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The Impact of a 10% Tax Rate and Redistribution on Resource Concentration in Networks

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Abstract

Background Resource disparities are common in social networks, often driven by competitive interactions. Exploring how interventions like taxation influence these inequalities can reveal mechanisms for more balanced distributions.

Objectives This study investigates the effects of a 10% tax rate and redistribution on inequality and resource stability within two network models: the 'Winner-Loser Model' which intensifies hierarchies through competitive interactions, and the 'Null Model', simulating equal opportunity exchanges.

Sample and Methods We used Monte Carlo simulations with agents starting at equal resource levels, interacting under the rules of each model. Taxation effects were measured through Gini coefficients and Lambda stability scores across various network sizes.

Results Taxation reduced Gini coefficients in both models, promoting more balanced distributions. Lambda values indicated that taxation improved stability, especially within the 'Winner-Loser Model', by diminishing extreme resource accumulation.

Conclusions The study demonstrates that while competitive dynamics naturally drive inequality, taxation and redistribution mechanisms can stabilize and reduce disparities. These findings suggest that even simple redistribution can reduce hierarchical resource concentration and counteract extreme inequalities in networked settings.

Take-home message for students Even a 10% tax can redistribute wealth and foster stability in resource exchanges, promoting more equitable outcomes; however, it does not entirely resolve the underlying issues of inequality.

Introduction

Understanding the relationship between social network structures and resource distribution is essential for addressing modern inequality, a key determinant of human health and development. Resource disparities within networks influence access to nutrition, healthcare, and social support, factors that critically shape health outcomes and public health interventions (World Health Organization 2003). The distribution of resources, wealth, and power significantly affects human well-being. Inequities in these distributions often exacerbate social and economic inequalities, which in turn affect population health (Wood et al. 2021).

Social network theory provides a valuable framework for analyzing how structural features, such as clustering, centralization, and hierarchy, influence the flow of resources and power within communities (Jackson and Rogers 2007; Mitchell 2006). These structural characteristics determine access to health-related resources, including clean water and medical care, and shape broader public health outcomes. Network-based resource allocation plays a role in the equitable distribution of public health resources, where a more egalitarian network structure tends to provide better outcomes for vulnerable populations (Chiang 2015). In complex systems, clustering strengthens local connectivity, which can facilitate rapid information and resource exchange, yet it also risks reinforcing inequalities if certain groups monopolize resources (Luthra and Todd). Hierarchical structures further concentrate resources and power in the hands of central or elevated positions, leading to more uneven distribution across the network (Davis et al. 2020; Jackson and Rogers 2007). The dynamics of inequality become particularly evident when comparing network types. Networks with fixed, clustered structures, as seen in models like the 'Winner-Loser', often generate significant disparities. In this model, initial advantages amplify over time, allowing "winners" to accumulate disproportionate resources while marginalizing others (Mesterton-Gibbons et al. 2016; Tsvetkova et al. 2018). Despite an initially equal distribution of resources, this model reinforces cycles of inequality that align closely with observed patterns in human hierarchies and socioeconomic stratification (Hermanussen et al. 2023). Conversely, the 'Null Model' provides a baseline by simulating random, unbiased interactions, reducing the likelihood of entrenched advantages or resource centralization (Hermanussen et al. 2023; Tsvetkova et al. 2018).

To understand network structures and their dynamics, existing research has focused on several foundational mechanisms in social network formation, such as homophily, opportunity constraints, and structural balances (Lewis 2015). Graph theory has proven indispensable in this field, providing core analytical concepts such as centrality (identifying influential nodes), clustering (evaluating node interconnectedness), and resilience (assessing a network's adaptability to disruption), which have been instrumental in studying social and biological networks (Arul et al. 2023; Gamboa 2023). Emerging methods, such as triadic motif analysis, offer deeper insights into cooperation, resource sharing, and interaction patterns within networks, further enriching our understanding of resource dynamics (Pinter-Wollman et al. 2014; Shizuka and McDonald 2015).

This study extends these frameworks by examining how taxation – a systemic intervention widely recognized for its role in redistributing wealth and reducing social inequities (Duff 2008; Mohs 2019) – affects inequality and network structures. Redistribution through taxation not only reduces disparities but also promotes equitable access to essential resources, which is vital for improving public health outcomes (Lee and Lee 2023; Maynard 2014). Here, we use taxation as a model to explore how systemic interventions influence resource flows and network dynamics, with implications for public health.

We begin by analyzing resource flows among agents in networks of varying sizes under two distinct interaction models. In the 'Winner-Loser Model', interactions are shaped by a state-dependent feedback system, where previous successes increase the likelihood of future resource accumulation, fostering hierarchical dynamics. Conversely, the 'Null Model' assumes random, unbiased exchanges, where resource flows are independent of prior outcomes, resulting in more egalitarian structures. To assess the impact of systemic intervention, we introduce a recurring 10% tax on resources within the network, with the collected tax redistributed equally among all members. Through Monte Carlo simulations, we conduct repeated trials to observe how resource exchanges evolve over time under these conditions. This approach allows us to evaluate the effects of redistribution on inequality, network structure, and the stability of resource distribution, offering insights into the potential of taxation to mitigate disparities and foster resilience in social systems.

Materials and Methods

Simulation Framework and Data

This study investigates the impact of taxation on resource distribution and social interactions within artificial societies, comparing two models: the 'Winner-Loser Model' and the 'Null Model', following the framework by (Hermanussen et al. 2023).

Simulation Setup

A Monte Carlo approach is used to simulate randomness in social interactions. Agents, representing members of the simulated society, interact according to the rules of the chosen model. The simulations include populations of 10, 20, 50, 100, or 200 agents. Each agent starts with 50 tokens to ensure a balanced initial state, equal for all agents, across all models and strategies. Tokens symbolize an agent's resource-holding power (RHP), reflecting their ability to acquire, hold, and exchange resources within the simulated society.

Interaction partners are selected from nearby neighbors, mimicking localized social interactions within a predefined region. The selection of interaction partners is randomized within the constraints of this localized network. Each iteration starts with a randomly selected agent and proceeds sequentially through the network until each agent has chosen an interaction partner and competed for resources. Each agent is required to choose one interaction partner per game round, but particularly in smaller networks, some agents may compete more frequently, as they select their own partners but can also be chosen again by others within the same game round. For each iteration, there will be 10 game rounds, allowing each agent to select an interaction partner 10 times.

The whole process is completed with 30 iterations, in the following referred to as one full simulation. Each simulation scenario is repeated five times with different random seeds to ensure diverse outcomes and mitigate the influence of any biases from initial conditions.

We will walk through one iteration of an exemplary network of 4 agents, all holding an initial RHP of 50, presented in Algorithm 1. From here, the next iteration would start or, if applied, the taxation process. But importantly, in either model, if an agent has

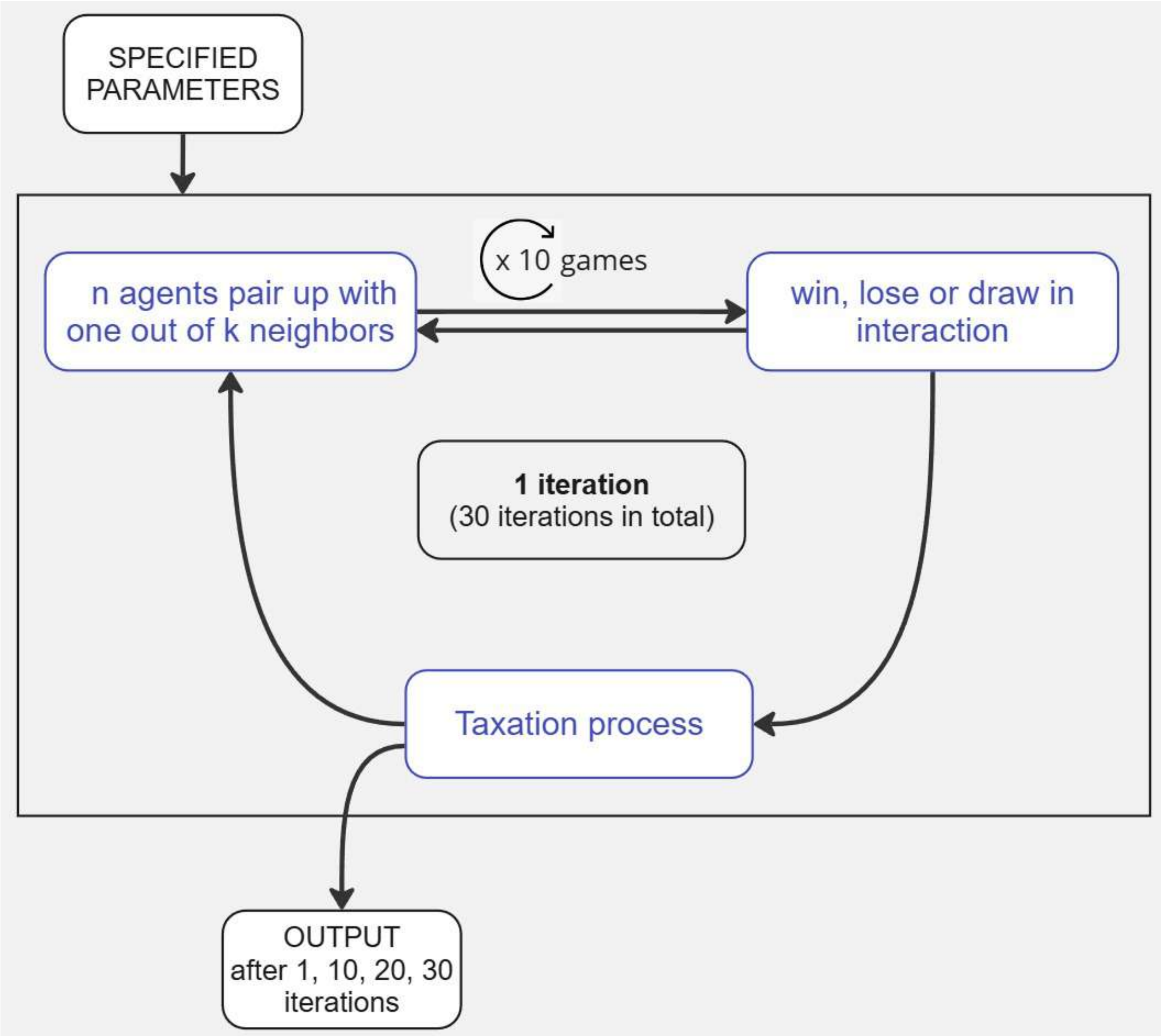

Figure 1 Self-illustrated graphical overview of the simulation workflow, shown is one iteration. A simulation consists of 30 iterations. Before starting, parameters such as i) sample size and number of neighbors, ii) model type, and iii) tax rates are set. Each combination is simulated for 30 iterations, with visual and numerical output collected at defined intervals. This process is repeated 5 times using different random seeds to ensure varied outcomes

0 tokens, they become inactive in terms of participation because they cannot provide tokens for interactions. If an agent remains at 0 tokens for too long without any mechanism to gain tokens (like redistribution), they will not be able to participate in future rounds. Furthermore, the number of tokens in the system does not change. In the given example, a total of 200 tokens (4 agents, 50 token each) are moving in the system.

Interaction Models

The 'Null Model' acts as a baseline, simulating a scenario where all individuals in a group have an equal chance of gaining resources, without any biases or preferences influencing interactions. It is expected to lead to social networks with no dominance hierarchies, as every individual has an equal opportunity to acquire resources, and prior encounters do not impact future interactions. The exchange of resources (tokens) is essentially random, driven purely by chance. This model is particularly useful for understanding how inequality or hier-

Algorithm 1

```
Starting game 1 with tokens: 50, 50, 50, 50
    Interaction between Agent 1 and 3 (Agent 1 wins): Agent 1 = 60, Agent 3 = 40
    Interaction between Agent 2 and 4 (Agent 2 wins): Agent 2 = 60, Agent 4 = 40
    Interaction between Agent 3 and 2 (draw):        Agent 3 = 50, Agent 2 = 50
    Interaction between Agent 4 and 3 (Agent 3 wins): Agent 4 = 30, Agent 3 = 60
        Final token after all interactions: 60, 50, 60, 30
Starting game 2 with tokens: 60, 50, 60, 30
    Interaction between Agent 1 and 2 (Agent 2 wins): Agent 1 = 50, Agent 2 = 60
    Interaction between Agent 2 and 1 (Agent 2 wins): Agent 2 = 70, Agent 1 = 40
    Interaction between Agent 3 and 1 (Agent 3 wins): Agent 3 = 70, Agent 1 = 30
    Interaction between Agent 4 and 2 (Agent 2 wins): Agent 4 = 20, Agent 2 = 80
        Final token after all interactions: 30, 80, 70, 20
[…]
Starting game 10 with tokens: 0, 100, 60, 40
    Interaction between Agent 1 and 3 (no interaction): Agent 1 = 0, Agent 3 = 60
    Interaction between Agent 2 and 4 (Agent 2 wins): Agent 2 = 110, Agent 4 = 30
    Interaction between Agent 3 and 1 (no interaction): Agent 3 = 60, Agent 1 = 0
    Interaction between Agent 4 and 2 (Agent 4 wins): Agent 4 = 40, Agent 2 = 100
        Final token after all interactions: 0, 100, 60, 40
```

archies might emerge (or fail to emerge) purely due to stochastic processes in the absence of systemic biases or preferential interactions. By controlling for these external factors, the ‘Null Model’ provides a neutral environment to assess the intrinsic dynamics of resource distribution.

The ‘Winner-Loser Model’ represents a more competitive social system, in which past interactions and outcomes shape future success. In this model, the exchange of tokens becomes biased toward individuals who have previously succeeded, reinforcing dominance hierarchies over time. Success in earlier interactions increases the probability of future success, as winning agents are more likely to gain tokens. This mechanism, akin to the “Matthew Effect” (Merton 1968), amplifies initial advantages, creating a feedback loop that drives inequality. For instance, agents who accumulate tokens early on are likely to continue gaining tokens, thus further cementing their dominance in the network. In contrast, losing agents face a compounding disadvantage, as their ability to gain resources diminishes over time. This model aligns with the findings of (Hermanussen et al. 2023), which demonstrated that initial advantages in resource accumulation lead to increased dominance and power imbalances by incorporating a feedback loop that mimics real-world processes where initial advantages are magnified.

Both models operate within localized social networks (i.e., agents interact primarily with nearby neighbors rather than the entire population), reflecting real-world constraints on social interactions, such as geographical proximity or communication limitations. Throughout the simulation, agents exchange tokens based on the principles of each model, with tokens representing an agent’s resource-holding power (RHP). Over time, the ‘Null Model’ is expected to result in a more egalitarian distribution of tokens, as random exchanges tend to balance out disparities. In contrast, the ‘Winner-Loser Model’ should give rise to the formation of dominance hierarchies, highlighting how even minor differences in resource accumulation can escalate, leading to larger power imbalances within the network.

Taxation and Redistribution

Taxation and the redistribution of resources are used to mitigate resource accumulation and prevent dominant individuals from monopolizing resources entirely. Such mechanisms and behaviors can be as simple as food sharing. They help balance access to resources and keep a group functioning harmoniously despite inherent social hierarchies.

In the simulation, a 10% tax is applied to the tokens (RHP) of agents after all rounds of competition are completed (10 interactions per agent). The total collected tax gets redistributed into the system, equally divided among all members of society, with the remainder being carried over into the next iteration. The exact tax amount is calculated by multiplying an agent's token count by 10%, rounded to the nearest integer. Within the 30 iterations, the taxation and redistribution process will be applied repeatedly, totaling 30 instances across the entire network. Agents with fewer than 5 tokens will be excluded from the tax collection; however, all agents, regardless of their token count, are entitled to receive an equal share of the redistributed tax. This approach ensures that while each agent benefits from an equal portion of the reinvested tokens, those with a higher RHP contribute proportionally more to the collective fund.

Proceeding with the example above of a network of 4 agents and 10 completed game rounds (1 iteration), the taxation process would apply as presented in Algorithm 2.

With increased tokens in the system, due to bigger networks, it happens more often that the tax is not exactly redistributable. The carried-forward remainder ensures that any leftover tokens are not lost, but can be reused in the subsequent iteration.

This mechanism aims to create a more equitable token distribution over time while still accounting for individual contributions and maintaining agent engagement in the game. In our example, Agent 1 will soon be able to participate in interactions again, made possible by taxation and redistribution.

Analysis

Visual Networks

Visualizations of the structure of the networks generated during iteration play a key role in interpreting the dynamics in the simulations. The networks are depicted by nodes (agents) and edges (interactions or exchange of tokens between agents). The nodes are color coded, depending on the agents' RHP:

- **Green:** ≤10 token
- **Orange:** 11 to 90 tokens
- **Red:** > 90 token

Edges between nodes indicate the direction of token transfer, with arrows pointing from the receiving to the subordinate agents. The network structure reveals properties such as degree of centrality (how connected an agent is), indicating which agents act as resource hubs.

The agents are designed to connect with nearby individuals (neighbors) in a manner that causes the concentration of connections toward the periphery of the network. Each agent looks ten positions to the left and ten to the right (five in 10-agent networks) for potential interaction partners. In smaller networks, this search radius often covers most, if not all, agents, leading to a denser and more interconnected visual representation. However, in larger networks, the same search behavior results in a more pronounced ring formation, as each agent's limited visibility restricts their connections.

Algorithm 2

```
Final token after all interactions: 0, 100, 60, 40
    Calculate the 10% tax amount:
        Agent 1: 0 * 0.1 = 0
        Agent 2: 100 * 0.1 = 10
Agent 3: 60 * 0.1 = 6
        Agent 4: 40 * 0.1 = 4
    Total collected tax: 10 + 6 + 4 = 20
    Equal redistribution: 20/4 = 5
    Remainder: 20 % 4 = 0
    Final token after redistribution:
        Agent 1: 0 + 5 = 5
        Agent 2: 90 + 5 = 95
        Agent 3: 54 + 5 = 59
        Agent 4: 36 + 5 = 41
The remainder of 0 is stored for the next iteration.
```

Triad Structures

Triad motifs refer to small groups of three agents and the relationships between them, revealing how resources are shared or monopolized within the network. By analyzing these triads, we can better understand how groups form, assert dominance, and how power dynamics are influenced by the uneven distribution of resources. To observe how network dynamics shift and hierarchies evolve – especially when affected by taxation and resource redistribution – we focus on five types of triads (Hermanussen et al. 2023; Shizuka and McDonald 2015):

- **Double Dominant (dd):** occurs when two agents are dominated by a third, signaling a concentration of power among a few agents.
- **Double Subordinate (ds):** when two agents consistently dominate a third, reflecting a scenario with dominant agents and a smaller group of subordinates.
- **Pass-Along (pa):** resources are transferred linearly from one agent to another, indicating hierarchical yet non-cyclic relationships.
- **Transitive (tr):** resources are exchanged in a self-contained sequence, creating a stable and transparent structure.
- **Cyclic (cy):** resources circulate among three agents in a balanced, reciprocal manner, without a clear hierarchy.

Radar charts visualize triad structures, with each axis corresponding to one of the five triad types. The sum of all occurrences across these triads is used as the maximum limit for all axes, allowing for proportional comparison of each triad type in that iteration.

Measurements of Inequality

To quantify and visualize inequality in token distribution and system stability, we use two key methods: the Gini coefficient (Gini 1912) and a factor we call “Lambda”. Lambda (λ) tracks how smoothly resources flow through the network over time. It measures the average difference in token counts between two time points, t_0 and t_1 for all agents in the system. The formula for Lambda is:

$$\lambda = \frac{1}{n} \sum_{i=1}^{n} \left| tokens_{t_0,i} - tokens_{t_1,i} \right|$$

Where:

- n is the total number of agents

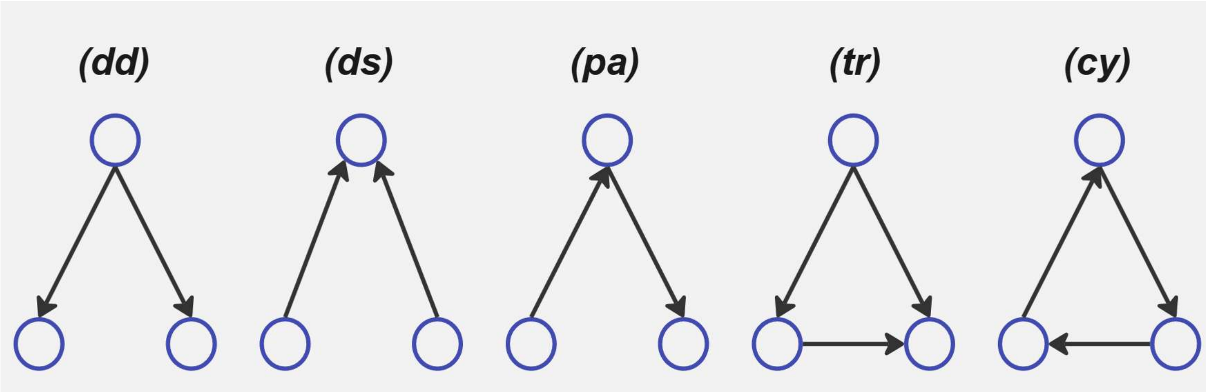

Figure 2 Self-illustrated visual representation of the five triad structures double dominant, double subordinate, pass-along, transitive and cyclic (left to right)

- $tokens_{t_0,i}$ and $tokens_{t_1,i}$ represent token count for agent i at times t_0 and t_1.

Lambda provides a measure of how much the token distribution changes over time. A Lambda of 0 means there is no change in token distribution between time points, indicating complete stagnation and lack of resource movement – this is undesirable, as it implies no dynamics or interaction. Higher Lambda values indicate larger shifts in resources, reflecting more volatility in the system, while lower values suggest smoother, more equitable exchanges.

While Lambda tells us how stable or chaotic the interactions and resource shifts are, Gini focuses on inequality. The Gini coefficient, ranging from 0 (perfect equality) to 1 (maximum inequality), provides a quantification of inequality. For instance, a Gini of 0.2 suggests that the majority (0.8) of a society shares the resources relatively equally. The Lorenz curve (Lorenz 1905) complements the coefficient by visually representing inequality, plotting the cumulative percentage of agents against the cumulative percentage of tokens they hold. The area between the Lorenz curve and the diagonal corresponds to the Gini coefficient, with a larger area indicating greater inequality. Plotted Lorenz curves can be found in the supplemental materials ("Supplementary_Plots.docx"). To track how resources shift over time and how taxation impacts concentration, we utilize bar plots to show token distributions at the start and after every 100 interactions (10 iterations).

Results

Gini Coefficient and Network Structure without Redistribution

The Gini coefficient, quantifying inequality, reaches extreme levels in the 'Winner-Loser Model'. In smaller networks (Figure 3C), the Gini coefficient rapidly increases from 0.62 to 0.9 within the first 20 iterations. Larger networks follow a similar trend, rising from 0.56 to 0.91 after 30 iterations (Figure 3D). In contrast, the 'Null Model' exhibits a more gradual increase in inequality. In 10-agent networks, the Gini coefficient starts at 0.4 and rises to 0.47, with fluctuations peaking at 0.64. Comparisons with other runs show that, typically, the Gini coefficient progresses from 0.4 to approximately 0.6 with fewer fluctuations (Figure 3A). The larger network in the 'Null Model' also follows a gradual trend, increasing from 0.32 to 0.55 (Figure 3B).

Across five runs, the 'Null Model'′ consistently maintains a Gini coefficient between 0.3 and 0.6, reflecting more balanced resource distribution compared to the 'Winner-Loser Model'. In the latter, all simulations begin with a higher level of inequality and consistently reach a Gini coefficient of approximately 0.9 by the 30th iteration (Table S1, S2 in supplements).

In smaller networks, regardless of the model, the results of early iterations are more diverse. The small 'Null Model' starts with an even token distribution, as reflected by the agents' colors (≤ 10 tokens in green, 11 to 90 tokens in orange, and > 90 tokens in red). However, as the simulation progresses, wealth begins to accumulate unevenly, with some agents gaining resources while others lose them (Figure 3A). A similar process occurs in the 'Winner-Loser Model', but with greater organization. In this model, a star structure emerges, with one central agent monopolizing all resources (Figure 3C). While the 'Null Model' remains unstructured regardless of network size, the 'Winner-Loser Model' quickly creates structured networks where wealth accumulates in a few agents. Notably, the 'Null Model' maintains a relatively stable middle class (orange), while the 'Winner-Loser Model' rapidly diminishes this group, regardless of network size.

Gini Coefficient and Network Structure with Redistribution

In the 10% tax model, the network started with a relatively high Gini coefficient in the 10-agent network of the 'Winner-Loser Model' at 0.49; we observe some fluctuations reaching up to 0.59 before stabilizing at 0.51 by the 30th iteration (Figure 4C). Similar trends appear across all network sizes, where taxation and redistribution slow down the rise in inequality compared to simulations without these mechanisms. In contrast to outcomes without taxation, the Gini coefficient is notably suppressed in the 'Winner-Loser Model', (Figure 4C, D), with results resembling the inequality patterns seen in the 'Null Model' without taxation (Figure 3A, B).

Taxation and redistribution also diminish inequality in the 'Null Model'. In smaller networks, the Gini coefficient decreases from 0.38 to 0.31, while larger networks show values from 0.22 to 0.23 (Figure 4A), with only minor variations. Taxation and redistribution mechanisms encourage an even spread of resources across the network. As seen in Figures 3 and 4, agents rarely accumulate excessive wealth (red) or face extreme losses (green). Instead, most agents maintain a balanced resource level, represented by the dominance of orange nodes. The mechanism also mitigated the extreme stratification in 'Winner-Loser Models'. Redistribution seems to prevent the collapse of the middle class, as orange nodes (agents with mid-range tokens) persist throughout the simulation (Figure 4C, D).

System Stability

As a general trend in the 'Null Model', Lambda fluctuates significantly in smaller networks but eventually stabilizes around 20, particularly in larger ones. In contrast, the 'Winner-Loser Model' shows significant drops in Lambda values, which begin high and decrease quickly towards zero as resources concentrate in one or a few agents. In this model, Lambda often remains very low, with minimal fluctuations, and even reaches 0 in 10-agent networks (Figure 5).

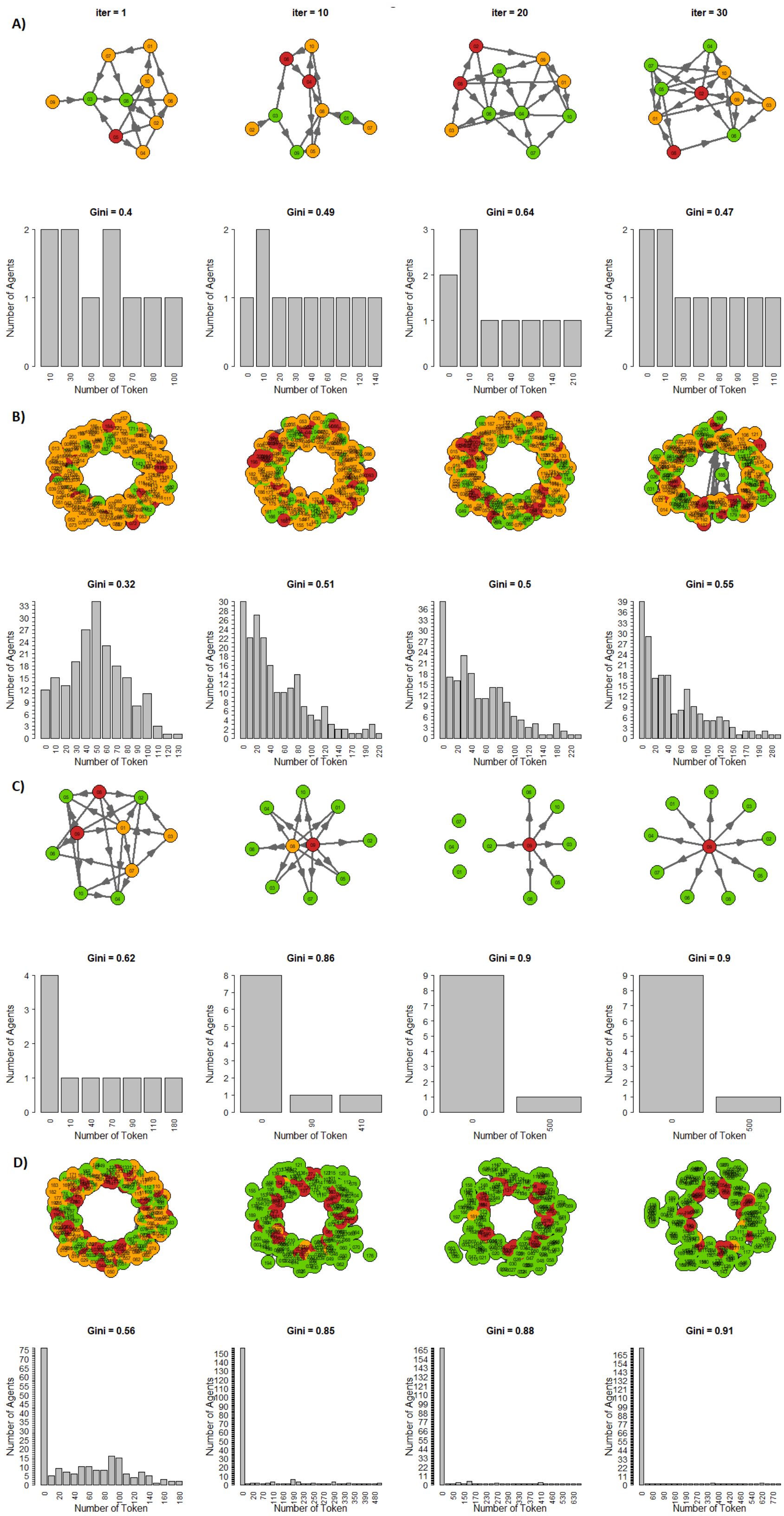

Figure 3 Network Structures without taxation, Gini coefficient and bar plots representing the number of tokens per agent of run 1. A) 'Null Model' with 10 agents, B) 'Null Model' with 200 agents, C) 'Winner-Loser Model' with 10 agents, D) 'Winner-Loser Model' with 200 agents

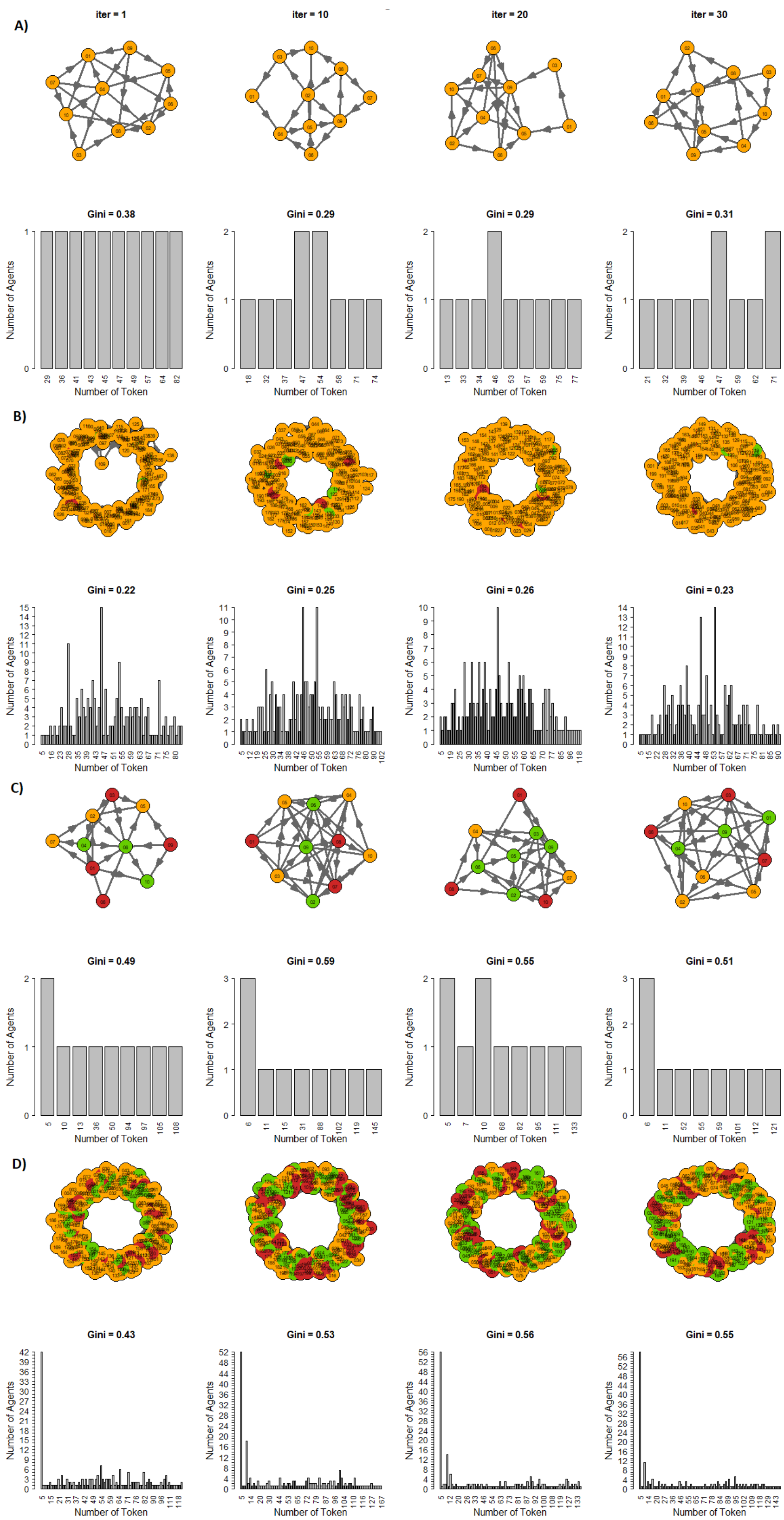

Figure 4 Network Structures with taxation, Gini coefficient and bar plots representing the number of token agents of run 1. A) 'Null Model' with 10 agents, B) 'Null Model' with 200 agents, C) 'Winner-Loser Model' with 10 agents, D) 'Winner-Loser Model' with 200 agents.

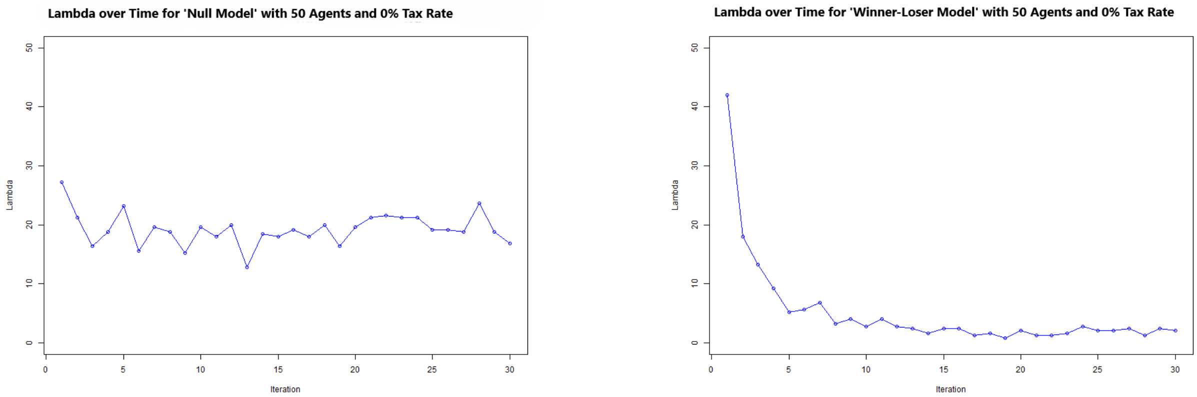

Figure 5 Run 1. Line graph with Lambda values (y-axis) measured over 30 iterations (x-axis) with 50 agents and no tax. 'Null Model' (left), 'Winner-Loser Model' (right)

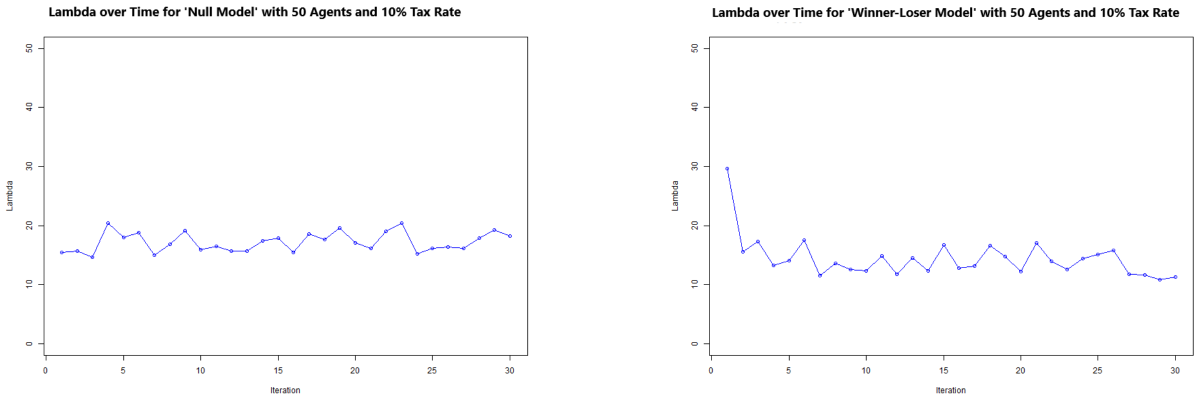

Figure 6 Run 1. Line Graph with Lambda values (y-axis) measured over 30 iterations (x-axis) with 50 agents and 10% tax. 'Null Model' (left), 'Winner-Loser Model' (right)

Taxation and redistribution seem to cushion this drop, as well as lowering the high peak at the beginning of the simulation. The 'Winner-Loser Model' now stabilizes with some variations around 15 (Figure 6). The 'Null Model' is expressing a similar pattern, except for the peak in the very beginning and Lambda stabilizing around 17 (Figure 6). However, as network size increases, the 'Null Model' demonstrates increased stability in Lambda, changing only one or two values over multiple iterations (e.g., fluctuating between a Lambda of 16 and 17). The 'Winner-Loser Model' achieves a similar level of stability only in the largest tested network size of 200 agents.

Triad Structure Formations

Without any taxation system (Table 1), in the 'Null Model', pass-along triad interactions are constantly the most recurrent kind of triad structure, followed by double subordinate and double dominant interactions in smaller and larger networks with a constant distance. This pattern stays consistent when taxation and redistribution are applied, with just minor fluctuations (Table 2).
The 'Winner-Loser Model' rapidly starts expressing double dominant triad structures only, with the other ones being suppressed to a minimum (Table 1). This changes when taxation and redistribution are included (Table 2). In the 'Winner-Loser Model', transitive triad interactions become more prominent in smaller networks, followed by double subordinate, double dominant, and pass-along. As the networks

Table 1 Run 1, no taxation – data about expressed triad structures at chosen iterations for the network sizes 10, 50 and 200. 'Neighbors' refers to the number of agents from which the active agent selects competitors during each interaction, 'dd' = double dominant, 'ds' = double subordinate, 'pa' = pass-along, 'tr' = transitive, 'cy' = cyclic triad interaction pattern

			'Null Model'					'Winner-Loser Model'				
Iteration	Agents	Neighbors	dd	ds	pa	tr	cy	dd	ds	pa	tr	cy
1	10	10	7	13	19	3	2	27	18	9	11	1
10	10	10	3	5	12	2	2	50	0	0	7	0
20	10	10	11	13	29	8	2	15	0	0	0	0
30	10	10	15	9	24	15	9	36	0	0	0	0
1	50	20	248	236	443	36	12	663	865	435	143	4
10	50	20	326	298	594	47	17	810	177	85	38	0
20	50	20	216	216	433	26	9	782	91	59	35	0
30	50	20	245	238	526	45	13	934	113	78	31	0
1	200	20	1131	1138	2273	175	58	2933	3315	2250	534	19
10	200	20	1009	1054	2052	149	49	4271	946	485	199	0
20	200	20	1156	1082	2158	164	61	2924	415	139	62	0
30	200	20	1069	1065	2116	132	52	2789	306	138	68	0

grow, transitive interactions decline and double subordinate triad structures take the lead, closely followed by double dominant and, with some distance, pass-along.
We also observe that from a network size of 50 agents, the expression of triad structures becomes more stable. The overall expression pattern shows less drastic changes throughout the 30 iterations in both the 'Winner-Loser Model' and the 'Null Model'. Full data sets of all runs can be found in the supplementary file Supplementary_Tables.xlsx.

Discussion

While the 'Null Model' was anticipated to yield more equitable results due to random interactions and the absence of competitive mechanisms, significant inequalities emerged, with Gini coefficients often exceeding 0.5 across iterations. This finding aligns with the theory that even in networks without hierarchy, resource distributions may still become skewed due to random accumulation patterns (Bressloff 2021). Additionally, clustering effects within the 'Null Model' highlight how structural features can exacerbate inequalities, even in randomized systems (Luthra and Todd). By contrast, the 'Winner-Loser Model' consistently produced high levels of inequality, reinforcing power-law distribution patterns and centralizing resources within a few agents, as predicted for competitive, hierarchical networks. Overall, the results reinforce the idea that hierarchical systems increase inequality, mirroring processes outlined by (Hermanussen et al. 2023), where wealthier agents amass resources through repeated successes. Such patterns are analogous to real-world systems, where entrenched economic hierarchies often resist mild redistributive efforts (Duff 2008).
Taxation and redistribution effectively reduced inequality in both models, yet their impact varied. In the 'Null Model', taxation stabilized Gini coefficients at lower levels across all network sizes (Figure 4A, B). This

result suggests that redistribution effectively mitigates resource disparities in systems where interactions lack cumulative advantage. In the 'Winner-Loser Model', taxation and redistribution effectively reduced inequality, but not to the same extent as in the 'Null Model'; Gini coefficients stabilized around 0.5, especially in larger networks (Figure 4D). The observed persistence of hierarchical dominance suggests that competitive advantages can resist mild redistributive measures. This underscores the need for stronger interventions, such as progressive taxation, which may align more closely with real-world scenarios (Maynard 2014).

Influence of Network Size

Network size significantly modulated the impact of taxation. Smaller networks in both models exhibited more pronounced inequality, likely due to limited interaction opportunities, which amplified resource accumulation among a few agents. Larger networks, in contrast, showed more stabilized inequalities under taxation, consistent with findings from studies on scale-free networks (Barabási and Albert 1999). This suggests that larger, interconnected systems facilitate redistributive mechanisms, reducing disparities and promoting equitable outcomes. However, the limitations of the 'Winner-Loser Model' highlight the need for stronger measures, such as progressive taxation, to reduce entrenched dominance and enhance equity.
These observations highlight the importance of network connectivity in redistributive efforts, suggesting that policies targeting inequality in smaller or isolated communities may require tailored interventions to counteract limited interaction opportunities.

Impact on Network Dynamics and Stability

The stabilization of Lambda, representing resource mobility, provides insight into the broader implications for social and health

Table 2 Run 1, 10% taxation and redistribution – data about expressed triad structures at chosen iterations for the network sizes 10, 50 and 200. 'Neighbors' refers to the number of agents from which the active agent selects competitors during each interaction, 'dd'= double dominant, 'ds' = double subordinate, 'pa' = pass-along, 'tr' = transitive, 'cy' = cyclic triad interaction pattern

			'Null Model'					'Winner-Loser Model'				
Iteration	Agents	Neighbors	Dd	ds	pa	tr	cy	dd	ds	pa	tr	cy
1	10	10	13	19	23	8	3	8	19	12	15	2
10	10	10	10	9	15	2	4	14	26	11	54	1
20	10	10	10	12	25	9	1	8	28	18	25	0
30	10	10	6	9	26	11	1	19	23	16	43	0
1	50	20	276	272	531	56	17	600	809	631	141	12
10	50	20	276	243	515	30	14	798	1096	618	270	1
20	50	20	222	226	482	45	17	849	859	595	211	5
30	50	20	232	244	494	46	6	973	1043	699	274	3
1	200	20	1008	951	2020	131	43	2243	2890	2280	513	13
10	200	20	982	1046	1950	144	56	3735	4488	2829	905	17
20	200	20	1090	1065	2088	125	43	4001	4559	2894	985	15
30	200	20	999	928	2003	177	45	3835	4188	2894	991	34

systems. In the 'Null Model', Lambda's stability across larger networks under taxation reflects enhanced system resilience, resembling Gamboa's findings (Gamboa 2023) on how equitable resource flows can sustain adaptive network interactions critical for public health. Stable exchange rates are critical for maintaining access to resources like healthcare, nutrition, and housing – key determinants of population health.

Conversely, the 'Winner-Loser Model' without taxation showed a sharp drop in Lambda, indicating reduced resource mobility as tokens accumulated among fewer agents (Figure 5). Taxation moderated these effects, supporting more dynamic exchanges (Figure 6). This highlights the potential of redistributive policies to mitigate systemic inequalities and foster resilience, which are crucial for equitable public health outcomes.

Triad Structure and Resource Dynamics

Analyzing triadic structures shows how taxation can reshape interaction patterns and impacts resource distribution within each model. In the 'Null Model', pass-along triads dominated, indicating a tendency toward cooperative, linear resource sharing without reinforcing power imbalances (Figure 7A, C). Taxation further stabilized these patterns, suggesting that in systems where agents interact randomly, redistributive efforts reinforce this cooperative flow, maintaining equitable exchanges and preventing significant resource concentration. In the 'Winner-Loser Model', double dominant triads were prevalent (Figure 8A, C) reflecting feedback loops that consolidate power among a few agents, leading to unequal access to resources. This concentration of power within certain triadic structures aligns with Merton's (1968) concept of feedback loops reinforcing dominance and mirrors patterns observed in biological systems, where uneven access to essential resources (such as nutrition or social support) can lead to disparities in growth and other developmental outcomes (Hermanussen et al. 2023). Taxation reduced the centralization of power within the double dominant triad structures and increased the prevalence of transitive and double subordinate structures (Figure 8B, D). This shift suggests that redistribution interrupts the reinforcement of dominance hierarchies, fostering more balanced and reciprocal exchanges. However, in larger networks, double dominant and double subordinate triads persisted, highlighting the resilience of hierarchical patterns even under redistributive mechanisms. This underscores the need for redistributive policies tailored to hierarchical systems, where more aggressive measures, such as progressive taxation, may better address entrenched inequalities.

Limitations

The study uses a fixed 10% tax rate, chosen for its computational manageability, which inherently simplifies the complexity of real-world tax systems. Progressive or variable taxation schemes could provide deeper insights into how redistributive policies influence inequality in diverse contexts. Exploring these alternatives could help bridge the gap between simulated and real-world dynamics and deepen our understanding of resource inequalities and its impact on public health.

Conclusion

We have demonstrated that taxation and redistribution play crucial roles in mitigating

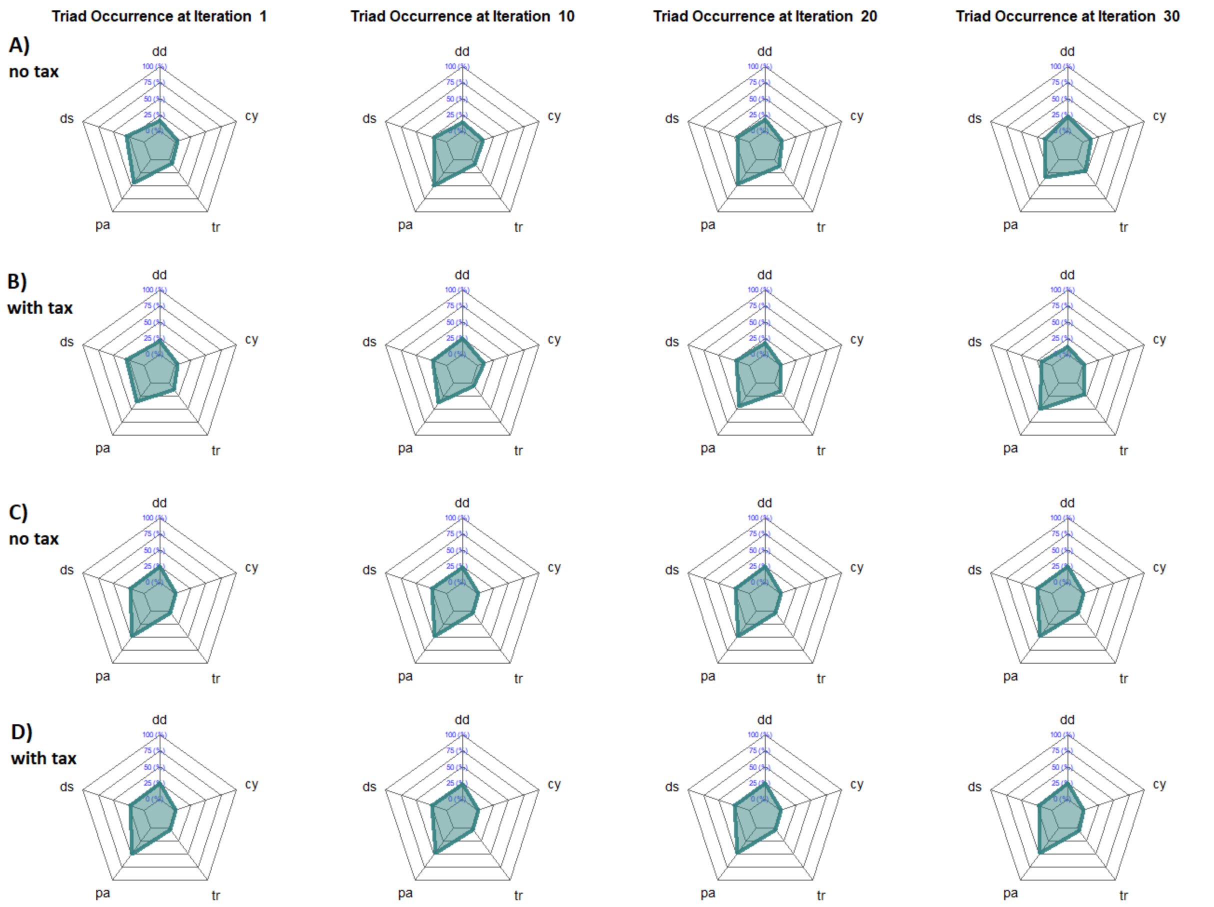

Figure 7 Radar plots of the 'Null Model' representing the frequency of which triad structures occur through the simulation. A) 10 agents without taxation, B) 10 agents with taxation, C) 200 agents without taxation, D) 200 agents with taxation.

inequality within both the 'Winner-Loser' and 'Null Model', although their effectiveness varies. The 'Null Model', initially expected to maintain more balanced distributions, revealed inherent inequalities, with taxation acting as a stabilizing force to foster more equitable resource sharing. In the 'Winner-Loser Model', where competition naturally drives hierarchy and resource concentration, taxation moderated inequality but could not fully dismantle dominant structures, especially in larger networks.

These findings emphasize the role of systemic interventions like taxation in addressing resource disparities, which are vital for equitable access to essential resources, including healthcare and social support. However, the limitations observed in the 'Winner-Loser Model', suggest that moderate taxation alone may be insufficient to fully counteract entrenched hierarchies. Future research could explore the impact of varying tax rates, progressive taxation, and additional redistributive measures across diverse network structures to achieve greater equity in competitive systems.

Data Availability

Statistics were conducted using R 4.3.0 (R Core Team 2023).

The datasets simulated during the current study and used R scripts are freely available at https://github.com/userleutner/RDNets and are based on the package 'hanna' v0.2.1 (Groth 2023).

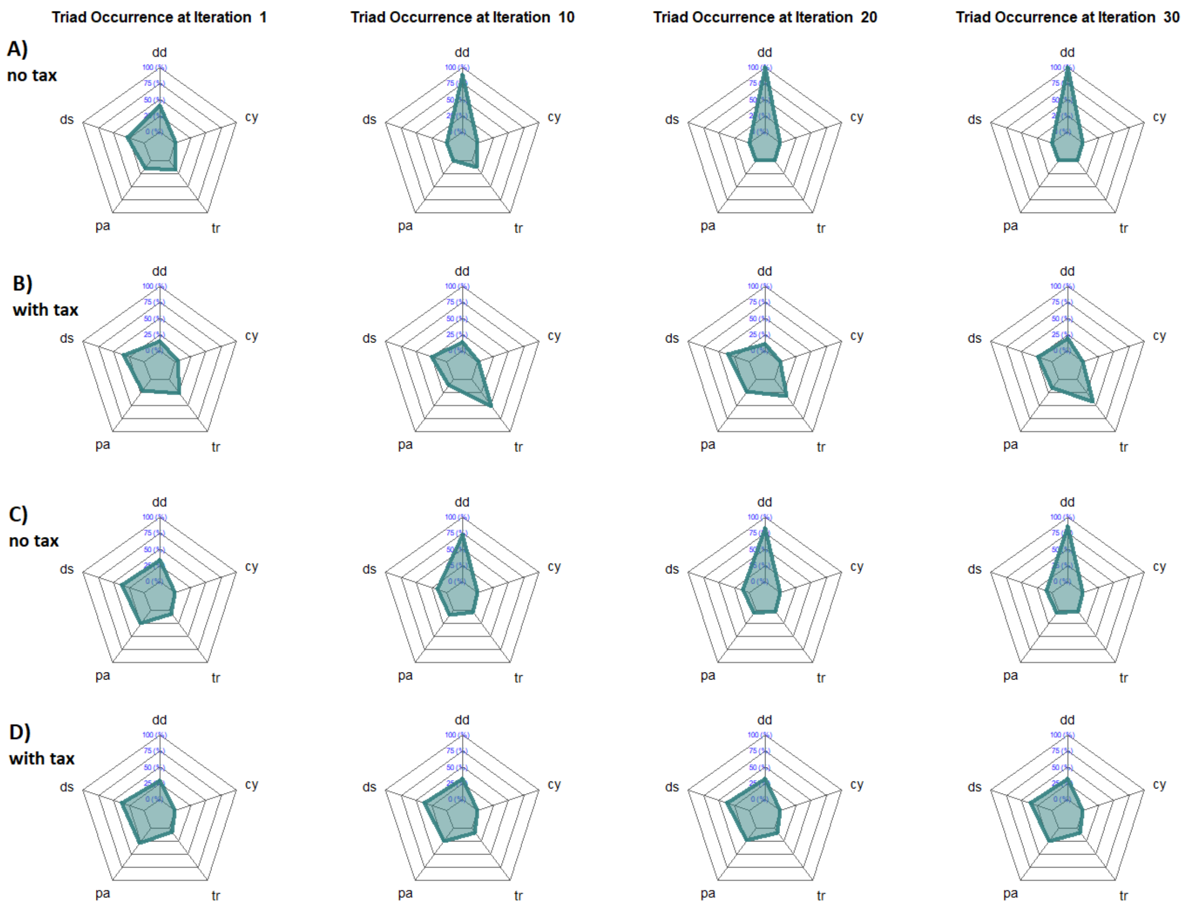

Figure 8 Radar plots of 'Winner-Loser Models' representing the frequency of which triad structures occur through the simulation. A) 10 agents without taxation, B) 10 agents with taxation, C) 200 agents without taxation, D) 200 agents with taxation. dd = double dominant, cy = cyclic, tr = transitive, pa = pass-along, ds = double subordinate

Supplementary Materials

All plots that have been generated during Run 1 can be found in "Supplementary_Plots.pdf". Additional data on triad structure frequencies, Gini coefficients, and Lambda values are provided in the supplementary file "Supplementary_Tables.xlsx".

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