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Dynamics of economic expectations: the rule of individual interactions in networked agent systems

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Brigitta Tóth-Bozó – Dietmar Meyer

Dynamics of economic expectations: the role of individual interactions in networked agent systems

Abstract

This paper presents a network-based agent model to analyse the dynamics of economic expectations in decentralized systems. Building on classical typologies of expectations and the literature on opinion dynamics, we simulate how individual beliefs evolve through directed, weighted networks. Each agent holds an initial expectation and a reliability index, and updates beliefs by averaging neighbours' expectations, weighted by their perceived credibility. We examine how network topology (random vs. scale-free), the presence and characteristics of opinion leaders, and the distribution of reliability influence convergence, consensus, and aggregate outcomes. A Monte Carlo-based ANOVA analysis reveals that network structure, and the distribution of influence significantly affect expectation dynamics, with strong interaction effects between bias and perceived reliability. The findings demonstrate that expectation formation is a socially embedded process, shaped not only by information but by trust, position, and interaction.

Keywords: expectation formation, network structure, opinion dynamics

JEL Codes: C63, D83, D85

1. Introduction

Expectations about economic variables — such as inflation, output, or interest rates — play a central role in both economic theory and policymaking. While early models already incorporated expectations (e.g., Metzler, 1941; Cagan, 1956), Muth's (1961) rational expectations hypothesis became a foundational concept in modern macroeconomic theory. Since then, a range of expectation types have emerged, including adaptive, extrapolative, and hybrid forms. These approaches differ in how agents incorporate information — whether by mechanically projecting from the past or by anticipating the future based on structural understanding.

Despite this diversity, expectation formation is often treated in isolation from the social and informational environments in which economic agents operate. Standard models assume that expectations are formed through individual belief formation and statistical rules, without considering how these beliefs evolve through interaction. Yet in decentralized systems, information is rarely processed independently: agents observe, filter, and integrate the expectations of others, particularly when trust, credibility, or influence comes into play. Network-based approaches offer a promising framework for modelling such information diffusion and socially embedded expectation updating.

In this paper, we integrate the typology of economic expectations with a network-based agent model. We construct a directed, weighted network of agents, where each node represents an individual holding an initial expectation and a reliability index. Agents revise their expectations in discrete time steps, averaging the expectations of their neighbours, weighted by the neighbours' reliability. This mechanism corresponds to a modified DeGroot process (DeGroot, 1974) situated between adaptive and extrapolative expectations, and augmented by a social filtering mechanism based on perceived credibility. Our contribution is twofold. First, we will look at the types of expectations used in the literature, according to three different groupings of our own. Second, the model in this study is a novel approach to the evolution of economic agents' expectations. Our results show that both the network structure and the distribution of influence (via reliability indices) significantly affect the dynamics of expectation formation. Dense and homogeneous networks tend to foster convergence and consensus, while scale-free structures often stabilize around a dispersed equilibrium without full agreement. These findings suggest that expectation evolution is not merely a cognitive or informational process, but also a social one — driven by structure, credibility, and interaction and the key factor is the connection structure between the agents.

Section 2 provides a review of the relevant literature, focusing on typologies of expectation formation and the integration of network-based approaches in economic modeling. Section 3 introduces the model, detailing the agent-based framework, the structure of directed weighted networks, and the mechanism by which agents update their expectations. Section 4 presents the simulation design and results, including both descriptive statistics and a sensitivity analysis based on ANOVA to assess the role of structural and behavioral parameters. Finally, Section 5 concludes the study by summarizing the main findings and highlighting their implications for understanding how individual expectations evolve in networked environments.

2. Literature review

2.1 The Role of Expectations in Economic Modelling

Expectations have long played a central role in economic theory, particularly in macroeconomics. As early as the mid-20th century, models began to incorporate how agents form beliefs about future economic variables such as inflation, output, and interest rates. The rational expectations hypothesis, introduced by Muth (1961), revolutionized economic modelling by assuming that agents' forecasts are consistent with the underlying model and utilize all available information efficiently. This paradigm became central in New Classical and New Keynesian models, influencing both theoretical dynamics and policy design. However, several alternative approaches emerged that challenged the rational expectations assumption. Adaptive expectations (Cagan, 1956; Friedman, 1957) posit that agents form beliefs by extrapolating from past values, adjusting gradually over time. Other models incorporate extrapolative or regressive behaviour (Metzler, 1941), while bounded rationality frameworks acknowledge cognitive limitations and learning processes (Simon, 1958; Evans and Honkapohja, 2001). More recently, heterogeneous expectations have gained prominence, particularly in agent-based and behavioural macroeconomic models (Hommes, 2013).

These perspectives differ in their assumptions about how expectations are formed over time — whether they are backward- or forward-looking — and whether they are treated as objective predictions or subjective interpretations. Adaptive and extrapolative expectations rely on past observations, while forward-looking models attempt to anticipate future developments. Some approaches view expectation formation as a mechanical or statistical process, whereas others incorporate subjective judgment influenced by trust, credibility, or social reference points. A growing body of theoretical and empirical research challenges the notion that expectations are formed in isolation from social context. Rather than relying solely on their own information or reasoning, economic agents often form beliefs through social interaction, imitation, and influence (Hommes, 2013; Manski, 2004). Experimental and theoretical studies show that individuals respond to the expectations of others, particularly when uncertainty is high or information is incomplete (Blume et al., 2011; Barr & Serra, 2010). In such environments, credibility, trust, and social status affect whose opinions are considered valid (Golub & Jackson, 2010; Acemoglu & Ozdaglar, 2011). Expectations are therefore not merely cognitive outputs, but the result of interpersonal influence, reputational filtering, and positional structures within informational and social networks. These insights support the use of network-based models, where expectation dynamics emerge from the structure and strength of directed social ties —

an approach we adopt in this paper. In line with this broader perspective, Witztum (2020) proposes a nuanced conceptualization of expectations as multidimensional mental structures. He distinguishes between three types: value expectations (v-expectations), which concern the expected future value of a variable; procedural expectations (p-expectations), which reflect beliefs about the behaviour and expectations of others; and consequence expectations (c-expectations), which relate to the anticipated outcomes of decisions based on v- and p-expectations. This framework highlights the importance of the social environment in shaping beliefs, especially through the p-expectation dimension, which directly involves forming expectations about others' expectations. Such a conceptualization aligns with our approach, which models expectation formation as an interactive, socially embedded process unfolding within a network structure.

2.2 Typology of expectations

Over the decades, economic theory has produced a wide range of expectation models, reflecting different assumptions about how agents process information, learn, and interact with their environment. This section presents a structured typology of expectations, based on key conceptual dimensions discussed in the literature and further developed in our approach.

- *Temporal orientation*: Backward-looking expectations, such as adaptive or extrapolative types, rely on past observations and trends. In contrast, forward-looking expectations are anticipatory, based on expectations about future conditions or equilibrium values. Rational expectations (Muth, 1961) assume full model consistency, while perfect foresight assumes knowledge of future states.
- *Mechanism of formation*: Expectations may be formed mechanically (objectively), through fixed rules (e.g., adaptive expectation, simple), or subjectively, incorporating beliefs about credibility, strategic behaviour, or reputational factors. Models with subjective expectations acknowledge that agents are not neutral processors of data, but weigh information based on trust, perceived expertise, or social position (Manski, 2004; Colucci & Valori, 2011).
- *Degree of aggregation*: Traditional representative-agent models treat expectations as homogeneous and aggregated, while more recent approaches emphasize heterogeneous beliefs and decentralized learning. Heterogeneous agent models and behavioural macroeconomics explore how differences in individual expectations affect macroeconomic outcomes (Hommes, 2013).

Several authors propose hybrid or mixed expectation models, where different types coexist or switch depending on context (Simonovits, 1999). These include rule-switching, bounded rationality, and context-dependent forecasting. Such models recognize that agents adapt not only their expectations, but also the way in which those expectations are formed. As discussed in Section 2.1, Witztum (2020) introduces a layered understanding of expectations as mental structures composed of value (v-), procedural (p-), and consequence (c-) expectations. Of particular relevance to our framework is the p-expectation, which emphasizes the importance of agents' beliefs about others' expectations. This component highlights that expectation formation is not only influenced by information, but by social cognition and interactive anticipation. It conceptually aligns with modelling expectations as embedded in a network, where agents respond not merely to data, but to the beliefs circulating in their environment. In this context, the typology of expectations serves as a conceptual foundation for network-based modelling. Our model builds on the tradition of adaptive and extrapolative expectations but adds a relational layer: expectations evolve not in isolation, but through interaction with neighbouring agents, weighted by credibility. This operationalizes subjective and procedural expectations in a formal, dynamic network setting.

2.3 Network-based approaches of expectation dynamics

Recent developments in expectation modelling increasingly incorporate network structures to capture the role of social and informational connectivity among economic agents. Instead of treating agents as isolated decision-makers, these approaches assume that beliefs evolve through interaction with others in a structured environment. This perspective has led to the emergence of formal models of opinion dynamics and network learning, many of which are rooted in linear averaging schemes. One of the foundational models in this domain is the DeGroot model (DeGroot, 1974), in which agents iteratively update their expectations by computing a weighted average of their neighbours' beliefs. The weight matrix defines the strength of influence and is typically fixed over time. This linear updating process leads, under certain conditions, to consensus, where all agents converge to a common expectation. The model has been extensively studied and generalized in various directions, particularly in the economics of networks and opinion dynamics (Jackson, 2008; Golub & Jackson, 2010). Several extensions of the DeGroot framework introduce heterogeneity, bounded confidence, or endogenous trust adjustment. For instance, Golub & Jackson (2010) show that under mild conditions, even with naive agents, consensus may approximate the "wisdom of crowds" — provided the network is sufficiently large and well-connected. In contrast, Acemoglu &

Ozdaglar (2011) explore cases where influential agents or "forceful minorities" can steer the consensus in biased directions. These models highlight that network topology, centrality, and the distribution of influence crucially shape collective outcomes. In economic applications, network-based models have been used to study learning, diffusion of information, financial contagion, and belief formation under uncertainty (Banerjee et al., 2013; Buechel et al., 2015). Despite this growing body of research, the integration of expectation typologies and network dynamics remains limited, particularly in agent-based macroeconomic settings. Most models either assume mechanical updating rules or focus on network effects in isolation from behavioural assumptions. Our approach builds on this literature by combining a DeGroot-type updating mechanism with subjective credibility weighting and heterogeneous agent roles, such as opinion leaders. We place agents in directed, weighted networks — both random (based on Erdős – Rényi model (1959)) and scale-free (based on Barabási – Albert model, 1999) — and model how expectations evolve through repeated interaction. Each agent attributes weight to its neighbours based on a reliability index, capturing perceived trust or authority. This framework allows us to study how network structure, influence asymmetries, and initial biases shape expectation dynamics over time.

We model a system of economic agents embedded in a network represented by a directed graph $G = (V, E)$, where V is the set of agents and $E \subseteq V \times V$ is the set of directed edges. A directed edge from agent j to agent i (denoted $j \rightarrow i$) indicates that agent i takes agent j's expectation into account when updating their own. The network is represented by a weighted adjacency matrix $\boldsymbol{A} \in \mathbb{R}^{n \times n}$ where each entry $A_{ij} \in [0,1]$ denotes the weight that agent i assigns to agent j's expectation. The rows of the matrix are normalized such that $\sum_j A_{ij} = 1$ for all i, ensuring that each agent computes a convex combination of their neighbours' expectations. We examine two types of static directed networks:

- Directed random graph model, wich is based on Erdős–Rényi (1959), where each potential edge is formed independently with a fixed probability;
- Directed scale-free networks, based on Barabási – Albert (1999) where new nodes preferentially attach to existing nodes with high in-degree, producing hub-like structures and degree heterogeneity.

The networks are generated exogenously and remain fixed throughout the simulation. Directionality captures asymmetric influence relationships, and the position of an agent in the network affects its exposure to others' expectations and its own influence over the group. In our model, each agent $i \in V$ is assigned two initial attributes:

- An initial expectation $x_i^0 \in \mathbb{R}$, representing the i[th] agent's initial belief about an economic variable;
- A reliability index $r_i \in [0,1]$, indicating the credibility or influence of the agent as perceived by others. The reliability indices of economic agents are known to all operators and do not change over time.

The initial expectations are drawn from a probability distribution defined by simulation parameters, typically centred around a reference mean. For selected agents designated as opinion leaders, an additional bias may be applied to shift their expectations away from the population average. Similarly, reliability indices are drawn from a chosen distribution, with opinion leaders possibly assigned fixed or systematically higher values to reflect their perceived authority. Both the distribution of expectations and the configuration of reliability indices vary across simulation scenarios, allowing us to examine the model's sensitivity to different structural and behavioural assumptions.

2.4 Expectation updating process

Time proceeds in discrete steps $t = 0,1,2, \ldots$. At each step, agents revise their expectations by averaging the expectations of those agents they observe, using the weights defined in the adjacency matrix $\boldsymbol{A}$. The updating rule is:

$$\boldsymbol{X}(t+1) = \boldsymbol{A}\boldsymbol{X}(t) \tag{1}$$

where $\boldsymbol{X}(t) \in R^n$ is the vector of expectations at time t, and $\boldsymbol{A}$ is the row-normalized weight matrix. This corresponds to a DeGroot-type learning process (DeGroot, 1974), in which each agent updates their expectation as a credibility-weighted average of their neighbours' expectations. The process iterates until convergence or until a maximum number of steps T is reached. Convergence is defined by $|X(t+1) - X(t)| < \varepsilon$, where ε is a small threshold and $\|\cdot\|$ denotes the Euclidean norm.

2.5 Aggregated output and indicators

Each simulation run generates a set of output indicators that summarise the collective behaviour of the agent system at the end of the updating process. These indicators allow us to analyse how the system evolves under different structural and behavioural settings. Specifically, we compute the following:

- Final mean expectation: denoted as $\bar{x}(t)$; this indicator represents the average of all agents' expectations after the system has reached convergence. Formally:

$$\bar{x}(t) = \frac{1}{n}\sum_{i=1}^{n} x_i(t) \quad (2)$$

  where $x_i(t)$ is the final expectation of agent i, and n is the total number of agents in the network. This measure reflects the collective position of the system after interaction has taken place. Comparing the final mean to the initial average allows us to assess whether external influences (e.g., opinion leaders) shifted the system-wide belief in a particular direction.

- Number of iterations to convergence: This variable records how many updating steps were required before the system stabilised — i.e., before the change in expectations between iterations dropped below a fixed threshold. It serves as a proxy for the speed of convergence and is influenced by both the network structure and the distribution of influence weights.
- Dispersion of final expectations: This refers to the standard deviation of the agents' expectations at convergence. A low dispersion value indicates that the agents' beliefs have become aligned, while a high dispersion suggests persistent disagreement or fragmentation within the network.
- Consensus indicator: A binary variable that equals 1 if the final standard deviation of expectations falls below a predefined threshold (e.g., $\sigma < 1$), indicating that the system has reached a state of near-unanimity. If the threshold is not met, the indicator equals 0. This metric captures whether a quantitative notion of consensus has emerged among the actors.

In summary, these four indicators provide a comprehensive picture of how the networked agent system evolves over time. They serve as the empirical basis for analysing the impact of different parameters (e.g., topology, reliability distribution, opinion leader configuration) on the dynamics of expectation formation in the subsequent simulation and evaluation sections.

3. Simulations

3.1 Simulation Setup

To analyse the dynamics of expectation formation in structured agent systems, we performed a series of simulations across multiple network configurations, agent properties, and initialization settings. The aim of these simulations was to observe how different topologies, distributions of influence, and initial belief structures affect the evolution and convergence of expectations. As we mentioned in Section 2.2, we considered two types of directed network topologies: a directed random graph based on Erdős – Rényi model (1959), characterized by homogeneous degree distribution, and a directed scale-free network based on Barabási – Albert (1999), which exhibit hub dominance and high degree heterogeneity.

Each network consisted of 200 agents, with directed edges representing the flow of influence. The networks were generated using standard algorithms from the NetworkX Python library. In the first section of the simulation, Erdős – Rényi graphs were generated with edge probability $p = 0.6$ (nx.gnp_random_graph(n=200, p=0.6)) ; Barabási–Albert graphs were created using preferential attachment and then converted to directed graphs by randomly assigning edge directions (nx.barabasi_albert_graph(n=200, m=3)).

Every agent was initialized with two properties:

- An initial expectation $x_i(0)$, whose distribution will be either uniform or normally distributed.
- A reliability index $r_i \in [0,1]$, which determined how much influence the agent exerted over its neighbours. I will also vary the distribution of this during the simulations, working with both uniform and normal distributions.

In each simulation, expectations were updated over discrete time steps following a DeGroot-type rule is (1), where $\mathbf{A}$ is a row-normalized adjacency matrix, with entries A_{ij} representing how much weight agent i assigns to agent j's current expectation, based on the directed network and reliability scores. The updating process continued until convergence (defined as $\| X(t+1) - X(t) \| < 10^{-6}$ or a fixed maximum number of iterations (typically 1000). At each run, we recorded several outcome variables, including:

- the final mean expectation across all agents,
- the standard deviation of expectations at convergence,

- the number of iterations until convergence,
- a binary consensus indicator, based on whether the final dispersion fell below a predefined threshold.

Across simulation batches, we systematically varied:

- the topology (Erdős – Rényi vs. Barabási – Albert);
- the distribution of initial expectations;
- the reliability index patterns;
- the presence and configuration of opinion leaders.

Simulations were implemented in Python 3.10 using NumPy, Pandas, and NetworkX and Matplotlib for visualization. Results were aggregated and analysed using exploratory data techniques and visualization. We use Monte Carlo methods to generate repeated realizations of each configuration to account for randomness in network generation and initial values.

The core simulation process consists of the following steps:

1. Network generation: for each simulation, a directed Erdős – Rényi graph was generated with 200 nodes and an edge probability of $p = 0.6$ or a Barabási – Albert graph with 200 nodes. The forst creates a relatively dense random network structure and the second creates a relatively sparse scale-free network structure, where new nodes preferentially attach to already well-connected nodes, resulting in the emergence of hubs and a highly heterogeneous degree distribution.

2. Initialization of expectations: each agent received an initial value (representing an economic expectation), drawn from a uniform or normal distribution over the interval $[200,600]$.

3. Edge weight assignment: directed edges were assigned weights sampled from a normal distribution with mean 0.5 and standard deviation 0.3, or uniform distribution, then clipped to the interval $[0,1]$ to ensure validity.

4. Normalization of incoming edge weights: for each agent, the weights of all incoming edges were normalized to sum to 1. This ensures that agents compute a convex combination of their neighbours' values.

5. Iterative update: in each iteration, agents updated their values by computing the weighted average of their neighbours' values (based on incoming edges and weights).

This process was repeated until convergence (defined as a maximum change below 10^{-6}) or a maximum of 1000 steps.

6. Aggregation: I ran all simulations one thousand times for all possible model variants. For each of the 1000 generated networks, the average number of steps to convergence and the average of initial and final values were recorded across agents and across runs.
7. Visualization: histograms of initial and final expectation values were plotted, along with vertical lines showing the mean values before and after convergence. These visualizations help illustrate the system-level behaviour that emerges from local interaction rules.

The iterative update function is implemented using NetworkX graph traversal and direct access to node and edge attributes. The convergence routine checks maximum absolute differences across node values at each step, ensuring the process halts once stability is reached. The simulation can be scaled by adjusting the number of network realizations (num_graphs), and the results are averaged across these Monte Carlo samples for robustness.

4. Results and analysis

4.1 Summary statistics and distributions

To gain a descriptive overview of the simulation outputs, we analysed the distribution of agents' final expectation values across multiple simulation runs. For each network type, we generated 1000 directed networks with 200 nodes and computed the average expectation value per node over all realizations. The results suggest that structural heterogeneity in networks — such as that observed in Barabási–Albert models—may be associated with greater dispersion in final expectations, especially when influence is concentrated in a few highly connected agents.

Number of versions	model (scale-free network or random graphs)	Initial expectation distribution	Reliability index distribution	Average initial expectation	Final initial expectation	consensus (Y/N)	average number of iterations
1.	scale-free	$x_i(0) \sim U(200,\ 600)$	$U(0{,}1)$	400,38	400,33	N	26,95
2.	scace-free	$x_i(0) \sim N(400,\ 200^2)$	$N(0{,}5,\ 0{,}3^2)$	399,96	400,05	N	21,48
3.	random	$x_i(0) \sim U(200,\ 600)$	$U(0{,}1)$	400,2	400,19	Y	9,01
4.	random	$x_i(0) \sim N(400,\ 200^2)$	$N(0{,}5,\ 0{,}3^2)$	399,98	399,94	Y	9,18
5.	scale-free	$x_i(0) \sim U(200,\ 600)$	$N(0{,}5,\ 0{,}3^2)$	400,16	400.31	N	23,75
6.	scale-free	$x_i(0) \sim N(400,\ 200^2)$	$U(0{,}1)$	400,30	400,52	N	23,55
7.	random	$x_i(0) \sim U(200,\ 600)$	$N(0{,}5,\ 0{,}3^2)$	400,08	400,09	Y	9,00
8.	random	$x_i(0) \sim N(400,\ 200^2)$	$U(0{,}1)$	399,66	399,62	Y	9,18
9.	random	$x_i(0) \sim \begin{cases} N(400,\ 200^2), for\ i \in\ A \subset \{1,\dots,n\}, \lvert A\rvert = 180 \\ 700, for\ i \in\ B = \{1,\dots,n\} \backslash A, \lvert B\rvert = 20 \end{cases}$	$r_i \sim \begin{cases} U(0,\ 0{,}5), for\ i \in\ A \subset \{1,\dots,n\}, \lvert A\rvert = 180 \\ 0{,}8, for\ i \in\ B = \{1,\dots,n\} \backslash A, \lvert B\rvert = 20 \end{cases}$	430,68	478,53	Y	9,62
10.	random	$x_i(0) \sim \begin{cases} N(400,\ 200^2), for\ i \in\ A \subset \{1,\dots,n\}, \lvert A\rvert = 180 \\ 700, for\ i \in\ B = \{1,\dots,n\} \backslash A, \lvert B\rvert = 20 \end{cases}$	$r_i \sim \begin{cases} U(0,\ 1), for\ i \in\ A \subset \{1,\dots,n\}, \lvert A\rvert = 180 \\ 0{,}8, for\ i \in\ B = \{1,\dots,n\} \backslash A, \lvert B\rvert = 20 \end{cases}$	429,83	445,01	Y	9,13
11.	scale-free	$x_i(0) \sim \begin{cases} N(400,\ 200^2), for\ i \in\ A \subset \{1,\dots,n\}, \lvert A\rvert = 180 \\ 700, for\ i \in\ B = \{1,\dots,n\} \backslash A, \lvert B\rvert = 20 \end{cases}$	$r_i \sim \begin{cases} U(0,\ 0{,}5), for\ i \in\ A \subset \{1,\dots,n\}, \lvert A\rvert = 180 \\ 0{,}8, for\ i \in\ B = \{1,\dots,n\} \backslash A, \lvert B\rvert = 20 \end{cases}$	429,63	478,04	N	201,79
12.	scale-free	$x_i(0) \sim \begin{cases} N(400,\ 200^2), for\ i \in\ A \subset \{1,\dots,n\}, \lvert A\rvert = 180 \\ 700, for\ i \in\ B = \{1,\dots,n\} \backslash A, \lvert B\rvert = 20 \end{cases}$	$r_i \sim \begin{cases} U(0,\ 1), for\ i \in\ A \subset \{1,\dots,n\}, \lvert A\rvert = 180 \\ 0{,}8, for\ i \in\ B = \{1,\dots,n\} \backslash A, \lvert B\rvert = 20 \end{cases}$	430,02	444,48	N	162,83

Table 1: Simulation results for random graph and scale-independent network models, testing different combinations of distributions for initial values and reliability indices. The simulations were performed in a Python environment using the NetworkX library.

Table 1 presents the summary statistics of multiple simulation configurations, comparing expectation dynamics under varying initial conditions and network topologies. In scenarios where both the network structure and the distributions (initial expectations and reliability indices) were symmetric and uniform (Versions 1–4), the final expectations remained close to the initial averages, with relatively low iteration counts. Notably, consensus was achieved only in the random (Erdős–Rényi) network variants (Versions 3–4), while scale-free networks (Version 2) failed to reach consensus despite having symmetric settings. In Versions 5–8 (highlighted), where the distributions of initial expectations and reliability indices were systematically alternated, the results further reinforce the role of network structure and parameter alignment. Even in balanced setups, scale-free networks (Versions 5–6) exhibited no consensus, whereas random graphs (Versions 7–8) achieved convergence reliably. The average iteration count was higher in the scale-free cases (~23,6 vs. ~9,0), indicating slower or more volatile convergence dynamics under topological heterogeneity. The most pronounced deviations appear in Versions 9–12, where asymmetric (skewed) distributions were introduced for both initial expectations and reliability. Here, final average expectations shifted significantly from the starting mean (e.g., from 430 to 478,5 in Version 9), suggesting strong influence of outlier agents. Interestingly, consensus still occurred in some Erdős–Rényi cases (Versions 9–10), but not in scale-free setups (Versions 11–12). Additionally, the average number of iterations rose sharply in the scale-free network with skewed input (Version 11: 201,8), underscoring the amplified impact of structural and informational asymmetries.

Overall, the simulation results indicate that the dominant factor shaping the evolution of expectations is not the initial distribution of values, nor the individual reliability of agents, nor even the presence of opinion leaders in isolation—but rather the structural configuration of the network itself. In particular, more uniformly connected and densely linked networks, such as Erdős–Rényi graphs, tend to foster faster convergence and higher likelihood of consensus. These topologies facilitate smoother information diffusion and reduce the risk of isolated clusters or over-concentration of influence. In contrast, scale-free networks, such as those generated by the Barabási–Albert algorithm, typically produce more fragmented expectation patterns and slower convergence. However, their hierarchical architecture supports localized consensus, the persistence of heterogeneity, and robustness against uniform belief imposition. This can be advantageous in environments where adaptability, diversity of views, or resistance to centralized influence are valued. These findings suggest that the structure of the interaction network acts as the primary moderator of how economic agents form and adjust their expectations. In more homogeneous and well-connected systems, economic agents are more likely to align their beliefs quickly, resulting in stable and predictable aggregate expectations. In contrast, in heterogeneous, hub-dominated structures, beliefs may remain dispersed or sensitive to the positioning of influential agents. Therefore, understanding the underlying network through which agents observe and influence one another is essential for anticipating how expectations evolve at the macro level—whether in markets, policy responses, or decentralized information systems.

4.2 ANOVA results

In order to rigorously assess which factors most influence the final average expectation in our network-based expectation model, we conducted a factorial analysis of variance (ANOVA) as a form of sensitivity analysis. This approach is appropriate here because the simulation involves multiple experimental factors (each at several levels), and we are interested in both their individual and combined effects on the outcome. By using ANOVA, we can determine whether variations in the output across different simulation settings are statistically significant or merely due to random chance. In essence, the ANOVA helps identify which model parameters have a measurable impact on agents' final aggregated expectations and which do not, as well as the relative strength of these effects. This adds a crucial layer of validation to the simulation results, ensuring that any observed differences in outcomes (under varying conditions) are robust and not an artifact of simulation noise. It also quantifies the comparative influence of each factor, guiding our understanding of the model's dynamics.

For this analysis, we varied three key simulation parameters in a full-factorial design and observed their effects on the equilibrium average expectation of the agents. The factors and their levels were as follows:

1. Opinion Leader Ratio: The proportion of agents designated as opinion leaders in the network. This was tested at four levels – *5%*, *10%*, *15%*, and *20%* of the total agent population were opinion leaders in different simulation runs.

2. Leader Bias (Initial Expectation Bias): The degree to which opinion leaders' initial expectations differed from the general population's average initial expectation. We considered two levels of bias – a moderate bias (leaders' initial expectations set 100 units above the population mean) and a high bias (leaders 200 units above the mean). These positive biases represent cases where opinion leaders start off significantly more optimistic than others (the direction of bias is positive in all cases).

3. Leader Reliability: The credibility or trustworthiness index of opinion leaders, which influences how much weight other agents place on a leader's opinion. We examined three levels of reliability – *low (0.5)*, *medium (0.7)*, and *high (0.9)* – on a 0–1 scale, where higher values mean agents consider the leader more reliable (and thus are more influenced by that leader's opinion).

In each simulation, agents interacted on a specified network structure (as described earlier in the modeling framework). To examine the role of network topology, we ran separate sets of simulations for two different network types: an random network based on Erdős – Rényi model and a scale-free network based on a Barabási – Albert model. In both cases the networks were directed (allowing asymmetric influence between agents), and all other conditions were held constant to enable a fair comparison. We used a fixed number of agents (with network size constant across runs) and identical initial distributions for non-leader agents' expectations (drawn from a normal distribution) as well as for non-leader trust indices (drawn from a uniform distribution) in all scenarios. This ensures that differences in outcomes can be attributed to the controlled factors listed above rather than incidental initial conditions. Each unique combination of the three factors (leader ratio × bias × reliability) was simulated multiple times to account for the stochastic nature of the model. Specifically, we performed 500 independent simulation runs for each combination of factor levels. With 4 levels of leader ratio × 2 levels of bias × 3 levels of reliability, this yields 24 distinct experimental conditions; at 500 runs each, a total of 12,000 simulation outcomes were collected per network type. We then conducted a three-factor ANOVA on the final average expectation results for each network type separately. The ANOVA (using an ordinary least squares model) evaluates the main effects of each factor and all possible interaction effects (up to two-way interactions) on the final average expectation. Separate analyses for the Erdős – Rényi and Barabási – Albert networks allow us to see how the network structure might modulate the influence of these factors. In each analysis, the F-statistics and corresponding p-values from the ANOVA indicate which effects are statistically significant contributors to variance in the final expectations.

ANOVA results for directed random graph model

The ANOVA on simulation outcomes from the directed Erdős–Rényi random network reveals clear and statistically significant effects for two of the three examined factors.

	sum_sq	df	F	PR(>F)
C(leader_ratio)	8.345760e+05	3.0	1361.930458	0.000000e+00
C(leader_bias)	5.161591e+05	1.0	2526.934031	0.000000e+00
C(leader_reliability)	4.919073e+02	2.0	1.204103	2.999973e-01
C(leader_ratio):C(leader_bias)	8.963546e+04	3.0	146.274591	4.269421e-93
C(leader_ratio):C(leader_reliability)	1.117364e+03	6.0	0.911704	4.851039e-01
C(leader_bias):C(leader_reliability)	8.352344e+01	2.0	0.204451	8.150977e-01
Residual	2.447479e+06	11982.0	NaN	NaN

In particular, both the opinion leader ratio and the leader bias have a strong influence on the final average expectation attained by the agents. Increasing or decreasing the proportion of opinion leaders in the network leads to substantial changes in the eventual collective expectation. Similarly, the initial expectation bias of the leaders (i.e., how far above the population's mean their expectations start) is a dominant factor in determining the equilibrium value of aggregate expectations. These conclusions are supported by very large F-statistics: the leader bias yielded the largest effect ($F(1, 11{,}982) \approx 2526.93, p < .001$), and the leader ratio also had an extremely large effect ($F(3, 11{,}982) \approx 1361.93, p < .001$). Such high F-values (far exceeding critical thresholds for significance) indicate that the variation in final outcomes due to changes in these factors is not due to chance but rather reflects systematic and meaningful influences. In contrast, the leader reliability factor did not show a significant main effect on the final expectations in the random network (F$(2, 11{,}982) \approx 1.20, p = .30$). Within the tested range of reliability indices (0.5 to 0.9), adjusting how trustworthy the opinion leaders were perceived did not result in measurable changes in the average expectation to which the population converged. This suggests that who the opinion leaders are (their proportion in the population) and what they initially believe (their bias) matter much more for the long-run collective outcome than how intrinsically "reliable" they are judged to be. Turning to interaction effects among the factors, the ANOVA results indicate that only one two-way interaction was statistically significant: the interaction between leader ratio and leader bias ($F(3, 11{,}982) \approx 146.27, p < .001$). This means that the impact of changing the fraction of opinion leaders depends on the level of their initial bias, and vice versa. In practical terms, the presence of more opinion leaders amplifies the effect of their bias on final expectations. For example, if only a small share of agents are opinion leaders, a strong bias (+200) might be required to meaningfully shift the aggregate expectation. But as the share of leaders increases, even a more modest bias (+100) can significantly alter the population-level outcome. Conversely, the effect of increasing the number of opinion leaders is especially pronounced when those leaders begin with strongly divergent views. This ratio–bias interaction underscores that the two factors reinforce one another: only when both are elevated does the collective expectation shift substantially from the baseline. Importantly, no interactions involving the leader reliability factor were significant: the interactions between reliability and leader ratio ($F(6, 11{,}982) \approx 0.91, p = 0.485$), and between reliability and leader bias ($F(2, 11{,}982) \approx 0.20, p = 0.815$), failed to reach significance. This supports the interpretation that the leader reliability parameter is not an influential moderator in this context — neither alone, nor in combination with the other key factors. The absence of any notable effect involving reliability suggests that the model's outcomes are robust to moderate variations in how much trust agents place in opinion leaders. This could reflect either a dampening effect of the averaging mechanism or that the tested range (0.5–0.9) was not wide enough to produce visible shifts. In summary, for the Erdős–Rényi network, opinion leader ratio and initial bias are the primary determinants of the final average expectation, while leader reliability has no significant impact on the outcome, either independently or interactively.

ANOVA results for directed random graph model

The ANOVA conducted on simulation outcomes from the Barabási–Albert scale-free network yields a pattern of results that aligns with the findings from the Erdős–Rényi case in several respects.

	sum_sq	df	F	PR(>F)
C(leader_ratio)	8.692966e+05	3.0	749.029996	0.000000e+00
C(leader_bias)	4.950529e+05	1.0	1279.687920	2.237535e-266
C(leader_reliability)	1.767982e+03	2.0	2.285074	1.018109e-01
C(leader_ratio):C(leader_bias)	9.921088e+04	3.0	85.485121	1.005948e-54
C(leader_ratio):C(leader_reliability)	1.579517e+03	6.0	0.680496	6.654503e-01
C(leader_bias):C(leader_reliability)	2.297085e+01	2.0	0.029689	9.707472e-01
Residual	4.635289e+06	11982.0	NaN	NaN

As with the random network, both the opinion leader ratio and the leader bias emerge as statistically significant and impactful factors. The leader ratio produced an F-statistic of $F(3, 11{,}982) \approx 749.03$, and the leader bias an even larger effect, with $F(1, 11{,}982) \approx 1279.69$ ($p < .001$ in both cases). These results confirm that increasing the share of opinion leaders or increasing the degree to which their initial expectations deviate from the average, results in systematic changes in the final average expectation of the population. However, compared to the Erdős–Rényi case, the magnitude of these effects is somewhat attenuated. While still highly significant, the F-statistics are lower, indicating that the scale-free structure dampens the strength of these influences. This is consistent with the idea that hierarchical networks, dominated by a few hub nodes, are somewhat less sensitive to uniform changes across the network than random, more homogeneous networks. As before, the leader reliability factor did not reach statistical significance ($F(2, 11{,}982) \approx 2.29, p = .10$). Although the F-value is slightly higher than in the Erdős–Rényi case, the result still fails to meet conventional significance thresholds. This supports the conclusion that within the tested reliability range (0.5– 0.9), agents' trust in opinion leaders does not significantly alter the long-run group expectation under a scale-free structure. Regarding interaction effects, only the interaction between leader ratio and leader bias was statistically significant ($F(3, 11{,}982) \approx 85.49, p < .001$). This mirrors the result from the Erdős–Rényi case, indicating that the joint presence of many opinion leaders and strong bias is required to meaningfully shift the aggregate expectation. When only one of these is present (e.g., high ratio but low bias, or low ratio and high bias), the system remains relatively close to the baseline outcome. The remaining two interaction terms — leader ratio × reliability ($F(6, 11{,}982) \approx 0.68$, $p = .67$), and leader bias × reliability ($F(2, 11{,}982) \approx 0.03, p = .97$) — were not statistically significant. This reinforces the earlier finding that leader reliability is neither a main driver nor an interactive moderator of expectation dynamics in this setting. Even in a network structure that concentrates influence among a few agents, making those agents more or less trusted does not significantly impact the collective outcome.

To summarize, the ANOVA results for the scale-free network model replicate the main findings from the random graph case: leader ratio and bias are the primary levers shaping final average expectations, while leader reliability remains largely irrelevant. However, the overall sensitivity of the system is lower in the scale-free network, suggesting that hierarchical structures confer a certain robustness or inertia in the face of opinion manipulation — a key insight when comparing network architectures in expectation formation.

5. Conclusion

In conclusion, our agent-based network model of expectation formation offers a novel perspective on how individual beliefs evolve through social structure. The simulations demonstrate that the topology of the communication network is a decisive factor in expectation dynamics – more so than the presence or attributes of opinion leaders themselves. Dense, homogeneous networks (as in the Erdős–Rényi case) tend to foster rapid convergence toward a shared expectation, essentially yielding consensus around the collective average. In contrast, scale-free networks with hub-and-spoke connectivity (as in the Barabási–Albert case) often fail to fully homogenize beliefs, stabilizing instead at a dispersed equilibrium where pockets of agents hold persistently different expectations. This finding highlights that it is the pattern of interactions – who connects with whom – that primarily drives whether a group's expectations coalesce or remain divergent. By explicitly accounting for these social interactions, the model shows that expectation formation is not merely an isolated cognitive process but a socially embedded one shaped by network structure and the flow of information and credibility across that structure. Traditional expectation models, whether rational (assuming fully informed, model-consistent forecasts) or adaptive (based solely on an agent's own past observations), typically ignore this relational dimension. Our results underscore how much they stand to miss: even with identical individual reasoning rules, different network structures produce markedly different aggregate outcomes. In short, incorporating network connectivity into expectation models proves crucial for capturing how individual beliefs actually co-evolve in a society, an aspect that standard models without social structure cannot address.

These insights build upon and extend the findings of prior research on expectation dynamics and social learning. Behavioral macroeconomic studies (e.g. Hommes, 2013) have long argued that heterogeneity and bounded rationality play a key role in economic expectations, but they often treat interactions in a stylized or aggregate manner. Our network-based approach contributes a concrete mechanism for such heterogeneity to manifest and persist: it shows how diverse individual expectations can propagate and influence one another through explicit links, sometimes preventing full agreement even when agents share the same updating rule. Likewise, in the literature on opinion diffusion and learning in networks, classical models like DeGroot's averaging process (DeGroot, 1974) and subsequent analyses by Golub and Jackson (2010) illustrate that network structure governs whose information ultimately prevails in the long run. In line with those theoretical results, we find that in a well-connected random network, no single agent (or small group) can dominate the outcome – the final expectation reflects a broad pooling of information, akin to a "wisdom of crowds" effect. However, our findings also resonate with the cautions raised by Golub and Jackson (2010) and others that unequal connectivity can skew influence. In our scale-free simulations, highly connected hubs exert disproportionate impact, and overall convergence is dampened – an outcome consistent with models where network centrality or influence weighting leads to biased or fragmented consensus. By demonstrating these effects in an agent-based economic context, our study bridges the gap between abstract network theory and applied expectation modeling. It reinforces the notion that social structure matters for aggregate expectations, complementing existing work on heterogeneous beliefs by pinpointing the structural channels through which those beliefs interact and spread.

Overall, the value of incorporating network effects into expectation modeling is twofold. First, it greatly enriches the realism of expectation dynamics in economic models. Instead of assuming a representative, monolithic expectation or purely independent learning, our approach captures how information and beliefs diffuse through social ties, subject to trust and credibility. This leads to emergent phenomena that traditional models cannot easily reproduce – for example, the possibility of sustained disagreement or belief clusters in an economy, even when everyone ultimately receives similar information. Such outcomes align with real-world observations (for instance, households or firms often hold varied forecasts about inflation or growth, influenced by their social circles), and our model provides a structural explanation for how that can occur. Second, embedding expectations in a network offers a more rigorous micro-foundation for the aggregation of expectations. Rather than imposing an ad-hoc aggregate expectation rule, we derive macro-level expectations (consensus values, dispersion, speed of convergence) from the bottom-up interaction of individuals. This helps address the longstanding "aggregation problem" by showing how micro-level social interactions translate into macro-level expectation outcomes. The network serves as a formal bridge between individual behavior and collective expectations, ensuring that any aggregate patterns are traceable to agent-level connectivity and influence. In sum, our findings make a strong case that economic expectation models should move beyond isolated-agent assumptions and incorporate the architecture of social information networks. Doing so not only fills a conceptual gap – acknowledging that expectations are formed in a social context – but also improves our ability to explain and predict aggregate dynamics of beliefs in economies.

Implications and future research: The implications of these results extend to both economic theory and policy. For economic modeling, incorporating network-based expectation formation could improve the predictive power of macroeconomic simulations and forecasts. For example, policy models (such as those used by central banks or planners) might benefit from accounting for the networked nature of expectation updating – recognizing that announcements or shocks will percolate through a web of interpersonal communications rather than instantly updating everyone uniformly. This could lead to new insights on how quickly and through which channels policies influence public expectations, and why pockets of agents may react differently. It also suggests that targeting key "hub" individuals or institutions (those with outsized network influence) could be an effective strategy to steer collective expectations, as network theory would imply and as our results confirm for scale-free structures. More broadly, understanding expectation formation as a network process opens the door to enriching existing macroeconomic frameworks (e.g. DSGE models or adaptive learning models) by endogenizing the flow of expectations across agents. Policymakers and economists may need to consider not just the content of information but its network distribution when evaluating expectation-driven outcomes like consumption, investment, or price-setting behavior.

There are several fruitful avenues for future research building on this work. One direction is to explore a wider variety of network structures and parameters – for instance, examining small-world networks or networks with community clusters could reveal how partial connectivity and local cliques affect expectation convergence versus persistent differences. Another extension would be to allow the network or agent characteristics to evolve over time. In reality, agents might adjust their reliability weights (trust) based on past forecasting accuracy or may form and sever connections (e.g. seeking new information sources), leading to dynamic networks. Incorporating such adaptive credibility or evolving topology would increase the model's realism and could show how stable expectation patterns might break or how consensus can be fostered or disrupted over time. Additionally, while our study treated opinion leaders as exogenously given, future models might endogenize leadership or influence – allowing agent influence to emerge from the process (for example, agents who consistently predict well gain followers). This would tie expectation formation to broader phenomena like reputation building and information cascades. Empirical validation is another important step: comparing the model's implications with survey data or laboratory experiments on expectation formation (cf. the learning-to-forecast experiments in Hommes, 2013) would help test the external validity of the network effects we observe. Finally, interdisciplinary crossover with sociology and network science could provide richer insights into how real social networks (online networks, professional networks, etc.) play into economic expectations. By integrating such perspectives, future research can continue to refine our understanding of expectations as emergent social phenomena, ultimately improving both theoretical models and practical policy tools in economics.

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