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Environmental Policy Timing in Adaptive Trade Networks: An Agent-Based Model

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Abstract

Environmental trade regulations act on trade networks that adapt over time. This paper develops a stylised agent-based computational model to study policy sequencing in adaptive international trade networks. Exporting countries continuously evaluate their existing trade relationships against alternative import markets. The introduction of environmental regulation alters the relative attractiveness of these markets, prompting exporters to adapt their trade relationships. These adaptations reshape the trade networks on which subsequent policy interventions operate. We show that the timing and sequence of regulatory interventions can therefore influence both the evolution of trade networks and environmental outcomes. In particular, different regulatory sequences generate distinct transition paths even when they ultimately result in identical regulatory coverage. The framework separates the effect of implementation timing from differences in regulatory participation and stringency. The results identify policy timing as a source of path dependence in adaptive trade networks. The study is a mechanism-based computational experiment rather than a forecast or causal estimate of observed regulatory effects.

Keywords: Agent-based computational economics, Adaptive networks, Policy sequencing, Trade networks, Network rewiring, Environmental regulation

1 Introduction

Global efforts to reduce deforestation are increasingly extending beyond domestic forest protection. One perspective is the regulation of international supply chains (Lambin & Meyfroidt, 2011; Pendrill et al., 2019). Policies such as the European Union Deforestation Regulation (EUDR), the United Kingdom's due diligence legislation, and the proposed United States FOREST Act seek to reduce the deforestation embodied in internationally traded commodities by changing the conditions under which products can enter regulated markets (European Parliament and Council of the European Union, 2023; Schilling-Vacaflor, 2021). Their underlying assumption is straightforward: by making access to major consumer markets conditional on compliance with deforestation standards, these policies create economic incentives for exporters to reduce deforestation within their supply chains in order to maintain access to regulated markets (Garrett et al., 2019; Lambin et al., 2018). They also provide a useful setting for computational economic analysis because their effects depend on repeated decisions by heterogeneous agents rather than on a single contemporaneous change in aggregate trade flows.

Whether these policies achieve their intended environmental benefits depends on how exporters respond. Exporters and importers form global trade networks that are not static and can adapt depending on exporters' responses (Barabási, 2016; Fagiolo, Reyes, & Schiavo, 2010). When regulations increase the costs of trading with one market, exporters can maintain existing relationships, establish new trading partnerships, or redirect exports towards less regulated destinations (Fernandes, Lefebvre, & Rocha, 2021; Head & Mayer, 2014; Tinbergen, 1962). As a result, countries continuously adapt their trade relationships and, thus, the structure of the network itself changes (Jackson, 2008; Roukny, Georg, & Battiston, 2014). The effectiveness of importer-side environmental regulation therefore depends not only on the policy itself, but also on how the

global trade network reorganises in response (Meyfroidt & Lambin, 2009; Pendrill et al., 2022; Searchinger, Wirsenius, Beringer, & Dumas, 2018).

This raises an important question for policy design. While a growing body of literature has examined trade leakage, embodied deforestation, and policy coordination (Barrett, 2003; Meyfroidt & Lambin, 2009; Nordhaus, 2015; Pendrill et al., 2019), much less attention has been paid to the role of policy timing. Should countries implement environmental regulations simultaneously, or does the timing of implementation itself alter the economic and environmental transition through an adaptive trade network? Although coordination is generally regarded as desirable (Barrett, 2003; Nordhaus, 2015), the timing of coordinated implementation remains largely underexplored in a setting where exporters continuously adjust their trading relationships between regulatory interventions.

This paper addresses this question using a stylised agent-based computational model of an adaptive international trade network. The model represents countries as boundedly rational agents connected through a directed, weighted, multiplex trade network covering four major forest-risk commodities: palm oil, soy, timber, and paper (Railsback & Grimm, 2019; Tesfatsion, 2006). Exporters evaluate existing and potential trading partners based on trade-group membership, geographic distance, realised or expected market importance, and policy exposure. Their individual decisions to maintain or replace existing trade relationships generate an evolving trade network from which both economic and environmental outcomes emerge (Helbing, 2012). When a relationship is replaced, the new relationship initially preserves the realised trade volume of the relationship it replaces. Its trade volume then gradually adjusts towards a destination volume determined by the relative market potential of the replaced and new partners. Trade adjustment therefore occurs along two margins: the extensive margin refers to changes in who trades with whom through partner replacement, while

the intensive margin refers to changes in how much is traded within the newly established relationship. Exporter- and commodity-specific environmental-risk intensities informed by Trase and FAOSTAT (Food and Agriculture Organization of the United Nations, 2024; Trase, 2024) provide an application-specific outcome measure that links evolving trade volumes to embodied deforestation-risk exposure. The network topology, behavioural parameters, and trade-group structure remain stylised and are not intended to reproduce observed bilateral trade flows.

Representing all four commodities within a multilayer network is useful because the effect of policy timing is heterogeneous across commodity-specific trade networks. Single-commodity simulations also produce timing-dependent outcomes, but the magnitude of these effects and the ranking of the policy scenarios differ across palm oil, soy, timber, and paper. Moreover, no individual commodity reproduces the aggregate result of the four-layer model. The multilayer specification therefore captures how heterogeneous commodity responses jointly shape the aggregate economic and environmental consequences of alternative implementation schedules. This is a result of aggregation across distinct commodity-specific dynamics, and does not imply direct interaction between commodity layers.

The analysis compares five policy scenarios: a baseline without regulation, an early-mover strategy, sequential coordination, simultaneous coordination, and delayed coordination. Policy timing is defined as the simulation period in which regulation becomes active for regulator r. Accordingly, the regulatory scenarios vary the activation periods of the European Union, United Kingdom, and United States while keeping the regulatory mechanism unchanged. In particular, the sequential, coordinated, and delayed-coordination scenarios contain the same regulating jurisdictions and maintain the same regulatory stringency, but differ in the timing with which this common regulatory coverage is reached. Comparing these scenarios therefore isolates the effect of implementation timing from differences in eventual policy participation,

regulatory design, or stringency, while allowing the network and its trade relationships to adapt between successive policy interventions. Earlier interventions alter trade links, trade volumes, and market potential, meaning that later interventions operate on a network configuration already shaped by previous adjustment. Treating the activation date of regulation as a policy-design dimension follows the broader precedent of environmental-policy models examining how the timing of intervention affects adjustment within an evolving economic system (Arfaoui, Brouillat, & Saint-Jean, 2014).

The paper makes three main contributions. First, it identifies regulatory implementation timing as an independent dimension of environmental trade-policy design. The model constructs a controlled policy experiment in which the sequential, coordinated, and delayed-coordination scenarios ultimately involve the same regulating jurisdictions, apply the same regulatory penalty, and operate through the same behavioural model, while differing only in the timing with which common regulatory coverage is reached. This design isolates the effect of timing from differences in policy participation or stringency. Because exporters adapt their trading relationships between interventions, later regulatory shocks act on networks that have already been transformed by earlier policy. The paper therefore identifies a source of path dependence through which identical eventual regulatory coverage can generate different economic and environmental transition dynamics.

Second, the paper models trade rerouting and relationship-level trade-volume adjustment as endogenous behavioural processes instead of treating observed changes in trade flows as a mechanical consequence of regulation. Exporters continuously evaluate whether existing relationships remain sufficiently attractive relative to feasible alternatives. When switching occurs, the existing relationship is replaced by a new partner and initially preserves the displaced trade volume. Conditional on survival, its volume then adjusts towards a destination volume determined by the market potential

of the new importer relative to that of the replaced importer. The framework therefore captures adaptation along both the extensive margin, through partner replacement, and the intensive margin, through relationship-level trade-volume adjustment.

Third, the model integrates adaptive network dynamics, economic performance, and exporter-specific deforestation risk within a single simulation framework. Deforestation intensity is attached to exporter–commodity pairs not importing destinations, which allows the analysis to distinguish environmental effects generated by changes in realised trade volume from those generated by changes in the composition of trade across exporters with different deforestation intensities. The framework therefore avoids assuming that trade rerouting itself constitutes an environmental improvement and instead makes the environmental outcome an endogenous consequence of the interaction between network adaptation, trade-volume adjustment, and the distribution of exporter-specific environmental risk.

Taken together, these contributions shift the analysis of environmental trade regulation from a static comparison of policy coverage toward the study of policy interventions in adaptive economic networks. The central contribution is therefore not to identify a universally optimal implementation sequence, but to show that the timing of otherwise comparable regulation can alter the trade-network configuration on which subsequent interventions operate, making policy outcomes path dependent even when eventual regulatory coverage is identical.

The remainder of the paper is organised as follows. Section 2 reviews the literature on embodied deforestation, environmental trade networks, policy coordination, and policy sequencing, highlighting the research gap addressed in this study. Section 3 presents the agent-based model, including the network representation, exporter decision process, trade-volume adjustment mechanism, environmental calibration, policy scenarios, and robustness design. Section 4 reports the simulation results, examining

policy-induced network adjustment, trade-volume adjustment, environmental outcomes, and the robustness of these results across alternative network realisations and behavioural assumptions. Section 5 discusses the implications of the findings for environmental policy coordination and adaptive trade networks, as well as the limitations and potential extensions of the modelling framework. Finally, Section 6 concludes.

2 Literature Review

International trade has become a major driver of embodied deforestation by linking consumption in importing economies to land-use change in commodity-producing regions. A substantial share of tropical deforestation and associated greenhouse gas emissions is embodied in internationally traded forest-risk commodities such as soy, palm oil, timber, and paper products, meaning that environmental impacts frequently occur outside the jurisdiction where final demand originates (Kanemoto, Moran, Lenzen, & Geschke, 2014; Pendrill et al., 2022, 2019). Recent research combining environmentally extended input–output analysis with network science further demonstrates that embodied deforestation propagates through interconnected systems of producer, intermediary, and consumer countries beyond isolated bilateral relationships (Global Canopy, 2024; Sun, Zhou, Zhu, & Xia, 2023). These findings have motivated a growing range of demand-side interventions aimed at reducing imported deforestation, including mandatory due diligence, traceability requirements, legality standards, and restrictions on placing forest-risk commodities on consumer markets, most prominently through the European Union Deforestation Regulation (EUDR) and similar initiatives in other jurisdictions (Bager, Persson, & dos Reis, 2021; Sotirov, Azevedo-Ramos, Rattis, & Berning, 2022; Vasconcelos, Bastos Lima, Gardner, & McDermott, 2024).

A persistent concern surrounding these policies is trade leakage. Restricting access to one market does not necessarily reduce global deforestation if exporters redirect

production towards less regulated destinations. This mechanism, documented across both the land-use displacement and carbon-leakage literatures, implies that environmental pressure may be redistributed geographically instead of being reduced globally (Abman, Jenkins, & Lundberg, 2026; Henders & Ostwald, 2014; Ingalls, Meyfroidt, To, Kenney-Lazar, & Epprecht, 2018; Meyfroidt, Lambin, Erb, & Hertel, 2013; Meyfroidt, Rudel, & Lambin, 2010; Pan, Kim, Ning, & Yang, 2020; Pirlot, 2024). Consequently, international coordination has become a central theme within the environmental policy literature. Existing research consistently demonstrates that broader regulatory participation reduces opportunities for leakage by limiting alternative export markets and strengthening incentives for more sustainable production compared with fragmented national action (Hsiao, 2026; Jakob, 2021; Perdana & Vielle, 2023; Pirlot, 2024).

Beyond the extent of coordination, recent research increasingly recognises that the temporal design of environmental policy also influences policy effectiveness. Related environmental-policy modelling treats regulatory timing as a dimension of policy design. For example, Arfaoui et al. (2014) examine how the timing of regulatory intervention affects adjustment in an agent-based model of environmental regulation. This provides a useful precedent for treating the point at which regulation becomes active within an evolving economic system as a distinct policy-design choice. The policy sequencing literature argues that the order in which policies are introduced shapes political feasibility, institutional learning, and reinforcing feedback processes that influence long-term outcomes (Meckling, Sterner, & Wagner, 2017; Pahle et al., 2018). Likewise, Furumo and Lambin (2021) demonstrate that successful zero-deforestation governance depends not only on individual interventions but also on how public regulation, private governance initiatives, incentives, and enabling measures are combined over time. However, this literature has largely examined the sequencing of different policy instruments and not the staggered implementation of comparable importer-side regulations across multiple jurisdictions.

At the same time, international trade is increasingly understood as a complex adaptive network composed of interconnected bilateral exchanges. Network-based studies have substantially improved understanding of embodied environmental flows, trade resilience, and the heterogeneous structural roles countries occupy within global supply chains, demonstrating that both environmental impacts and economic shocks propagate through interconnected network structures whose topology influences system-wide outcomes (Jafari, Engemann, & Zimmermann, 2024; Kanemoto et al., 2014; Pendrill et al., 2019; Sun et al., 2023). Nevertheless, most existing studies analyse historically observed or static trade networks, implicitly treating network structure as fixed without allowing exporters to replace relationships, establish new partnerships, and reorganise supply chains in response to changing regulatory environments.

Taken together, these research streams reveal a computational gap. The coordination literature primarily compares the extent of policy participation, while the policy-sequencing literature focuses on the ordering of interventions. Environmental trade-network studies provide important evidence on embodied environmental flows, network topology, and leakage, but commonly treat the network as observed or fixed. These approaches provide limited scope for analysing repeated policy interventions in which decentralised agents replace relationships, alter trade volumes, and thereby change the network environment encountered by subsequent interventions.

The present paper addresses this gap with a stylised agent-based computational model. Its purpose is not to forecast bilateral trade or estimate the causal effect of a particular regulation. Rather, it is to isolate the conditions under which policy timing generates path dependence in an adaptive economic network.

Addressing this question requires more than observing changes in aggregate trade flows. Trade leakage is fundamentally an adaptive network process driven by decentralised behavioural responses (Abman et al., 2026; Grugni, Savin, & van den Bergh,

2026). Exporters evaluate the attractiveness of existing relationships, search for alternative markets, establish new trading partnerships, and reinforce successful trade corridors over time (Dhyne, Kikkawa, Mogstad, & Tintelnot, 2021; Earnest & Wilkinson, 2018). These individual decisions reshape the structure of the trade network itself, altering future trading opportunities and creating feedback mechanisms through which subsequent adaptation occurs (Dhyne et al., 2021; Grugni et al., 2026). The network is therefore an endogenous component of the policy mechanism through which policy effects propagate (Dhyne et al., 2021; Grugni et al., 2026). Capturing these dynamics requires a modelling framework capable of simultaneously representing heterogeneous decision-makers, endogenous network evolution, behavioural adaptation, and path-dependent adjustment (Earnest & Wilkinson, 2018; Grugni et al., 2026).

While empirical analyses remain indispensable for identifying realised policy effects, they are necessarily constrained to historically observed implementation pathways and generally treat network evolution as an observed outcome, without explicitly modelling the underlying behavioural process (Aller, Ductor, & Herrerias, 2015; Kopp & Salecker, 2020). Likewise, equilibrium-based approaches typically represent trade adjustment through aggregate responses and are less suited to modelling relationship-level partner search, endogenous network rewiring, and emergent structural change (Dhyne et al., 2021; Klein, van den Bergh, Foramitti, & Konc, 2025). Recent research has increasingly demonstrated the value of agent-based modelling for analysing adaptive climate-policy systems in which macro-level outcomes emerge from repeated interactions among heterogeneous agents operating under changing institutional environments (Gerst et al., 2013; Klein et al., 2025; Wieners, Lamperti, Dosi, et al., 2026). Agent-based models are particularly well suited to studying transition dynamics, policy interactions, and counterfactual policy scenarios that cannot be recovered from historical observations alone (Gerst et al., 2013; Wieners et al., 2026). Accordingly, an agent-based computational framework is appropriate for the present question because

the mechanism operates through repeated decentralised decisions, endogenous network changes, and transition dynamics between successive policy interventions (Grugni et al., 2026; Kopp & Salecker, 2020).

This paper therefore treats the timing of regulatory activation as the computational treatment in a controlled adaptive-network experiment. The comparison among sequential, coordinated, and delayed coordination holds eventual regulatory participation and policy stringency constant while allowing exporters to adapt between interventions. The resulting contribution is a computational account of how policy sequencing can generate path dependence through the interaction of network rewiring and relationship-level trade-volume adjustment.

3 Model

3.1 Model Overview

The model represents international trade in forest-risk commodities as an adaptive multilayer network in which countries act as exporters and importers connected through commodity-specific bilateral trade relationships. The purpose of the model is not to reproduce a particular historical trade network quantitatively, but to isolate the mechanism through which the timing of importer-side environmental regulation affects exporter adaptation, trade-network evolution, and embodied deforestation risk. In particular, the model examines whether regulatory interventions with the same eventual coverage can generate different outcomes when they are activated at different points in an adapting trade network. The framework is therefore designed as a stylised policy experiment with empirically calibrated environmental-risk and geographic inputs, and is not intended as a forecasting model. The model is consequently intended to provide a transparent computational laboratory for studying adaptive policy interventions, rather than a predictive representation of observed bilateral trade.

The model contains $N = 30$ countries and four commodity layers,

$$C = \{\text{palm oil}, \text{soy}, \text{timber}, \text{paper}\}.$$

Exporters are indexed by i, current importing partners by j, potential importing partners by k, commodities by c, and simulation periods by t. One simulation period corresponds to one year, and the baseline simulation horizon is $T = 20$ years. Each of the $N = 30$ country nodes has a fixed model ID, ISO3 code, and country identity, which remain unchanged throughout the simulation. All countries participate in all four commodity layers. Exporter and importer are relationship-specific roles not separate agent types. For a directed trade relationship $i \to j$, country i acts as the exporter and country j as the importer; the same country may therefore act as an exporter in some relationships and as an importer in others. The European Union is represented by its constituent country nodes, which are treated collectively as a regulatory group when EU regulation becomes active, whereas the United Kingdom and the United States are represented by individual country nodes. These countries otherwise follow the same network and behavioural rules as all other agents and are distinguished only by their regulatory status. To ensure that policy shocks operate on a meaningfully exposed network, the EU regulatory group, the UK node, and the US node each receive at least eight incoming links per commodity layer at $t = 1$. Where the initialisation process does not generate the required exposure, existing exporter links are minimally reassigned towards the relevant regulatory market. This one-for-one reassignment preserves each exporter's initial out-degree and the initial trade volume associated with the reassigned relationship.

The central mechanism is illustrated in Figure 1. The model begins from a stylised international trade network at time t. If an importer-side environmental regulation is active, exporters connected to the regulated market experience a reduction in

the attractiveness of that destination. Each exporter then evaluates both its existing trading relationships and feasible alternative importers. Existing and potential relationships are scored using the same basic economic logic: group embeddedness increases attractiveness, geographic distance reduces it, economically important markets are preferred, and policy exposure reduces attractiveness.

Potential partners are subsequently separated into local and global alternatives according to whether they belong to the exporter's existing trade group. The model assigns an opportunity value to each set of alternatives, incorporating the switching cost required to access it. Exporters compare the value of the available alternatives with the score of their current relationship. If the current relationship remains sufficiently attractive, it is maintained. If the alternatives are more valuable, the exporter replaces the current importer with a new partner.

Conditional on switching, the exporter first determines whether adaptation occurs locally, within its existing trade group, or globally, across group boundaries. A particular destination is then selected probabilistically from the relevant candidate pool. The replaced relationship is removed and replaced one-for-one by the new relationship. The new relationship initially preserves the realised trade volume of the relationship it replaces. Its destination volume depends on the market potential of the new importer relative to that of the replaced importer. Conditional on survival, trade volume adjusts linearly towards this destination volume over a baseline period of five years.

The resulting link replacements and volume adjustments create a new network at $t + 1$. Economic fitness and embodied deforestation risk are calculated on this updated network. Any regulatory intervention scheduled for the following period then acts on the already adapted network. Consequently, the timing of regulation can matter even when the same jurisdictions ultimately regulate: each successive shock acts on a network whose structure and trade volumes have been shaped by all previous adjustments.

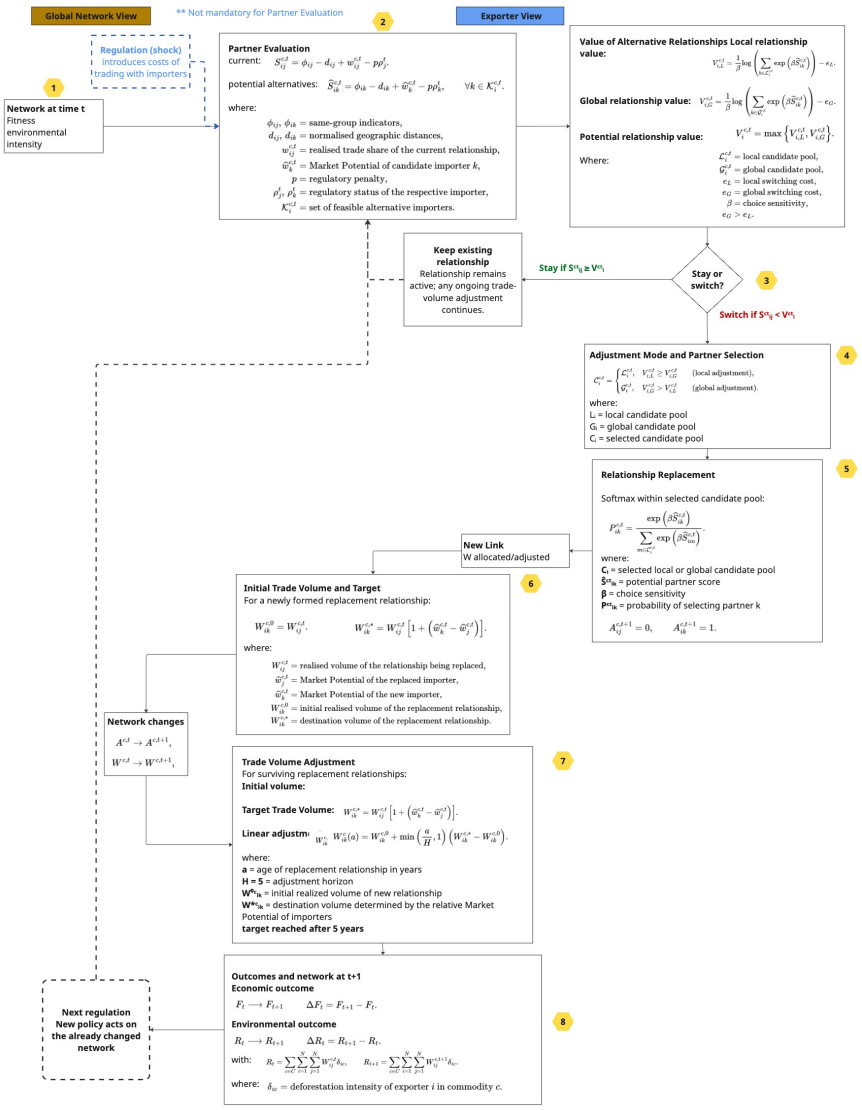


Fig. 1 Behavioural and network flow of the adaptive trade-network model.

The model evolves through eight phases, illustrated in Figure 1:

1. **Network at time t.** Each period begins from the current commodity-specific trade networks, including active relationships, realised trade volumes, relationship adjustment information, market potential, and the regulatory conditions active in period t.

2. **Partner evaluation.** Every exporter evaluates its existing relationships against feasible alternative importers. Existing and potential partners are assessed using group membership, geographic distance, realised or expected market importance, and regulatory exposure. In the baseline scenario, no regulatory penalty applies; in a regulatory scenario, active regulation reduces the attractiveness of the affected importing destinations.
3. **Stay or switch.** The exporter compares the value of its current relationship with the opportunity value of the available alternatives. The current relationship is retained if it remains sufficiently attractive; otherwise, the exporter switches.
4. **Adjustment mode and partner selection.** Conditional on switching, the exporter first selects the local or global candidate pool according to their relative opportunity values. A new importing partner is then selected probabilistically from the chosen pool using the softmax choice rule.
5. **Relationship replacement.** The old relationship is removed and the selected relationship is created one-for-one. All replacement decisions are based on the same network at time t and are applied simultaneously.
6. **Initial and destination trade volumes.** The replacement relationship initially preserves the realised trade volume of the displaced relationship. Its destination volume is determined by the market potential of the new importer relative to that of the replaced importer.
7. **Trade-volume adjustment.** Conditional on survival, a replacement relationship adjusts linearly from its initial volume towards its destination volume over the adjustment horizon.
8. **Outcomes and network at $t+1$.** The updated relationships and trade volumes determine the economic and environmental outcomes and form the network at $t+1$.

The next period repeats the same behavioural sequence. Any subsequent regulation therefore acts on the network configuration produced by previous endogenous adaptation.

It deliberately contains a limited number of behavioural parameters. Structural network characteristics determine the opportunity set available to exporters, while four parameters govern the core adjustment mechanism: the regulatory penalty p, the local and global switching costs e_L and e_G, and the choice-sensitivity parameter β. A fifth parameter, the adjustment horizon H, governs how quickly the trade volume of a surviving replacement relationship reaches its destination volume. These parameters are treated as transparent modelling assumptions, not econometrically estimated coefficients, and are therefore subjected to dedicated robustness analysis.

The baseline values are

$$p = 0.50, \qquad e_L = 0.10, \qquad e_G = 0.20, \qquad \beta = 4, \qquad H = 5. \tag{1}$$

The restriction $e_G > e_L$ reflects the additional frictions associated with establishing trading relationships outside existing economic groups. International-trade research consistently documents the importance of geographic, informational, institutional, and border-related frictions for bilateral trade and market entry (Allen, 2014; Anderson & van Wincoop, 2004; Chaney, 2014; Tinbergen, 1962). The model captures these mechanisms parsimoniously through geographic distance, trade group membership, and differential local and global switching costs without introducing a large set of separately calibrated behavioural coefficients.

3.2 Network View

At the aggregate level, the model can be understood as a repeated transition from the trade network at time t to an adapted trade network at $t+1$:

$$\text{Network}_t \to \text{Partner evaluation} \to \text{Stay or switch} \to \text{Partner selection}$$
$$\to \text{Relationship replacement} \to \text{Trade-volume adjustment} \to \text{Outcomes and network}_{t+1}.$$

This sequence constitutes the baseline behavioural backbone of the model and operates in every simulation period, including in the absence of regulation. Regulation enters Partner evaluation as an additional exogenous condition when it is active for a potential or current importing partner. It changes the attractiveness of regulated destinations but does not activate the adaptation process itself.

The information required to generate the network in period $t+1$ is collected in the model state

$$\mathcal{S}_t = \left\{ \left(A^{c,t}, W^{c,t}\right)_{c \in C}, \mathcal{J}_t, \boldsymbol{\rho}^t \right\}, \tag{2}$$

where $\mathcal{J}_t$ contains the relationship age and destination volume of each replacement relationship that is still undergoing trade-volume adjustment:

$$\mathcal{J}_t = \left\{ \left(i, j, c, a_{ij}^{c,t}, W_{ij}^{c,*}\right) : i \to j \text{ is undergoing trade-volume adjustment at } t \right\}. \tag{3}$$

The adjacency matrices $A^{c,t}$ and trade-volume matrices $W^{c,t}$ describe the current commodity-specific networks. The vector $\boldsymbol{\rho}^t = (\rho_1^t, \ldots, \rho_N^t)$ records the exogenously specified regulatory conditions active in period t. Market potential does not need to be stored separately because it is recalculated from $W^{c,t}$ at the beginning of each period.

Fixed country identities, trade-group assignments, bilateral distances, and deforestation-risk intensities are not part of the time-varying model state. Neither are the behavioural parameters p, e_L, e_G, β, and H, which remain fixed within a simulation run.

For each commodity c, the network is directed and weighted. Its topology is represented by the adjacency matrix

$$A^{c,t} \in \{0,1\}^{N\times N}, \tag{4}$$

where

$$A_{ij}^{c,t} = \begin{cases} 1, & \text{if exporter } i \text{ trades commodity } c \text{ with importer } j \text{ at } t, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

Self-links are excluded, such that $A_{ii}^{c,t} = 0$.

The corresponding weight matrix

$$W^{c,t} \in \mathbb{R}_{\geq 0}^{N\times N} \tag{6}$$

records the simulated trade volume associated with each relationship. Hence,

$$W_{ij}^{c,t} > 0 \quad \text{only if} \quad A_{ij}^{c,t} = 1.$$

The weights should be interpreted as relative trade-volume units and not as predictions of monetary bilateral trade values. Maintaining separate adjacency and weight matrices allows policy adjustment to operate both through the extensive margin meaning the replacement of trading partners and through the intensive margin meaning changes in the realised volume associated with newly established relationships.

Each country is assigned to one of $K = 5$ fixed synthetic trade groups. Let $\kappa(i)$ denote the trade group of country i. Same-group membership is represented by

$$\phi_{ij} = \mathbf{1}[\kappa(i) = \kappa(j)]\,. \tag{7}$$

The groups are deliberately simulated and are not estimated from a historical network. They represent persistent forms of economic embeddedness, including institutional familiarity, established logistics, regulatory compatibility and lower information frictions. Their purpose is to distinguish adjustment within familiar trading structures from more costly cross-group rerouting. This interpretation is consistent with the broader gravity and network literature showing that geography, information and established trading connections are important determinants of international trade (Allen, 2014; Anderson & van Wincoop, 2004; Chaney, 2014; Tinbergen, 1962).

Bilateral geographic distance enters separately from group membership. Let $d_{ij} \in [0, 1]$ denote normalised distance between countries i and j, with larger values representing greater geographic separation. Min–max normalisation ensures that distance is measured on a scale comparable to the other components of the relationship score. The inclusion of distance follows the central implication of gravity models of trade that bilateral trade becomes less attractive as trade frictions associated with geographic separation increase (Head & Mayer, 2014; Tinbergen, 1962).

At initialisation, each exporter i in commodity c is assigned up to

$$\bar{d} = 5$$

trading partners. The initial network is constructed using the same basic economic logic that governs partner attractiveness during the simulation. Initial relationships

therefore reflect trade-group membership and geographic distance. This creates an initial network in which existing relationships are already broadly consistent with the behavioural rules of the model, while still allowing endogenous adjustment as relative market conditions evolve. Market potential is not used directly in the initial partner assignment because it is an endogenous network-level variable that can only be calculated once the initial weighted trade network has been formed. After initialisation, market potential is updated from the current distribution of trade and becomes available for subsequent partner evaluations.

Initial active-link weights are drawn from

$$W_{ij}^{c,1} \sim U(2, 8), \tag{8}$$

introducing heterogeneity in the economic importance of initial trade relationships. These initial trade volumes represent already established relationships at the start of the simulation. They therefore do not enter the trade-volume adjustment process. Trade-volume adjustment applies only to new relationships created through partner replacement during the simulation. To ensure that policy shocks operate on a meaningfully exposed network, each designated regulating importer—the EU, UK and US—is guaranteed at least eight incoming links per commodity layer at $t = 1$. This is an experimental exposure condition, not a behavioural assumption. Without it, the initialisation process could generate a regulator with no incoming relationships and therefore no policy-exposed links, making the corresponding policy intervention mechanically indistinguishable from the baseline.

All scenarios within a simulation start from exactly the same initial network. Differences between scenarios therefore arise only from the timing of regulatory activation and the adaptation induced by those interventions.

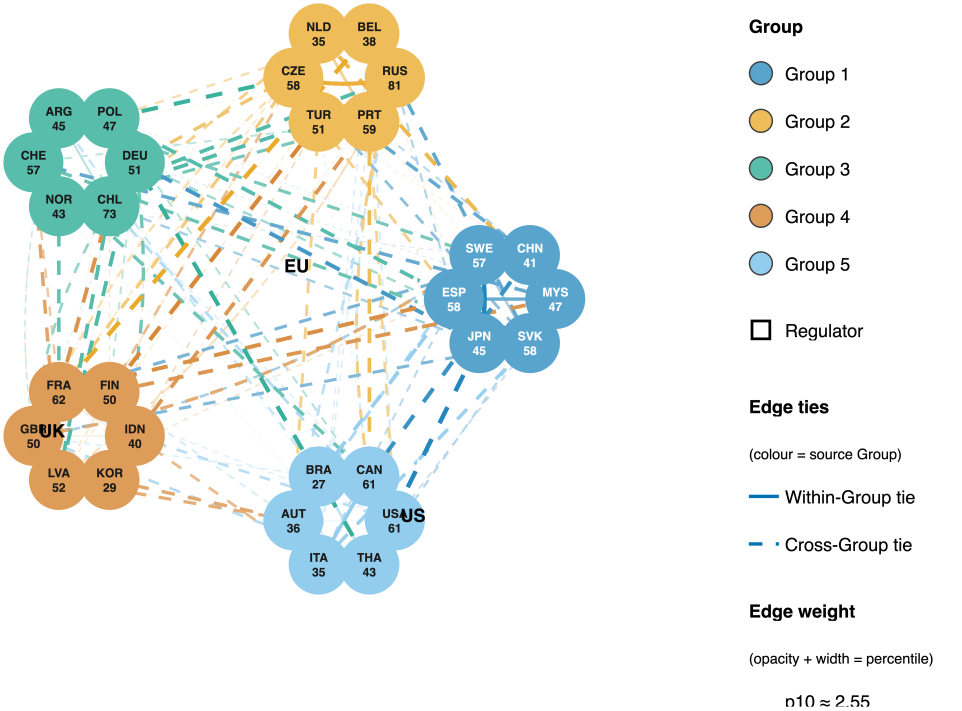


Fig. 2 Initial palm-oil trade network at $t = 1$. Nodes represent country agents and colours indicate fixed synthetic trade groups

Importantly, the baseline network is not static. Even without regulation, exporters repeatedly compare existing relationships with alternative markets. Relationships may therefore be replaced organically when better opportunities emerge. This generates endogenous baseline network turnover against which the additional adaptation caused by regulation can be evaluated. No separate exogenous link-drop probability is required.

Importer-side regulation enters through the indicator

$$\rho_j^t = \begin{cases} 1, & \text{if importer } j \text{ is regulated at } t, \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

Once activated, regulation remains in force. The policy does not mechanically remove trade links or impose an exogenous reduction in trade volume. Instead, it lowers the attractiveness of the regulated importer in exporter decision-making. Any subsequent changes in the network are therefore generated endogenously.

All exporter decisions during period t are evaluated using the same network snapshot $(A^{c,t}, W^{c,t})$. The resulting replacement decisions are then implemented simultaneously, i.e., in a synchronous update. This avoids introducing artificial path dependence through the computational order in which exporters happen to be processed.

After exporter decisions have been implemented, the network moves from

$$(A^{c,t}, W^{c,t}) \quad \text{to} \quad (A^{c,t+1}, W^{c,t+1}).$$

Surviving replacement relationships created in previous periods also advance along their trade-volume adjustment paths during this transition. The updated network is then used to compute economic and environmental outcomes.

The empirically calibrated environmental-risk component is given by exporter- and commodity-specific deforestation-risk intensities

$$\delta_{ic} \in [0, 1].$$

Palm-oil and soy intensities are obtained from Trase supply-chain risk indicators (Trase, 2024), while timber and paper intensities are derived from FAOSTAT forestry production and forest-area statistics (Food and Agriculture Organization of the United Nations, 2024). Because the underlying indicators originate from different data sources and scales, raw values are min–max normalised separately within each commodity layer. The transformation preserves relative cross-country differences within each

commodity while preventing measurement scale from mechanically determining the results. The resulting δ_{ic} should therefore be interpreted as a relative deforestation-risk intensity and not as an estimate of physical hectares of deforestation.

The environmental risk embodied in link (i, j, c) is

$$r_{ij}^{c,t} = W_{ij}^{c,t}\delta_{ic}, \tag{10}$$

and total embodied environmental risk is

$$R_t = \sum_{c\in C}\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}^{c,t}\delta_{ic}. \tag{11}$$

This formulation links the empirically calibrated environmental-risk component directly to the endogenous trade network. Changes in R_t can therefore arise from changes in total realised trade volume as well as from changes in the composition of trade across exporters with different deforestation intensities. Network-based research has similarly shown that embodied environmental pressures are distributed through interconnected trade systems rather than isolated bilateral exchanges (Kanemoto et al., 2014; Pendrill et al., 2019; Sun et al., 2023).

The updated network also generates the model's economic fitness measure, denoted F_t. Fitness summarises the quality of the active trading relationships under the same structural and regulatory environment that exporters use when making their partner decisions. Higher fitness therefore indicates a network composed of relatively attractive trading relationships, while decreases in fitness capture disruption associated with regulatory shocks and network restructuring. Fitness is a model-based measure of network economic performance and should not be interpreted as a monetary welfare estimate.

For exporter i in commodity c, fitness is calculated as the trade-share-weighted score of its active relationships,

$$F_i^{c,t} = \sum_{j:A_{ij}^{c,t}=1} w_{ij}^{c,t} S_{ij}^{c,t}, \tag{12}$$

and aggregate network fitness is

$$F_t = \sum_{c \in C} \sum_{i=1}^{N} F_i^{c,t}. \tag{13}$$

Because the same relationship score enters both exporter decisions and the fitness measure, F_t should be interpreted as an internally consistent measure of network relationship quality rather than as monetary welfare or social surplus.

The critical dynamic feature is that the next regulatory intervention acts on the already adapted network. Thus,

$$\text{shock at } t \rightarrow \text{adaptation} \rightarrow \text{network}_{t+1} \rightarrow \text{possible shock at } t+1.$$

The time intervals between policy shocks consequently give exporters time to redirect trade and allow newly formed relationships to adjust towards their destination volumes. Policy timing therefore changes the network configuration on which subsequent regulation operates.

3.3 Exporter View

The network transition described above is generated by exporter-level decisions. In every period t, each exporter evaluates each of its current relationships against the corresponding set of feasible alternative importers. This Partner-evaluation phase operates in both the Baseline and regulatory scenarios. When regulation is active,

regulatory exposure enters the evaluation as an additional exogenous condition that reduces the attractiveness of the affected importing destinations.

For an existing relationship from exporter i to importer j in commodity c, the share of the exporter's current commodity-specific trade carried by that relationship is

$$w_{ij}^{c,t} = \frac{W_{ij}^{c,t}}{\sum_{m:A_{im}^{c,t}=1} W_{im}^{c,t}}. \tag{14}$$

The relationship score is then

$$S_{ij}^{c,t} = \phi_{ij} - d_{ij} + w_{ij}^{c,t} - p\rho_j^t. \tag{15}$$

The score captures four mechanisms. First, ϕ_{ij} rewards same-group relationships, representing lower informational, institutional and logistical frictions. Second, d_{ij} penalises geographic separation, consistent with gravity-based explanations of bilateral trade (Head & Mayer, 2014; Tinbergen, 1962). Third, $w_{ij}^{c,t}$ rewards economically important existing relationships. Larger trade shares can be interpreted as reflecting accumulated relationship-specific capital, established logistics, contractual arrangements and commercial familiarity; empirical research documents considerable persistence in economically important trade relationships because abandoning them entails sunk and relationship-specific costs (Drozd & Nosal, 2012). Fourth, policy exposure reduces the relationship score through $p\rho_j^t$.

The group, distance and trade-importance terms deliberately enter with equal unit weights. Introducing separate coefficients for each component would add additional unestimated behavioural parameters without improving identification of the mechanism of interest. The regulatory response is instead governed by the explicit policy penalty

$$p = 0.50,$$

whose sensitivity is evaluated separately in the robustness analysis.

Potential partners are evaluated using an analogous score. Before candidate evaluation, importer-specific market potential is calculated from the current network. Total imports received by importer k in commodity c are

$$M_k^{c,t} = \sum_i W_{ik}^{c,t}. \tag{16}$$

Market potential is then normalised relative to the largest importer in the commodity layer:

$$\widehat{w}_k^{c,t} = \frac{M_k^{c,t}}{\max_m M_m^{c,t}}, \qquad \widehat{w}_k^{c,t} \in [0,1]. \tag{17}$$

Market potential acts as an endogenous global variable in the model. It is calculated from the distribution of trade across the entire commodity-specific network and is available to all exporters when they evaluate potential partners. Exporter decisions subsequently change bilateral trade flows, which changes the distribution of imports and therefore market potential in the following period. This creates a feedback between individual exporter decisions and the network-level information used in subsequent decisions.

The Partner Score, market potential, and trade-volume adjustment mechanism perform distinct but interdependent functions. The Partner Score determines the relative attractiveness of existing and potential importing partners and therefore influences with whom an exporter trades. Market potential enters the score of a potential partner as one component of expected economic attractiveness. If a replacement occurs, the market potential of the new importer relative to that of the replaced importer also determines the destination volume $W_{ik}^{c,*}$ of the new relationship. The trade-volume adjustment mechanism does not determine partner choice or the destination volume; it determines how quickly the realised volume of a surviving replacement relationship

moves from $W_{ik}^{c,0}$ towards $W_{ik}^{c,*}$. Exporter decisions consequently change the distribution of trade, which updates importer market potential and feeds back into subsequent Partner evaluation and destination-volume calculations.

A country is a feasible new partner only if it is not the exporter itself, is not already an active partner of that exporter in the commodity layer, has positive current market potential, and has not already been reserved as another replacement partner by the same exporter during the current period. If no feasible replacement exists, the current relationship is retained.

For each feasible candidate $k \in \mathcal{K}_i^{c,t}$, the potential relationship score is

$$\widehat{S}_{ik}^{c,t} = \phi_{ik} - d_{ik} + \widehat{w}_k^{c,t} - p\rho_k^t. \tag{18}$$

Existing and potential relationships therefore share the same scoring structure. The distinction lies in the economic component: existing relationships are evaluated using their realised share of exporter trade, whereas potential partners are evaluated using expected market potential.

The feasible alternatives are then divided into local and global opportunity sets:

$$\mathcal{L}_i^{c,t} = \left\{ k \in \mathcal{K}_i^{c,t} : \phi_{ik} = 1 \right\}, \tag{19}$$

$$\mathcal{G}_i^{c,t} = \left\{ k \in \mathcal{K}_i^{c,t} : \phi_{ik} = 0 \right\}. \tag{20}$$

Instead of evaluating only the single highest-scoring alternative, the model assigns an inclusive value to each opportunity set. This captures the option value associated with having several attractive destinations available. Local opportunity value is defined as

$$V_{i,L}^{c,t} = \frac{1}{\beta} \log \left(\sum_{k \in \mathcal{L}_i^{c,t}} \exp\left(\beta \widehat{S}_{ik}^{c,t} \right) \right) - e_L, \tag{21}$$

and global opportunity value as

$$V_{i,G}^{c,t} = \frac{1}{\beta} \log \left(\sum_{k \in \mathcal{G}_i^{c,t}} \exp \left(\beta \widehat{S}_{ik}^{c,t} \right) \right) - e_G. \tag{22}$$

If a candidate set is empty, its opportunity value is unavailable. The overall value of potential relationships is

$$V_i^{c,t} = \max \left\{ V_{i,L}^{c,t}, V_{i,G}^{c,t} \right\}. \tag{23}$$

The switching costs are

$$e_L = 0.10, \qquad e_G = 0.20, \qquad e_G > e_L.$$

The higher global cost reflects the additional search, information, logistics and institutional frictions associated with moving beyond established trading groups (Allen, 2014; Anderson & van Wincoop, 2004; Chaney, 2014; Tinbergen, 1962). No additional percentage premium is imposed elsewhere in the model. These frictions are represented directly through the difference between e_L and e_G.

The exporter next compares the score of the current relationship with the value of the available alternatives. The decision rule is

$$\text{stay} \quad \text{if} \quad S_{ij}^{c,t} \geq V_i^{c,t}, \tag{24}$$

and

$$\text{switch} \quad \text{if} \quad S_{ij}^{c,t} < V_i^{c,t}. \tag{25}$$

If the exporter does not switch, the existing relationship remains active. Its adjacency entry and trade volume are carried into the network update unchanged, except

where the relationship is itself an earlier replacement link that is still undergoing trade-volume adjustment. Thus, "stay" means that no new partner is formed, not that the relationship is removed or mechanically weakened.

This decision rule also generates organic network turnover in the baseline scenario. Even when $\rho_j^t = 0$ for every importer, changes in market potential and relative relationship attractiveness can cause exporters to replace existing links. Policy shocks therefore operate on top of an endogenously evolving counterfactual and are compared with an endogenously evolving baseline.

If the exporter switches, the first decision is whether adjustment occurs locally or globally. The model selects the candidate pool associated with the higher opportunity value:

$$\mathcal{C}_i^{c,t} = \begin{cases} \mathcal{L}_i^{c,t}, & V_{i,L}^{c,t} \geq V_{i,G}^{c,t}, \\ \mathcal{G}_i^{c,t}, & V_{i,G}^{c,t} > V_{i,L}^{c,t}. \end{cases} \tag{26}$$

A particular importer k is then selected probabilistically from this pool using a softmax rule:

$$P_{ik}^{c,t} = \frac{\exp\left(\beta \widehat{S}_{ik}^{c,t}\right)}{\sum_{m \in \mathcal{C}_i^{c,t}} \exp\left(\beta \widehat{S}_{im}^{c,t}\right)}, \tag{27}$$

with baseline choice sensitivity

$$\beta = 4.$$

The same choice-sensitivity parameter β enters the inclusive opportunity values and the softmax partner-selection rule. Higher values of β place greater weight on the highest-scoring alternatives, while lower values give relatively more weight to the broader candidate set. Sensitivity to β is examined in the robustness analysis.

Switching follows a one-for-one replacement rule. If exporter i replaces partner j with partner k, the old adjacency entry is removed,

$$A_{ij}^{c,t+1} = 0,$$

and the new relationship is activated,

$$A_{ik}^{c,t+1} = 1.$$

The exporter therefore restructures its trading portfolio while preserving the number of partners.

The replacement relationship initially preserves the realised trade volume of the relationship it replaces:

$$W_{ik}^{c,0} = W_{ij}^{c,t}. \tag{28}$$

Market potential determines the destination volume of the replacement relationship. Specifically, this volume depends on the difference between the normalised market potential of the new importer k and that of the replaced importer j:

$$W_{ik}^{c,*} = W_{ij}^{c,t} \left[1 + \left(\widehat{w}_k^{c,t} - \widehat{w}_j^{c,t}\right)\right]. \tag{29}$$

Because both Market-Potential values lie in the interval $[0, 1]$, the multiplicative adjustment factor lies in the interval $[0, 2]$. A new importer with higher market potential than the replaced importer generates $W_{ik}^{c,*} > W_{ik}^{c,0}$. Equal market potential leaves the destination volume unchanged, such that $W_{ik}^{c,*} = W_{ik}^{c,0}$, while lower market potential generates $W_{ik}^{c,*} < W_{ik}^{c,0}$. Trade volume can therefore increase, remain unchanged, or decrease following relationship replacement.

The gradual adjustment of newly established relationships is motivated by international-trade evidence showing that exporters commonly enter new markets at relatively small scales and expand their sales as relationships survive and market information accumulates (Albornoz, Calvo Pardo, Corcos, & Ornelas, 2012). This is also consistent with models of relationship-specific capital, in which establishing and developing trading relationships requires time and accumulated commercial knowledge

(Drozd & Nosal, 2012). These studies motivate the gradual-adjustment mechanism, but do not directly calibrate its speed in the present model.

Conditional on survival, trade volume adjusts linearly from its initial volume towards this destination volume:

$$W_{ik}^{c}(a) = W_{ik}^{c,0} + \min\left(\frac{a}{H}, 1\right)\left(W_{ik}^{c,*} - W_{ik}^{c,0}\right), \tag{30}$$

where a denotes the age of the replacement relationship in years. The baseline adjustment horizon is

$$H = 5.$$

The relationship therefore reaches its destination volume after five years if it survives throughout the adjustment period. The five-year horizon is treated as a transparent baseline assumption rather than as a precisely estimated structural coefficient, and the robustness analysis evaluates alternative horizons of three and seven years.

Simulation time t and relationship age a represent different clocks. The simulation begins at $t = 1$, but a replacement relationship created during the transition from t to $t + 1$ enters the network at $t + 1$ with relationship age $a = 0$. It therefore retains its initial volume in the period in which it is formed. In each subsequent transition, a surviving replacement relationship increases its age by one year and adjusts by the corresponding linear increment. If it is replaced before reaching $W_{ik}^{c,*}$, its adjustment path ends and the newly created relationship begins a separate path at $a = 0$. No separate adjustment-speed parameter η is used in the final model.

This mechanism is particularly important for the paper's policy-timing question. Market potential determines the trade volume towards which a new relationship adjusts, while the adjustment horizon determines how quickly that destination volume is reached. If two regulatory shocks are separated by several years, replacement

relationships created after the first shock have more time to move towards their destination volumes before the next intervention. A more rapid sequence gives the network less time to adjust. Consequently, differences between policy schedules arise not only from which relationships are exposed to regulation, but also from the trade-volume adjustment paths already under way when each subsequent intervention takes effect.

After all exporter decisions have been evaluated against the common period-t network snapshot, the corresponding changes are implemented simultaneously. Existing links that remain active, newly established links, and surviving replacement relationships that are still undergoing trade-volume adjustment together constitute the network at $t+1$. Environmental risk R_{t+1} and economic fitness F_{t+1} are then computed from this new network, after which the next period begins.

3.4 Policy Scenarios

The model compares five policy scenarios. All scenarios use the same initial network, behavioural rules, parameter values and environmental calibration. They differ only in the identity and timing of importer-side regulatory activation.

Three importing jurisdictions are designated as potential regulators: the European Union, the United Kingdom, and the United States. Once regulation becomes active for a jurisdiction, it remains active for the remainder of the simulation. Regulation is an exogenous global condition: its activation periods are specified by the policy scenario and are not determined by exporter decisions or by the evolution of the trade network. Exporters respond to this condition through the score penalty $p\rho_j^t$, but their decisions do not determine whether or when regulation becomes active. Regulation therefore differs from market potential, which is an endogenous global variable generated by the current distribution of trade and updated through exporter adaptation. Regulation changes exporter incentives but does not directly remove trade relationships or exogenously alter trade volumes.

The scenarios are:

1. *Baseline*: no importer introduces deforestation-related regulation during the simulation horizon. Network change arises solely from endogenous exporter adaptation and provides the counterfactual against which policy-induced changes are evaluated.
2. *Early mover*: the EU regulates from $t = 6$, while the UK and US remain unregulated throughout the simulation.
3. *Sequential*: the EU regulates at $t = 6$, the UK at $t = 10$, and the US at $t = 14$.
4. *Coordinated*: the EU, UK and US regulate simultaneously at $t = 6$.
5. *Delayed coordination*: the EU regulates at $t = 6$, followed by simultaneous UK and US regulation at $t = 12$.

The early-mover scenario represents unilateral regulation. The sequential, coordinated and delayed-coordination scenarios ultimately contain the same three regulating jurisdictions and apply the same regulatory penalty. They therefore differ in the temporal architecture through which common regulatory coverage is reached while final policy participation and stringency remain constant.

This design isolates the mechanism of interest. Under simultaneous coordination, all three regulatory shocks affect the same pre-adjustment network at $t = 6$. Under sequential or delayed coordination, later regulators act on networks that have already responded to earlier interventions. In those scenarios, exporters may have redirected trade to different destinations, newly established relationships may still carry reduced volumes, and older replacement relationships may already have partially or fully adjusted towards their destination volumes. Policy sequencing therefore changes both the topology and the maturity structure of the network encountered by subsequent shocks.

The model is consequently designed to examine transition dynamics as well as final network structure. The relevant comparison is not simply whether broader regulatory

participation reduces embodied deforestation. Instead, the model asks whether identical eventual policy coverage produces different economic and environmental outcomes when the network is given different amounts of time to adapt between regulatory interventions.

Table 1 summarises the baseline specification used across all five scenarios.

Table 1 Baseline model specification

Parameter	Interpretation	Baseline	Model role
N	Number of country agents	30	Size of the stylised network
$\|C\|$	Commodity layers	4	Palm oil, soy, timber and paper
K	Trade groups	5	Fixed synthetic economic groups
$\bar{d}$	Maximum initial partners per exporter and commodity	5	Finite portfolio of economically relevant relationships
$W_{ij}^{c,1}$	Initial trade weight	$U(2,8)$	Generates heterogeneous initial relationship volumes
p	Regulatory penalty	0.50	Reduces attractiveness of regulated current and potential partners
e_L	Local switching cost	0.10	Cost of adjustment within the exporter's trade group
e_G	Global switching cost	0.20	Higher cost of cross-group adjustment
β	Choice sensitivity	4	Controls concentration of opportunity valuation and softmax partner selection
H	Trade-volume adjustment horizon	5 years	Time required for a surviving replacement relationship to reach its Market-Potential-based destination volume
T	Simulation horizon	20 years	One period corresponds to one year

The behavioural parameters are not interpreted as empirically estimated coefficients. They are baseline assumptions chosen to represent the economic mechanisms required by the model while keeping the behavioural structure parsimonious. Their influence is evaluated systematically through Monte Carlo and parameter-sensitivity exercises, including alternative regulatory penalties, switching costs, choice sensitivities and adjustment horizons. The environmental calibration is additionally subjected

to a permutation placebo in which deforestation intensities are reassigned across exporters within commodity layers. These exercises distinguish conclusions that follow from the model's adaptive mechanism from results that depend on a particular numerical calibration.

Table 2 distinguishes the empirically calibrated environmental-risk and geographic inputs from the assumed components of the model. This distinction is important for interpreting the simulations as controlled mechanism experiments and not as reconstructions of observed bilateral trade.

Table 2 Provenance of model components

Model component	Status	Source or role
Geographic distance	Empirical	Country coordinates and bilateral distance input
Regulator identities	Empirical	EU, UK and US regulatory nodes
Deforestation-risk intensities	Empirical/semi-empirical	Trase for palm oil and soy; FAOSTAT-based indicators for timber and paper
Network topology	Synthetic	Generated at initialisation to support controlled network experiments
Trade groups	Synthetic	Five fixed groups representing persistent structural frictions
Initial trade weights	Synthetic	Drawn from $U(2, 8)$
Behavioural parameters	Assumed and sensitivity-tested	p, e_L, e_G, β, and H

3.5 Model Evaluation

The model was developed and assessed through a sequential mechanism-verification and robustness process. The first specification introduced endogenous partner evaluation and relationship replacement in the absence of regulation. Probabilistic partner selection was then added through the softmax choice rule, followed by local and global switching frictions. The trade-volume adjustment mechanism was introduced only after the extensive-margin network dynamics had been examined. Importer-side regulation was subsequently added as an exogenous condition affecting partner scores, and

the policy-timing scenarios were introduced in the final stage. The assessment therefore focuses on conceptual grounding, implementation verification, structural plausibility, and sensitivity to modelling assumptions. It does not constitute predictive validation against observed bilateral trade flows.

First, the behavioural structure is conceptually grounded in established empirical regularities of international trade. Partner attractiveness depends on geographic distance, existing trade importance, group embeddedness, and switching frictions, reflecting the persistence and spatial concentration of international trading relationships documented in the trade literature (Chaney, 2014; Drozd & Nosal, 2012; Head & Mayer, 2014; Tinbergen, 1962). The model does not claim that the numerical behavioural coefficients are empirically estimated; their role is to provide a transparent implementation of these mechanisms.

Second, implementation verification is built into the experimental design. All policy scenarios within a given simulation begin from the same initial network. Exporter decisions within a period are evaluated against the same period-t network snapshot and are applied simultaneously, preventing computational ordering from generating artificial path dependence. Common random numbers are used for paired scenario comparisons in the Monte Carlo exercises. The deforestation-intensity permutation test provides an additional internal check: because δ_{ic} enters environmental accounting but not partner choice, its permutation leaves switching and trade-volume dynamics unchanged while altering only calculated environmental risk.

Third, the synthetic network is constructed to contain the structural features required by the mechanism under study: heterogeneous trade volumes, finite exporter portfolios, and both within- and cross-group relationships. These are modelling design features and do not imply that the simulated topology reproduces the observed global

trade network. The exposure guarantee for the EU, UK, and US is likewise an experimental condition ensuring that each regulatory shock acts on an initially exposed network and is not a calibration of regulator centrality.

Finally, uncertainty in the stylised model is evaluated explicitly through multiple calibrations and network realisations. The complete scenario experiment is repeated across 100 independently initialised networks and across alternative specifications of the adjustment horizon, regulatory penalty, switching costs, and choice sensitivity. The environmental allocation is additionally subjected to a within-commodity permutation placebo. Together, these exercises assess whether the reported computational mechanism and the relative performance of policy schedules depend on a particular random network realisation, behavioural calibration, adjustment speed, or environmental-risk assignment. They establish robustness within the model rather than empirical validity outside it.

During the preparation of this manuscript, the authors used ChatGPT by OpenAI to support language editing, manuscript organisation, and consistency checks. The authors subsequently reviewed and edited the resulting material and take full responsibility for the content of the manuscript.

3.6 Robustness and Falsification Tests

Because the network structure is partly synthetic and the behavioural parameters are modelling assumptions rather than econometrically estimated coefficients, the analysis does not rely on a single network realisation or parameter configuration. The baseline simulations are complemented by a set of Monte Carlo robustness, sensitivity, mechanism, and falsification exercises designed to establish whether the policy-timing results arise from the adaptive-network mechanism and not from a particular random draw or numerical calibration.

A central principle of the robustness design is to vary one modelling dimension at a time while leaving the remaining behavioural logic unchanged. For parameter robustness exercises, the same policy scenarios are therefore rerun under alternative parameter values. Within each Monte Carlo replication, all scenarios start from the same initialised network and, where stochastic partner selection is involved, from the same random-number state. This use of common random numbers permits paired comparisons across policy scenarios and prevents differences in stochastic draws from being interpreted as policy effects.

The baseline network is synthetically initialised and therefore represents one possible realisation of the structural trade environment. To ensure that the findings are not driven by a particular topology, the complete set of five policy scenarios is repeated across 100 independently initialised networks. Each replication generates a new network structure and set of initial trade weights, while all five scenarios within that replication begin from the same network.

Let $r = 1, \ldots, 100$ denote the Monte Carlo replication. Scenario effects can then be evaluated within the same network realisation, for example through

$$\Delta R_{s,r} = R^{T}_{s,r} - R^{T}_{\text{Baseline},r}, \tag{31}$$

where s denotes a policy scenario. Analogous paired comparisons are constructed for network fitness, realised trade volume, and switching activity.

The Monte Carlo analysis therefore evaluates both average policy effects and their variation across alternative network configurations. In addition to mean outcomes, the analysis reports dispersion and the frequency with which each policy schedule generates the lowest final environmental risk. This is particularly important because the objective of the model is not to identify a universally optimal sequence for every

conceivable trade network, but to determine whether systematic differences between policy timings emerge across heterogeneous network structures.

The baseline model assumes that a surviving replacement relationship requires

$$H = 5$$

years to reach its destination trade volume. Because the exact speed at which a newly established international trade relationship adjusts towards its potential trade volume cannot be identified directly from the aggregate data used in the model, the trade-volume adjustment mechanism is tested using

$$H \in \{3, 5, 7\}. \tag{32}$$

For each value of H, all five scenarios are evaluated across the same 100 initial-network realisations. The experiment therefore contains

$$100 \times 3 \times 5 = 1500$$

complete simulations. The behavioural decision rule and destination-volume mechanism remain unchanged; only the period required for surviving replacement links to reach their destination trade volume varies.

This test is particularly relevant to the sequencing mechanism because the adjustment horizon determines how far newly established relationships can move towards their destination volumes between successive regulatory interventions. If the relative performance of policy schedules were entirely generated by the five-year baseline assumption, changing H would substantially alter the policy ranking.

The policy penalty p determines how strongly regulatory exposure reduces the attractiveness of regulated importers in both current and potential partner scores:

$$S_{ij}^{c,t} = \phi_{ij} - d_{ij} + w_{ij}^{c,t} - p\rho_j^t.$$

The baseline uses $p = 0.50$. Because this parameter is not structurally estimated, the simulations are repeated for $p \in \{0.25, 0.50, 0.75\}$ while maintaining the same network structure, switching rule, and policy schedules. This exercise evaluates whether the main policy-timing mechanism depends on the assumed strength of the regulatory incentive or persists across weaker and stronger importer-side shocks.

The distinction between local and global adjustment relies on the assumption that adaptation outside an exporter's established trade group is more costly:

$$e_G > e_L.$$

The baseline specification,

$$(e_L, e_G) = (0.10, 0.20),$$

is compared with a lower-friction environment,

$$(e_L, e_G) = (0.05, 0.10),$$

and a higher-friction environment,

$$(e_L, e_G) = (0.20, 0.40).$$

The relative difference between local and global adaptation is therefore preserved while the overall level of switching frictions changes.

As with the adjustment-horizon test, each switching-cost regime is evaluated across 100 initial networks and all five scenarios. This test examines whether the timing result depends on the ease with which exporters can restructure their partner portfolios.

It also allows the analysis to distinguish policy effects that arise in highly flexible trade networks from those that persist when relationship replacement is comparatively costly.

Stochastic partner selection is governed by the softmax parameter β. The baseline uses $\beta = 4$, while robustness specifications consider

$$\beta \in \{2, 4, 8\}. \tag{33}$$

A lower value produces more diffuse partner selection, allowing relatively low-scoring destinations to be selected more frequently. A higher value concentrates probability increasingly on the best-scoring destinations. Repeating the analysis across this range tests whether the policy results depend on a particular degree of stochasticity in exporter choice.

Again, the full design contains

$$100 \times 3 \times 5 = 1500$$

simulations. Because β changes the stochastic partner-selection process rather than the underlying definition of relationship attractiveness, this exercise specifically tests whether the timing mechanism survives alternative degrees of behavioural concentration.

A further exercise examines the mechanism through which changes in the trade network translate into changes in embodied deforestation risk. Recall that

$$R_t = \sum_{c,i,j} W_{ij}^{c,t} \delta_{ic}.$$

Changes in R_t may arise because realised aggregate trade changes following relationship replacement, or because trade becomes redistributed across exporter–commodity pairs with different deforestation intensities. The environmental effect is therefore decomposed into a trade-volume component and a compositional component.

This decomposition is important because the model does not assume that changing importer j mechanically changes exporter-specific intensity δ_{ic}. If a Brazilian soy exporter redirects the same volume from one importer to another, for example, its exporter-specific environmental intensity remains unchanged. Environmental improvements generated by destination switching must therefore arise through the associated trade-volume adjustment or through broader changes in the distribution of trade across heterogeneous exporters.

The decomposition consequently provides a mechanism check on the interpretation of the main environmental results, not an additional behavioural assumption.

The sensitivity of the results to imputed environmental intensities is tested separately by multiplying only imputed values of δ_{ic} by 0.75, 1.00, and 1.25, with values constrained to $[0, 1]$. Directly sourced intensities remain unchanged. The same benchmark network path and random-number state are used under each multiplier, so only environmental accounting changes.

Finally, the environmental calibration is subjected to a falsification test. For each Monte Carlo replication, the empirically calibrated values of δ_{ic} are randomly reassigned across countries within each commodity layer. The permutation preserves the complete marginal distribution of environmental risk for palm oil, soy, timber, and paper, but removes the empirical association between a particular exporter and its deforestation-risk intensity.

Formally, for each commodity c, the placebo intensity vector is

$$\delta_{\cdot c}^{\mathrm{P}} = \mathcal{P}_c\left(\delta_{\cdot c}\right), \tag{34}$$

where $\mathcal{P}_c(\cdot)$ denotes a random permutation of the country assignments within commodity c.

The behavioural parameters remain at their baseline values,

$$p = 0.50, \qquad (e_L, e_G) = (0.10, 0.20), \qquad \beta = 4, \qquad H = 5.$$

The placebo is repeated across 100 network realisations and the five policy scenarios.

This test exploits an important separation within the model: δ_{ic} enters the environmental outcome measure but not exporter partner selection. Consequently, changing the assignment of deforestation intensities should not alter network topology, switching behaviour, or trade-volume paths for an otherwise identical simulation. It changes only the environmental risk attributed to those trade flows. Equality of behavioural outcomes between the original and permuted runs therefore also serves as an internal falsification check on the implementation.

The purpose of the permutation exercise is not to test whether the empirical geography of deforestation is generally irrelevant. Rather, it evaluates whether the central policy results are mechanically driven by a fortuitous alignment between the synthetic network structure and the empirical location of high-deforestation-risk exporters. If the timing effect survives the removal of that alignment, the mechanism can more credibly be attributed to endogenous network adaptation rather than to a specific assignment of environmental intensities.

Taken together, these exercises test the model along four conceptually distinct dimensions: stochastic uncertainty in the initial network, uncertainty in behavioural calibration, uncertainty in the speed of trade adjustment, and dependence on the empirical environmental-risk allocation. The robustness analysis therefore evaluates not only whether the quantitative magnitude of the results changes, but whether the

central conclusion concerning policy timing and adaptive network dynamics survives changes in the assumptions most directly connected to the model mechanism.

4 Results

4.1 Baseline Network Dynamics

The baseline scenario provides the no-policy counterfactual against which all regulatory scenarios are evaluated. Because the trade network adapts endogenously even in the absence of regulation, policy effects are measured relative to the corresponding baseline trajectory rather than relative to the initial network alone.

Across the Monte Carlo simulations, mean final baseline risk increases moderately with the adjustment horizon, from 404.58 at $H = 3$ to 409.88 under the five-year benchmark and 413.59 at $H = 7$. The baseline therefore provides a horizon-specific counterfactual for each policy comparison.

The baseline nevertheless remains an adaptive network. Exporters continue to evaluate existing relationships against feasible alternatives, and relationships can therefore be replaced even without a regulatory shock. This endogenous turnover is important for the scenario comparison because regulation acts on top of a network that would already have evolved in its absence.

4.2 Policy Timing and Network Adjustment

The policy scenarios generate different network and environmental outcomes despite sharing the same underlying computational model. The comparison is therefore designed to identify how differences in implementation timing propagate through an adaptive network, rather than to estimate the effect of a specific observed regulation. Under the benchmark five-year adjustment specification, mean final embodied

deforestation risk across the 100 network realisations is

$$R_T = \begin{cases} 409.88, & \text{Baseline,} \\ 388.40, & \text{Early mover,} \\ 380.24, & \text{Sequential,} \\ 382.48, & \text{Coordinated,} \\ 381.55, & \text{Delayed coordination.} \end{cases}$$

Table 3 Mean final environmental risk across adjustment horizons

Scenario	$H = 3$	$H = 5$	$H = 7$
Baseline	404.58	409.88	413.59
Early mover	368.35	388.40	398.48
Sequential	359.59	380.24	390.39
Coordinated	362.67	382.48	393.27
Delayed coordination	360.39	381.55	391.19

Under the benchmark calibration, all four regulatory scenarios reduce mean final embodied risk relative to the corresponding no-policy network. The differences between the three multi-regulator scenarios are smaller than their differences relative to baseline, but they are economically meaningful because sequential, coordinated, and delayed coordination ultimately involve the same regulating jurisdictions.

At the benchmark specification, sequential regulation produces the lowest mean final risk, followed closely by delayed and coordinated regulation. Sequential is also the lowest-risk policy in 39 of the 100 networks, compared with 29 for coordinated regulation, 28 for delayed coordination, and 4 for the early-mover scenario.

The comparison between delayed and sequential regulation is particularly close. Their mean final risks differ by approximately 1.31 risk units, and delayed coordination produces lower risk than sequential regulation in 48 of the 100 paired networks.

The result is therefore not that a single timing strategy dominates mechanically. Instead, policy timing systematically changes the adjustment path, while the precise ranking of alternative schedules remains conditional on the underlying network structure. Later interventions operate on networks that have already been altered by previous shocks, and the set of existing relationships when the next regulator enters depends on the adaptation generated by earlier interventions.

4.3 Economic Adjustment and Trade-Volume Adjustment

The addition of relationship-level trade-volume adjustment provides an intensive-margin mechanism through which regulatory timing affects outcomes. A newly formed relationship initially preserves the realised volume carried by the relationship it replaces:

$$W_{ik}^{c,0} = W_{ij}^{c,t}, \tag{35}$$

and, conditional on survival, adjusts linearly towards the Market-Potential-based destination volume defined in Equation 29.

Under the benchmark five-year adjustment specification, the environmental decomposition provides direct evidence that this volume-adjustment mechanism is quantitatively important. In the delayed-coordination scenario, mean final realised trade is approximately 2536.43, compared with 2741.78 in the corresponding baseline networks.

This difference arises because policy-induced partner replacement creates relationships whose volumes are still adjusting towards destination volumes that can be above or below their initial volumes. Consequently, a network can already have completed the extensive-margin act of partner substitution while its intensive-margin adjustment remains incomplete.

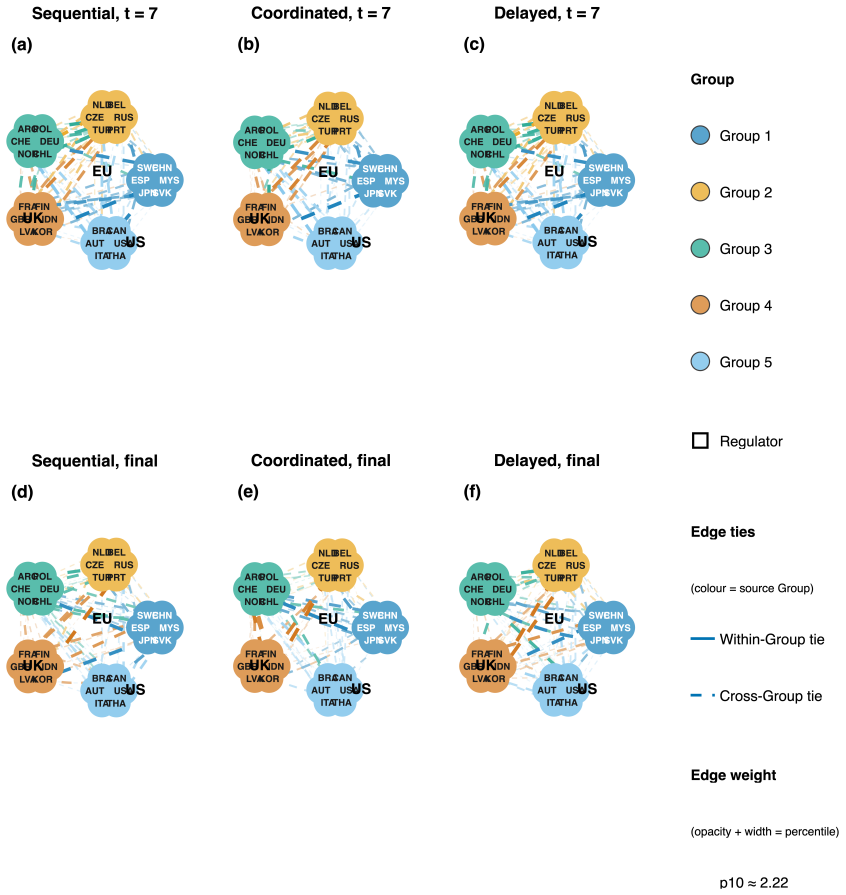


Fig. 3 Evolution of the palm-oil trade network under alternative policy-timing scenarios. Panels (a)–(c) show the network at $t = 7$, immediately after the first regulatory intervention has affected exporter decisions, and panels (d)–(f) show the corresponding final networks. Sequential and delayed coordination share the same regulatory history at this early stage and therefore initially follow the same network path, whereas simultaneous coordination exposes exporters to the complete regulatory regime at $t = 6$. The final panels show how subsequent differences in regulatory timing generate distinct network configurations. Node positions and group assignments are fixed across panels to make network changes directly comparable.

The distinction is important for interpreting policy sequencing. Time between shocks allows surviving replacement relationships to progress along their adjustment paths. A later regulatory intervention therefore encounters not only a different set of partners but also a different distribution of relationship ages and realised trade volumes.

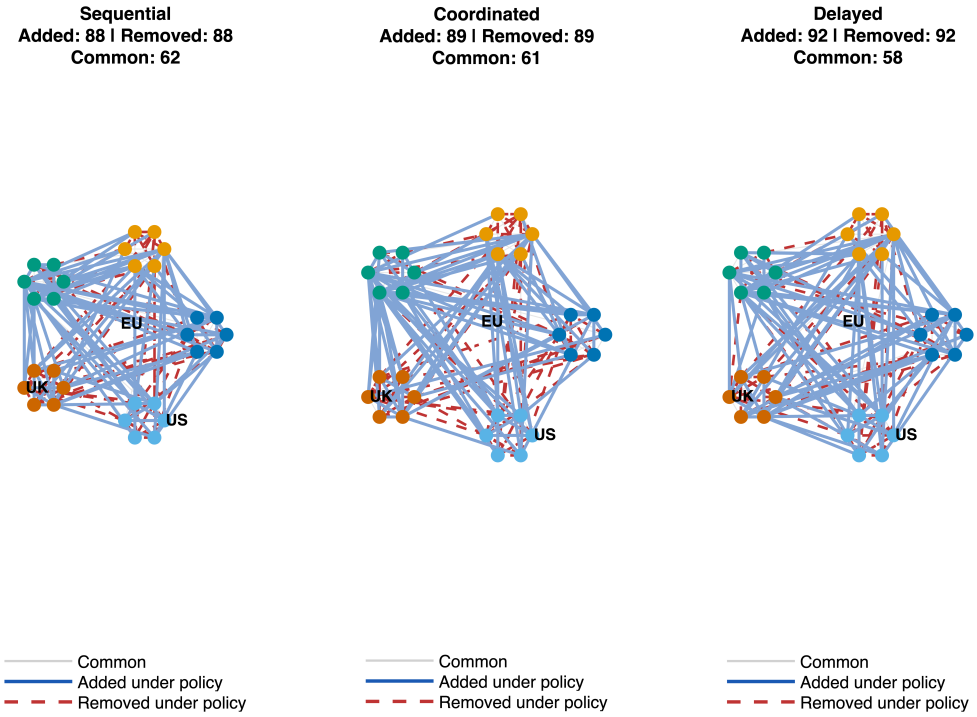


Fig. 4 Final palm-oil network rewiring relative to the paired no-policy baseline. Each panel compares the final network under a regulatory timing scenario with the final network generated from the same initial conditions under baseline evolution. Grey links are common to both networks, blue links are present under regulation but absent from the paired baseline, and dashed red links are present in the baseline but absent under regulation. The figure illustrates that alternative implementation schedules generate different final network structures even when eventual regulatory coverage is identical.

The simulations consequently imply that sequencing operates through two related processes: network rewiring and subsequent trade-volume adjustment within newly established relationships. The amount of adjustment completed before the next intervention affects the network state on which that intervention operates.

4.4 Environmental Outcomes and Mechanism Decomposition

Embodied deforestation risk is defined as

$$R_t = \sum_{c,i,j} W_{ij}^{c,t} \delta_{ic}. \tag{36}$$

Because δ_{ic} depends on the exporter and commodity rather than the importing destination, redirecting a fixed quantity of trade from importer j to importer k does not mechanically lower environmental risk. The environmental effect can instead arise through changes in aggregate realised trade volume and through changes in the distribution of trade across exporter–commodity pairs with different deforestation intensities.

To distinguish these mechanisms, the change in environmental risk relative to baseline is decomposed into a volume effect and a composition effect. The decomposition is exact:

$$\Delta R = \Delta R^{\text{volume}} + \Delta R^{\text{composition}}. \tag{37}$$

Table 4 reports the mean final decomposition across the 100 network realisations and the three adjustment horizons.

Table 4 Decomposition of the policy-induced change in final environmental risk

H	Scenario	ΔR	Volume effect	Composition effect
3	Early mover	-36.23	-36.69	0.46
3	Sequential	-44.99	-45.37	0.38
3	Coordinated	-41.91	-41.40	-0.51
3	Delayed coordination	-44.20	-43.20	-1.00
5	Early mover	-21.48	-23.99	2.51
5	Sequential	-29.64	-31.00	1.37
5	Coordinated	-27.39	-28.80	1.41
5	Delayed coordination	-28.32	-30.78	2.45
7	Early mover	-15.11	-17.45	2.34
7	Sequential	-23.20	-24.68	1.47
7	Coordinated	-20.33	-22.32	1.99
7	Delayed coordination	-22.40	-24.14	1.74

The decomposition produces a clear result. Almost the entire reduction in embodied deforestation risk is generated by the trade-volume channel. Under the benchmark delayed-coordination scenario, for example, the total reduction relative to baseline is 28.32 risk units. The volume component contributes a reduction of 30.78 units, while

the composition component contributes +2.45 units and therefore offsets part of the environmental improvement.

This pattern is not specific to delayed coordination. The volume effect is negative in all 100 network realisations for most scenario–horizon combinations and in at least 98 of 100 realisations in every combination. By contrast, the composition effect reduces environmental risk in only 32–57 of the 100 networks, depending on the scenario and adjustment horizon.

The environmental effect generated by the model should therefore not be interpreted as systematic rerouting towards "cleaner" destinations. Under the benchmark calibration, regulation reduces embodied deforestation risk primarily through the realised volume paths generated as replacement relationships adjust towards destination volumes determined by relative market potential.

This result also clarifies the economic interpretation of the timing mechanism. The spacing of successive regulatory shocks determines how far replacement relationships have adjusted towards their destination volumes before another intervention occurs. The reduction in embodied deforestation-risk exposure therefore depends partly on the intensive-margin transition generated by relationship-level trade-volume adjustment as well as on changes in network topology.

4.5 Robustness

The robustness analysis examines whether the policy-timing result depends on the synthetic initial network or on the main behavioural assumptions governing trade-volume adjustment, regulatory pressure, switching frictions, and stochastic partner selection. A final permutation placebo tests whether the environmental results depend on the empirical country allocation of deforestation intensities.

4.5.1 Initial Networks and Adjustment Horizon

The first robustness exercise jointly varies the initial network realisation and the trade-volume adjustment horizon. The complete five-scenario experiment is repeated across 100 independently initialised networks for

$$H \in \{3, 5, 7\},$$

yielding 1500 simulations.

Mean final environmental risk is reported in Table 5.

Table 5 Mean final environmental risk across adjustment horizons

Scenario	$H = 3$	$H = 5$	$H = 7$
Baseline	404.58	409.88	413.59
Early mover	368.35	388.40	398.48
Sequential	359.59	380.24	390.39
Coordinated	362.67	382.48	393.27
Delayed coordination	360.39	381.55	391.19

Every regulatory scenario produces substantially lower mean final environmental risk than baseline at each adjustment horizon.

Sequential regulation has the lowest mean final risk at all three adjustment horizons. The individual-network rankings nevertheless remain heterogeneous. At $H = 3$, sequential regulation is the lowest-risk policy in 34 networks, compared with 31 for delayed coordination, 29 for coordinated regulation, and 6 for early mover. At $H = 5$, the corresponding frequencies are 39, 28, 29, and 4; at $H = 7$, they are 39, 30, 29, and 2.

The comparison with sequential regulation remains close: delayed coordination generates lower risk than sequential regulation in 51%, 48%, and 41% of networks under $H = 3$, 5, and 7, respectively, despite having a higher mean at each horizon.

The adjustment-horizon exercise therefore supports two conclusions. First, the environmental effect of regulation is robust to heterogeneous initial network structures and alternative adjustment speeds. Second, the precise ranking of the different timing schedules remains network-dependent, particularly when comparing sequential and delayed coordination.

4.5.2 Regulatory-Penalty Sensitivity

The regulatory penalty is varied according to

$$p \in \{0.25, 0.50, 0.75\}.$$

Table 6 reports mean final environmental risk.

Table 6 Mean final environmental risk under alternative regulatory penalties

Scenario	$p = 0.25$	$p = 0.50$	$p = 0.75$
Baseline	409.88	409.88	409.88
Early mover	390.44	388.40	416.21
Sequential	391.28	380.24	417.20
Coordinated	394.08	382.48	417.12
Delayed coordination	390.31	381.55	417.06

The relationship between regulatory strength and environmental risk is non-monotonic. Moving from the weak to the benchmark penalty increases the policy-induced risk reduction, but at $p = 0.75$ all four regulatory scenarios produce slightly higher mean final risk than baseline. The stronger shock induces extensive restructuring and, under the model's endogenous destination-volume rule, raises final realised trade above the corresponding baseline.

At $p = 0.25$, delayed coordination has the lowest mean final risk, 390.31, followed closely by early mover at 390.44 and sequential regulation at 391.28. Sequential

is nevertheless the lowest-risk policy in 31 networks, compared with 29 for delayed coordination, 22 for early mover, and 18 for coordinated regulation.

At the benchmark $p = 0.50$, sequential regulation has both the lowest mean and the highest winner frequency, producing the lowest risk in 39 networks. At $p = 0.75$, early mover has the lowest mean among the policy scenarios, while coordinated regulation is the most frequent lowest-risk policy, with 31 networks, followed by early mover with 30, delayed coordination with 20, and sequential regulation with 19.

The penalty sensitivity therefore identifies an important boundary condition: a stronger regulatory penalty does not necessarily produce a larger environmental improvement once network adaptation and destination volumes are endogenous. Mean policy effects are negative at $p = 0.25$ and $p = 0.50$ but positive at $p = 0.75$.

The adjustment variables clarify this reversal. For delayed coordination, mean total switching rises from approximately 5655 at $p = 0.25$ to 6800 at $p = 0.50$ and 6012 at $p = 0.75$, while mean final realised trade changes from approximately 2608 to 2536 and 2794, respectively. Stronger regulatory pressure therefore changes both network rewiring and the destinations selected, but its environmental effect is not monotonic.

4.5.3 Switching-Cost Sensitivity

The switching-cost robustness exercise compares

$$(e_L, e_G) \in \{(0.05, 0.10), (0.10, 0.20), (0.20, 0.40)\}.$$

All regulatory scenarios retain lower mean final risk than baseline across all three switching-cost regimes. For delayed coordination, the mean environmental-risk reduction relative to baseline increases from approximately 13.53 under low switching costs to 28.32 under the benchmark and 46.64 under high switching costs.

Table 7 Mean final environmental risk under alternative switching costs

Scenario	Low costs	Baseline costs	High costs
Baseline	412.15	409.88	407.29
Early mover	404.21	388.40	364.94
Sequential	398.34	380.24	360.67
Coordinated	399.09	382.48	367.30
Delayed coordination	398.62	381.55	360.65

The switching response changes strongly with adjustment frictions. Mean total switches in the delayed-coordination scenario decline from approximately 7930 under low costs to 6800 under the benchmark and 4432 under high costs.

The lowest-risk timing schedule nevertheless remains conditional on the network and cost regime. Under low switching costs, sequential regulation has the lowest mean final risk, while coordinated regulation is the most frequent winner, in 40 networks. Under benchmark costs, sequential has the lowest mean and is lowest in 39 networks. Under high switching costs, delayed coordination has the lowest mean by only 0.02 risk units and is lowest in 44 networks, compared with 32 for sequential regulation.

Regulatory scenarios produce lower mean final network fitness than baseline under every switching-cost regime. The average fitness gap is largest under low switching costs, where frequent restructuring prevents relationships from settling into high-fitness configurations, and smaller under high switching costs, where fewer relationships are replaced. The economic consequence of regulation therefore depends strongly on adaptation frictions, but the rerun provides no evidence that inexpensive switching raises final fitness above baseline.

4.5.4 Choice-Sensitivity Robustness

Choice sensitivity is varied according to

$$\beta \in \{2, 4, 8\}.$$

Table 8 Mean final environmental risk under alternative choice sensitivities

Scenario	$\beta = 2$	$\beta = 4$	$\beta = 8$
Baseline	447.31	409.88	385.23
Early mover	461.42	388.40	356.20
Sequential	462.13	380.24	351.52
Coordinated	462.06	382.48	358.05
Delayed coordination	462.53	381.55	351.02

The environmental effect depends qualitatively on choice sensitivity. At $\beta = 2$, every regulatory scenario produces higher mean final risk than baseline. At $\beta = 4$ and $\beta = 8$, every regulatory scenario produces lower mean final risk than baseline.

Among the policy scenarios, early mover has the lowest mean final risk at $\beta = 2$, sequential regulation at $\beta = 4$, and delayed coordination at $\beta = 8$. Early mover is the lowest-risk policy in 38 networks at $\beta = 2$; sequential is lowest in 39 at $\beta = 4$; and sequential and delayed coordination are tied at 36 networks each at $\beta = 8$.

Higher choice sensitivity is associated with fewer switches but also lower final environmental risk in these simulations. For delayed coordination, mean total switching falls from approximately 11232 at $\beta = 2$ to 6800 at $\beta = 4$ and 3420 at $\beta = 8$, while mean final risk falls from approximately 462.53 to 381.55 and 351.02.

The fitness results again indicate that adaptation behaviour affects the economic consequences of regulation. Under the rerun specifications, final network fitness varies systematically with choice sensitivity and policy timing.

4.5.5 Deforestation-Intensity Permutation Placebo

The final falsification test randomly reassigns the empirical values of δ_{ic} across countries within each commodity layer while preserving the commodity-specific distribution of deforestation intensities. Because δ_{ic} does not enter exporter partner choice, the permutation changes the environmental accounting but not network behaviour.

The resulting mean final risks are shown in Table 9.

Table 9 Original and permuted mean final environmental risk

Scenario	Original risk	Permuted risk	Effect vs. permuted baseline
Baseline	409.88	408.42	—
Early mover	388.40	383.81	-24.61
Sequential	380.24	376.68	-31.74
Coordinated	382.48	379.19	-29.22
Delayed coordination	381.55	378.14	-30.28

All four policy scenarios continue to generate lower mean environmental risk than the permuted baseline. The mean effects relative to the permuted baseline are -24.61 for early mover, -31.74 for sequential regulation, -29.22 for coordinated regulation, and -30.28 for delayed coordination.

The mean scenario ordering is also preserved:

$$R_{\text{Sequential}} < R_{\text{Delayed}} < R_{\text{Coordinated}} < R_{\text{Early}} < R_{\text{Baseline}}.$$

Under the permuted environmental calibration, sequential regulation is the lowest-risk policy in 39 networks, coordinated regulation in 33, delayed coordination in 24, and early mover in 4. Mean risk remains below the permuted baseline for every policy scenario, although individual policy effects are not negative in every network except under sequential regulation.

Permuting deforestation intensities therefore does not remove the average environmental effect of regulation or the average timing pattern. This result is consistent with the environmental-risk decomposition: the policy-induced reduction in risk is driven predominantly by the trade-volume and adjustment mechanism and not by systematic reallocation towards exporter–commodity pairs with lower deforestation intensities.

A separate calibration check multiplies only the imputed deforestation intensities by 0.75, 1.00, and 1.25 while holding each scenario's network path fixed. All policy scenarios reduce final risk relative to baseline under every multiplier. In this fixed

benchmark network, coordinated regulation has the lowest final risk under all three calibrations. The environmental ranking is therefore insensitive to the scale assigned to imputed intensities within this network, while the Monte Carlo exercises continue to show that rankings vary across network realisations.

4.5.6 Robustness Summary

Taken together, the robustness exercises support a more nuanced conclusion than universal dominance by any one policy schedule. Under the benchmark calibration, regulatory policy reduces embodied deforestation risk relative to the no-policy baseline, and implementation timing affects the resulting transition path. Differences between policy schedules remain observable across alternative initial networks, adjustment horizons, switching-cost regimes, regulatory penalties, choice sensitivities, and environmental-risk allocations. However, the sign and magnitude of the environmental effect are not invariant across all specifications.

The precise ranking of sequential, coordinated, and delayed implementation is contingent. Sequential regulation has the lowest benchmark mean and remains lowest across all three adjustment horizons. Delayed coordination becomes marginally preferable under high switching costs and at the weak regulatory penalty, while early mover has the lowest policy-scenario mean under the strongest penalty and lowest choice sensitivity. Individual network realisations frequently produce different rankings.

The robust result is therefore not that delayed coordination is universally optimal. Rather, the simulations show that policy timing interacts with endogenous network adaptation and relationship-level trade-volume adjustment. Even when regulatory jurisdictions and eventual policy coverage are identical, differences in when shocks arrive alter the network structure inherited by subsequent interventions and thereby change economic and environmental outcomes.

5 Discussion

This study investigates how the timing of importer-side environmental regulation affects an adaptive international trade network. The model is designed as a stylised mechanism experiment rather than as a forecasting or causal-estimation framework. Countries repeatedly evaluate their existing trading relationships against feasible alternative importers, while regulation changes the relative attractiveness of regulated destinations. When switching occurs, relationships are replaced one-for-one and the new relationship initially inherits the realised volume of the displaced relationship before adjusting towards a destination volume determined by relative importer market potential. The central implication is that policy interventions change the network state inherited by subsequent interventions.

The main result is that implementation timing affects transition dynamics even when the sequential, coordinated, and delayed-coordination scenarios involve the same regulating jurisdictions, the same regulatory penalty, and the same behavioural rules. Under simultaneous coordination, all regulatory interventions act on the same pre-adjustment network. Under sequential and delayed coordination, later interventions act on networks that have already experienced partner replacement and trade-volume adjustment. The timing of a policy therefore changes not only when regulation becomes active, but also the topology, relationship ages, trade volumes, and market-potential structure to which subsequent regulation is applied. This provides a mechanism through which identical eventual regulatory coverage can generate different transition paths.

The results do not establish that one implementation sequence is universally optimal. Under the benchmark calibration, sequential regulation produces the lowest mean final embodied deforestation risk, followed closely by delayed and simultaneous coordination. However, the relative ranking varies across network realisations and parameterisations. Sequential, coordinated, and delayed coordination each emerge as

the lowest-risk policy in a substantial proportion of simulations. The robust conclusion is therefore that policy timing is an economically relevant dimension of regulation, not that sequential regulation should be adopted in all circumstances.

This heterogeneity follows directly from the structure of the model. The initial network determines which exporters are connected to regulated destinations, which alternative markets are available, and how attractive those alternatives are. Regulatory interventions then modify partner incentives and induce network changes that affect future market potential. The same later intervention can consequently produce different outcomes depending on the sequence of earlier interventions. In this sense, the model identifies path dependence as an emergent consequence of repeated policy shocks interacting with endogenous network adaptation.

The multilayer specification further qualifies the aggregate results. Timing effects arise in the palm-oil, soy, timber, and paper layers, but the magnitude of the effects and the ranking of policy schedules differ across commodities. The aggregate outcome therefore reflects the combination of heterogeneous commodity-specific network responses. It does not imply direct interaction between commodity layers, since exporter decisions and trade-volume adjustment remain commodity-specific. This distinction is important for policy evaluation: results obtained for one forest-risk commodity should not automatically be interpreted as representative of the wider group of commodities affected by environmental regulation.

The environmental-risk results also require careful interpretation. In the model, deforestation-risk intensity is attached to exporter–commodity pairs and does not depend directly on the importing destination. Redirecting a fixed trade volume from one importer to another therefore does not mechanically reduce environmental risk. The decomposition shows that the benchmark reduction in embodied risk is generated predominantly by changes in realised trade volume, while the composition component is smaller and frequently offsets part of the reduction. The environmental effect

is consequently linked mainly to the intensive-margin adjustment of trade relationships rather than to systematic rerouting towards exporters with lower deforestation intensity.

This mechanism should not be interpreted as evidence that global production has necessarily become environmentally cleaner. The model measures deforestation risk embodied in simulated trade flows, not total production-side deforestation. Production quantities, prices, production technologies, and exporter-specific deforestation intensities are not endogenous. The model therefore cannot determine whether a reduction in embodied trade risk reflects lower production, displacement to other markets, changes in production composition, or genuine improvements in production practices. The appropriate interpretation is that importer-side regulation changes environmental exposure associated with the simulated trade network under the model's specified adjustment rules.

The trade-volume mechanism also explains why the spacing of regulatory interventions matters. A replacement relationship initially preserves the volume of the displaced relationship and subsequently moves towards a market-potential-based destination volume over the adjustment horizon. When interventions are separated by several periods, replacement relationships have more time to adjust before the next shock. A later regulator therefore encounters not only a different set of partners but also a different distribution of relationship ages and realised trade volumes. Policy sequencing affects environmental outcomes through this interaction between network rewiring and the maturity of ongoing volume adjustments.

The robustness analysis supports the existence of this mechanism but does not imply invariance of the environmental effect. The timing result remains visible across alternative initial networks, adjustment horizons, switching-cost regimes, regulatory penalties, choice sensitivities, and environmental-risk assignments. Nevertheless, the sign and magnitude of the policy effect vary in some specifications. At the strongest

regulatory penalty, all regulatory scenarios generate higher mean final risk than the corresponding baseline. The same occurs under the lowest choice sensitivity. These results identify important boundary conditions: a stronger penalty can induce extensive restructuring and redirect relationships towards destinations with higher market-potential-based volumes, while diffuse partner choice can increase switching and alter the resulting trade-volume path.

The non-monotonic penalty response should therefore not be interpreted as evidence that strong environmental regulation is generally harmful. It shows that, within this model, the environmental consequence of a regulatory penalty depends on its interaction with partner-selection behaviour, switching frictions, and the destination-volume rule. Stronger regulation changes the network more substantially, but greater network disruption does not automatically imply lower embodied environmental risk.

The switching-cost results provide a related qualification. Higher switching costs reduce relationship replacement and therefore limit the speed of network adaptation. At the same time, the reduction in policy risk relative to the regime-specific baseline can become larger. This result reflects the joint evolution of policy and counterfactual networks and should not be interpreted as evidence that high switching costs are desirable. Higher frictions may reduce environmental exposure in the simulated trade measure while also limiting economic flexibility and imposing adjustment costs.

The fitness results indicate that the environmental and economic consequences of regulation do not necessarily move in the same direction. Regulatory scenarios produce lower final values of the model-based network-fitness measure than the corresponding baseline in the switching-cost experiments. The difference is largest when switching costs are low, when frequent restructuring prevents relationships from settling into higher-scoring configurations. Fitness is an internally defined measure of relationship quality based on the model's partner-attractiveness score; it is not a measure of GDP,

profit, welfare, or monetary efficiency. The result nevertheless indicates that environmental improvements in the benchmark simulations may be accompanied by disruption in the quality of trading relationships.

The environmental-intensity permutation provides a complementary implementation check. Because δ_{ic} enters environmental accounting but not partner selection, reassignment of intensities across exporters within each commodity layer leaves network topology, switching behaviour, and trade-volume paths unchanged for otherwise identical simulations. The average policy pattern remains broadly similar after this reassignment. This suggests that the average timing result is not driven solely by a favourable alignment between the synthetic network and the empirical distribution of environmental intensities. It does not imply that environmental geography is irrelevant: individual outcomes continue to depend on which exporters carry higher risk, and this dependence could be stronger in observed networks than in the synthetic networks used here.

Several limitations qualify the findings. First, countries rather than firms are the decision-making agents. The model therefore abstracts from firm-level heterogeneity in compliance costs, productivity, contractual relationships, production technologies, and access to alternative markets. Second, the regulatory penalty, switching costs, choice sensitivity, and adjustment horizon are transparent modelling assumptions rather than structurally estimated coefficients. The sensitivity analysis assesses how the results respond to these assumptions, but it cannot substitute for empirical estimation.

Third, the trade topology and group structure are synthetic. Geographic distance, regulatory identities, and environmental-risk inputs are calibrated using external information, but the model is not intended to forecast bilateral trade flows for particular countries. Its results should therefore be interpreted as mechanism-based simulation

evidence. The model demonstrates how path dependence can arise under the specified behavioural rules; it does not estimate the causal effects of the EU, UK, or US regulations in the observed economy.

Fourth, the model does not include endogenous prices, production responses, general-equilibrium feedbacks, or changes in environmental intensity. Producers cannot respond to regulation by changing production methods or reducing the environmental intensity of their output. This limitation is particularly important because the dominant environmental effect operates through realised trade volume. A model incorporating production-side responses could produce different implications for the relationship between regulatory timing, trade diversion, and total environmental damage.

Fifth, the destination-volume mechanism is deliberately parsimonious. Replacement relationships adjust linearly towards a market-potential-based destination volume over a common horizon. Actual relationship development is likely to be nonlinear and heterogeneous across firms, commodities, and destinations. The robustness analysis shows that the timing mechanism survives alternative adjustment horizons of three and seven years, but it does not establish that the assumed adjustment process is empirically correct.

Finally, the model is evaluated through internal implementation checks, common-random-number comparisons, Monte Carlo simulations, sensitivity analysis, and the environmental-intensity permutation. These exercises establish robustness within the model, not predictive validity outside it. Future work should initialise the model using observed multilayer trade networks and compare simulated relationship survival, partner replacement, and volume adjustment with observed country- or firm-level trade data.

These limitations define a clear research agenda. Combining observed trade networks with estimated switching costs, firm-level heterogeneity, endogenous prices,

production responses, and heterogeneous relationship-development processes would allow the mechanism to be tested empirically. Allowing environmental intensities to respond to regulation would also make it possible to distinguish trade suppression, trade diversion, compositional change, and genuine production-side environmental improvement.

The policy implication is not a universal prescription for simultaneous or sequential coordination. Rather, implementation timing should be treated as part of environmental policy design. Where switching costs are high and relationship adjustment is slow, the spacing of interventions may affect both the economic disruption and the environmental exposure inherited by later regulators. Where exporters can redirect trade rapidly, staggered implementation may generate different leakage and volume effects from simultaneous implementation. The appropriate timing strategy is therefore likely to depend on the structure, flexibility, and environmental heterogeneity of the affected trade network.

Overall, the study shows that environmental trade regulation should be analysed as an intervention in an evolving economic network rather than as a one-time shock to fixed bilateral trade flows. Once exporters can redirect relationships and adjust trade volumes over time, the history of previous interventions becomes part of the state of the system. The most robust conclusion is that policy timing changes the transition path. The identity of the preferred policy sequence is less stable and remains conditional on network structure, regulatory strength, choice behaviour, and adaptation frictions. Evaluations based only on eventual regulatory coverage therefore overlook an important dimension of environmental policy effectiveness.

6 Conclusion

This paper develops a stylised agent-based computational model of policy sequencing in an adaptive international trade network, using environmental regulation as

the application. Exporters continuously evaluate existing and potential trading relationships according to group embeddedness, geographic distance, market importance, and regulatory exposure. When alternatives become sufficiently attractive, exporters replace existing partners, preserve the displaced trade volume initially, and subsequently adjust towards Market-Potential-based destination volumes. The simulations show that the timing of coordinated environmental regulation shapes transition dynamics even when participating jurisdictions and eventual regulatory coverage are identical. Under the benchmark specification, sequential regulation produces the lowest mean final embodied deforestation risk across 100 network realisations, followed closely by delayed and coordinated regulation. However, no timing strategy dominates across all networks or parameterisations. Delayed coordination becomes marginally preferable under high switching costs and weak regulatory pressure, while early mover has the lowest policy-scenario mean under the strongest penalty and lowest choice sensitivity. The central result is therefore not a universal ranking of policy sequences, but that policy timing constitutes an economically meaningful dimension of regulation because adaptive trade networks transmit each intervention into the configuration encountered by the next one. The environmental decomposition shows that the benchmark reduction in embodied deforestation risk is primarily an intensive-margin trade-volume effect. Across the benchmark and alternative adjustment horizons, the volume component accounts for most of the mean reduction, while the composition component is smaller and frequently offsets part of it. The permutation placebo likewise preserves lower mean policy risk after environmental intensities are reassigned across exporters. The environmental effect is therefore not driven by a particular alignment between the synthetic network and the empirical distribution of deforestation intensity, but predominantly by network and trade-volume adjustment. The robustness analysis confirms the timing mechanism across independently initialised networks and alternative

adjustment horizons, penalties, switching costs, and choice sensitivities, while identifying important boundary conditions. At $p = 0.75$ and $\beta = 2$, regulatory scenarios produce higher mean risk than baseline. Regulatory scenarios also retain lower final network fitness than baseline across all tested switching-cost regimes.

These findings suggest a distinction that is important for both modelling and policy analysis: the existence of a timing effect is more robust than the identity of the optimal timing strategy. Environmental regulation interacts with the structure and adaptive capacity of the trade network through which it operates. Evaluations based only on final regulatory coverage therefore miss part of the policy mechanism. The results also caution against interpreting reductions in embodied deforestation risk as evidence of environmentally cleaner trade without examining the underlying adjustment channel. In the benchmark model, most of the reduction reflects lower realised trade generated by relationship-level adjustment. Future research incorporating endogenous production decisions, changes in deforestation intensity, prices, and firm-level heterogeneity will be necessary to determine how importer-side regulation divides its environmental effect between trade adjustment, changes in trade composition, and genuine improvements in production-side environmental performance.

More broadly, the paper demonstrates the value of treating international environmental regulation as an intervention in an evolving economic network, not a one-off shock to fixed bilateral trade flows. Once economic agents can redirect relationships and adjust trade volumes over time, the history of previous interventions becomes part of the structure of the system. Policy timing, regulatory strength, choice behaviour, and adaptation frictions therefore jointly determine environmental and economic outcomes. The policy implication is not a prescription for universal simultaneous or sequential coordination. It is that the temporal architecture of international environmental regulation should be treated as part of policy design itself.

Appendix A Model Notation and Parameters

Table A1: Model notation

Symbol	Name	Definition
Indices and sets		
i	Exporter	Exporting country agent.
j	Current importer	Importing country connected to exporter i through an existing trade relationship.
k	Potential importer	Candidate importing country considered as a replacement partner.
c	Commodity	Commodity layer, $c \in C = \{\text{palm oil, soy, timber, paper}\}$.
t	Time	Simulation period. One period corresponds to one year.
$\mathcal{K}_i^{c,t}$	Feasible alternatives	Set of feasible replacement partners available to exporter i in commodity c at time t.
$\mathcal{L}_i^{c,t}$	Local alternatives	Feasible candidate importers belonging to the same trade group as exporter i.
$\mathcal{G}_i^{c,t}$	Global alternatives	Feasible candidate importers outside exporter i's trade group.
$\mathcal{C}_i^{c,t}$	Candidate pool	Local or global candidate set used for probabilistic partner selection after the adjustment mode has been selected.
Network structure and structural variables		
$\mathcal{S}_t$	Model state	Time-varying information required to generate the network and outcomes in period $t+1$, consisting of the adjacency and trade-volume matrices, currently adjusting relationships, and regulatory conditions.

Continued on next page

Table A1 — continued

Symbol	Name	Definition
$\mathcal{J}_t$	Adjusting relationships	Set of replacement relationships still undergoing trade-volume adjustment, including each relationship's age and destination volume.
$A^{c,t}$	Adjacency matrix	Directed binary trade network for commodity c at time t.
$A_{ij}^{c,t}$	Active relationship	Equals one if exporter i trades commodity c with importer j at time t, and zero otherwise.
$W^{c,t}$	Trade-volume matrix	Matrix containing realised trade volumes for commodity c at time t.
$W_{ij}^{c,t}$	Trade volume	Realised trade volume carried by relationship $i \to j$ in commodity c at time t.
$\kappa(i)$	Group assignment	Fixed trade-group membership of country i.
ϕ_{ij}	Same-group indicator	Equals one if countries i and j belong to the same trade group and zero otherwise.
d_{ij}	Normalised distance	Min–max normalised geographic distance between countries i and j, bounded between zero and one.
ρ_j^t	Regulatory status	Equals one if regulation is active for importer j at time t and zero otherwise. The regulatory-status vector is $\boldsymbol{\rho}^t = (\rho_1^t, \ldots, \rho_N^t)$.
Exporter decision variables		
$w_{ij}^{c,t}$	Current trade share	Share of exporter i's commodity-specific trade carried by current importer j: $$w_{ij}^{c,t} = \frac{W_{ij}^{c,t}}{\sum_{m:A_{im}^{c,t}=1} W_{im}^{c,t}}.$$

Continued on next page

Table A1 — continued

Symbol	Name	Definition
$M_k^{c,t}$	Importer demand	Total realised imports received by candidate importer k in commodity c.
$\widehat{w}_k^{c,t}$	Market potential	Normalised demand of candidate importer k relative to the largest importer in the commodity layer.
$S_{ij}^{c,t}$	Current-partner score	Attractiveness score of an existing relationship, combining group membership, distance, realised trade importance, and regulatory exposure.
$\widehat{S}_{ik}^{c,t}$	Potential-partner score	Attractiveness score of a feasible alternative importer, combining group membership, distance, expected market potential, and regulatory exposure.
$V_{i,L}^{c,t}$	Local opportunity value	Inclusive value of feasible same-group alternatives after accounting for the local switching cost.
$V_{i,G}^{c,t}$	Global opportunity value	Inclusive value of feasible cross-group alternatives after accounting for the global switching cost.
$V_i^{c,t}$	Overall opportunity value	Maximum of the local and global opportunity values.
$P_{ik}^{c,t}$	Partner-selection probability	Softmax probability that exporter i selects candidate importer k from the chosen candidate pool.
Trade-volume adjustment		
$W_{ik}^{c,0}$	Initial replacement volume	Trade volume assigned to a newly formed replacement relationship: $W_{ik}^{c,0} = W_{ij}^{c,t}$.

Continued on next page

Table A1 — continued

Symbol	Name	Definition
$W_{ik}^{c,*}$	Destination volume	Market-potential-based volume towards which a surviving replacement relationship adjusts: $$W_{ik}^{c,*} = W_{ij}^{c,t}\left[1 + \left(\widehat{w}_k^{c,t} - \widehat{w}_j^{c,t}\right)\right].$$
a	Relationship age	Age of a replacement relationship, measured in years since its creation.
$W_{ik}^{c}(a)$	Adjusted trade volume	Realised volume of a surviving replacement relationship at age a.
Environmental and economic outcomes		
δ_{ic}	Deforestation-risk intensity	Normalised deforestation-risk intensity associated with exporter i and commodity c.
$r_{ij}^{c,t}$	Link-level environmental risk	Embodied deforestation-risk exposure associated with relationship $i \to j$: $$r_{ij}^{c,t} = W_{ij}^{c,t}\delta_{ic}.$$
R_t	Total environmental risk	Aggregate embodied deforestation-risk exposure across all countries and commodity layers.
$F_i^{c,t}$	Exporter–commodity fitness	Trade-share-weighted quality of exporter i's active relationships in commodity c.
F_t	Network fitness	Aggregate relationship-quality measure across exporters and commodities. It is a model-based performance measure and not monetary welfare.

Continued on next page

Table A1 — continued

Symbol	**Name**	**Definition**
Q_t	Total realised trade	Total realised trade volume across all active relationships and commodity layers.
ΔR	Environmental-risk change	Difference in embodied deforestation-risk exposure between the relevant policy scenario and comparison case.
ΔR^{volume}	Volume component	Component of the environmental-risk change associated with differences in realised trade volume.
$\Delta R^{\text{composition}}$	Composition component	Component associated with differences in the allocation of trade across exporter–commodity pairs with different deforestation-risk intensities.

Table A2 Model parameters and structural assumptions

Symbol	Description	Baseline	Classification
p	Regulatory penalty applied to regulated importers	0.50	Behavioural parameter
e_L	Local switching cost	0.10	Behavioural parameter
e_G	Global switching cost	0.20	Behavioural parameter
β	Choice sensitivity in opportunity valuation and partner selection	4	Behavioural parameter
H	Trade-volume adjustment horizon	5 years	Behavioural/dynamic parameter
N	Number of country agents	30	Structural assumption
$\|C\|$	Number of commodity layers	4	Structural assumption
K	Number of trade groups	5	Structural assumption
$\bar{d}$	Maximum number of initial partners per exporter–commodity pair	5	Structural assumption
$W_{ij}^{c,1}$	Distribution of initial active-link trade volumes	$U(2, 8)$	Initialisation assumption
T	Simulation horizon	20 years	Experimental design
–	Minimum incoming links to each regulating importer in each commodity at $t = 1$	8	Experimental exposure condition

The distinction between model variables and free parameters is important. Although the multilayer network requires a relatively large set of state and derived variables, the behavioural specification is deliberately parsimonious. Exporter behaviour is governed by five parameters: the regulatory penalty p, local and global switching costs e_L and e_G, choice sensitivity β, and the relationship-adjustment horizon H. The remaining quantities in Table A2 define the synthetic network structure, initialisation, or experimental design and do not govern exporter behaviour.

Uncertainty surrounding these behavioural assumptions is examined through the robustness analysis, which varies the regulatory penalty, switching-cost regime, choice sensitivity, and adjustment horizon, while stochastic uncertainty in the synthetic network is evaluated across independently initialised network realisations.

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Data and Code Availability

The MATLAB code, model inputs, scenario definitions, robustness and falsification tests, and scripts required to reproduce the results and network figures are publicly available at https://github.com/Julia-0306/Policy_Timing_ABM.