complex multinational exposures, not as a replacement for internal bank risk models. Its most plausible role is as a dashboard-based escalation aid that complements existing borrower-risk assessments and supervisory review.

For a bank, unusually high DL, ΔR, or deterioration in sync score for a major multinational borrower would not mechanically alter PD, LGD, or regulatory capital. It would instead warrant closer review of segment profitability, intra-group cash-flow concentration, legal-entity dependencies, collateral enforceability across jurisdictions, and the consistency of borrower documentation used in credit monitoring.

The discussion also has implications for the design of RegTech and SupTech. The paper suggests that supervisory monitoring may benefit from combining three types of information: tariff exposure, network centrality, and AI-supported compliance capacity. Taken together, these indicators provide a more structural view of where regulatory strain

Table 3 Comparative framework for TP supervision

Feature	AI-Multilayer model	Manual audits	Traditional ML Flags	Peer compliance scoring
Risk detection	Dynamic, real-time via network centrality	Ex-post, episodic	Correlated but static	Heavily lagged
Audit prioritization	Systemic exposure–based	Volume-based	Pattern-based	Market share–based
cross-border supervision	Integrated via structural sync	Highly fragmented	Not inherently scalable	Low replicability
Explainability	Explainable via sync metrics & Bayesian updating[a]	Human judgment–based	Opaque black-box	Score rationale is often unclear
Alignment with OECD TP review and explainable supervisory use	High, if used as explainable decision support with human review	Low to moderate	Moderate	Low

[a]A Bayesian synchronization logic assumes that each subsidiary emits observable signals with a probability distribution conditional on compliance status. Sync score architecture could also extend to AI-audited ESG claims. Synchronization metrics may identify nodes with unreliable or opaque sustainability data, enhancing traceability and regulatory alignment

may arise within multinational groups than isolated transaction checks or static balance-sheet measures alone. The contribution is therefore architectural rather than econometric. It shows how a network-aware compliance framework might support more targeted monitoring of complex corporate exposures in an environment shaped by trade fragmentation, digital reporting, and growing supervisory reliance on technologically assisted oversight.

At the same time, the approach's limits remain important. All quantitative relationships in the paper are generated from synthetic data under stylised assumptions. The coefficients and summary patterns should therefore be read as model-implied directional relationships rather than empirically verified magnitudes. This caution applies especially to the audit-risk indicator, which is best interpreted as a proxy for supervisory attention rather than as an observed measure of enforcement behaviour. The paper does not claim to estimate realised bank-level losses, prudential capital effects, or actual audit outcomes. Future work using proprietary firm-level, banking, or supervisory data would be needed to determine whether similar relationships emerge in observed practice.

Within these limits, the paper supports three main conclusions. First, tariff shocks can generate structural TP distortions by weakening comparability and increasing pricing uncertainty. Second, AI-supported compliance systems may mitigate part of that strain by improving benchmarking, anomaly detection, and documentation quality. Third, the effectiveness of such systems depends in part on where they are deployed within the corporate network, with stronger effects arising at structurally central subsidiaries. These simulations do not constitute direct empirical proof, but they do provide a coherent conceptual basis for integrating TP risk into broader supervisory and banking regulatory discussions.

Figures 4 and 5 provide a visual summary of the simulation outcomes and the role of AI-supported transfer pricing compliance within the network framework.

Policy integration

To translate the conceptual framework developed in this paper into supervisory practice, it is necessary to situate the model within existing prudential and regulatory oversight processes. Central banks, financial supervisors, and international regulatory bodies increasingly rely on digital monitoring systems capable of processing complex corporate structures and large volumes of cross-border financial information. In this context, AI-supported network diagnostics may complement existing supervisory tools by highlighting structural vulnerabilities within MNE networks.

A potential operational application of the multilayer framework is the integration of network-based indicators into supervisory monitoring dashboards. Within such systems, subsidiaries of a multinational group could be assigned a synchronization score designed to capture the degree of structural coherence among TP outcomes, tariff exposure, and network centrality. In practice, this score would reflect the interaction between three model-generated dimensions: pricing deviation from arm's-length benchmarks, structural importance within the corporate network, and the presence of AI-supported compliance capacity.

Entities with high synchronization scores may signal areas where pricing coherence and governance structures are relatively stable, whereas low scores may indicate potential vulnerabilities in pricing alignment or in the robustness of documentation. Rather than serving as automatic enforcement triggers, such indicators would function as risk-screening tools, helping supervisory teams prioritise areas where further review may be warranted. For example,

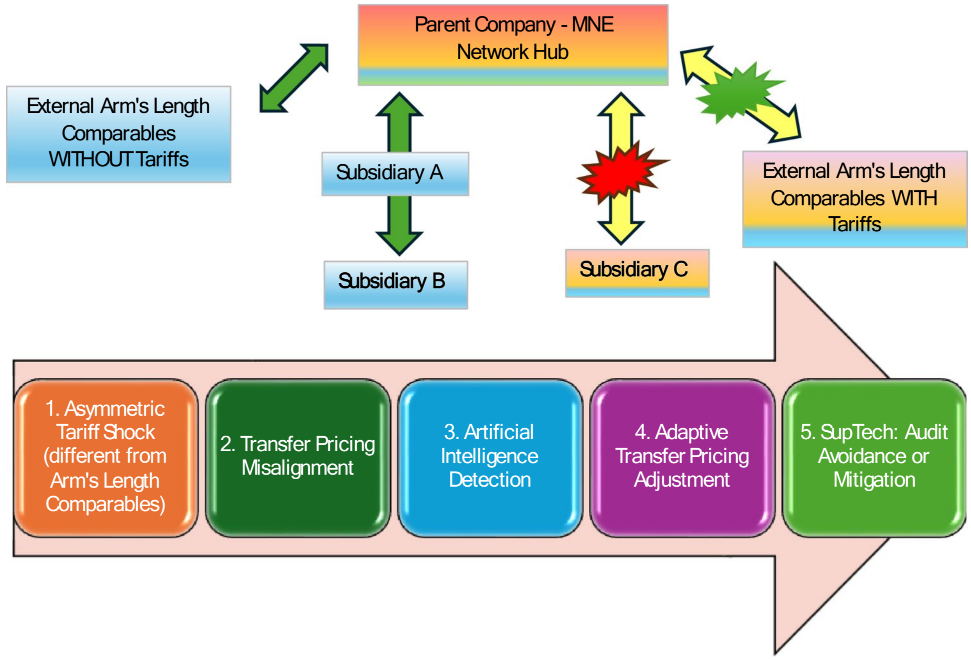

Fig. 5 AI-supported TP compliance

structurally central subsidiaries experiencing tariff-related distortions could be prioritised for deeper analytical review, documentation checks, or cooperative engagement with tax authorities.

This type of screening mechanism could support supervisory workflows in several ways. First, it could assist regulators in identifying subsidiaries whose structural position within multinational networks makes them more relevant for compliance monitoring. Second, it could help supervisory teams allocate limited audit and review resources toward entities where pricing distortions may propagate more widely through corporate structures. Third, it could provide an additional analytical layer to support dialogue among tax authorities, prudential supervisors, and multinational firms on documentation quality and governance practices.

Importantly, such systems would need to operate within the governance constraints that apply to algorithmic supervisory tools. Contemporary regulatory frameworks emphasise explainability, auditability, proportionality, and human oversight when artificial-intelligence systems are used in compliance-sensitive environments.

In practical terms, explainability requires that any synchronization score or AI-generated signal be interpretable by supervisors and regulated entities. Auditability requires traceability of the underlying data sources, benchmark selection logic, and model adjustments used to generate the indicators. Proportionality implies that escalation thresholds should vary with the materiality of the exposure and the entity's structural relevance within the corporate network. Finally, human oversight requires that AI outputs remain advisory signals supporting supervisory judgment rather than automated enforcement triggers.

When designed this way, AI-supported monitoring tools can remain compatible with emerging governance expectations while improving supervisors' ability to identify structural vulnerabilities within complex multinational corporate groups.

From a broader regulatory perspective, integrating network-based compliance indicators could complement existing international initiatives on cross-border taxation and financial governance. Efforts such as the OECD Pillar Two framework, EU cross-border reporting regimes, and emerging AI governance standards all emphasise the need for improved transparency and coordination across jurisdictions. Network-aware compliance diagnostics could provide additional analytical support to these initiatives by identifying where trade disruptions, pricing distortions, and corporate structural complexity intersect.

Overall, the framework illustrates how AI-supported compliance tools and network analytics might enrich supervisory monitoring in a more fragmented global economy. By combining indicators of tariff exposure, network centrality, and pricing coherence, supervisors may be better placed to identify emerging compliance vulnerabilities within complex multinational groups while preserving interpretability, proportionality, and human review.

Conclusion

This article develops a simulation-based framework linking tariff shocks, TP distortions, AI-supported compliance capacity, and the network structure of multinational enterprises. Using stylised simulations of MNE group structures, the analysis shows three consistent patterns: tariff exposure is associated with greater deviation from arm's-length pricing and wider profit misallocation; stronger AI compliance capacity reduces these distortions; and mitigation effects appear stronger when compliance capabilities are located at structurally central entities within the network.

The prudential relevance of these simulations is indirect but potentially useful. The framework should therefore be interpreted as a supervisory-risk architecture that illustrates how tariff-related pricing distortions might become visible in monitoring systems used for complex cross-border corporate exposures. Indicators derived from tariff exposure, pricing deviation, and network centrality may serve as supervisory overlays for monitoring large cross-border corporate borrowers. Such signals are not substitutes for internal bank models or regulatory capital metrics, but they may help identify cases where opacity in intra-group structures warrants closer supervisory or credit-risk review.

The study remains exploratory. Its results derive from stylised simulations rather than observed firm-level data, and the estimates should be interpreted as indicative patterns within an assumed system. Future research could test the framework using empirical multinational network data and examine how such indicators might be incorporated into supervisory monitoring tools. In an era of fragmented trade, algorithmic oversight, and growing supervisory complexity, TP is no longer merely a tax issue. It is becoming a crossroad where corporate governance, financial stability, agentic AI, and regulatory supervision increasingly converge.

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Declarations

Conflict of interest No competing or conflicts of interest.

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