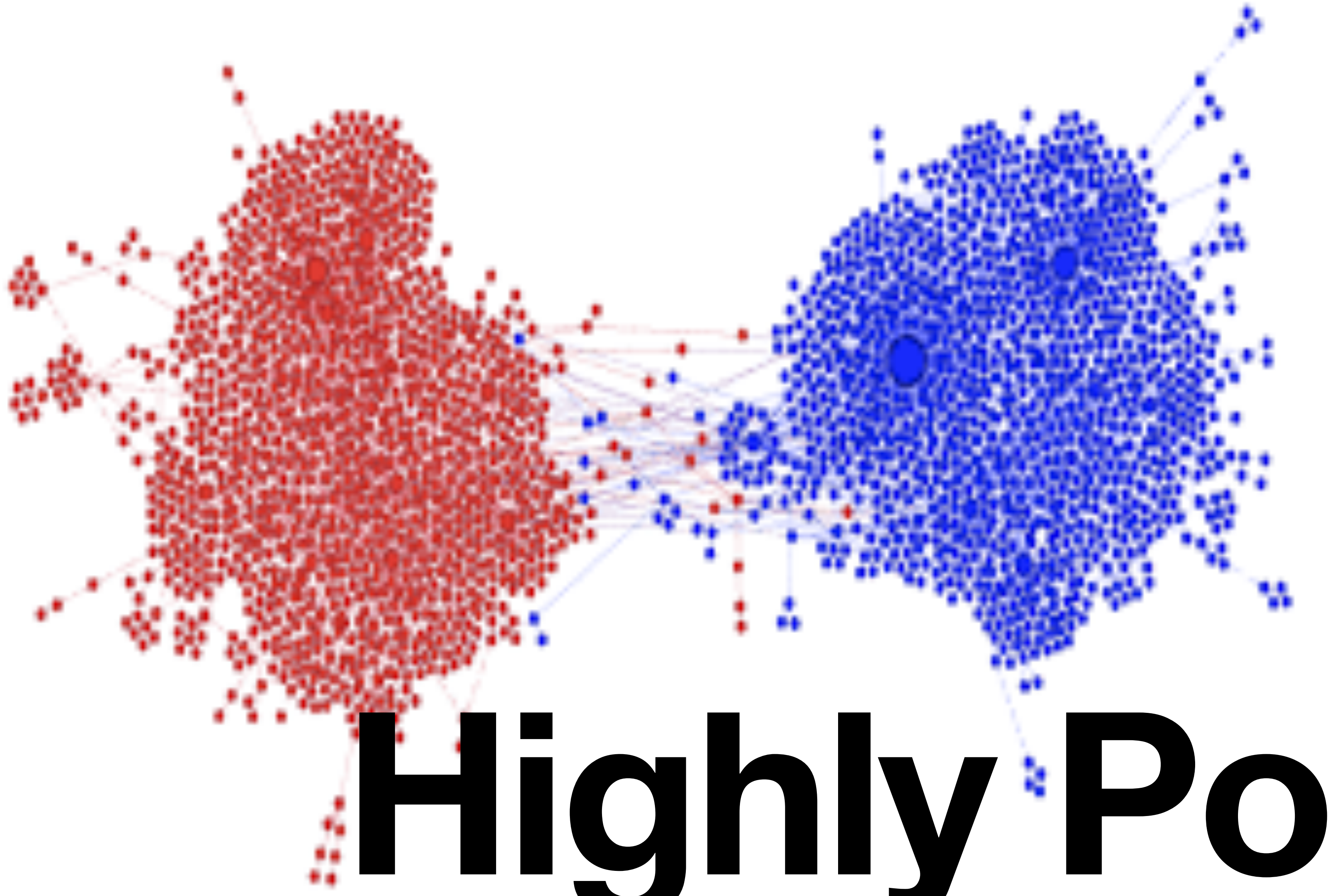


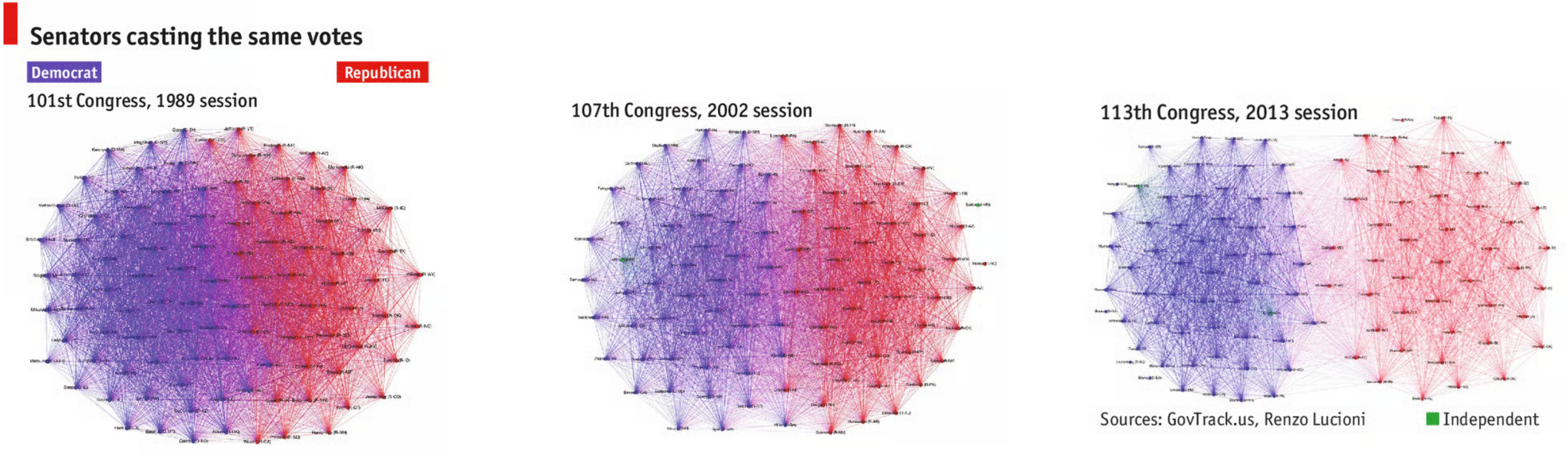
Highly Polar and the Chamber of Echoes

The dynamics of co-evolving networks in social spaces

Y. Berkelmans, Y. Duan, P. Kreiter | 30.01.2026

Real-world example of political polarization

United States of Amobea



https://www.economist.com/united-states/2013/12/05/united-states-of-amoeba

Agenda

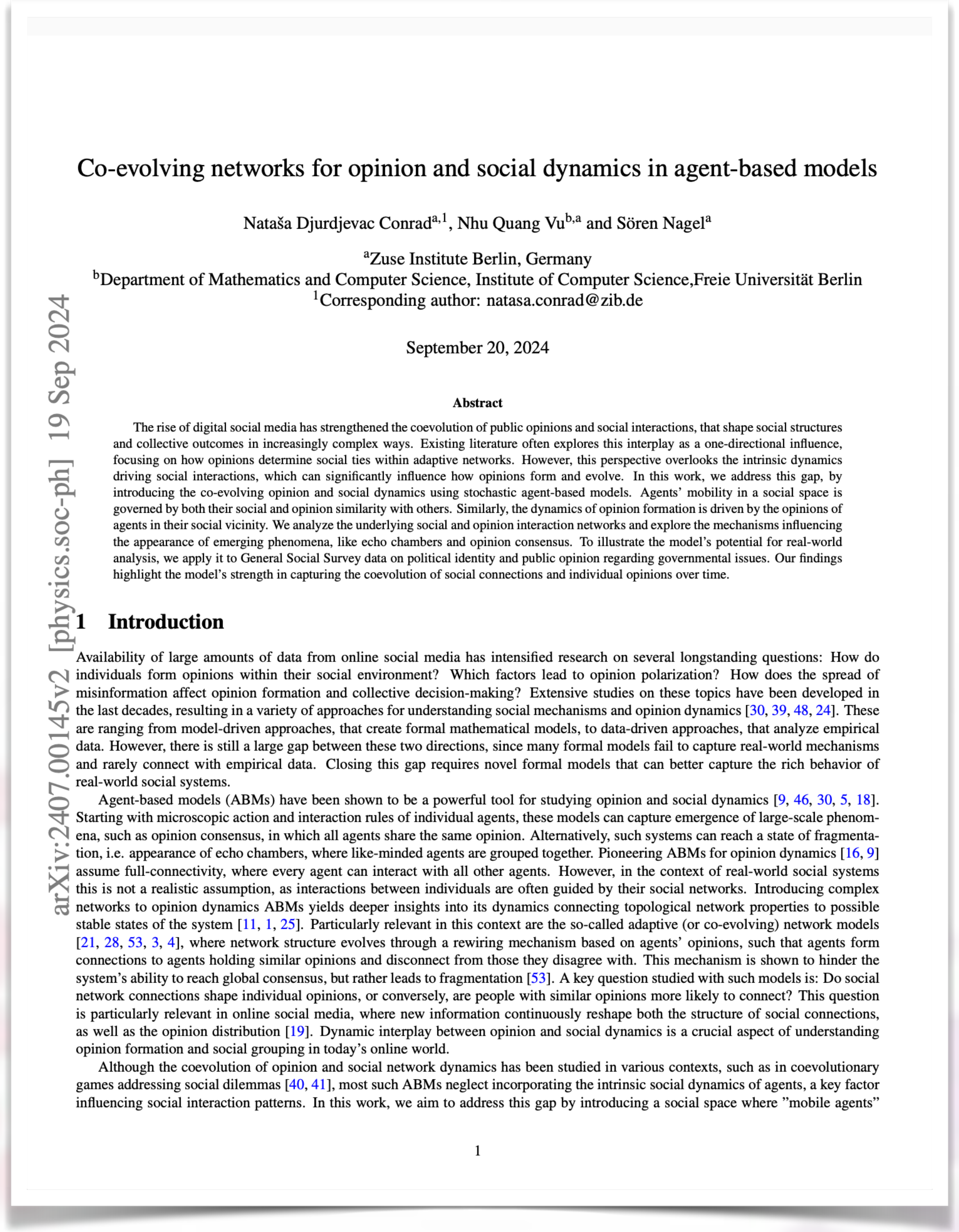
1. How do we model social media spaces?
2. Which conditions lead to polarisation and echo chambers?
3. What do our findings imply for real-world social spaces?

Why modeling echo chambers is difficult

- Traditional models fix opinions or network structure
- No feedback between interaction and belief
- Social media requires co-evolution of both

Modeling social media as a co-evolving system

- Agents represent users
- Continuous social position (latent similarity)
- Continuous opinion value
- Network structure evolves endogenously



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Co-evolving networks for opinion and social dynamics in agent-based models

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Abstract

The rise of digital social media has strengthened the coevolution of public opinions and social interactions, that shape social structures and collective outcomes in increasingly complex ways. Existing literature often explores this interplay as a one-directional influence, focusing on how opinions determine social ties within adaptive networks. However, this perspective overlooks the intrinsic dynamics driving social interactions, which can significantly influence how opinions form and evolve. In this work, we address this gap, by introducing the co-evolving opinion and social dynamics using stochastic agent-based models. Agents' mobility in a social space is governed by both their social and opinion similarity with others. Similarly, the dynamics of opinion formation is driven by the opinions of agents in their social vicinity. We analyze the underlying social and opinion interaction networks and explore the mechanisms influencing the appearance of emerging phenomena, like echo chambers and opinion consensus. To illustrate the model's potential for real-world analysis, we apply it to General Social Survey data on political identity and public opinion regarding governmental issues. Our findings highlight the model's strength in capturing the coevolution of social connections and individual opinions over time.

1 Introduction

Availability of large amounts of data from online social media has intensified research on several longstanding questions: How do individuals form opinions within their social environment? Which factors lead to opinion polarization? How does the spread of misinformation affect opinion formation and collective decision-making? Extensive studies on these topics have been developed in the last decades, resulting in a variety of approaches for understanding social mechanisms and opinion dynamics [30, 39, 48, 24]. These are ranging from model-driven approaches, that create formal mathematical models, to data-driven approaches, that analyze empirical data. However, there is still a large gap between these two directions, since many formal models fail to capture real-world mechanisms and rarely connect with empirical data. Closing this gap requires novel formal models that can better capture the rich behavior of real-world social systems.

Agent-based models (ABMs) have been shown to be a powerful tool for studying opinion and social dynamics [9, 46, 30, 5, 18]. Starting with microscopic action and interaction rules of individual agents, these models can capture emergence of large-scale phenomena, such as opinion consensus, in which all agents share the same opinion. Alternatively, such systems can reach a state of fragmentation, i.e. appearance of echo chambers, where like-minded agents are grouped together. Pioneering ABMs for opinion dynamics [16, 9] assume full-connectivity, where every agent can interact with all other agents. However, in the context of real-world social systems this is not a realistic assumption, as interactions between individuals are often guided by their social networks. Introducing complex networks to opinion dynamics ABMs yields deeper insights into its dynamics connecting topological network properties to possible stable states of the system [11, 1, 25]. Particularly relevant in this context are the so-called adaptive (or co-evolving) network models [21, 28, 53, 3, 4], where network structure evolves through a rewiring mechanism based on agents' opinions, such that agents form connections to agents holding similar opinions and disconnect from those they disagree with. This mechanism is shown to hinder the system's ability to reach global consensus, but rather leads to fragmentation [53]. A key question studied with such models is: Do social network connections shape individual opinions, or conversely, are people with similar opinions more likely to connect? This question is particularly relevant in online social media, where new information continuously reshape both the structure of social connections, as well as the opinion distribution [19]. Dynamic interplay between opinion and social dynamics is a crucial aspect of understanding opinion formation and social grouping in today's online world.

Although the coevolution of opinion and social network dynamics has been studied in various contexts, such as in coevolutionary games addressing social dilemmas [40, 41], most such ABMs neglect incorporating the intrinsic social dynamics of agents, a key factor influencing social interaction patterns. In this work, we aim to address this gap by introducing a social space where "mobile agents"

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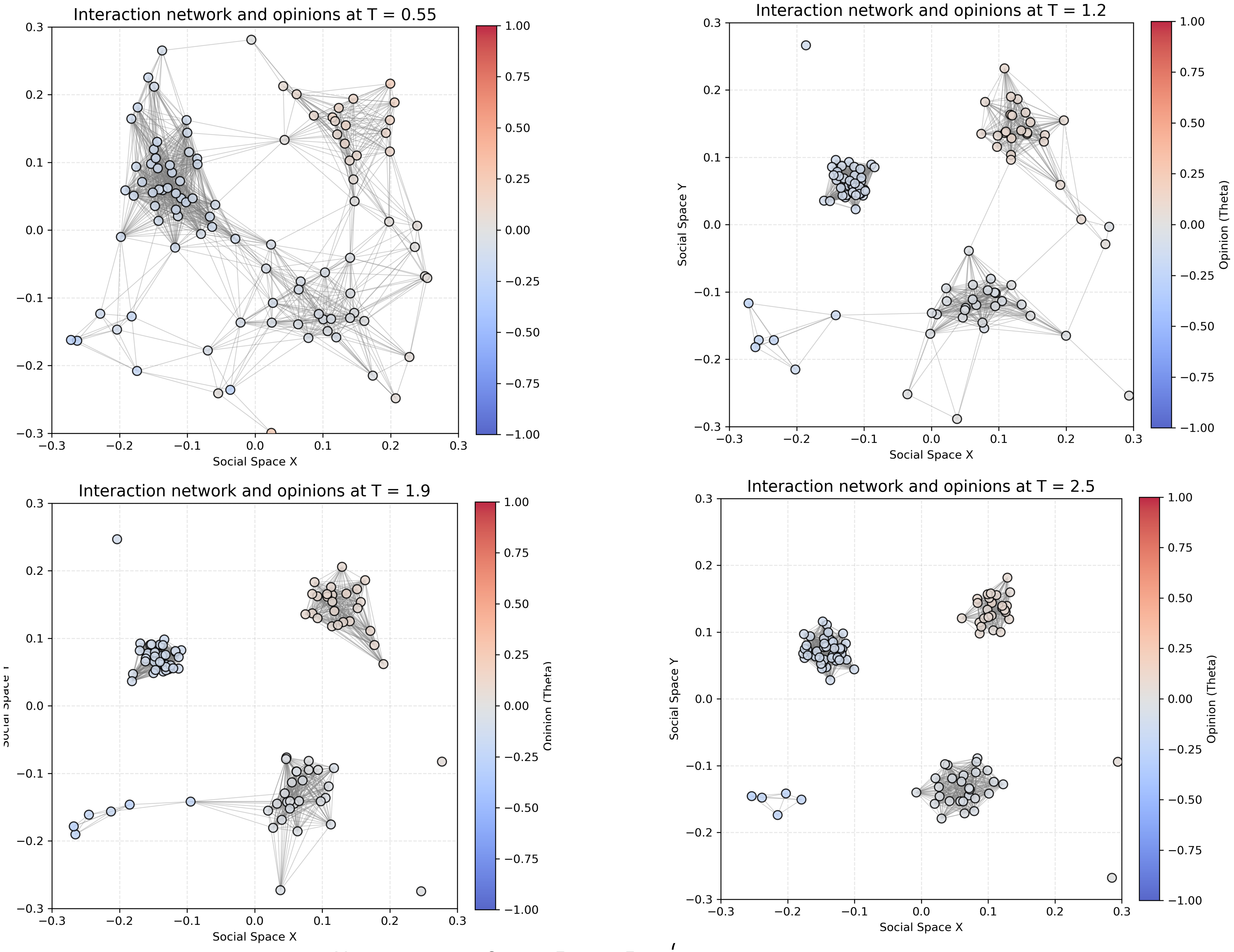
Conrad et Al., 2024

Model mechanisms and parameters

- Opinion influence strength (α): the speed that agent adjusts their view with neighbors
- Social influence strength (β): the intensity that agents move socially
- Homophily: preference for similar opinions
- Noise (σ): random external influences
- Interaction thresholds (R_op, R_sp): determine who can interact

Emergence of echo chambers over time



N = 100, α = 40, β = 10, R_sp = R_op = 0.15, σ_sp = σ_op = 0.05

Echo chambers emerge naturally

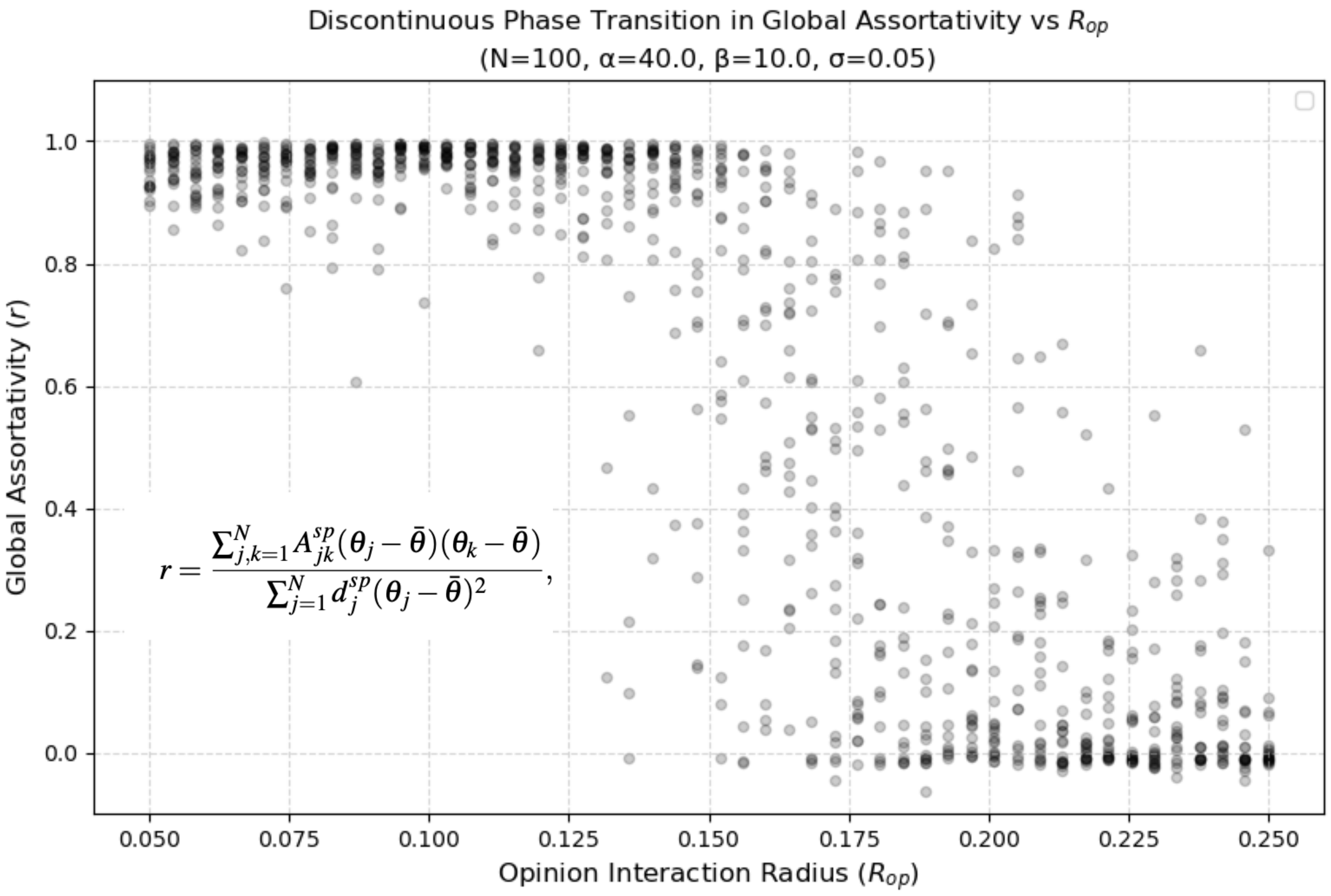
Network segregation reinforces opinion alignment

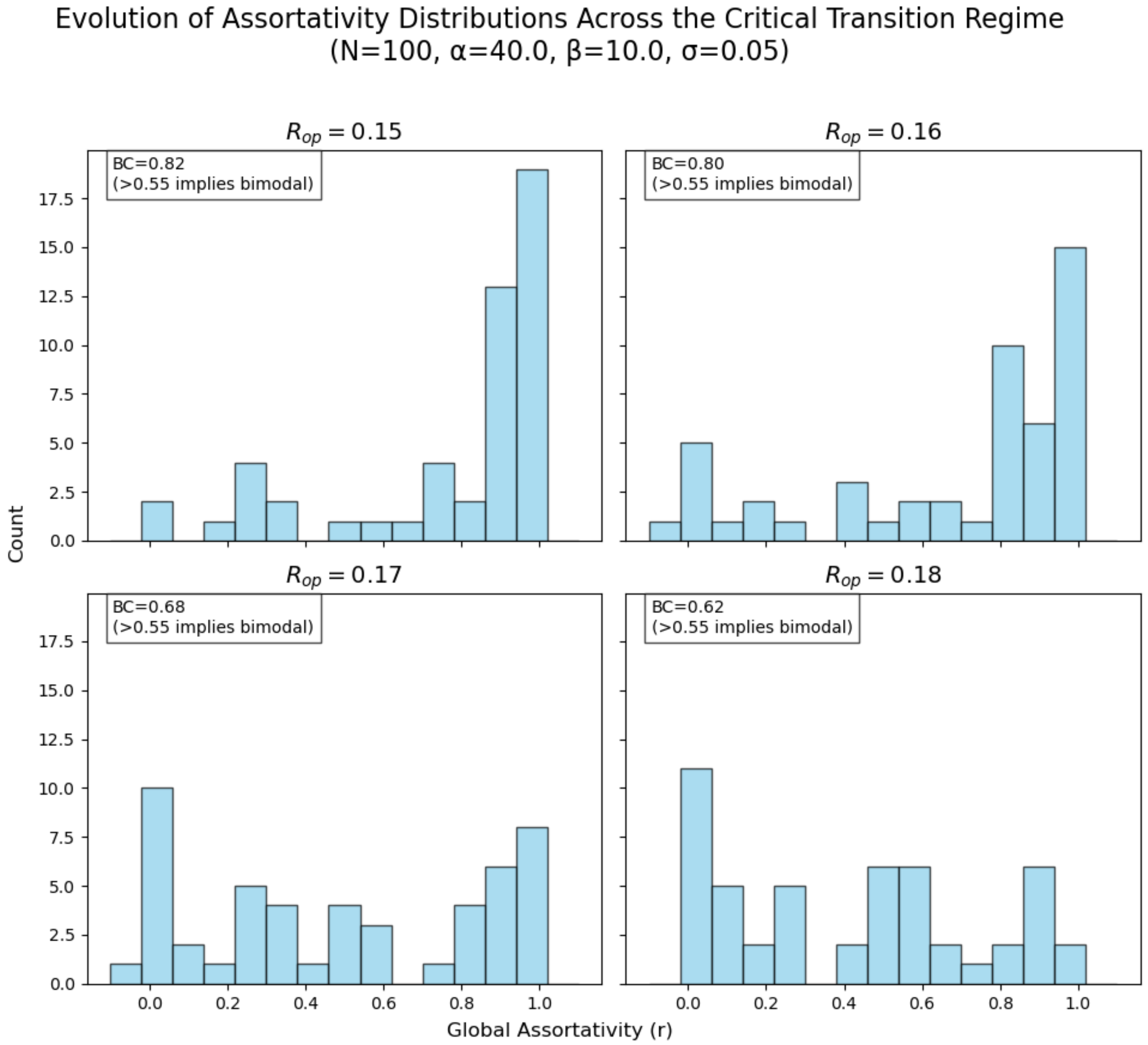
Exposure alone does not prevent polarization

Hypothesis Overview

RQ1	Do structural segregation and steady-state opinion follow continuous or discontinuous phase transitions in co-evolving networks?
H1	Both structural segregation and opinion divergence follows a discontinuous phase transition.
RQ2	How does the opinion influence strength (α) and social influence strength (beta) determine the emergence of consensus/fragmentation?
H2	Stronger sentiments should lead to quicker emergence of polarised opinions and/or consensus.
RQ3	Does polarisation in co-evolving social networks exhibit hysteresis, and what mechanisms prevent depolarisation once echo chambers form?
H3	We expect a critical parameter at which the polarisation occurs and a second lower critical parameter at which depolarisation happens.
RQ4	Does removing edges between nodes re-introduce a mixed state when starting from a polarised regime?
H4	We should be able to find a critical fraction of removing edges at which depolarisation occurs.
RQ5	Does noise facilitate depolarisation?
H5	Higher degrees of stochasticity should make polarisation less likely and aid depolarisation as it destabilises attractors.

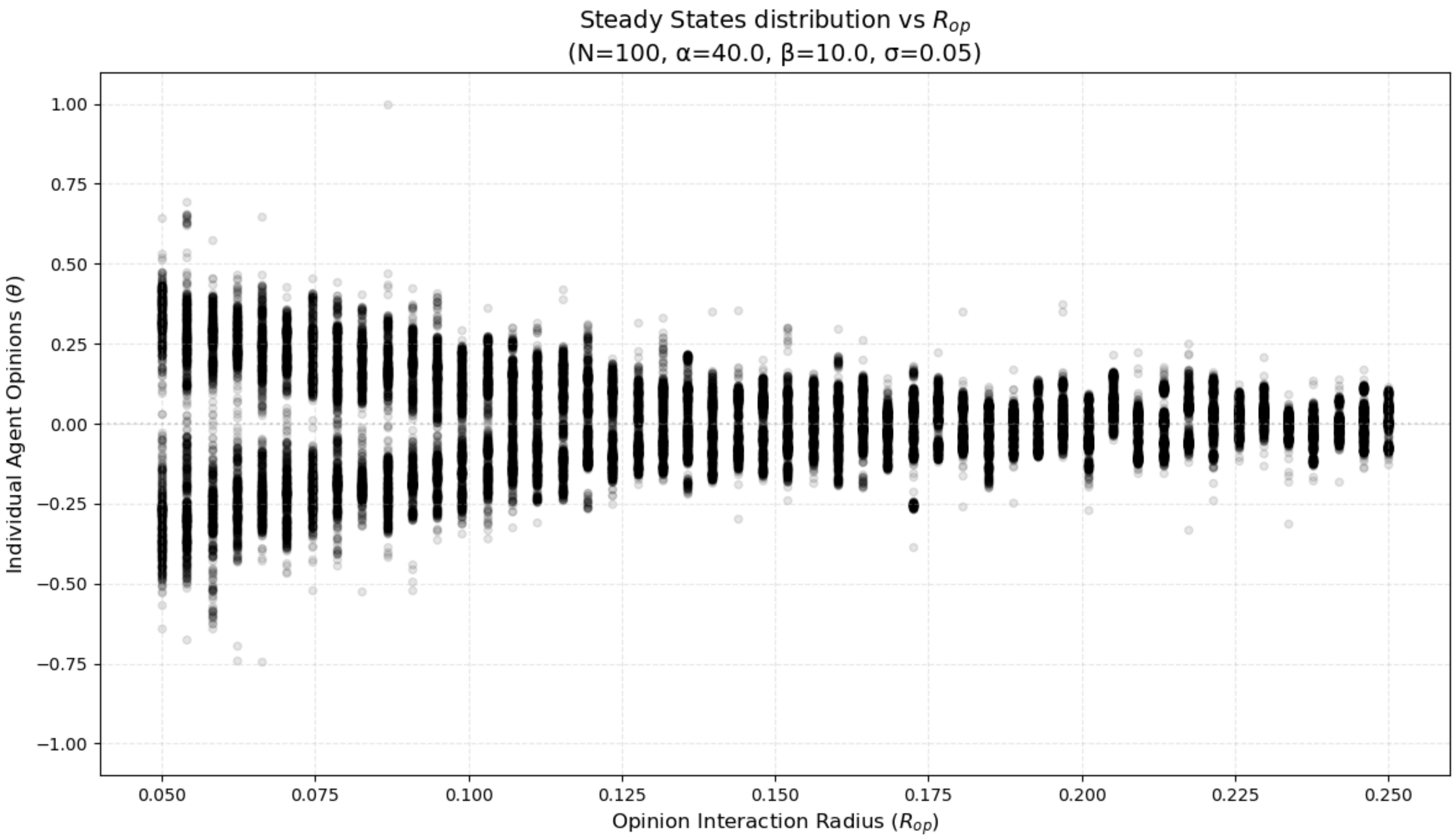
Network segregation is an abrupt collapse





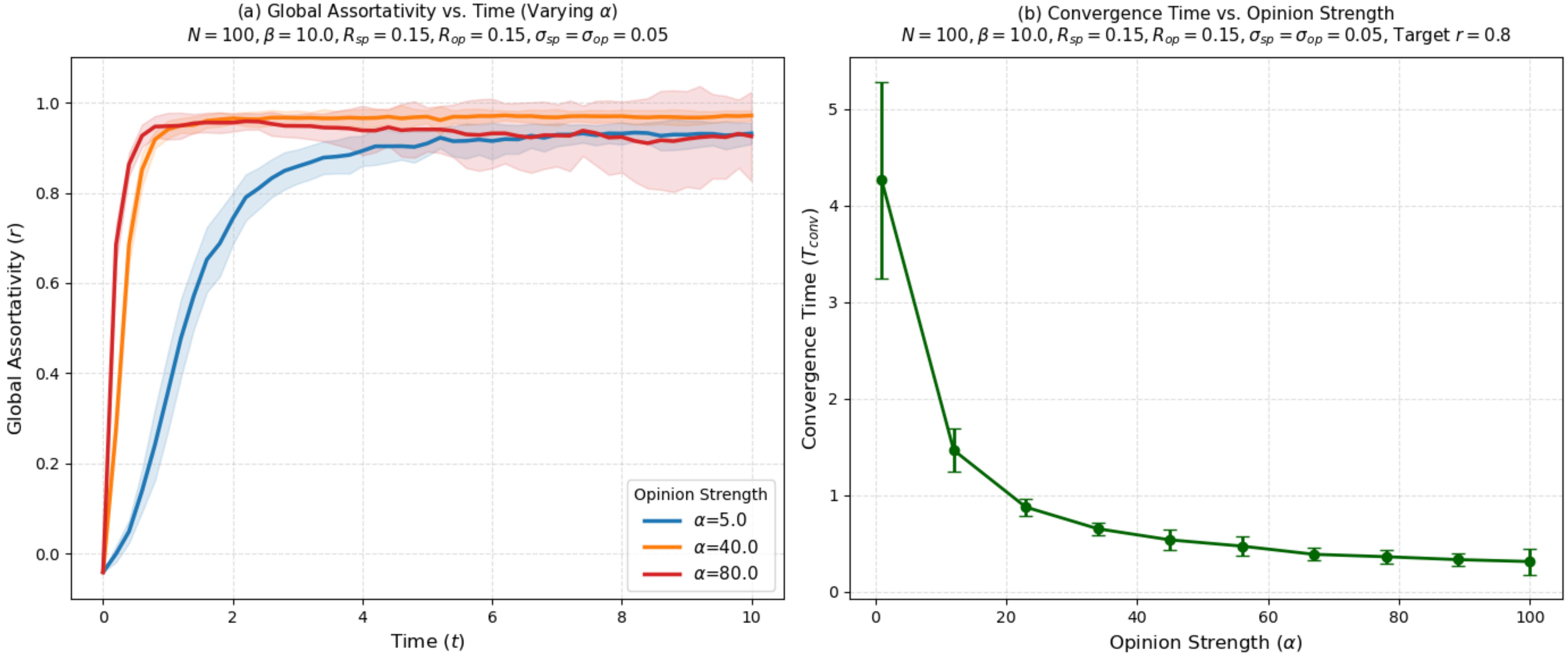
H1a: Structural segregation follows a discontinuous phase transition. ✅

... while opinions vary gradually



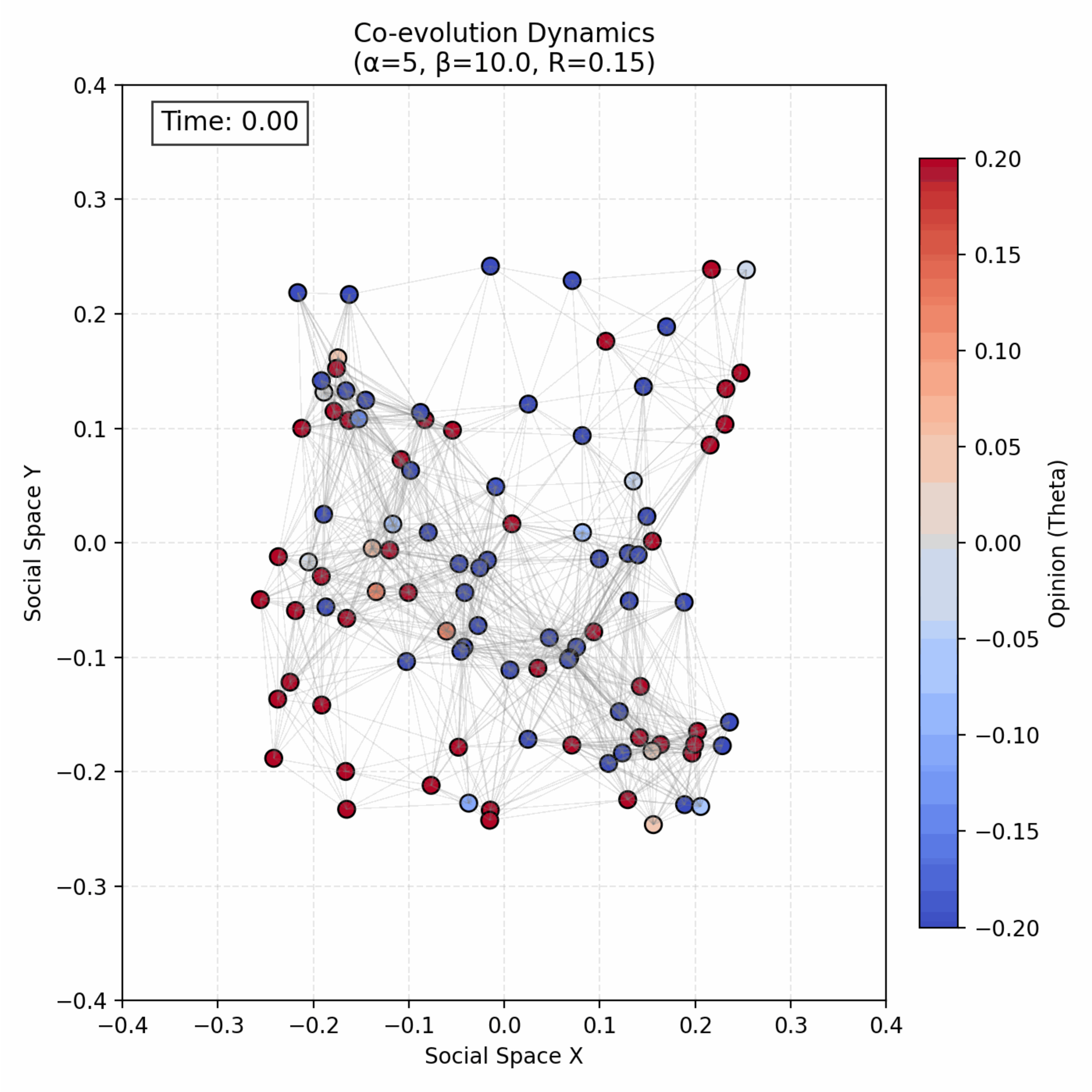
H1b: Steady state opinion follows a discontinuous phase transition. ❌

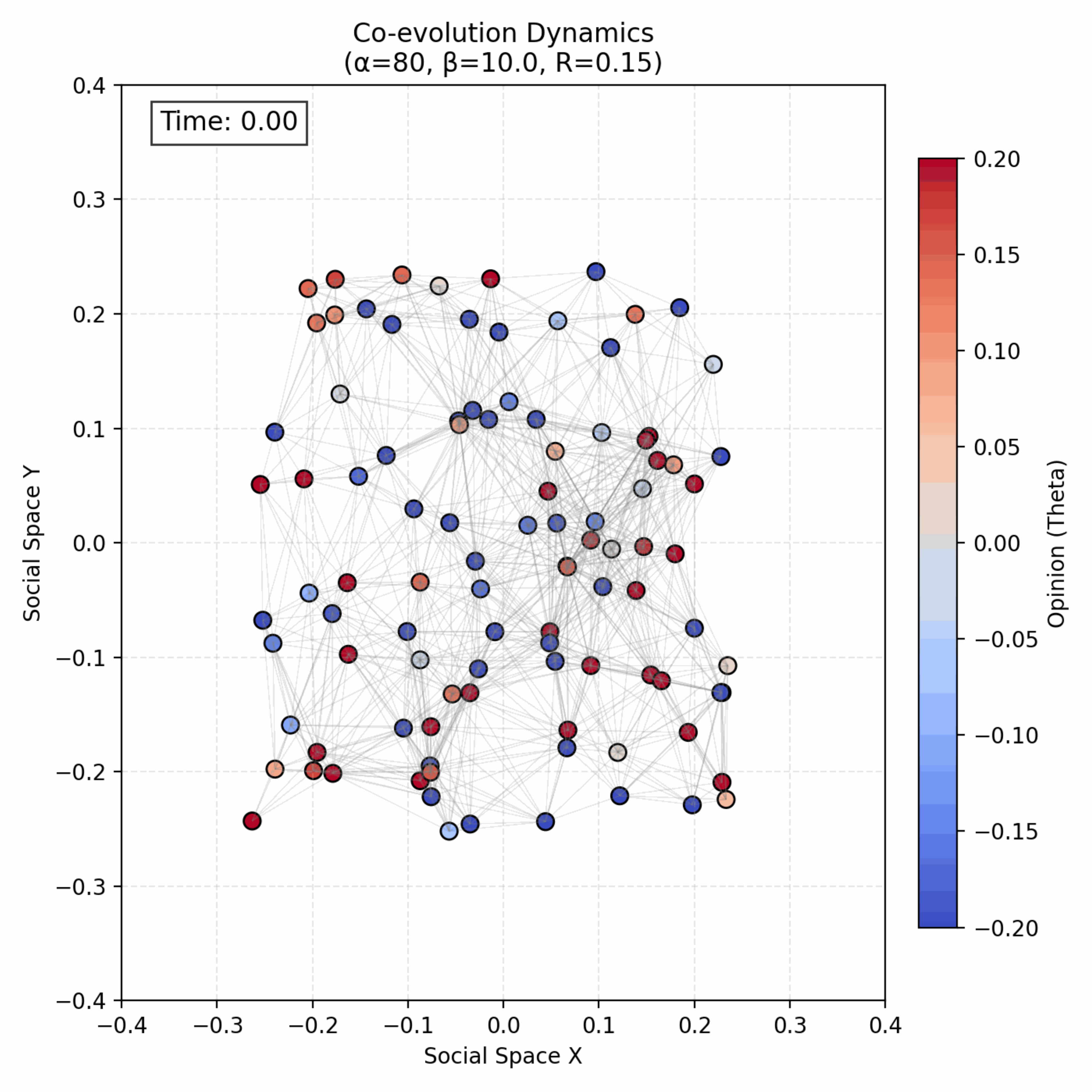
Stronger sentiments accelerates polarization



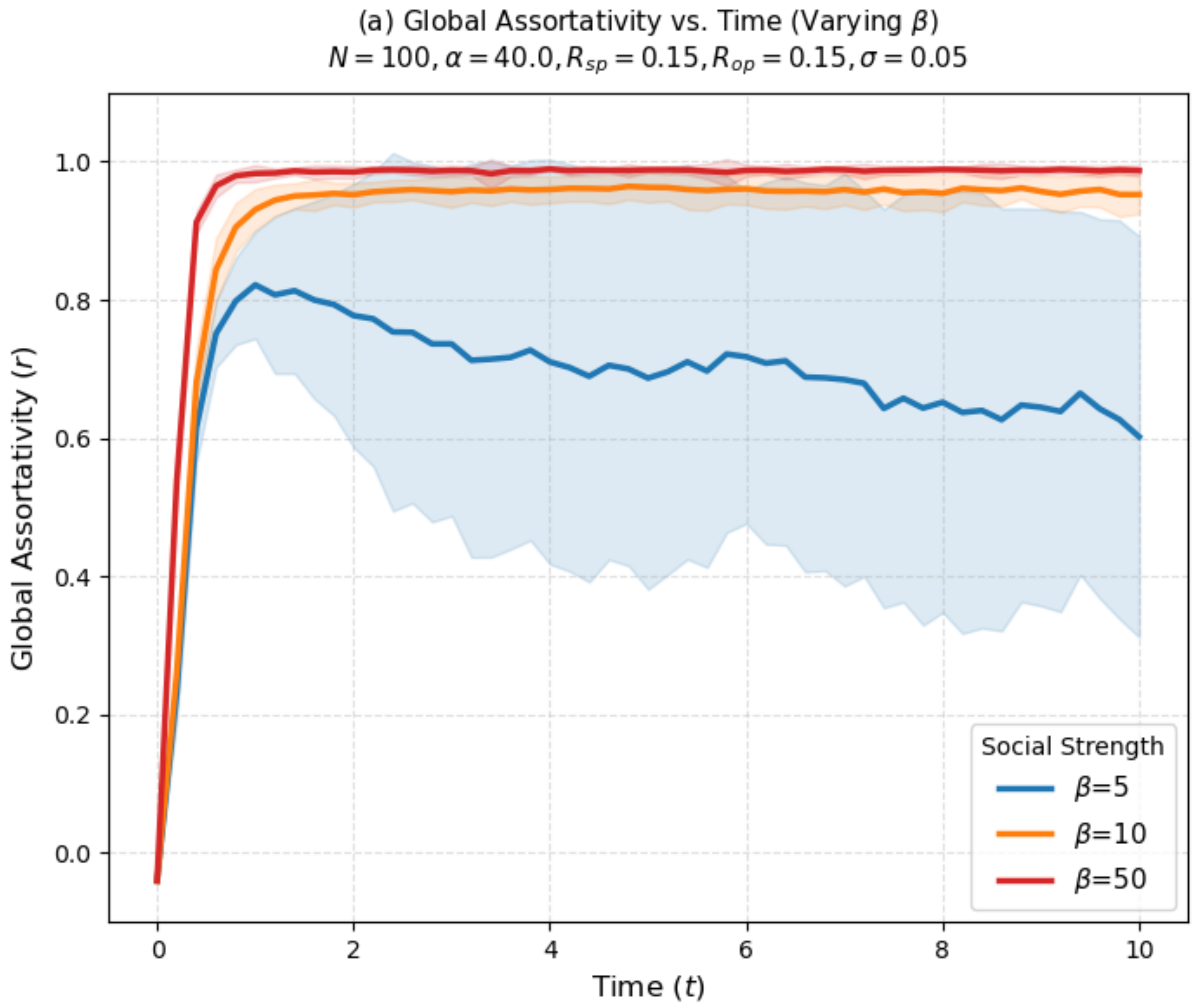
H2a: Stronger opinion influence strength (α) leads to quicker emergence of polarization. ✅

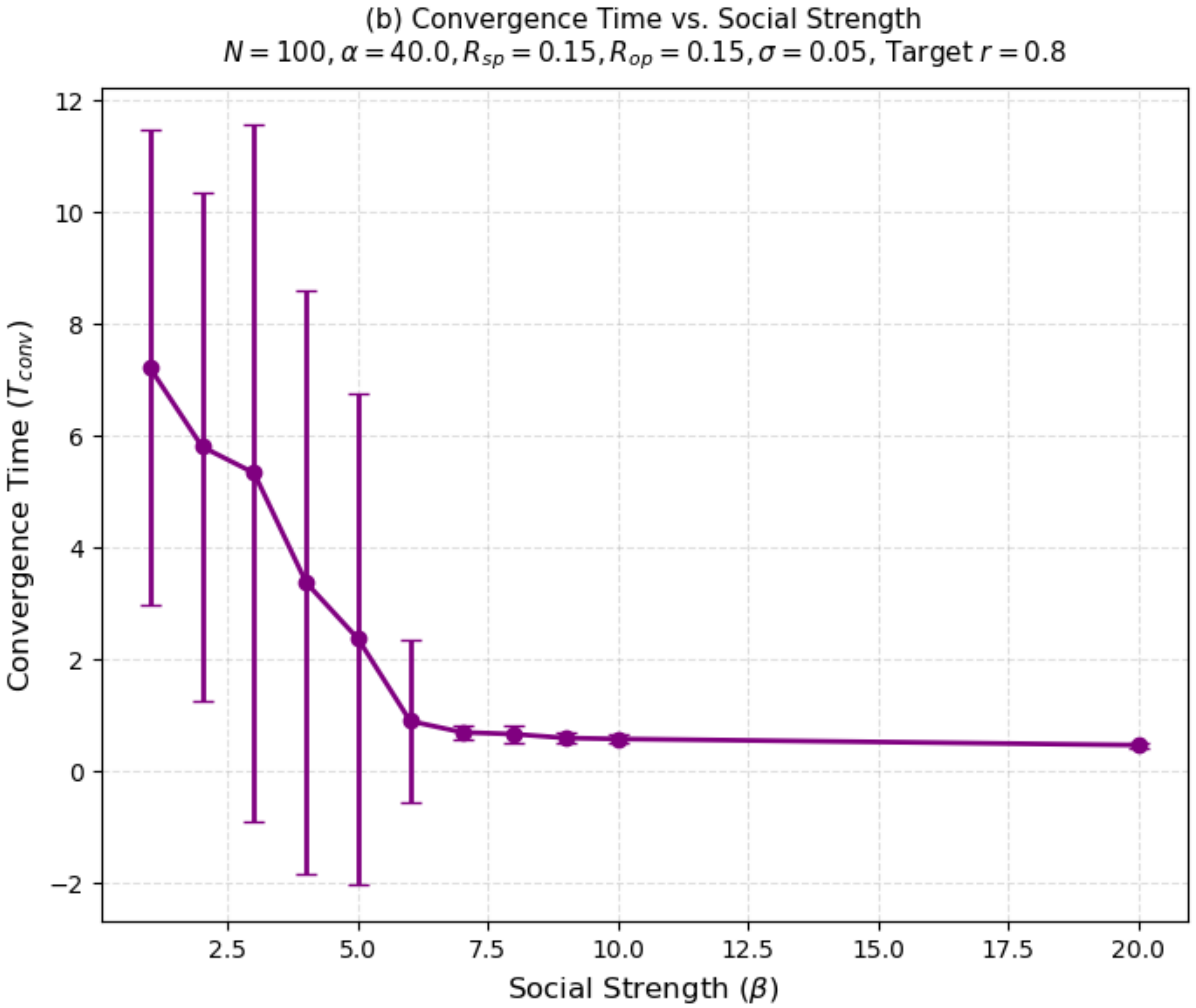
Stronger sentiments accelerates polarization





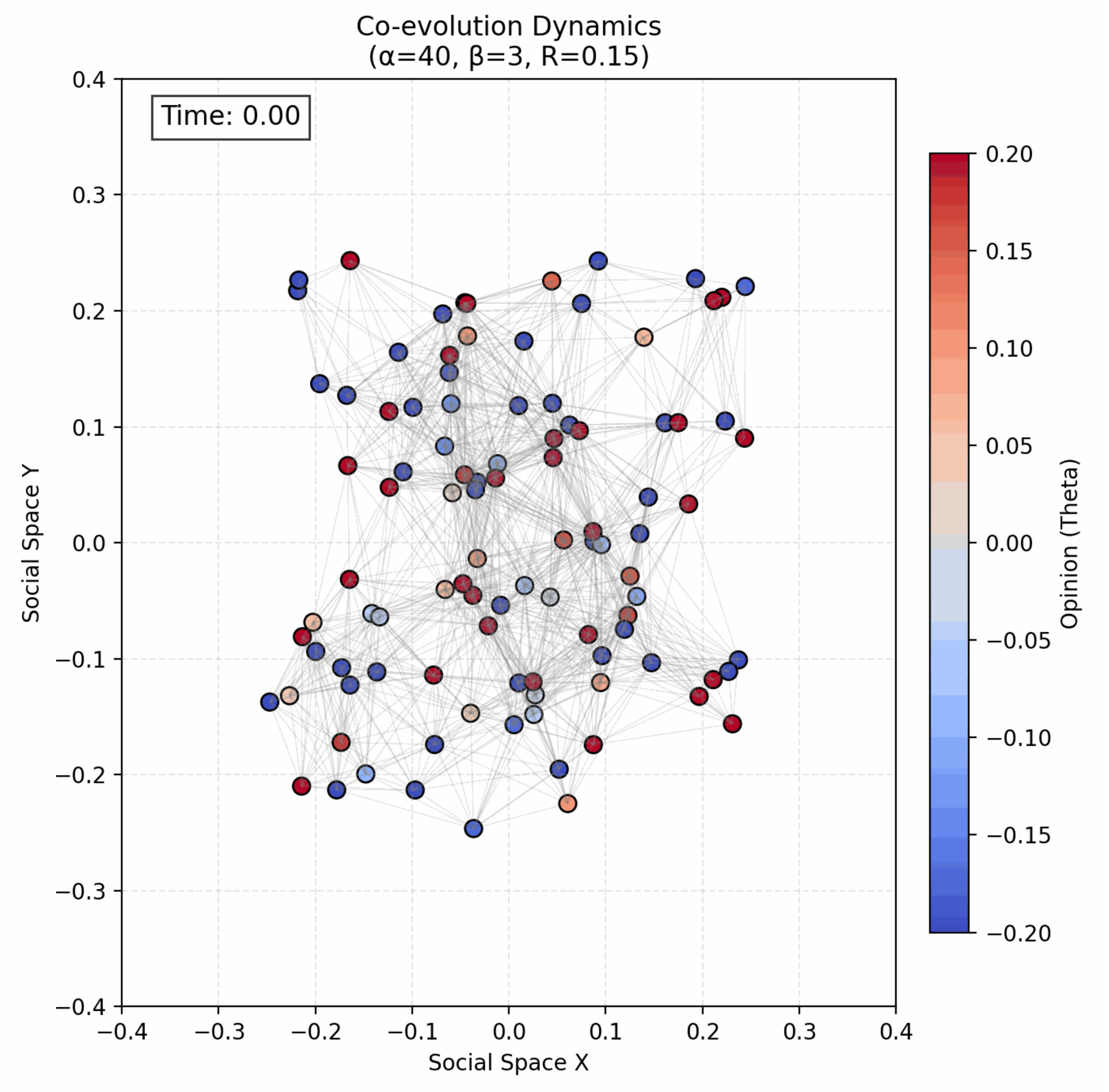
Faster sorting accelerates polarization

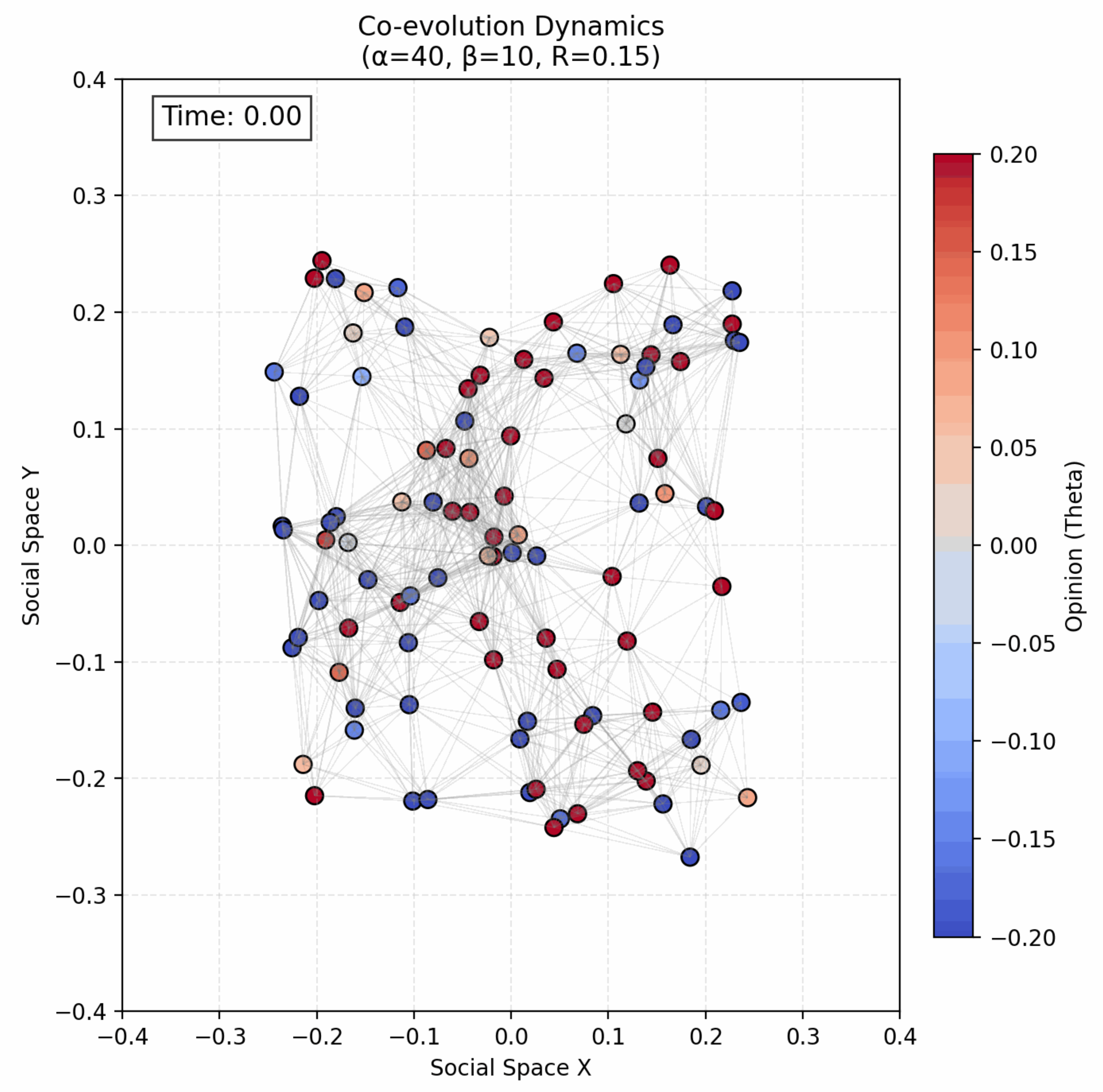




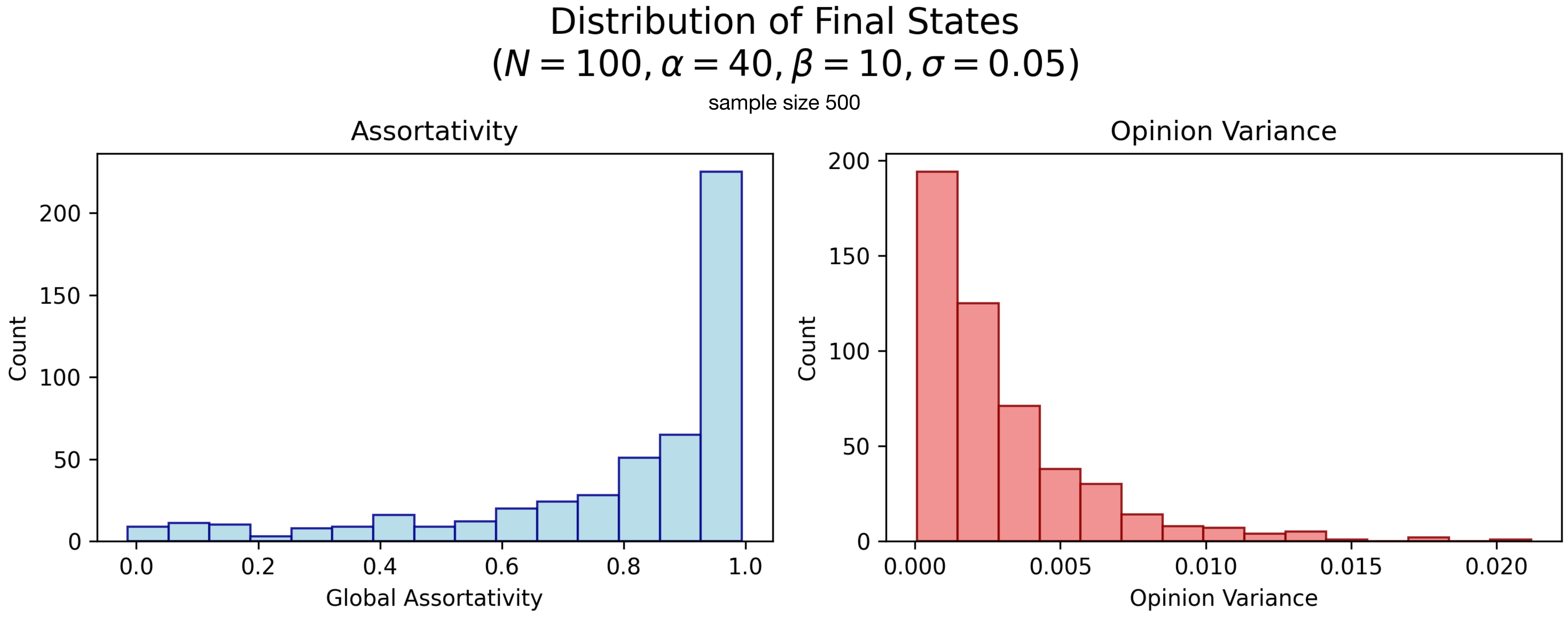
H2a: Stronger social influence strength (β) leads to quicker emergence of polarization. ✅

Faster sorting accelerates polarization





Model sensitivity towards initial states can be approximated by strongly skewed distributions



Treating polarisation with randomness

Run model to settled, polarized state

Apply treatment

- Random edge removal
- Increasing noise term

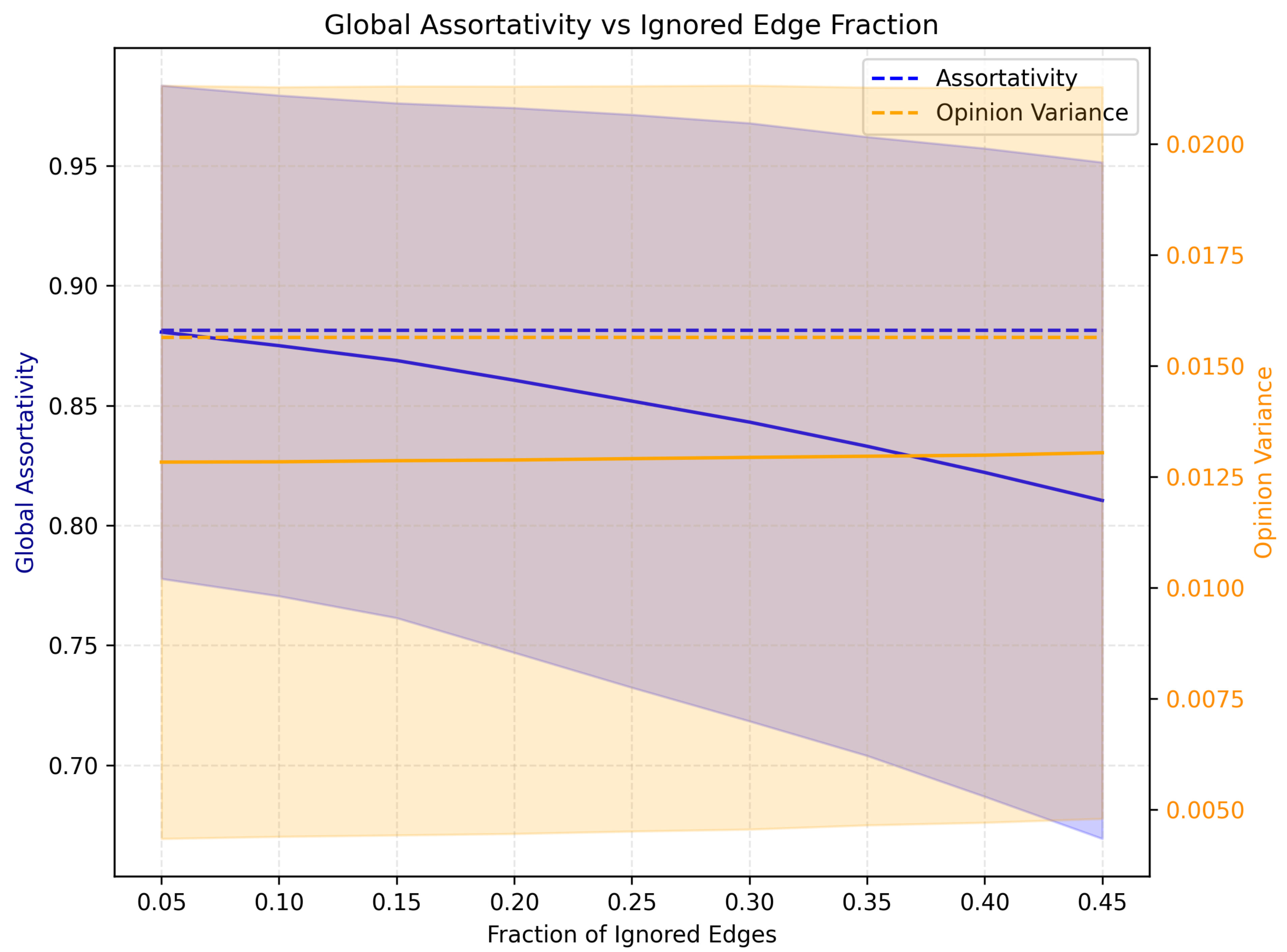
Run model with treatment

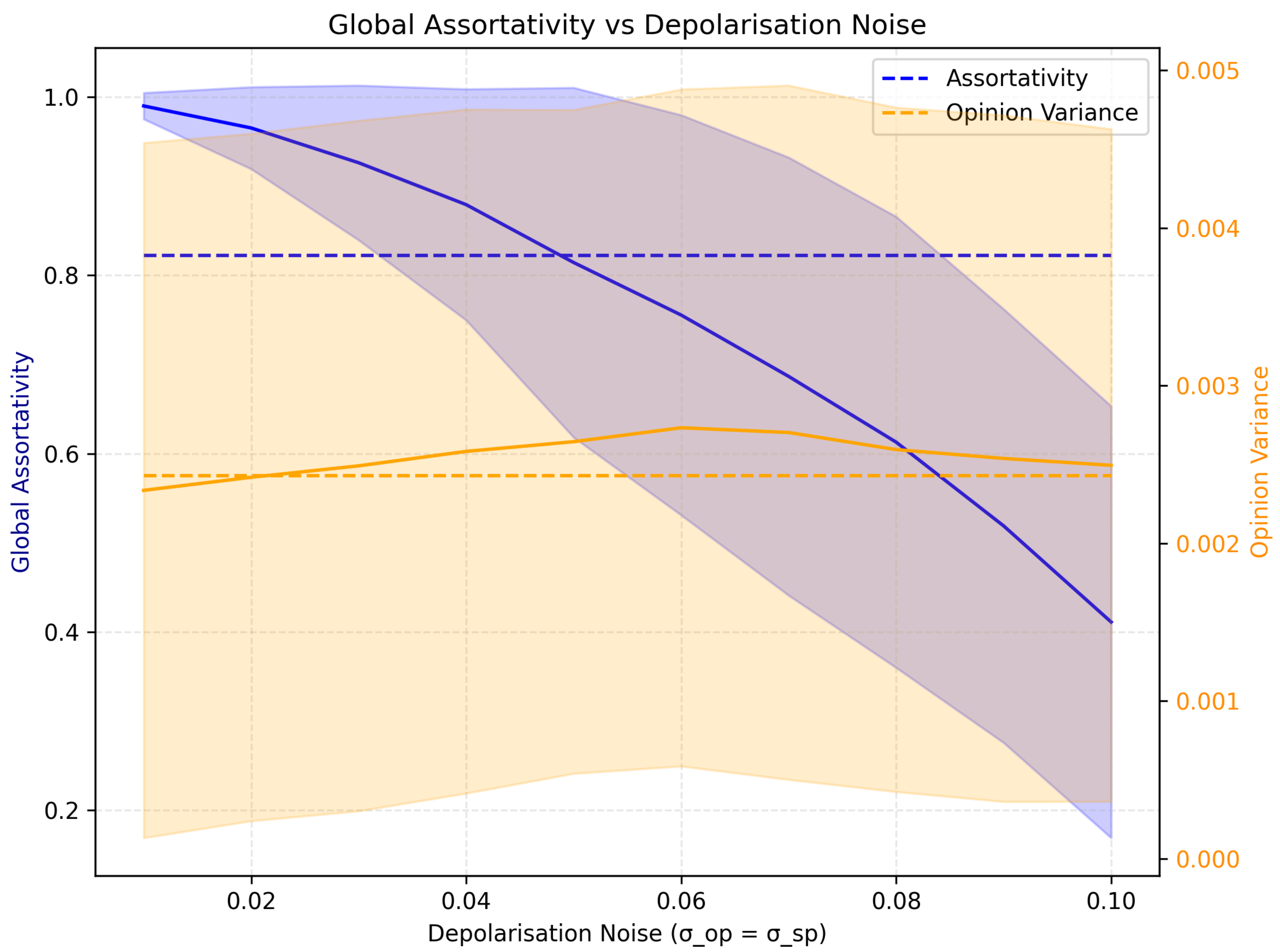
H3 We expect a critical parameter at which the polarisation occurs and a second lower critical parameter at which depolarisation happens.

H4 We should be able to find a critical fraction of removing edges at which depolarisation occurs.

H5 Higher degrees of stochasticity should make polarisation less likely and aid depolarisation as it destabilises attractors.

Once polarised, social spaces are unlikely to revert to a mixed opinion state post intervention





Random edge removal and noise increase lead to a decrease in assortativity but do not increase opinion variance.

Verdict on our hypotheses

RQ1	Do structural segregation and steady-state opinion follow continuous or discontinuous phase transitions in co-evolving networks?
H1	Both structural segregation and opinion divergence follows a discontinuous phase transition.
RQ2	How does the opinion influence strength (α) and social influence strength (beta) determine the emergence of consensus/ fragmentation?
H2	Stronger sentiments should lead to quicker emergence of polarised opinions and/or consensus.
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The chamber of echoes has been opened
And closing it proves to be quite hard

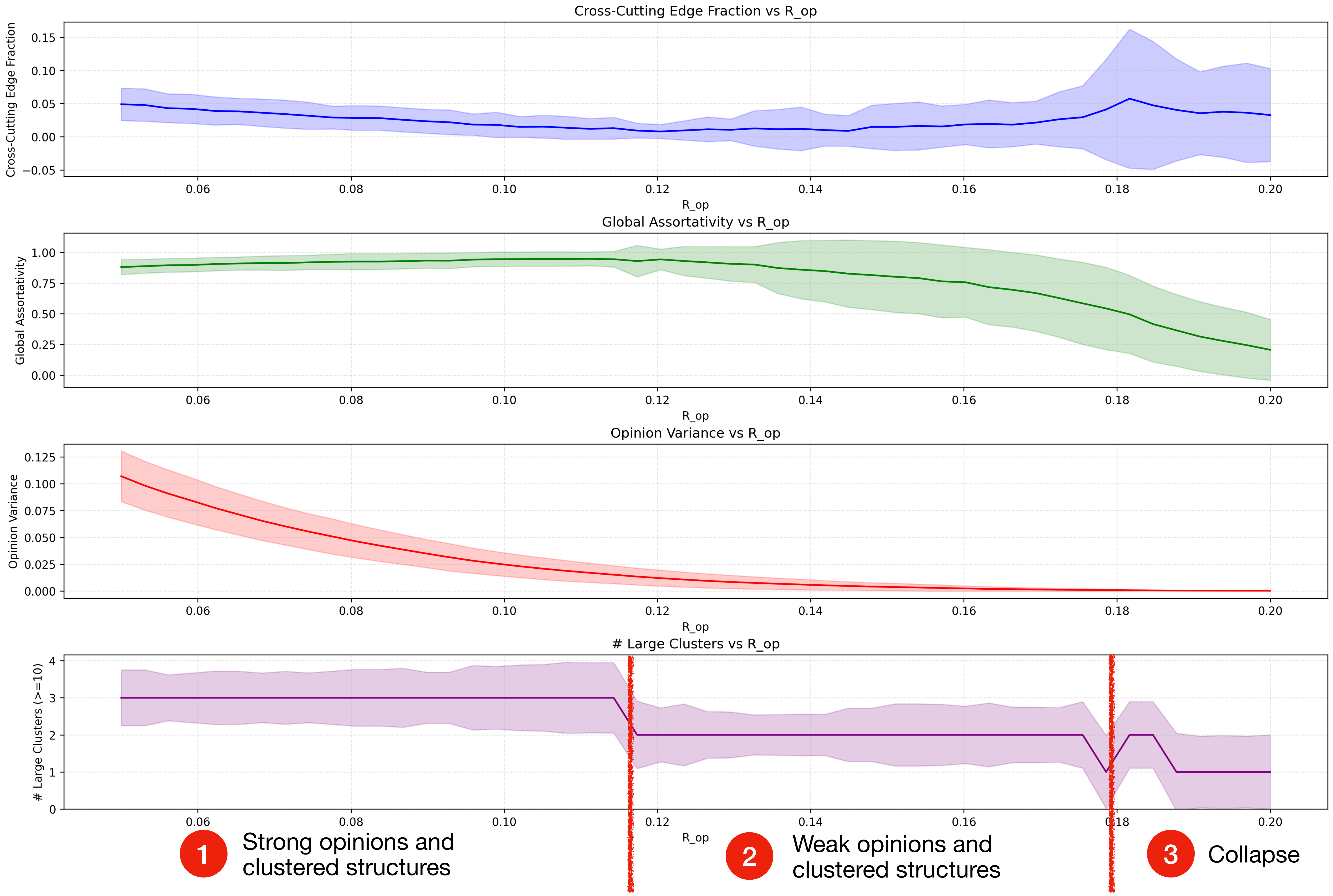
- Polarization emerges generically from co-evolving social interaction networks, even in the absence of algorithmic curation
- Initial conditions shape the outcome but not the existence of polarisation
- Once polarisation is locked in, returning to a mixed-state opinion space via noise increase is not possible

Backup

Increasing the attention radius of agents leads to an opinion and social space collapse

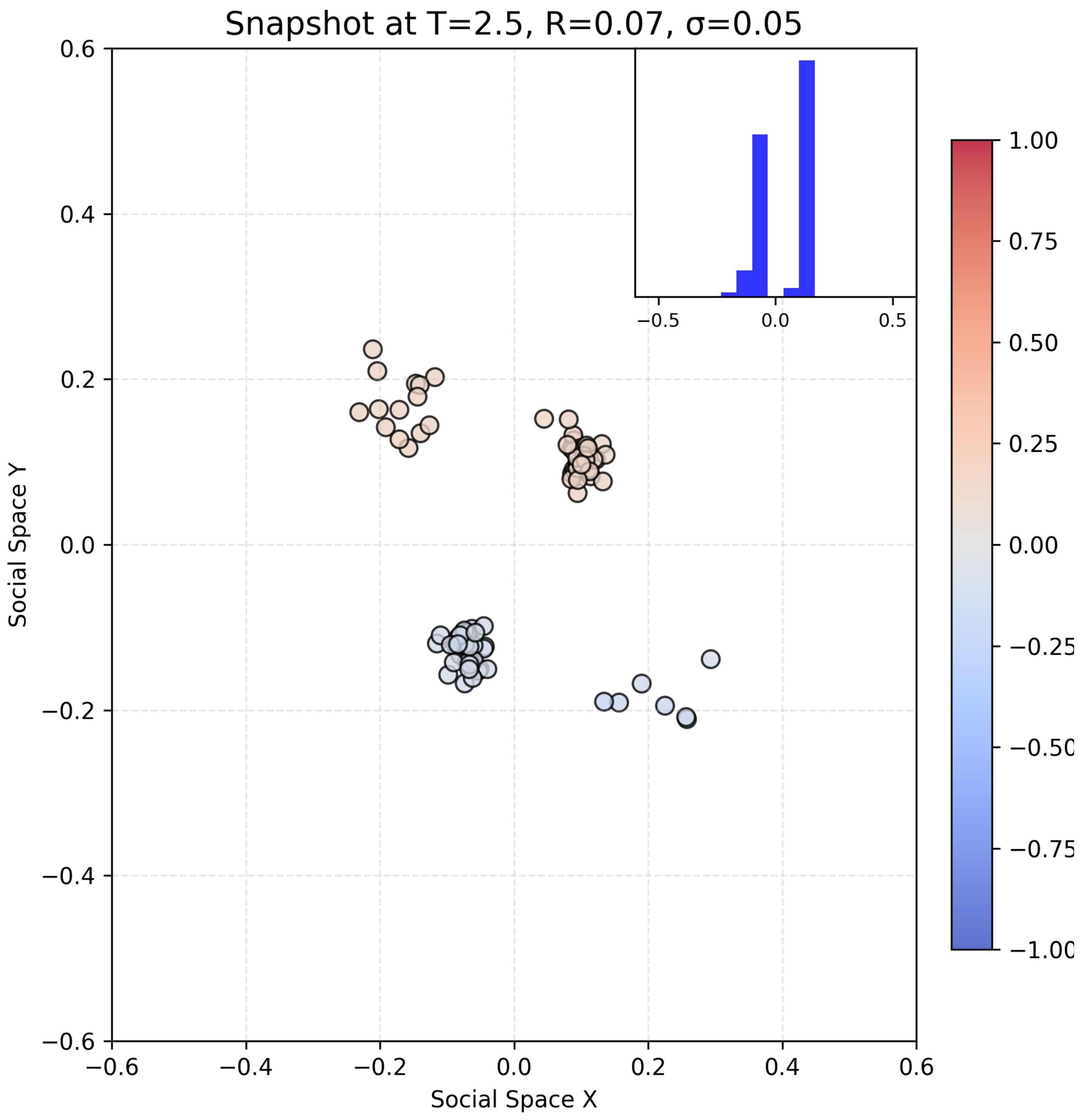
When increasing the attention radius, we observe three operating regimes:

1. Strongly held opinions lead to clear clustering
2. Weak opinions being to dissolve social clustering
3. Collapse into one social position and one opinion

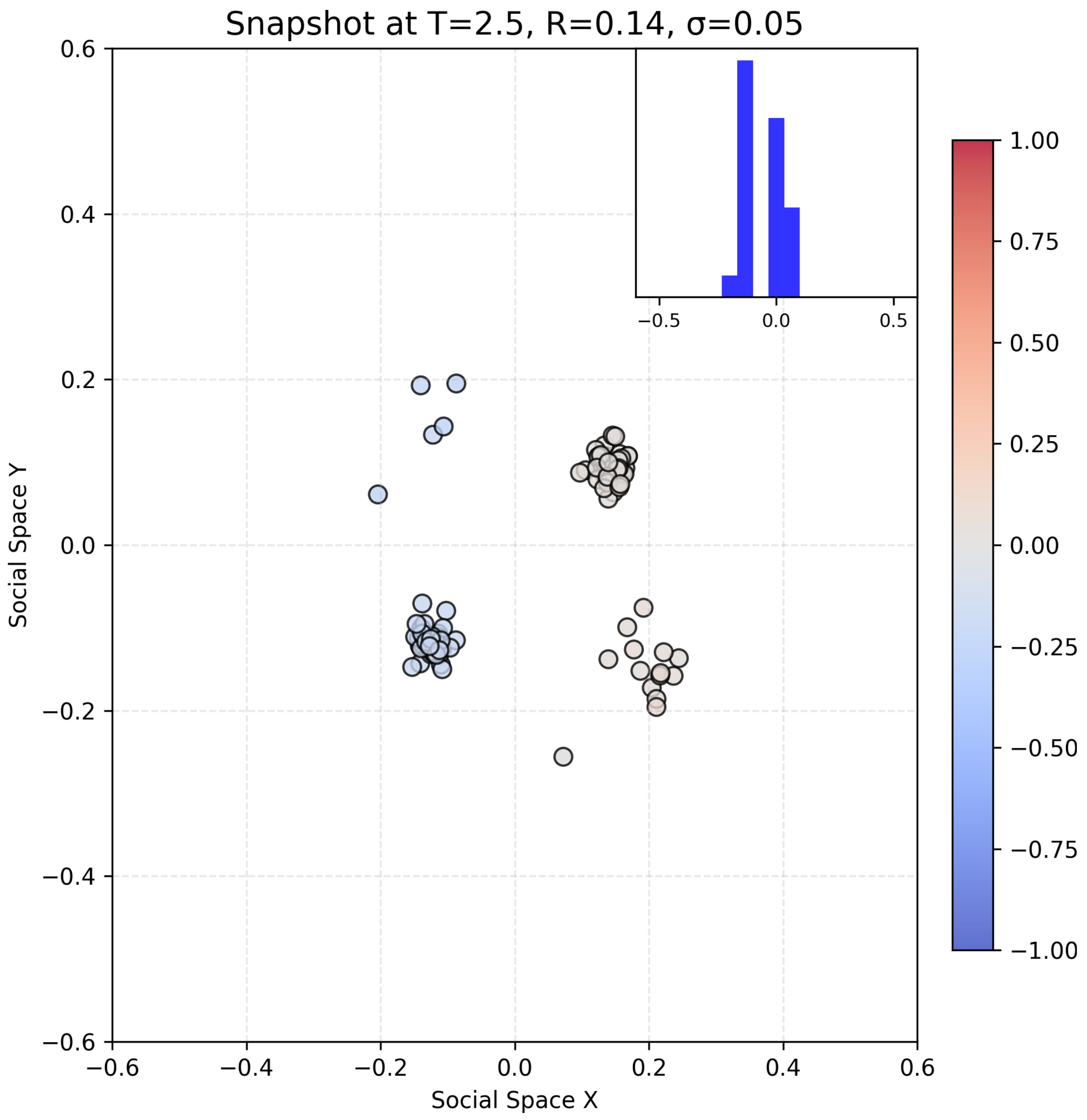


Snapshots of the social spaces show clear differences between the three regimes

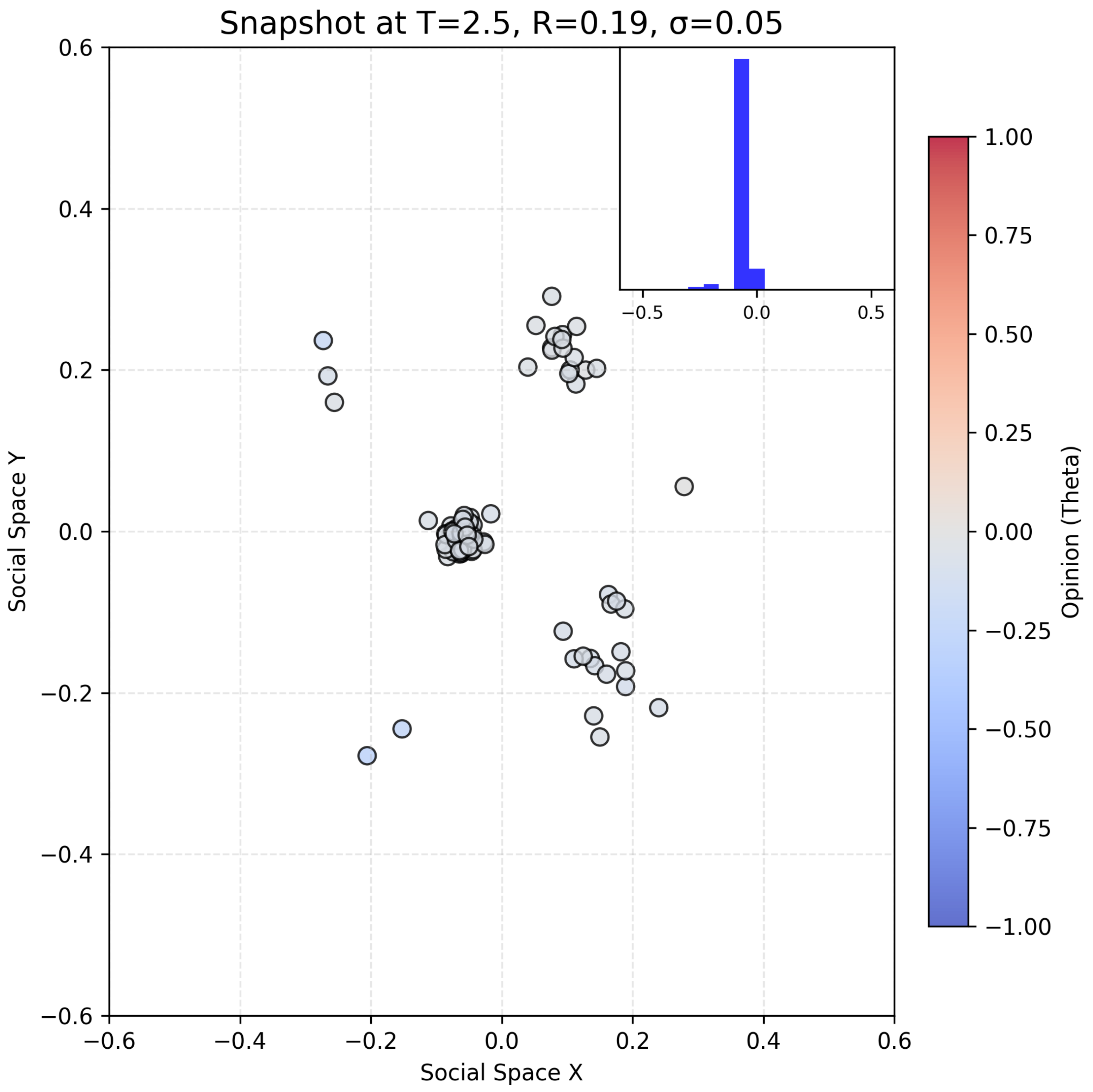
1 Strong opinions and clustered structures



2 Weak opinions and clustered structure



3 Collapse

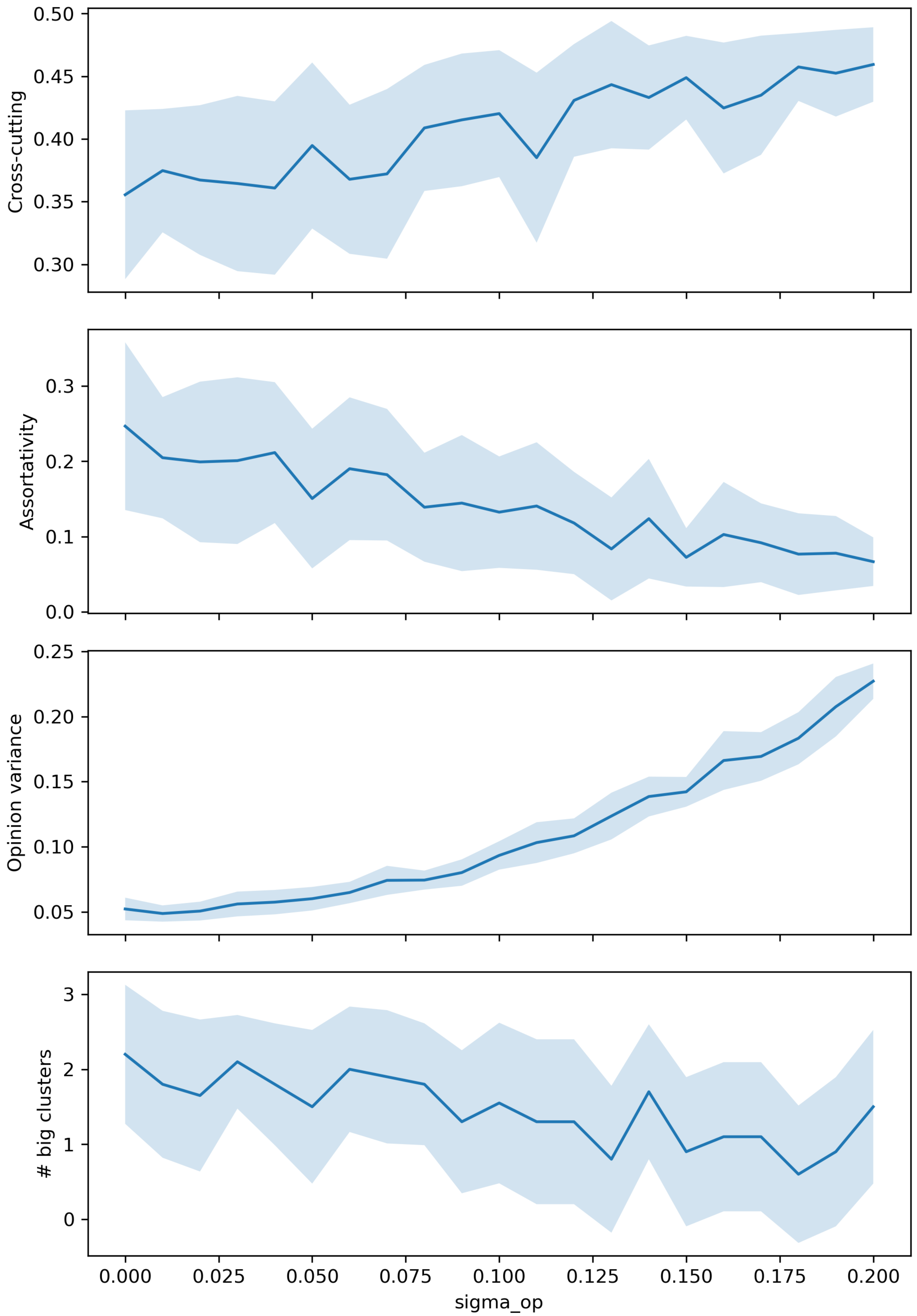


Dynamics of the model

$$dx_k = \frac{1}{N}\sum_{j=1}^{N} U(x_k, x_j, \theta_k, \theta_j)dt + \sigma_{sp} dW_k^{sp}(t),$$

$$d\theta_k = \frac{1}{N}\sum_{j=1}^{N} V(x_k, x_j, \theta_k, \theta_j)dt + \sigma_{op} dW_k^{op}(t),$$

Effect of opinion noise on echo chamber formation



N = 200, α = 1, β = 1, R_sp = 0.2, R_op = 0.12, σ_sp = 0.05