Emergence and collapse of trade networks from first principles: an agent-based modeling simulation

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ABSTRACT

This paper introduces a first-principle agent-based model of trade networks, where agents are cities or delimited geographical areas that extract resources, sustain populations, and exchange surplus across distance with evolving trade ties. The model reproduces two key dynamics. First, trade links emerge through a percolation-like transition with the increase in trade propensity or transport efficiency rises, and the connectivity expands until constrained by resource and spatial limits. Second, targeted node removal experiments show that highly connected regimes are fragile to shocks, while more localized and redundant structures preserve resilience. These results highlight a fundamental trade-off between efficiency and robustness, offering a clear benchmark to study the emergence, persistence, and collapse of trade networks in both modern and historical times.

KEYWORDS

agent-based model, trade network, emergence, collapse, cliodynamics, simulation

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1 INTRODUCTION

Throughout history, advances in transport and communication technologies have played a decisive role in shaping the trade networks: improvements in maritime navigation, caravan routes, or later steamships and the telegraph, all created sudden expansions in connectivity [36]. These innovations enabled flows of goods and information across distances that were previously prohibitive. As a result, local exchanges could turn into regional or even intercontinental networks [49, 55]. The technological capacity to reduce distance frictions has often marked critical turning points in the organization of trade [1, 22]. Yet, such networks have not been permanent or guaranteed to persist. Historical evidence shows that they can collapse or undergo deep crises [26]. Prominent examples are the collapse of Late Bronze Age trade systems, where a dense web of interactions suddenly stop to exist [16], and the financial crisis of 1857, often regarded as the first global financial crisis, enabled by faster travel and communication technologies [20].

The broader problem addressed here is to understand the dynamics of trade networks: how they emerge [56], how they expand under technological improvements [1], and how they may collapse under stress [23]. Trade networks can be seen as complex systems where local interactions aggregate into global patterns [58], and their resilience is not only a matter of economic flows but also of systemic structure and connectivity [61]. Despite their importance, no minimal framework exists to explain both the emergence and the collapse of trade networks.

In this paper, we address this gap adopting a "first principles" approach [13], presenting a stylized netwoek-based agent-based model of commercial entities (cities or circumscribed geographical areas) that extract resources, hold stock, and sustain populations while forming and losing trade ties. We simulated this model, observe under which condition a trade network emerges, and tested its behavior when the when the node with the higher population was removed.

Despite its simplicity, the model generates two notable dynamical behavior. First, as a global propensity to trade increases, the system crosses a connectivity threshold reminiscent of percolation: many links become simultaneously active once incentives are greater than distance frictions related to travel technology. Improving travel technology through weaker distance decay produces a non-monotonic response: connectivity initially rises, then concentrates along high-throughput corridors that reduce redundancy. The second finding is that, with this highly integrated regime, shocks propagate widely and the system is vulnerable to collapse. On the other hand, with less traveling capacity, and so an higher difficulty to trade to a distant place, flows remain more local and redundant, phases are less synchronized, and the aggregate population is more resilient to the main node removal. These patterns arise endogenously from growth, depletion, and conservative stock reallocation, without strategic behavior or equilibrium assumptions.

The paper proceed as it follows. Section 2 reviews related work on coupled resource–population dynamics and trade kernels. Section 3 details the model and experimental design. Section 4 reports results on network emergence, the effect of travel technology, and shock responses via node removal. Section 5 discusses mechanisms and implications for resilience, while Section 6 concludes and lists avenues for empirical calibration and further exploration.

2 BACKGROUND

The study of population–resource dynamics spans two centuries. Malthus linked population pressure to subsistence limits [43], and Verhulst formalized self-limiting growth with the logistic law [57]. Lotka and Volterra added predator–prey feedbacks that generate oscillations and instability [42, 59]. Spatial structure followed from von Thünen's transport-cost model [60], later refined by gravity and entropy-maximizing formulations ensuring feasible flows [62]. From the 1980s, coupled-map lattices showed that simple logistic elements with diffusive coupling can yield synchronization, clustering, and chaos [31, 32]. Network synchronization theory then tied

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global stability to graph spectra [5, 7, 45], shaping later resource–trade models.

Gravity models provide a central framework for bilateral trade, with flows scaling with economic size and decaying with distance, from Tinbergen's empirical formulation to structural versions that account for multilateral resistance [4, 27, 54]. Estimation advances established Poisson pseudo-maximum likelihood for heteroskedastic, zero-inflated flows [50]. Supply-side foundations linked gravity to technology via heterogeneous-productivity Ricardian models [21]. New economic geography explained agglomeration and core–periphery outcomes under trade costs [29, 38]. Historical and archaeological work used entropy-maximizing interaction to recover hierarchies [46, 63]. Network analyses documented heavy tails and clustering [18, 48, 52].

Over the past two decades, the study of trade and resource networks has converged with advances in complex systems and network science. Multilayer and adaptive networks clarified how co-evolving node states and links drive systemic transitions [11, 25, 34]. Within economics, global value chain research employs network representations to analyze interdependencies and shock vulnerability [15, 19]. Empirical studies show that with globalization the world trade network became more modular yet increasingly synchronized, amplifying crisis propagation [3, 17, 30]. Parallel work in ecology and coupled human–natural systems examined how over-connectivity erodes resilience and facilitates collapse [28, 39, 51]. Archaeological modeling of maritime networks finds that improved mobility can first enhance integration and later destabilize systems by concentrating flow through hubs [12, 24, 35]. Methodologically, these developments emphasize parsimonious, non-equilibrium formulations with explicit constraints and spatial coupling.

Recent work connects dynamics, resilience, and evolving topology with new evidence and tools. Supply disruptions propagate through input–output and trade networks, shaping aggregate outcomes and recovery [2, 14, 19]. Structural shifts include re-centralization, modularity changes, and clustering that alter shock transmission [17, 30, 37, 41]. Multilayer and adaptive frameworks formalize co-evolution and identify when added connectivity enhances efficiency versus undermines robustness [11, 25, 33, 34, 40]. Cross-domain analyses offer early-warning signals and motif-level diagnostics for cascading risk and heterogeneous resilience [28, 39, 51, 65]. Economic complexity maps capability diffusion and green diversification constraints [6, 53]. Maritime assessments document technology-driven topology changes with implications for redundancy and systemic risk [44]. Together, these advances support transparent, feasibility-preserving dynamics compatible with data-driven evaluation [9].

The present model unifies resource–population dynamics [47] and trade interaction within a discrete-time [10], first-principles framework that remains transparent and fully dynamical. Unlike structural gravity models that impose equilibrium or welfare consistency [4, 21] and network analyses that describe rather than generate connectivity [18, 52], this formulation derives network evolution directly from relative stock disparities, transport frictions, and conservative reallocation rules. It extends classical coupled-map approaches [31, 32] by incorporating heterogeneous endowments, spatial geometry, and adaptive link reinforcement that allow the trade structure to evolve endogenously. In contrast to archaeological or agent-based reconstructions that rely on behavioral heuristics [35, 46], all coordination and collapse here arise from intrinsic feedbacks between growth, depletion, and exchange. The system exhibits two key transitions consistent with empirical evidence: a percolation-like densification of trade links as incentives overcome distance decay, and a non-monotonic effect of travel efficiency in which reduced friction first promotes integration and later concentrates flows through fragile hubs. These results parallel recent findings on modular-to-hub transitions and resilience loss in global and historical networks [15, 19, 41, 65], providing a concise, reproducible benchmark for studying synchronization, robustness, and systemic collapse in evolving trade systems.

3 METHODS

The methodology section divides in three section: first, the agent-based model is described; second, the modeling hypothesis are explicated; third, the experimental design used to generate the results is presented.

3.1 Model description

This theoretical agent-based model provides a stylized representation of a system of cities or distinct geographical regions in which populations can grow and engage in trade. Its purpose is to capture the minimal mechanisms underlying the emergence and persistence of a trade network when only a single type of resource is considered. Time is discrete and the model last T time steps. Agents are the nodes of the trade network, and they are indexed by $i, j \in 1, \ldots, N$, where n is the number of nodes, and stand for cities or defined geographical areas, which have three properties: resource dotation r_i, a resource stock $s_i(t)$ and a population $p_i(t)$. The resource dotation r_i is a parameter and stands for the availability of natural resources in the specific node. The stock $s_i(t)$ represent the amount of extracted resources while the population stands for the number of people living there at the node i. The resources and the population are assumed to be homogeneous, so that there is no distinction of resource type, individuals' age or any other features. The distances between nodes are collected in a symmetric matrix D with $d_{ii} = \infty$ to rule out self–trade and $d_{ij} > 0$ to maintain physical sense. Each nodes have a certain level of commerce relationship which is stored into a relationship matrix $A(t)$.

At each step, the model updates (i) stocks via extraction and consumption, (ii) population via stock–limited growth, (iii) bilateral trade flows and their stock effects, and (iv) the trade relationship matrix.

(i) Resource extraction and consumption. Both a linear resource inflow and linear per–capita consumption are assumed; this keeps the mechanism clear and avoids curvature or a dependency of the results to specific production functions. Stocks obey the following equation

$$s_i'(t) = \max\left(s_i(t) + \delta r_i - \gamma p_i(t),\ 0\right) \tag{1}$$

where γ is the per–capita resource consumption and δ is the extraction rate. $s_i'(t)$ is the resources updated stock on which the actual stock $s_i(t)$ is later computed with trade.

(ii) Population dynamics with stock–limited carrying capacity. Population growth is logistic–like, with the effective carrying capacity limited by current stocks $s_i(t)$. More specifically the portance of the system is

$$k_i(t) = \min\left(p_{max}, s_i(t) + 1\right) \tag{2}$$

and the limited growth is computed as

$$g_i(t) = \alpha\Big(1 - \frac{p_i(t)}{k_i(t)}\Big), \tag{3}$$

and consequently update

$$p_i(t+1) = p_i(t)\big(1 + g_i(t)\big) \tag{4}$$

where α is natural population growth rate. The $s_i(t) + 1$ inside $k\_i(t)$ is a numerical regularizer that prevents division by zero when stocks are depleted. The form ensures growth is positive when populations sit below the local capacity and negative when they overshoot it.

(iii) Endogenous trade formation and stock reallocation. Trade is directed from stock–rich to stock–poor cities, attenuated by distance and facilitated by existing relationships. Let $\Delta s_{ij}(t) = s_i(t) - s_j(t)$ and define the relative disparity

$$\tilde{\Delta} s_{ij}(t) = \begin{cases} \dfrac{\Delta s_{ij}(t)}{\max\big(s_i(t), s_j(t)\big)}, & \max\{s_i(t), s_j(t)\} > 0, \\ 0, & \text{otherwise.} \end{cases}$$

So, a raw unnormalized trade preference from i to j is

$$m_{ij}(t) = \begin{cases} \beta\, \tilde{\Delta} s_{ij}(t)\, \dfrac{a_{ij}(t)}{d_{ij}^{\eta}}, & \Delta s_{ij}(t) > 0 \text{ and } i \neq j, \\ 0, & \text{otherwise,} \end{cases} \tag{5}$$

where β is overall trade inclination of the system and η is a distance–decay exponent that stands as a proxy for transport technology. These equations encode four different elements: (1) only stock–rich to stock–poor flows ($\Delta s_{ij} > 0$), (2) a linear effect of trade inclination β to avoid scale effects, (3) gravity–like distance friction with exponent η, where an higher η means trade is more local, and (4) a positive effect of an already existence relationship on the overall trade ($a_{ij}(t)$). We then normalize outflows so that no node can ship more than it both intends and possesses. Let $l_i(t) = \sum_j m_{ij}(t)$. Actual trades are

$$c_{ij}(t) = \begin{cases} 0, & l_i(t) = 0, \\ m_{ij}(t)\, \dfrac{\min\big(s_i(t), l_i(t)\big)}{l_i(t)}, & l_i(t) > 0. \end{cases} \tag{6}$$

Stocks are then recomputed by net trade:

$$s_i(t+1) = \Big[s'_i(t) + \sum_j c_{ij}(t) - \sum_i c_{ij}(t)\Big]. \tag{7}$$

(iv) Relationship reinforcement and decay. Trade ties reinforce with diminishing returns and also decay in the absence of interaction. We update

$$a_{ij}(t+1) = \Big(a_{ij}(t) + \rho \log\big(1 + c_{ij}(t)\big)\Big)(1 - \zeta). \tag{8}$$

The logarithm keeps reinforcement sublinear and models the fact that large one–off shipments do not create unrealistically strong ties, while ζ stands for institutional forgetting or maintenance costs.

3.2 Modeling hypothesis

The model is a stylization of both complex and complicated systems with many features. We simplify it in order to make it analyzable and to observe the overall effect of only some specific phenomena. We have therefore developed a set of modeling hypotheses, which are explicated in this section. First, both resource extraction and consumption are linear and stock-limited, as this is the simplest way to couple demography to subsistence without hiding behavior behind arbitrary nonlinearities. Second, the gravity-style trade assumes that the farther a node is, the harder it is to reach. This is standard and interpretable. Third, the row-wise normalization enforces feasibility and represents the need for shipping availability while preserving relative propensities. Fourth, the updating of trade links—balancing relationship learning and forgetting—captures the well-known path dependency in trade. Moreover, population growth in each city follows logistic dynamics up to a carrying capacity, and no competition or other constraints preventing commerce between cities are assumed. Finally, the time step is left unspecified; however, since the analysis focuses on long-term dynamics, disruptive events are assumed not to influence long-run growth trajectories.

3.3 Experimental design

The model was implemented in Python and executed with Python 3.13.7 in a Jupyter notebook. Numerical computations were carried out using NumPy v.2.3.3, while visualizations were produced with Matplotlib v.3.10.6. The full codebase, including the model, the experimental runs, and the visual outputs presented in this paper, is openly available in the associated repository, available at this link: https://anonymous.4open.science/r/tradenetworkmodel-DA73/. This setup was chosen to ensure maximum reproducibility of the work. For the experiments, a specific combination of parameters was identified to generate the target behavior. Table 1 reports this configuration, and the repository also includes a preliminary exploration of alternative parameter values.

4 RESULTS

This section shows the main results, that are the emergence of a network of trade relations and the impact of improvements in travel technology.

4.1 Commercial network emergence

Figure 2 shows two regimes separated by a sharp crossover in the trade propensity β. For low β ($\lesssim$ 0.1) the average number of active partners per city (mean degree) is near zero. As β rises into $\sim$ 0.1–0.3, connectivity increases abruptly—consistent with a percolation-like transition where many links become simultaneously viable once trade incentives outweigh distance friction and limited stocks (see Figure 3 for a detail). Beyond a critical region $\beta_c \approx$ 0.3–0.5, the slope flattens and the mean degree sits on a broad plateau, indicating nil sensitivity: additional propensity to trade does not translate into more realized connections.

Table 1: Model parameters and initialization ranges.

Symbol	Value / Range	Description
n	50	Number of cities.
α	0.002	Natural population growth rate.
β	0.5	Trade propensity.
γ	0.03	Per-capita resource consumption.
δ	10	Stock extracted per resource unit.
η	0.5	Distance–decay exponent (transport effici
ρ	1	Relationship reinforcement rate.
ζ	0.01	Relationship decay rate.
$p_{\max}$	20000	Bare carrying-capacity cap per city.
T	5000	Maximum time steps.
R_i	$[1,\ 10]$	Exogenous resource availability (city-spec
D_{ij}	$[5,\ 100]$	Inter-city distance bounds; symmetric, D_{ii}
$S_i(0)$	$[500,\ 1000]$	Initial stock per city.
$P_i(0)$	$[500,\ 1000]$	Initial population per city.

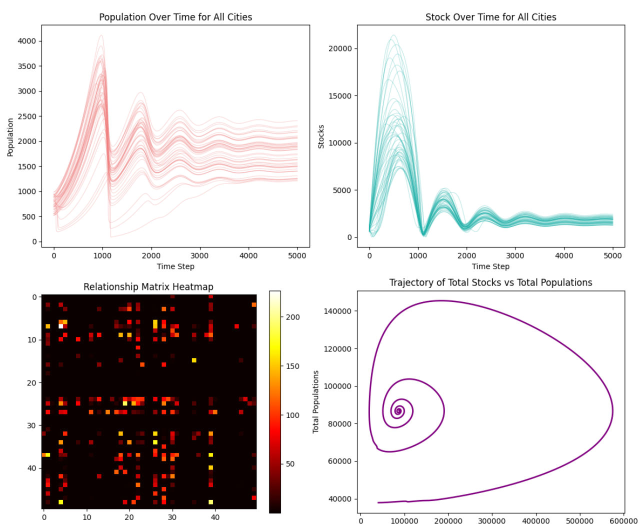

Figure 1: Example of simulation model results with a run using the parameters specified in the Table 1

Mechanistically, this saturation can be explained. Shipments are row-normalized and stock-bounded; once most feasible rich-poor dyads (given resources, η distance decay, and network size) are already active, increasing β only rescales propensities that are immediately clipped by stock budgets and distance penalties. In short, the system becomes supply-/geometry-limited rather than propensity-limited, hence the "phase transition" from rapid densification to a connectivity plateau.

Figure 4 depicts population dynamics across cities at three trade propensities. Each panel plots $p_i(t)$ for all cities. With no trade ($\beta = 0$), trajectories exhibit sizeable, city–specific boom–bust oscillations and long transients; phases and amplitudes differ widely, while at intermediate coupling ($\beta = 0.30$), oscillations persist but phases begin to synchronize and amplitudes shrink; also, cross–sectional

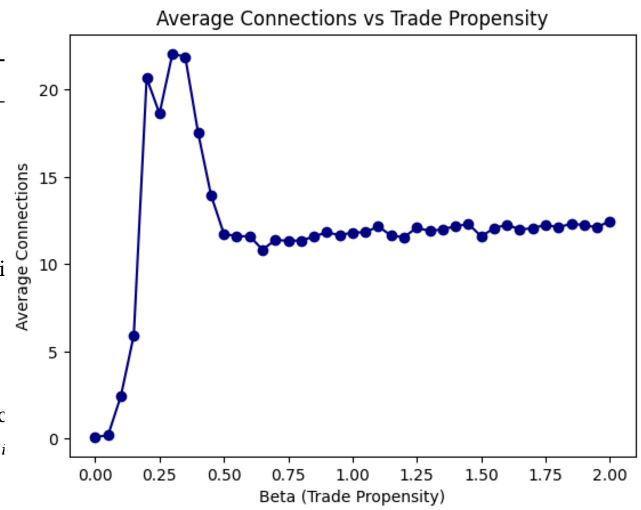

Figure 2: Different average nodes connection with respect with the trade propensity β

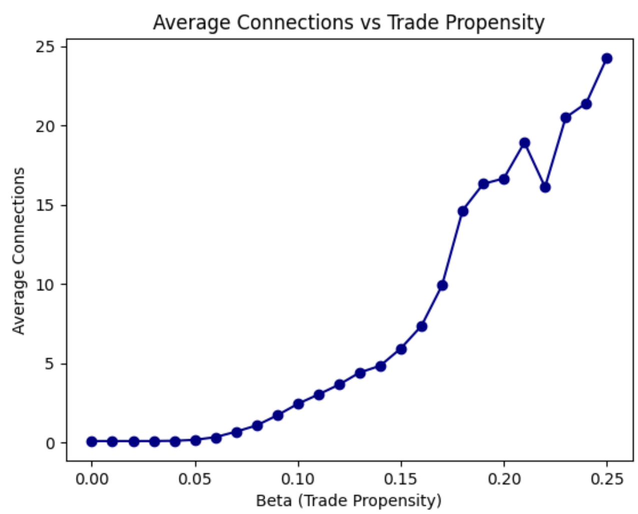

Figure 3: Zoom of the different average nodes connection with respect with the trade propensity β, with $0 \le \beta \le 0.25$

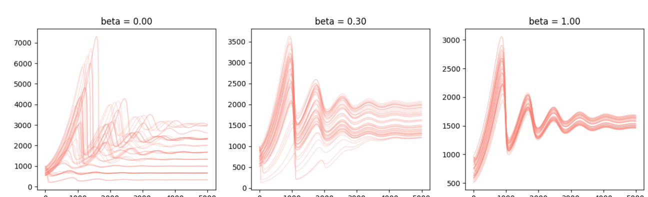

Figure 4: Nodes' population time-series for different values of trade preference β

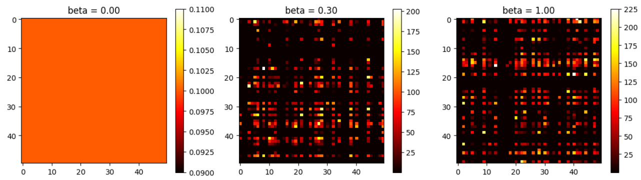

Figure 5: Heatmap of the commerce relationship strength a_{ij} for each for different values of trade preference β

dispersion narrows. At higher coupling ($\beta = 1.00$), the system is effectively phase–locked and behaves more like a single node: cities oscillate in near unison around a common level with markedly reduced amplitude and spread.

One can observe that increasing β turns exchange into a diffusive coupling on stocks: rich to poor shipments damp local overshoots and fill deficits, pushing cities toward a shared effective carrying capacity. Because shipments are budget– and distance–constrained, the coupling acts as both (i) damping (less overshoot) and (ii) synchronizing (phase alignment via resource mixing). Relationship level a_{ij} further stabilizes active channels, sustaining the coupling over time. The net effect is a transition from many weakly coupled, heterogeneous oscillators to a strongly coupled, synchronized ensemble with lower variance.

Figure 5 pairwise interaction structure at three trade propensities, presenting the network of relationship. Namely, each panel shows the pairwise matrix across cities (colors = interaction intensity over the run). With $\beta = 0$, the matrix is flat at its baseline value: no shipments occur by construction when there is no trade inclination between nodes, so commercial ties never grow. At $\beta = 0.30$, a sparse but heterogeneous pattern emerges: many short-range dyads activate and stabilize, and $\beta = 1.00$ the network changes little, with a little increase in the connection. Increasing β first pushes the system through a connectivity onset, since links become viable once incentives beat distance, then into a capacity-limited regime where row-normalization and finite stocks clip further expansion.

4.2 Travel technology effect

Figure 6 presents the average connectivity as a function of the distance–decay exponent η, a parameter that increases the penalization of distance and stands for the travel technology; therefore, better travel technology corresponds to smaller η. The curve shows three regimes with a sharp transition. For scarse technology ($\eta \gtrsim 1$), average degree is near zero because distance suppresses most trades. As η decreases toward 0.7, the distance penalty relaxes and connectivity rises abruptly to a peak, consistent with a percolation-like transition. Finally, when η becomes very small and distance is almost irrelevant, the network does not continue to densify: mean degree drops from the peak as shipments concentrate along more high-throughput corridors. The outcome is a more connected and efficient network—fewer links, with lower average weights better distributed.

Figure 7 confirms the interpretation offered earlier: aggregate population remains high and fairly flat for most values of η (about 8.2–8.6×10^4 here), but decreases sharply in a narrow band around the connectivity peak (roughly $\eta \approx 0.65$), where it drops to nearly

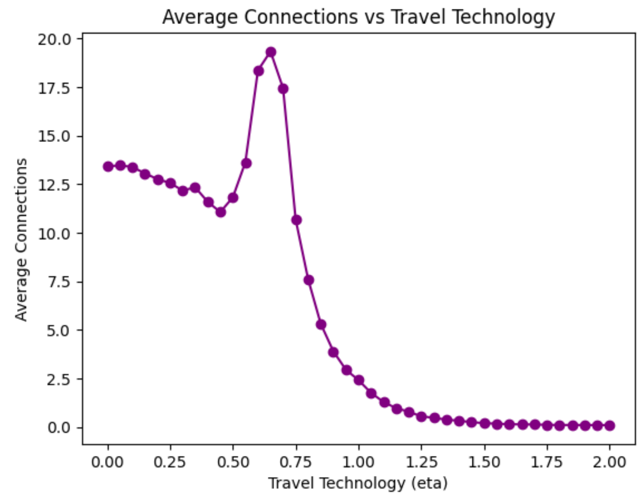

Figure 6: Different average nodes connection with respect with the travel technology η

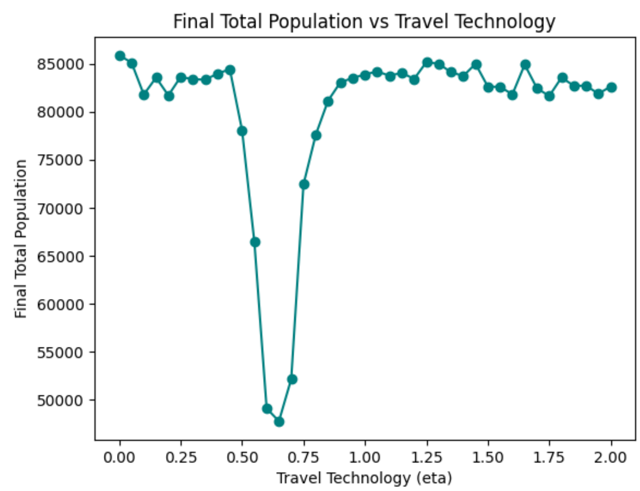

Figure 7: Different total population in every nodes with respect with the travel technology η

5×10^4 before recovering. So, we discover from this chart that in this transitional regime the network becomes less efficient: many links activate simultaneously, export budgets are split across numerous weak ties, and relationship reinforcement spreads flows thinly across suboptimal routes.

4.2.1 Node removal effect. Now, the question to ask is what the optimal state of the system is between the one observed with different parameters' values. While it makes little sense to discuss it in qualitative terms, one aspect that can be examined is its capacity to respond to shocks, regardless of its robustness or resilience. To this end, the impact of removing the largest node was investigated to understand how the system adapts to the shock. The node was removed from all previously conducted simulations, which were

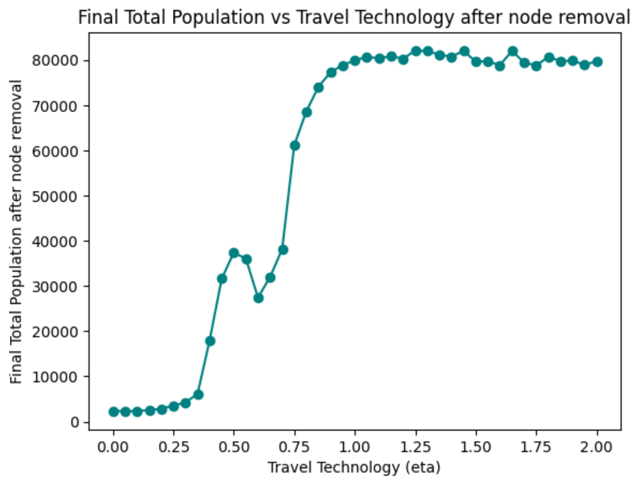

Figure 8: Different total population in every nodes with respect with the travel technology η, after the removal of the biggest node and 2000 extra time-steps

then reloaded and executed for an additional 2000 time steps. In this process, the population, resources, and stock of the node in question were set to 0 (which is functionally equivalent to a remotion).

Figure 8 depicts the total total population after removing the largest node, as a function of the distance–decay exponent η. The curve shows a sharp transition: for very small η the system collapses after the shock, with aggregate population falling to a few thousand or to 0; as η increases into a narrow band around $\eta \approx 0.75$, total population rises abruptly and then stabilizes on a broad plateau near 8×10^4 for $\eta \gtrsim 0.9$, which is analogous to what observed before. The mechanism is consistent with the earlier connectivity results. When travel is easy (small η), trade consolidates into synchronized, high-throughput corridors; removing the largest nodes cuts the coupling propagates a system-wide deficit. With stronger distance friction (larger η), flows are more local and redundant, so synchronization weakens, and the damage is contained, so the post-shock population remains high.

5 DISCUSSIONS

In our results we observe the emergence of trade connections between nodes that did not have an a priori relationship. We refer to this as "emergence" since the formation of a structured network is not a necessary outcome of the model [8]. Rather, it depends on the interplay between available resources, distance effects, and technological factors that affect mobility. For example, improvements in travel technology appear to shape the average connectivity in ways not directly encoded in the model assumptions. This suggests that relatively simple mechanisms may help to generate complex trade structures. While preliminary, such insights could contribute to discussions on how early trade networks might have originated.

This point is relevant for at least two reasons. First, our general understanding of how trade networks initially emerged remains limited, and so a simple model may offer useful perspectives or provide a framework for evaluating existing hypotheses and the relationships between their results and the artifacts they rely on. Second, the dynamics explored here resonate with current observations in different domains, where new forms of networks arise from the accumulation and distribution of resources. An example can be found in the technological sector, where the concentration of capabilities around companies developing generative AI systems creates novel reciprocal dependencies [64].

The results indicate the presence of a phase transition in the formation of trade links. As travel technology improves, connectivity initially increases at an exponential rate but eventually reaches a plateau with much slower growth. This apparent saturation can be understood in mechanistic terms. Once most feasible links between resource-rich and resource-poor nodes are activated, additional increases in trade propensity do not translate into more links. Instead, shipments remain constrained by stock limitations and distance-related penalties. In this regime, the system appears to shift from being limited by interaction capability to being limited by supply and geometry. Such a transition may help explain why network densification does not proceed indefinitely, even under conditions of improved mobility.

A further element emerging from the analysis is the propagation of failures when travel technology surpasses a certain threshold. In this context, we examined the effects of a targeted attack, deliberately removing the most central node in the network, that differs from the random failures, where resilience is typically higher (especially with network which degree distribution is skewed). The results suggest that under specific conditions even the loss of a single key node may trigger wider disruptions.

An important question raised by the results is how the network responds to failures: how does the network react to such failures? And why it does in the setting that looked "optimal" when the trade network emerges? The interpretation of optimality, which is the key to this answer, depends on the criteria adopted. If it is defined in terms of resilience to shocks, the plateau observed at higher values of η seems to offer an advantage over the highly mobile regime. In this case, the system is less efficient in terms of connectivity but more robust to the loss of a critical node. This trade-off suggests that network efficiency and resilience may not coincide, and their balance could vary across contexts.

Similar to the dynamics observed in trade evolution, the node removal experiments also reveal phase transitions under certain parameter combinations. In these cases, small variations in travel technology can lead to sharp changes in population outcomes, making it difficult to assess what is beneficial for those governing or embedded in the network. While technological innovation may bring short-term advantages and well-being, it may also reduce systemic resilience when considered in isolation. The intention here is not to adopt a Luddite position and argue against innovation, but rather to highlight its dual nature. If new technologies increase well-being while introducing risks, it may be valuable to pursue complementary strategies or implement measures that mitigate those risks.

The implications of these results may extend to the interpretation of historical cases of collapse in trade networks. For instance, it could be explored whether advances in maritime travel technology during the Bronze Age contributed to systemic fragility, so that the failure of one or a few nodes—whether caused by internal or external shocks—triggered a wider breakdown. In this view, technological progress may have simultaneously expanded connectivity and increased vulnerability. A similar logic can be applied to more recent contexts. Financial crises acquired a global character when interconnection among markets and the speed of communication surpassed critical thresholds. It is not by chance that the first global financial crisis occurred in 1857, when faster transatlantic travel and the spread of the telegraph within regions accelerated information flows.

6 CONCLUSIONS

This paper presented a first-principles agent-based model of trade networks, combining resource extraction and consumption dynamics, population growth, and distance-dependent exchange. The simulations show that network emergence follows a percolation-like transition: as trade propensity or transport efficiency increases, connectivity rises sharply until constrained by stock and spatial limits. Under these conditions, the model shown that shocks spread widely and the system becomes vulnerable to collapse, while more localized and redundant structures show greater resilience.

The results highlight a trade-off between efficiency and robustness in emerging trade networks, providing a transparent benchmark to study systemic fragility and may inform interpretations of both historical trade collapses and modern supply chain vulnerabilities. Future work could include the calibration of the model with empirical historical and modern data, to see how it holds and which kind of phenomena explains (for example, the emergence and collapse of Mediterranean trade network during the Bronze age). Also, the dynamics of the model could be explored in greater depth, for example identify the bifurcation points and exploring the behavior in a wider parameters' set. Finally, the effect of different resources distribution could be assess.

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