Connecting the Dots: How Social Networks Shape Macroeconomic Expectations

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Abstract

Social networks play a crucial role in diffusing information, influencing individuals' behaviour, and affecting the stability of economic expectations. However, the effects of social networks on economic expectations remain understudied in the literature. This study examines the effects of social networks on the formation of economic expectations of bounded rational agents by incorporating a network component into a heuristic switching framework.

The findings indicate that the behaviour of a highly central agent can affect the simulation outcomes in both complex and simple network structures, albeit in varying strengths. Additionally, the complexity of network structure has a substantial impact on the speed and strength of the propagation of specific behaviours across the network, amplifying the influence of highly connected agents. The study concludes that incorporating network effects provides valuable insights into the formation of economic expectations. The model used in this study can serve as a starting point for future research aimed at better capturing realistic expectation formation processes and their implications for economic behaviour. This could assist policymakers in creating more efficient monetary policies that account for the impact of social networks.

Keywords: Behavioural Macroeconomics, Bounded Rationality, Social Networks, Expectation Formation

JEL Codes: D83, D84, D85, E03, E37, E52

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1 Introduction

The rise of social networks platforms has significantly altered the communication landscape by enabling individuals to more efficiently access and process vast amounts of information in real-time (Luarn et al., 2014). In this context, recent research suggests that social networks, which refer to reciprocal, interpersonal, or institutional relationships, have a significant impact on individual behaviour and the economic outcomes of interactions (Bailey et al., 2018). Particularly within the realm of social network sites, social networks became a critical conduit for transmitting economic information, as well as for the contagion and dissemination of economic narratives (Flynn and Sastry, 2022).

According to Shiller (2017), economic narratives encompass stories and explanations that provide individuals and organisations a means of interpreting economic news and developments. They help to elucidate the pivotal factors of the past and provide valuable insights into the mechanisms likely to play a vital role in the future (Andre et al., 2021). As such, these narratives exhibit a powerful effect on shaping expectations, beliefs, and attitudes, which in turn can influence economic outcomes (Roos and Reccius, 2021). This significance is supported by research, including Macaulay and Song (2022), which demonstrated that inflation narratives can have actual macroeconomic impacts. Considering the predominant influence of expectations on the momentum of prices and shaping market sentiments, inflation expectations exert a considerable influence on the evolution of the actual inflation rate by potentially prompting self-reinforcing dynamics, as evidenced by (Baumann et al., 2021).

It seems crucial to comprehend the intricate interplay among social networks, economic narratives, and the formation of expectations within macroeconomic models. However, the role of economic narratives in shaping expectations appears to be understudied in the existing literature. Although there is vast amount of research on expectation formation processes under bounded rationality, it mostly focuses on studying heterogeneous expectations at an aggregate level, overlooking potential interaction effects between agents or actions within their network (Steinbacher et al., 2021). Consequently, there seems to be a dearth of studies exploring how the expectation formation process of heterogeneous agents under bounded rationality may be influenced by the underlying network structure in a macroeconomic context.

The aim of this study was to investigate to what extent different network structures and behavioural strategies influence the formation of economic expectations under bounded rationality. Specifically, I hypothesised that the stability of expectations can be affected by certain agents which are particularly well-connected to other nodes within the network. Agents with more central positions in the network might have a stronger impact on the overall expectation formation process and a higher level of inter-connectivity between agents could amplify this effect. The analysis demonstrated that an agent possessing a high degree centrality and propagating a specific behaviour had a significant impact on the simulation outcome. The results of the study suggest that the complexity of the network structure is able to enhance this effect. These findings provide valuable insights into the effects of social interactions on the process of forming expectations. As such, they offer a more comprehensive understanding of the role of social networks in shaping expectations and how narratives are formed, disseminated, and incorporated into the economic decision-making process.

The outline of the paper is as follows: In Section 2, the literature review will provide a background of the relevant research in the field, specifically regarding the role of social networks in the dissemination of information, as well as the crucial role of narratives and communication in shaping expectation and literature on bounded rationality, social learning and expectation formation. Section 3 will describe the subjective model used in this study, including the integration of the network component in the expectation formation process. In Section 4, the key findings and limitations of the research will be presented and discussed, followed by conclusions and recommendations for future research in Section 5.

2 Literature Review

This paper relates to three strands of the literature: First, this paper is primarily situated within the literature on Agent-Based Macroeconomics. While many macro agent-based models only partially account for the local interaction among agents at the micro level, the decision-making is often purely self-referential and their spatial position typically not of major importance (Dawid and Delli Gatti, 2018; Steinbacher et al., 2014). The predominant focus of research on agent-based modelling that explores social networks and local interaction solely pertains to asset prices and stock markets (Han and Yang, 2013; Khashanah and Alsulaiman, 2016, 2017; Panchenko et al., 2013) , the emergence of information cascades (Benhammada et al., 2021; Makarewicz, 2017), as well as the analysis of financial markets (Iori and Mantegna, 2018; Oldham, 2019) or credit contagion in interbank networks (Biondi and Zhou, 2019; Clemente et al., 2020). As such, my paper contributes to the literature of Agent-Based Macroeconomics by providing a conceptual framework incorporating a social network component into the expectation formation process within a New Keynesian framework with bounded rational, heterogeneous expectations. The agents within the economy populate a Barabasi-Albert Network (Barabási and Albert, 1999) and switch endogenously between different forecasting heuristics based on a combination of the discrete choice approach (Manski and McFadden, 1981) and the opinion model proposed by Degroot (1974).

Second, this paper is also situated within the context of the existing literature which recognises the significant role of social networks in the dissemination of information, as well as the crucial role of narratives and communication in shaping expectations (e.g. Andre et al., 2021; Bailey et al., 2018; Bargigli and Tedeschi, 2014; Flynn and Sastry, 2022; Gorodnichenko et al., 2021). In the context of the recent increase in inflation rates, there is an increasing body of literature that is devoted to exploring rich social network data in order to study various phenomena, such as the effects of policy communication (Lamla and Vinogradov, 2021), the role of narratives in economics (Macaulay and Song, 2022) and the use of text-based probability models to detect inflation narrative dynamics in the media (Angelico et al., 2022; Müller et al., 2022).

Third, this paper relates to the broader literature of bounded rationality, social learning and expectation literature. A significant portion of the theoretical literature has been working on formalising alternative approaches to the rational expectations (RE) assumption, describing the decision-making process of heterogeneous agents under bounded rationality. These approaches are often built on the assumption that agents lack the ability to comprehend the complexity of the underlying model, following the ideas of Simon (1957) and Selten (1998). Specifically, agents are believed to have cognitive limitations that prevent them from processing this type of information and developing rational expectations. Empirical evidence from laboratory experiments and survey data has supported these cognitive constraints (Branch, 2004; Carroll, 2003; Hommes, 2011; Pfajfar and Žakelj, 2014). Instead, people tend to use heuristics when making decisions under uncertainty (Gigerenzer and Selten, 2002; Luan et al., 2019). The heuristic switching framework is a popular way to incorporate bounded rationality in macroeconomic models, assuming that agents update their forecasts based on past mistakes (Branch and McGough, 2010; Brock and Hommes, 1997, 1998). This framework uses a discrete choice model, which allows agents to switch between different expectation heuristics based on their historical predictive accuracy (Manski and McFadden, 1981; McFadden, 1974). Similiar approaches are often used in business cycle models to incorporate heterogeneous expectations (De Grauwe, 2011; De Grauwe and Foresti, 2020; De Grauwe and Ji, 2019, 2020, 2022; Hommes, 2013; Hommes et al., 2017; Proaño and Lojak, 2020), to study the efficiency of micro- and macroprudential measures (Assenza et al., 2018; Lengnick and Wohltmann, 2016) or the impact of bounded rationality on monetary policy in empirically enriched New Keynesian models (Gabaix, 2020). Anufriev and Hommes (2012) have highlighted that applying the heuristic switching framework in macroeconomic models can successfully replicate the empirical data obtained in laboratory environments. Multiple other studies and laboratory experiments corroborate this notion and indicate that the expectation formation of economic agents can be modelled as an alternation of simple, heterogeneous forecasting heuristics (Assenza et al., 2014; Pfajfar and Žakelj, 2014, 2018),

I propose an extension to these existing frameworks by incorporating an additional network component. Specifically, my approach accounts for agents' beliefs being updated as a convex combination of the probability distribution, which results from a heuristic switching framework, and the update rule proposed by Degroot (1974). Thereby, agents in the model consider not only their perceived true state of the world but also the heuristics adopted by their neighbours in their network vicinity. This integration of network structure allows for a more realistic representation of the interplay between beliefs and social influence in expectation formation, compared to models that do not consider the role of social networks.

3 Model

3.1 Agent Population & Network Structure

My investigation assumes a societal structure comprised of a collection of agents denoted as $N = 1, 2, ..., 100$, which are embedded on a random graph using Barabási–Albert preferential attachment with heterogeneous weights (Barabási and Albert, 1999). One salient characteristic of the Barabási-Albert network is its growth mechanism, which relies on preferential attachment. This probabilistic process involves expanding a graph by attaching new nodes, each with edges that are preferentially linked to m existing nodes with a high degree. Two exemplary sub-networks resulting from this process with $m = 5$ and $m = 95$ are illustrated in Figure 1:

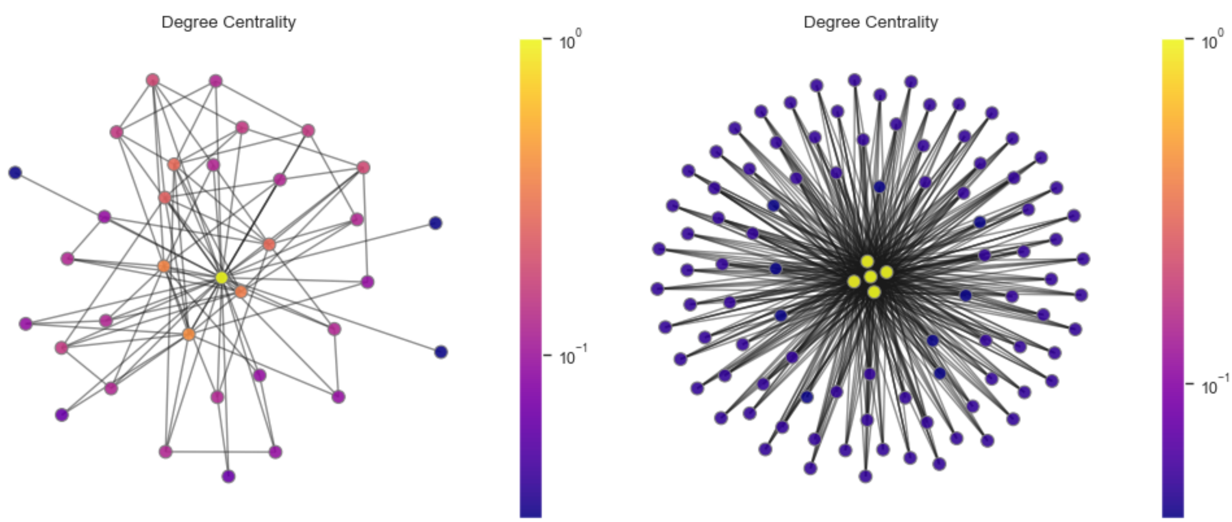


Figure 1: Resulting network structures under different complexity levels

The node(s) positioned at the center of each network represent the agent(s) with the highest degree centrality. The centrality measures the number of connections that an agent has with its neighbouring nodes. The corresponding degree centrality is color-coded and visualised on the right-hand side of the figures. Notably, the more complex network exhibits multiple agents with similar centrality degrees, while only one agent is significantly well-connected in the less complex network.

3.2 Economy

The behavioural macroeconomic model, proposed in De Grauwe (2011) and further developed in De Grauwe and Ji (2020, 2022), constitutes the foundation of this approach. The model is an extension of the New Keynesian business cycle framework presented in Galí (2008) and includes heterogeneous forecasting rules, departing from the assumption of rational expectations. It comprises an aggregate supply equation, an aggregate demand equation, and a Taylor rule.

The demand side of the economy is given by the New Keynesian IS curve which is derived from the Euler equation under bounded rationality:

$$x_t = a_1 \tilde{E}_t(x_{t+1}) + (1 - a_1)x_{t-1} - a_2(i_t - \tilde{E}_t(\pi_{t+1})) + \epsilon_t^x \tag{1}$$

x_t represents the output gap, i_t the nominal interest rate, $\tilde{E}_t(\pi_{t+1})$ the expected output gap in period t and $\tilde{E}_t(\pi_{t+1})$ the expected inflation rate, respectively. a_2 denotes the inverse elasticity of substitution of demand. The tilde above $\tilde{E}_t$ indicates bounded rational expectations (BRE) and implies that expectations are not formed fully rationally.

The New Keynesian Phillips curve (NKPC) represents the supply side of the economy and positively relates the inflation rate π_t to the output gap x_t and the expected future inflation rate $\tilde{E}_t(\pi_{t+1})$. The NKPC is given by

$$\pi_t = b_1 \tilde{E}(\pi_{t+1}) + (1 - b_1)\pi_{t-1} + b_2 y_t + \epsilon_t^\pi \tag{2}$$

where $\tilde{E}(\pi_{t+1})$ is the expected inflation rate and x_t is the output gap in period t. b_2 represents the slope of the Phillips curve, to which extent inflation adjusts to changes in the output gap and how flexible firms are in their price-setting behavior. I follow De Grauwe and Ji **?** in including lagged inflation and output in the supply equation as well as the demand equation. The inertial response of consumption and the lagged price adjustment (also referred to as persistence) is often microfounded within New Keynesian models by the assumption of habit information (Smets and Wouters, 2007) or rule-of-thumb consumer behaviour (Amato and Laubach, 2003).

The Taylor rule according to which the central bank reacts to current fluctuations in the inflation rate and the output gap by changing the nominal interest rate is given by:

$$i_t = (1 - c_3)[c_1(\pi_t - \pi^*) + c_2 y_t] + c_3 i_{t-1} + \epsilon_t^i \tag{3}$$

Here, the central bank is expected to raise interest rates if the output gap widens or observed inflation rises relative to the announced inflation target. Furthermore, the central bank is assumed to smooth the interest rate through consideration of the lagged interest rate t_{t-1} measured by the coefficient c_3.

In addition, I added noise terms to the equations (1), (2) and (3) describing the exogenous shocks affecting the economy. I let ϵ_t^x, ϵ_t^π and ϵ_t^i follow a white-noise process, where I assumed ϵ_t^x, ϵ_t^π and ϵ_t^i to be normally distributed random variables with a zero mean and a constant standard deviation of σ^x, σ^π and σ^i, e.g. $\epsilon_t^x \sim N(0, \sigma^x)\ and\ \epsilon_t^\pi \sim N(0, \sigma^\pi)\ and\ \epsilon_t^i \sim N(0, \sigma^i)$.

The set of possible expectation heuristics is based on those also employed in De Grauwe and Ji (2020). Agents who have confidence in the target inflation rate π^* explicitly announced by the central bank are called targeters. Targeters thus expect the central bank's target inflation rate to materialise in $t + 1$ or the output gap to converge to its natural potential output in the following period. Therefore, they use the following heuristic to forecast:

$$\tilde{E}_t^{targeting}(x_{t+1}) = 0 \tag{4}$$

$$\tilde{E}_t^{targeting}(\pi_{t+1}) = \pi^* \tag{5}$$

In particular in the case of inflation, this forecasting rule can be understood as credibility of the central bank. The degree of credibility of the central bank is thus defined as the share of inflation targeters in the total population of agents.

Naive or static expectations represent the second heuristic used. Agents applying this heuristic use the realisation of the variable observed in the last period as an estimate for the next period De Grauwe and Ji (2020); Lengnick and Wohltmann (2016). Therefore, they use

$$\tilde{E}_t^{stat}(k_{t+1}) = k_{t-1} \ with \ k \in \{\pi, y\} \tag{6}$$

as a forecasting rule.

Following Schmitt (2021), the type of heuristic j agent i choose among the set of forecasting heuristics $\{tar, stat\}$ in forecasting variable $k \in \{x, \pi\}$ can be formalised by:

$$\tilde{E}_{i,t}(k_{t+1}) = \begin{cases} \tilde{E}_{i,t}^{tar}(k_{t+1}) & \text{if } \ I_i^k(t) = 1 \\ \tilde{E}_{i,t}^{stat}(k_{t+1}) & \text{if } \ I_i^k(t) = 0 \end{cases} \tag{7}$$

Now considering $\omega_i^{k,tar}(t)$, and $\omega_i^{k,stat}(t)$ as the actual switching probabilities that agent i will opt for heuristic $j \in \{tar, stat\}$ to forecast variable $k_{t+1} \in \{\pi, y\}$ in period t, the **indicator function** can be formalized by

$$I_i^k(t) = \begin{cases} \lambda_i^{k,tar}(t) = 1, & \text{with } prob \ \omega_i^{k,tar}(t) \\ \lambda_i^{k,tar}(t) = 0, & \text{with } prob \ \omega_i^{k,stat}(t) \end{cases} \forall_{i \in \{1,..,n\}} \tag{8}$$

The **indicator matrix** $I_t^k = \{0,1\}^{n\times 2}$ indicating the actual choice forecasting choice of all agents is defined by:

$$I_t^k = \begin{bmatrix} \lambda_1^{k,tar}(t) & |\lambda_1^{k,tar}(t)-1| \\ \lambda_2^{k,tar}(t) & \vdots \\ \vdots & \vdots \\ \vdots & \vdots \\ \lambda_n^{k,tar}(t) & |\lambda_n^{k,tar}(t)-1| \end{bmatrix} = (\lambda_i^k(t))_{i=1,..,n;k\in\{\pi,y\}} \tag{9}$$

where $|\lambda_i^{k,tar}(t)-1| = \lambda_i^{k,stat}(t)\ \forall\ i$. The **number of agents** that follow each forecasting rules can now easily be defined by

$$n_t^{k,tar} = \sum_{i=1}^{N} \lambda_i^{k,tar}(t) \tag{10}$$

$$n_t^{k,stat} = \sum_{i=1}^{N} |\lambda_i^{k,tar}(t)-1| \tag{11}$$

Finally, the **relative number of agents** that follow each forecasting heuristic is defined by

$$w_t^{k,tar} = \frac{n_t^{k,tar}}{N} \tag{12}$$

and

$$w_t^{k,stat} = \frac{n_t^{k,stat}}{N} \tag{13}$$

Obviously, the relative numbers of agents add up to 1, so the following can also be used as a formalisation of the relative number of targeters (naives):$w_t^{k,tar} = 1 - w_t^{k,stat}$ ($w_t^{k,stat} = 1 - w_t^{k,tar}$).

Market Expectations. After setting up the expectation heuristics and specifying the selection mechanism, the conditional expectation operator in equations (1) and (2) is replaced with the respective proportions $w_t^{k,j}$ weighted expectation heuristics $E_t^j(\tilde{k}_{t+1})$ with $j \in \{tar, stat\}$ and $k \in \{x, \pi\}$ } to derive the market expectations (Arifovic et al., 2013; Brazier et al., 2008):

$$\begin{aligned}\tilde{E}_t(\pi_{t+1}) &= w_t^{\pi,tar} E_t^{tar}(\pi_{t+1}) + w_t^{\pi,stat} E_t^{stat}(\pi_{t+1}) \\ &= w_t^{\pi,tar}\pi^* + w_t^{\pi,stat}\pi_{t-1}\end{aligned} \tag{14}$$

and

$$\begin{aligned}\tilde{E}_t(y_{t+1}) &= w_t^{y,tar} E_t^{tar}(y_{t+1}) + w_t^{y,stat} E_t^{stat}(y_{t+1}) \\ &= w_t^{y,tar}\bar{y} + w_t^{y,stat} y_{t-1} \\ &= w_t^{y,stat} y_{t-1}\end{aligned} \tag{15}$$

Based on the share of agents given by equation (12) and (13), the optimistic or pessimistic market sentiments can now be formally depicted. The definition of market sentiments is again based on De Grauwe and Ji (2020) and works as follows:

$$S_t = \begin{cases} w_t^{k,stat} - w_t^{k,tar} \text{if } k_{t-1} > 0 \\ -w_t^{k,stat} - w_t^{k,tar} \text{if } k_{t-1} < 0 \end{cases} \tag{16}$$

where S_t is the index of market sentiment ranging from -1 to $+1$ and $k \in \{x, \pi\}$.

3.3 Discrete-Choice-Based Expectation Formation

Building on the work of Gigerenzer and Selten (2002), I contend that the widely-held assumption of fully rational agents who maximise expected utility in decision-making is an oversimplified view of human behaviour. Instead, I acknowledge that cognitive limitations prevent individuals from forming fully rational expectations. While still considered as bounded rational agents, individuals rely on behavioural heuristic decision-making principles to form expectations. Furthermore, agents are assumed to continuously evaluate and revise their choice of forecasting rules, using a criteria for success to assess the performance of different expectation heuristics (Branch and McGough, 2010). This heuristic switching framework relies on the Discrete-Choice approach (McFadden, 1974), which has been also applied in prior research (e.g. Branch and McGough, 2010; De Grauwe and Foresti, 2020; Lengnick and Wohltmann, 2016).

This criterion for success is determined by the deviation of the predicted value from the realised value. Let the attractiveness of an expectation heuristic $j \in \{tar, stat\}$ of the variable $k \in \{x, \pi\}$ thus be given by the Mean squared forecast error (MSFE):

$$A_t^{k,j} = -(k_{t-1} - \tilde{E}_{t-2}^j(k_{t-1}))^2 + \zeta A_{t-1}^{k,j} \tag{17}$$

with $k \in \{\pi, y\}$ and $j \in \{tar, stat\}$

The parameter ζ, where $0 \leq \zeta \leq 1$, can be interpreted as a memory parameter, representing the degree to which agents consider forecast errors from the past when evaluating forecasting rules (Franke and Westerhoff, 2018). A higher value of ζ indicates that agents place more emphasis on past forecast accuracy and less on past errors. Conversely, a lower value of ζ indicates that agents are less influenced by past forecast accuracy and give more weight to the most recent forecast error.

The probability of an agent selecting a particular alternative j is derived from the utility of that alternative relative to the sum of the utility of all available alternatives. The probabilities are normalised between zero and one, where the sum of the utility of all available alternatives always adds up to one. The selection probability of a specific forecasting heuristic j for variable k in period t is determined by the **multinomial logit law of motion** (Branch and McGough, 2010). This law of motion defines the probability $\beta_t^{k,j}$ of choosing the heuristic $j \in \{tar, stat\}$ from the set of all available heuristics for variable $k \in \{x, \pi\}$ in period t.

$$\beta_t^{k,j} = \frac{\exp\{\theta A_t^{k,j}\}}{\exp\{\theta A_t^{k,tar}\} + \exp\{\theta A_t^{k,stat}\}} \tag{18}$$

where $A_j^{k,j}$ is the attractiveness measure of the heuristic $j \in \{tar, stat\}$ for variable $k \in \{x, \pi\}$ in period t and ϕ represents a non-negative Intensity of Choice (IoC) parameter. The shares of the individual heuristics are therefore positively dependent on the attractiveness measure $A_t^{k,j}$ of the respective heuristic j. Specifically, the smaller the forecast errors associated with a particular heuristic j in the past, the higher its attractiveness measure becomes, and consequently, the higher the probability of using this heuristic for forecasting purposes.

Assuming $\beta_i^{k,tar}(t) = \beta^{k,tar}(t)$ and $\beta_i^{k,stat}(t) = \beta^{k,stat}(t)\ \forall\ i$, let the **Switching Probabilities Matrix (SPM)** resulting from the discrete choice model be defined by:

$$\mathbf{SPM} = B_t^k = \begin{bmatrix} \beta_1^{k,tar}(t) & \beta_1^{k,stat}(t) \\ \beta_2^{k,tar}(t) & \beta_2^{k,stat}(t) \\ \beta_3^{k,tar}(t) & \cdots \\ \vdots & \vdots \\ \vdots & \vdots \\ \beta_n^{k,tar}(t) & \beta_n^{k,stat}(t) \end{bmatrix} = (\beta_i^{k,j}(t))_{i=1,..,n;k\in\{y,\pi\};j\in\{tar,stat\}} \tag{19}$$

Each row represents an agent $i \in [0, N]$, while each column represents a heuristic $j \in \{tar, stat\}$. Each element β indicates the probability choice of agent i for heuristic j of variable k based on the heuristic switching model.

3.4 Network-Based Expectation Formation

Similar to the rationale of heuristic decision principle, it is assumed that individuals, due to cognitive limitations, rely on information from their social network when making decisions under uncertainty (Azzimonti and Fernandes, 2022). This is called informational social influence and can represented by the DeGroot Model Buechel et al. (2015). This model adopts social influence by this type of linear updating setting as experimental and empirical evidence suggests individuals follow a rule-of-thumb learning process (e.g. Chandrasekhar et al., 2020; Choi et al., 2008; Corazzini et al., 2012).

The DeGroot-type linear updating setting applied here uses an average-based updating process for belief dynamics, where agents' choice of forecasting rule is influenced by the perceived true state of the world and the actions of their neighbours in the previous period. Hence, agents update their opinions quasi-naively to an probability distribution that better fits the decisions made in their network vicinity. This network can be formally described by a $n \times n$ row stochastic matrix denoted by $T = (V, A, g)$. Specifically, $g_{ij} \geq 0$ for all $i, j \in N$, and $\sum g_{ij} = 1$ for all $i \in N$. This adjacency matrix characterises the degree of interaction among the agents, where the value g_{ij} on $arc(i, j) \in A$ represents the weight that agent i assigns to the current belief of agent j during the process of updating their own belief for the subsequent time period. The corresponding adjacency matrix (herein called the **Trust Matrix (TM)**) can be depicted as follows:

$$\mathbf{TM} = T = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ g_{31} & \cdots & \cdots & g_{3n} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ g_{n1} & g_{n2} & \cdots & g_{nn} \end{bmatrix} = (g_{ij})_{i,j=1,..,n} \tag{20}$$

The social influence of neighbour's' decisions is measured by a matrix derived from the inner product of this **Trust Matrix (TM)** and the **Indicator Matrix (IM)** of variable k from period $t-1$. The resulting **Conformity Probabilities Matrix (CPM)** for variable k in period t is then given by:

$$\mathbf{CPM}_t^k = C_t^k = T \cdot I_{t-1}^k$$

$$= \begin{bmatrix} g_{11}\lambda_1^{k,tar}(t-1) + g_{12}\lambda_2^{k,tar}(t-1) + ... + g_{1n}\lambda_n^{k,tar}(t-1) & A_{11}\lambda_1^{k,stat}(t-1) + \dots \\ \vdots & \vdots \\ g_{n1}\lambda_1^{k,tar}(t-1) + g_{n2}\lambda_2^{k,tar}(t-1) + ... + g_{nn}\lambda_n^{k,tar}(t-1) & \vdots \end{bmatrix}$$

$$\mathbf{CPM}_t^k = \begin{bmatrix} \zeta_1^{k,tar}(t) & \zeta_1^{k,stat}(t) \\ \zeta_2^{k,tar}(t) & \zeta_2^{k,stat}(t) \\ \zeta_3^{k,tar}(t) & \dots \\ \vdots & \vdots \\ \vdots & \vdots \\ \zeta_n^{k,tar}(t) & \zeta_n^{k,stat}(t) \end{bmatrix} = (\zeta_i^{k,j}(t))_{i=1,..,n;k\in\{\pi,y\};j\in\{tar,stat\}}$$

where each row represents an agent $i \in [0, N]$, while each column represents a heuristic $j \in \{tar, stat\}$. Each element ζ indicates the probability choice of agent i for heuristic j of variable k based on the DeGroot Model.

This model combines the discrete-choice-based model **SPM** and the DeGroot-based model **CPM** through a convex linear combination. The probability distributions over a discrete set of alternatives are weighted by a persuasion parameter and additive linked to create the **weighted probabilities matrix (wPM)**:

$$\mathbf{wPM}_t^k = \Omega_t^k = \chi * C_t^k + (1-\chi) * B_t^k \tag{21}$$

The persuasion parameter χ is assumed to be between 0 and 1. Thereby, the persuasion parameter denotes the tendency of agents to either trust their own information ($\chi < 0.5$) or being more influenced by their network ($\chi > 0.5$). The **weighted probabilities matrix** is then calculated as follows:

$$\mathbf{wPM}_t^k = \begin{bmatrix} \chi * \zeta_1^{k,tar}(t) + (1-\chi) * \beta_1^{k,tar}(t) & \chi * \zeta_1^{k,stat}(t) + (1-\chi) * \beta_1^{k,stat}(t) \\ \chi * \zeta_2^{k,tar}(t) + (1-\chi) * \beta_2^{k,tar}(t) & \chi * \zeta_2^{k,stat}(t) + (1-\chi) * \beta_2^{k,stat}(t) \\ \chi * \zeta_3^{k,tar}(t) + (1-\chi) * \beta_3^{k,tar}(t) & \cdots \\ \vdots & \vdots \\ \vdots & \vdots \\ \chi * \zeta_n^{k,tar}(t) + (1-\chi) * \beta_n^{k,tar}(t) & \chi * \zeta_n^{k,stat}(t) + (1-\chi) * \beta_n^{k,stat}(t) \end{bmatrix}$$

e.g.

$$\mathbf{wSPM}_t^k = \Omega_t^k = \begin{bmatrix} \omega_1^{k,tar}(t) & \omega_1^{k,stat}(t) \\ \omega_2^{k,tar}(t) & \omega_2^{k,stat}(t) \\ \omega_3^{k,tar}(t) & \cdots \\ \vdots & \vdots \\ \vdots & \vdots \\ \omega_n^{k,tar}(t) & \omega_n^{k,stat}(t) \end{bmatrix} = (\omega_i^{k,j}(t))_{i=1,..,n;k\in\{\pi,y\};j\in\{tar,stat\}} \tag{22}$$

where $\omega_i^{k,tar}(t)$, and $\omega_i^{k,stat}(t)$ state the actual switching probabilities used in equation (9) that agent i will opt for heuristic $j \in \{tar, stat\}$ to forecast variable $k_{t+1} \in \{\pi, y\}$ in period t.

3.5 Solution of the model

The solution of the model is now found by substituting (3) into (1) as well as the forecasts specified in (21) and (22) into (1) and (2) and rewriting in matrix notation. This yields:

$$\underbrace{\begin{bmatrix} 1+a_2c_2(1-c_3) & a_2c_1(1-c_3) \\ -b_2 & 1 \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} x_t \\ \pi_t \end{bmatrix}}_{Z_t} =$$

$$\underbrace{\begin{bmatrix} 1+a_1w_{x,t}^{stat}-a_1 & w_{\pi,t}^{stat} \\ 0 & 1+b_1w_{\pi,t}^{stat}-b_1 \end{bmatrix}}_{B_t} \underbrace{\begin{bmatrix} y_{t-1} \\ \pi_{t-1} \end{bmatrix}}_{Z_{t-1}} +$$

$$+ \underbrace{\begin{bmatrix} a_2w_{\pi,t}^{stat}-a_2c_1(c_3-1) \\ b_1w_{\pi,t}^{tar} \end{bmatrix}}_{a} \pi^* + \underbrace{\begin{bmatrix} -a_2c_3 \\ 0 \end{bmatrix}}_{b} i_{t-1} + \underbrace{\begin{bmatrix} -a_2\epsilon_t^i+\epsilon_t^x \\ \epsilon_t^\pi \end{bmatrix}}_{\varepsilon_t}$$

i.e.

$$\boldsymbol{AZ_t = B_tZ_{t-1} + a\pi^* + bi_{t-1} + \varepsilon_t}$$

where bold characters refer to matrices and vectors. The solution for Z_t is given by

$$\boldsymbol{Z_t = A^{-1}[B_tZ_{t-1} + a\pi^* + bi_{t-1} + \varepsilon_t]} \tag{23}$$

The solution exists if the matrix A is non-singular, i.e. $(1+a_2c_2(1-c_3))+b_2a_2c_1(1-c_3) \neq 0$. The system describes the solutions for π_t and y_t. Finally, the solution for i_t is found by substituting x_t and π_t obtained from (23) into (3)

3.6 Parametrization

Behavioural economic models with an evolutionary switching mechanism between heterogeneous expectations are often highly complex, nonlinear systems, exhibiting diverse dynamic properties that impede analytical solutions (Hommes, 2013). However, computer-based simulations bears the advantages of artificial laboratory experiments, allowing variables and confounding variables to be well controlled in experimental research (Steinbacher et al., 2021). Hence, my approach utilises agent-based Monte Carlo simulations to model the local interaction of 100 agents in a heterogeneous expectations environment under bounded rationality. The weights in equation (1) were obtained by removing all self-loops from the network and normalising the adjacency matrix. Table 1 provides an overview of the parameters used in the simulations, which are largely consistent with those employed in the research of De Grauwe and Ji (2020).

Calibration			
Parameter	Description	Value	Source
a_1	Coefficient of expected output in IS equation	0.5	(Smets and Wouters, 2003)
a_2	Inverse elasticity of substitution	1	(Clarida et al., 2000)
b_1	Coefficient of expected inflation in PC equation	0.5	(Smets and Wouters, 2003)
b_2	Phillips curves coefficient of the output gap	0.02	(De Grauwe and Ji, 2020)
c_1	Interest rate control parameters of output gap	0.5	(Blattner and Margaritov, 2010)
c_2	Interest rate control parameters of inflation	1.5	(Blattner and Margaritov, 2010)
c_3	Interest smoothing parameter in Taylor equation	0.5	(Blattner and Margaritov, 2010)
$\pi*$	Inflation target	0	(De Grauwe and Ji, 2020)
σ^x	Standard deviation of the output gap	0.5	(De Grauwe and Ji, 2020)
σ^π	Standard deviation of the inflation rate	0.5	(De Grauwe and Ji, 2020)
σ^i	Standard deviation of the nominal interest rate	0.5	(De Grauwe and Ji, 2020)
ϕ	Intensity of Choice	2	(De Grauwe and Ji, 2020)
ζ	Memory Parameter	0.5	(De Grauwe and Ji, 2020)
χ	Persuasion Parameter	0.5	(Own calibration)

Table 1: Parameter values of the calibrated model

4 Validation

De Grauwe and Ji (2020) already verified external validity by comparing their model output to empirical data using quarterly observations for the US and the Eurozone. I calibrated the model to replicate the behaviour of the benchmark De Grauwe and Ji (2020) model qualitatively. I visually analysed the distributions and moments of data resulting from the simulations of the benchmark model and two network-enriched versions with two specifications of the network parameters ($m = 5$ and $m = 95$) over 10000 periods. I then compared the resulting histograms of the output gap and inflation. See Figure (2) for the results.

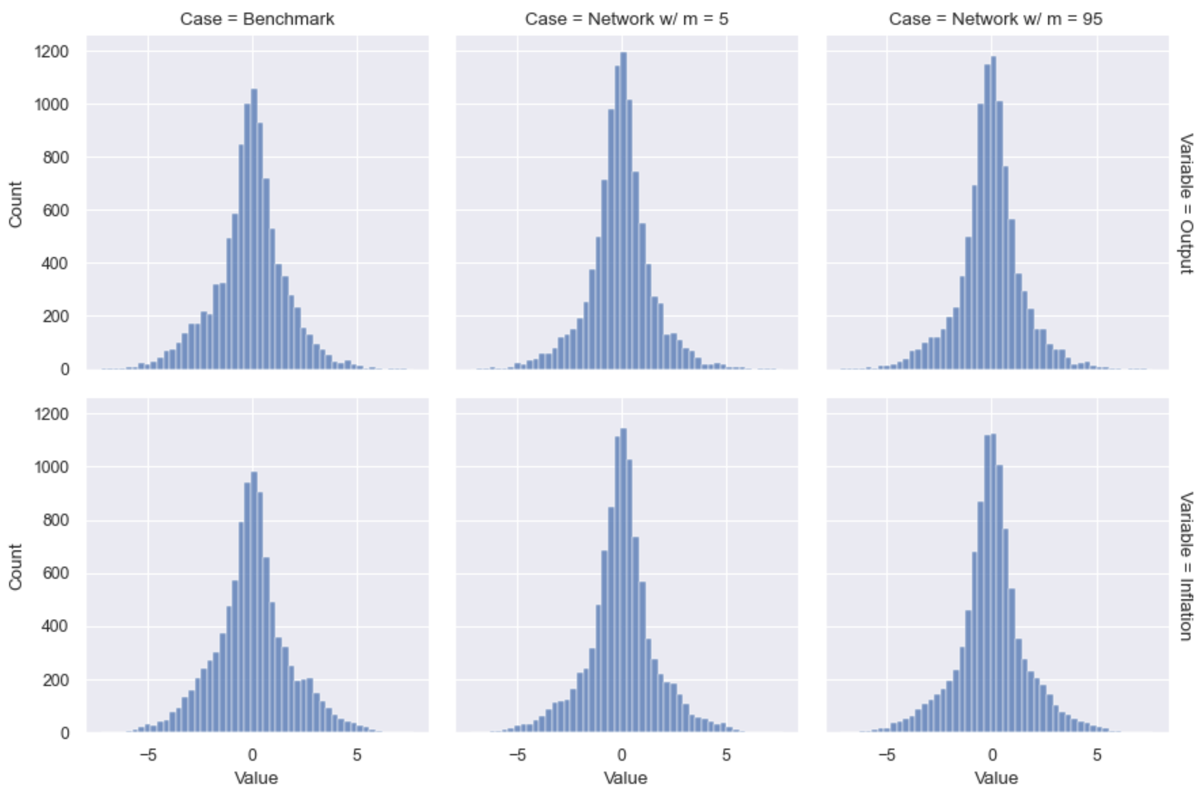


Figure 2: Histograms of the output gap and inflation

The histograms in the first row depict the distributions of the output gap for the benchmark model, the network-enriched version with $m = 5$ in the middle, and the network-enriched version with $m = 95$ to the right. The histograms for inflation are presented in the second row. The distribution of the output gap and inflation is almost identical in all cases.

However, it is noticeable that the network-enriched versions show slightly a stronger agglomeration of output and inflation in the centre of the distribution.

Furthermore, the distribution of market sentiments exhibited similar characteristics as the benchmark model compared to the network-enriched version under the same calibration as shown in Figure (3).

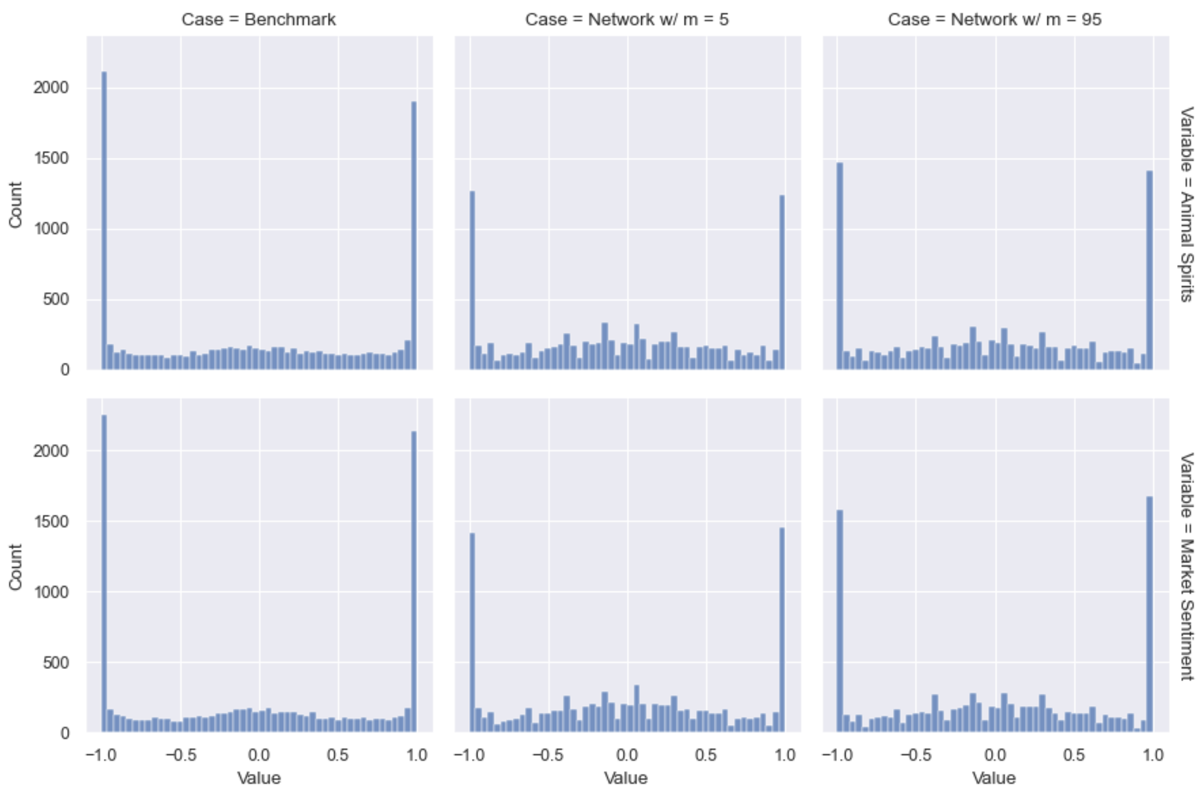


Figure 3: Histograms of the market sentiments

The histograms in the first row depict the distributions of the market sentiments of the output gap for the benchmark De Grauwe Model, the network-enriched version with $m = 5$ in the middle, and the network-enriched version with $m = 95$ to the right. The market sentiments for the inflation are presented in the second row. It is noticeable that the network-enriched versions of the model show weaker market sentiments and a stronger agglomeration of market expectations around the centre of the distribution.

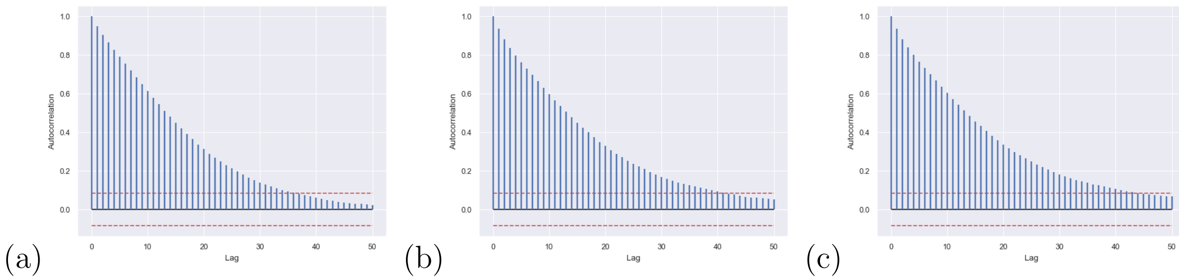


Figure 4: Autocorrelation of the output gap for (a) benchmark (b) $m = 5$ (c) $m = 95$

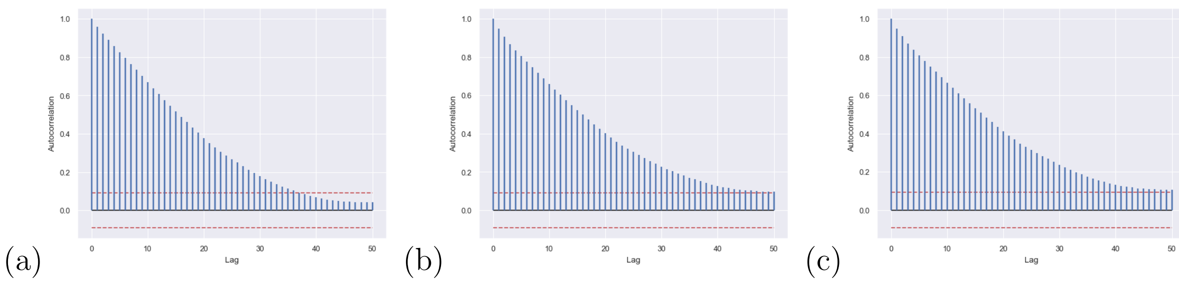
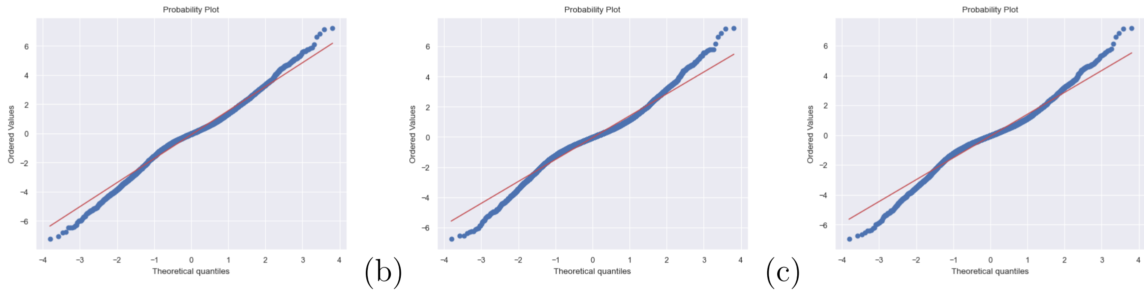


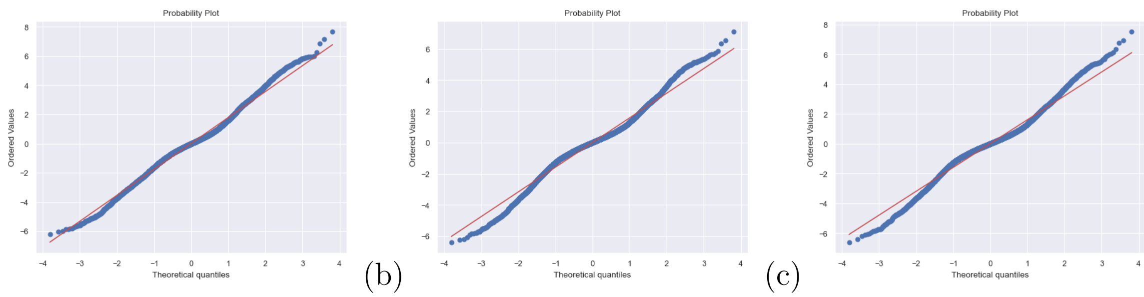
Figure 5: Autocorrelation of the inflation rate for (a) benchmark (b) $m = 5$ (c) $m = 95$

Empirical regularities in the form of lead and lag patterns have been studied by Fuhrer and Moore (1995) and Cassou and Vázquez (2014). These regularities include, among others, the persistent auto-correlation of inflation and the output gap as well as the non-normality distribution of the output gap. The simulated auto correlations of output gap and inflation for the benchmark and the two network-enriched model variants are shown in Figures (4) and (5). The model replicated the pattern of serial correlations of inflation and output gap obtained in De Grauwe and Ji (2020), which resembled those obtained in reality.
Finally, I computed the Quantil-Quantil-Plots and checked by observation whether a normal distribution is present. As shown in Figure (6) and (7), this is not the case for any of the simulated models, as indicated by the deviation of the points from the angle bisector.
Thus, the behavioural model predicts that the business cycle is characterised by periods of tranquillity (excess kurtosis) and booms and busts (fat tails), and this is even more pronounced in the network-enriched models. In conclusion, the network-enriched model is able to replicate the results of the benchmark using an additional network component, which opens up space for further investigations.



(a) (b) (c)

Figure 6: Quantil-Quantil-Plots of the output gap for (a) benchmark (b) $m = 5$ (c) $m = 95$



(a) (b) (c)

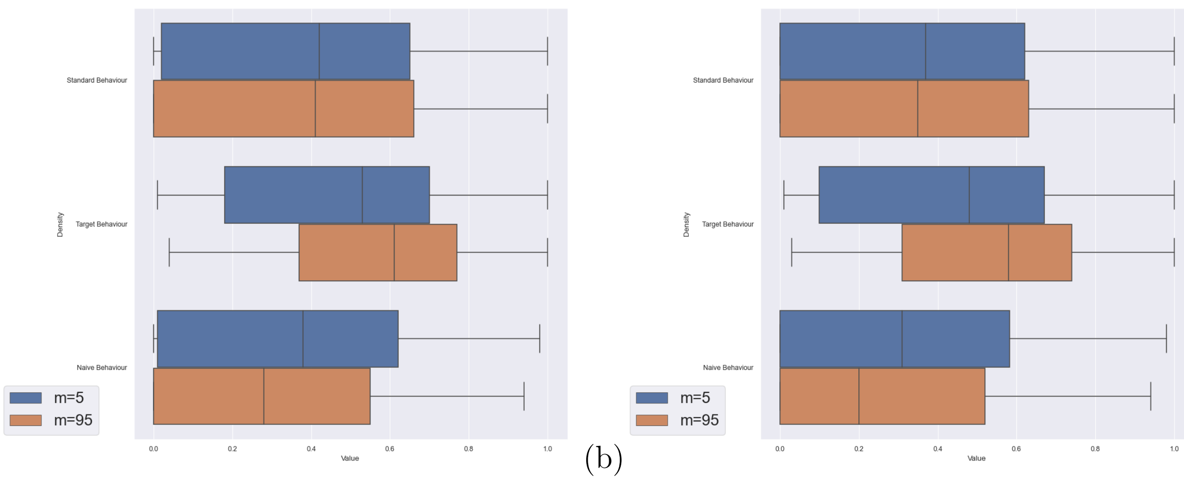
Figure 7: Quantil-Quantil-Plots of the inflation rate for (a) benchmark (b) $m = 5$ (c) $m = 95$

5 Results

In this study, I analysed the effect of three different behavioural strategies and network complexity levels on expectation formation process. The first strategy, referred to as 'Standard Behaviour,' follows the standard network topology as outlined in the model section. The other two strategies, 'Target Behaviour' and 'Naive Behaviour,' involve the agent with the highest degree centrality adopting targeted or naive expectations, respectively, regardless of their network environment. This was achieved by setting the persuasion parameter of these agents to 0 and fixing their choice of heuristic to the corresponding forecasting rule.

In order to investigate the influence of network complexity, I considered two different network topology settings for each treatment. Specifically, the first network setting corresponded to a moderate complexity of the Barabasi-Albert network, where the network parameter m was set to 5. The second network setting, on the other hand, corresponded to a higher complexity, where the parameter m was set to 95, resulting in a more complex network structure.

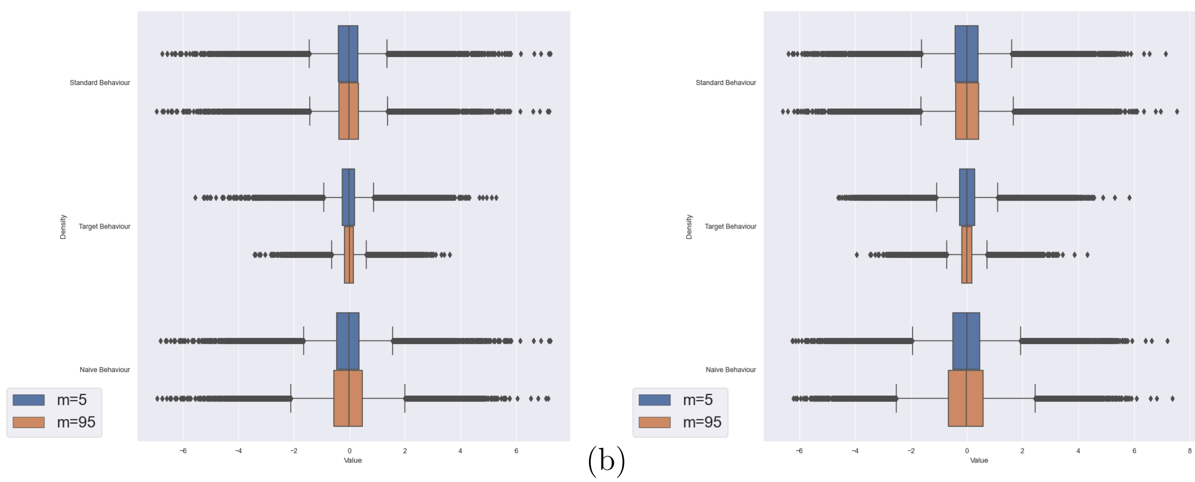
A visual representation of the two network structures is shown in Figure (1). Using the Python programming language and Seaborn library, I constructed boxplots to visually depict the resulting distribution under each treatment, providing insights into the presence of outliers, skewness, and central tendency. The data was generated by simulating the model 10000 periods with identical seeds.



(a) (b)

Figure 8: Boxplots of targeters for (a) Output (b) Inflation

Figure (8) shows the boxplots for the fraction of targeters. The medians of the distribution, as well as the interquartile ranges and adjacent values, show no significant effect of the structural properties of the network under the ‘Target Behavioural’ strategy for both variables. However, under the 'Target Behavioural' strategy, the boxes for both variables are shifted to the right. Moreover, in the case of a more complex network ($m = 95$), the median is slightly shifted to the right, as are the lower and upper 5% and 95% quantiles, indicating that the distribution tends to take on higher values. In both cases, the quartiles are higher than those of the standard strategy, while the dispersion is lower. Additionally, the adjacent values on the lower end of the distribution have decreased for the more complex network. Similar results were observed for the distribution of the targeters under the 'Naive Behavioural' strategy, with a smaller interquartile range on the upper end of the distribution compared to the 'Standard Behavioural' strategy. The median of the distribution is shifted significantly to the left in the case of a more complex network, and the whole distribution exhibits a larger dispersion than the 'Target Behavioural' strategy. Additionally, for both variables, the medians under the 'Target Behavioural' and the 'Naive Behavioural' strategy lie outside the boxes of the respective other strategies in the case of the more complex network, suggesting a significant difference between the two strategies. There were no outliers in any of the cases, and all boxplots showed a substantial negative skew.



(a) (b)

Figure 9: Boxplots of market expectations for (a) Output (b) Inflation

Figure (9) depicts the results of the boxplots for the market expectations of the output gap and inflation rate. Across all strategies and cases, the medians centred around zero, which indicated no significant differences. However, the boxes revealed differences in market expectations' variability across the various strategies. The "Standard Behavioural" strategy and "Naive Behavioural" strategy exhibited larger boxes, indicating more dispersed data. In contrast, the 'Target Behavioural' strategy had shorter boxes, indicating that its data points were more consistently clustered around the centre values. Although the interquartile ranges for all strategies were relatively small, the 'Naive Behavioural' strategy exhibited the greatest dispersion in its expectations, followed by the 'Standard Behavioural' strategy and the 'Target Behavioural' strategy. This outcome was expected as the target expectations assumed that the target rate would materialise in the next period, bringing market expectations closer to the median of zero. This also applies to the overall spread depicted by the adjacent values. In the 'Target Behavioural' strategy, the adjacent values decreased significantly compared to the 'Standard Behavioural' strategy, while they increased under the 'Naive Behavioural' strategy. Although the 'Standard Behavioural' strategy seemed not affected by network complexity, the 'Target Behavioural' strategy and 'Naive Behavioural' strategy did exhibit differences based on the complexity of the network. Notably, the impact of network complexity was most significant with regard to outliers. Under the 'Target Behavioural' strategy, the more complex the network, the greater the impact in terms of interquartiles and adjacent values in general, and outliers of the distribution in particular.

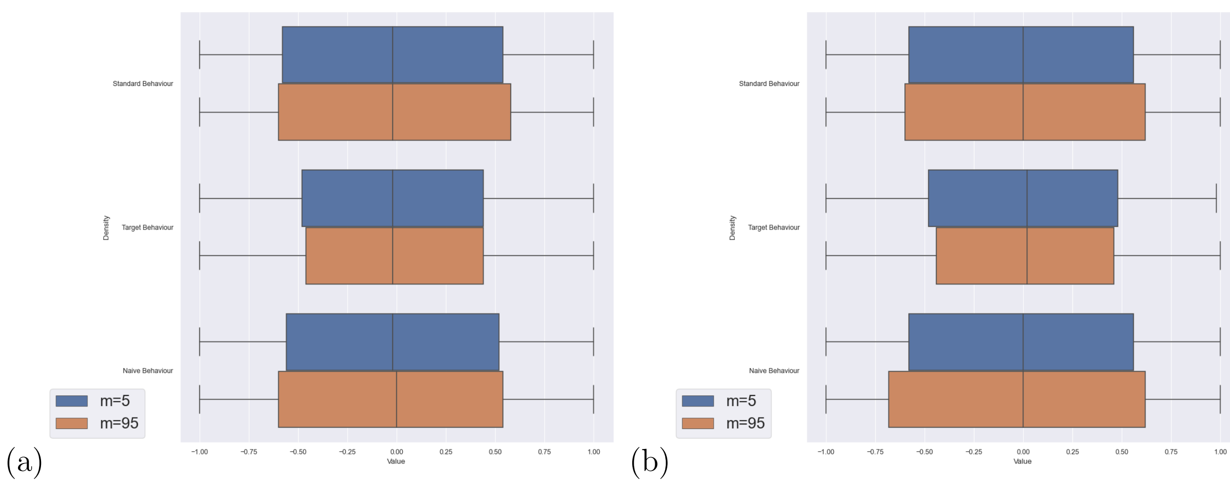


Figure 10: Boxplots of market sentiments of (a) Output (b) Inflation

Interestingly, a different result was observed when examining the distribution of market sentiments. The findings are displayed in Figure (10). Comparing the medians of the different strategies for market sentiments did not reveal significant differences. In the case of a more complex network, the 'Naive Behavioural' strategy had a slightly shifted median to the right, but all medians fell within the interquartile boxes of the other treatments. This suggests that there were no major differences between the distributions. However, under the "Target Behavioural" strategy, the interquartile ranges decreased, indicating a moderation of market sentiments. Conversely, in the "Naive Behavioural" strategy, the interquartile ranges decreased towards both ends of the distribution when compared to the "Standard Behavioural" strategy. The most significant difference was observed in the inflation market sentiment under the "Naive Behavioural" strategy, which displayed much more dispersion towards both ends of the scale compared to the "Standard Behavioural" strategy and the "Target Behavioural" strategy. This effect was even more pronounced under a more complex network. However, this difference was not observed under the other strategies or for the market sentiments related to the output gap.

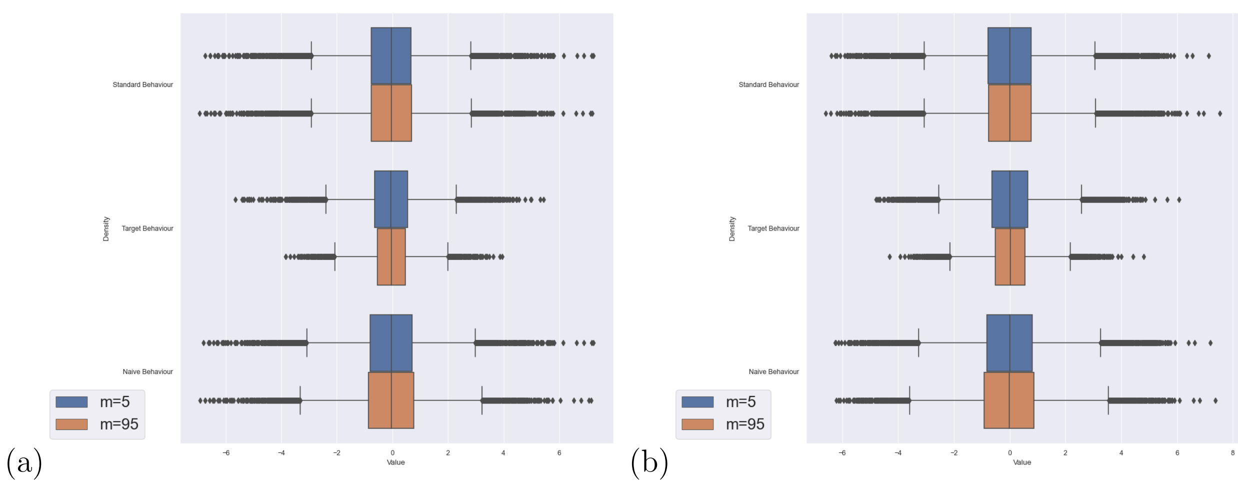


Figure 11: Boxplots of (a) Output (b) Inflation

Figure (11) displays the boxplots of the output gap and inflation rate, respectively. Median values for both variables were centered around zero and did not differ significantly across strategies. The boxes were similar in size for the "Standard Behavioural" strategy and "Naive Behavioural" strategy, but the "Target Behavioural" strategy produced slightly less dispersion. However, adjacent values were influenced by both the strategies and the network structure. The "Target Behavioural" strategy had fewer adjacent values and outliers compared to the "Standard Behavioural" strategy. Conversely, the "Naive Behavioural" strategy showed the opposite effect. Moreover, this effect was magnified with increased network complexity under both the "Target Behavioural" strategy and the "Naive Behavioural" strategy for both the output gap and the inflation rate.

6 Discussions

This study investigated the impact of several behavioural strategies and network complexity levels on expectation formation process. The analysis accounted for several distributions, such as the fraction of targeters, market expectations, market sentiments, and the distribution of the output gap and inflation rate. The behavioural strategies varied based on the decision-making process of the best-connected agent, which utilised either a combination of the discrete choice approach and the DeGroot model ("Standard Behaviour"), targeting expectations ("Target Behaviour"), or naive expectations ("Naive Behaviour") in each period. These best-connected agents, who had the highest centrality degree, acted as "influencers," having a substantial impact on others while remaining uninfluenced themselves. The analysis demonstrated that an agent possessing the highest degree centrality and promoting a specific behaviour significantly impacted the simulation's entire outcome. Specifically, an agent with high degree centrality who exhibits target expectations increased market stability, resulting in less uncertainty and more predictable outcomes. Conversely, an agent with high degree centrality but naive expectations lead to more of dispersion and variability in the market.

As previously mentioned, narratives can be used to interpret economic news and translate it into expectations (Andre et al., 2021; Roos and Reccius, 2021; Shiller, 2017). Within the model framework, heuristics functioned as implicit narratives. The assumption was that the appropriate forecasting strategy is selected based on available information and peer behaviour. In this case, the central bank's target represented a type of "true" information. Social learning within the network served not to learn the actual level of inflation, but rather to determine which expectation rule to adopt and ensure that the transmission of the "correct" information occurred more quickly. The findings suggest that the extent of this transmission is potentially triggered by the underlying network structure. The impact on the dispersion and outliers of the output gap and inflation rate distributions was particularly pronounced under a more complex network structure. However, the influence was also evident in the case of low complexity, even though the strength of this impact varied depending on the complexity. Thus, this finding is of particular interest to policy makers, as outliers in these economic variables are generally viewed as unfavourable situations. This underscores the importance of comprehending network structures and their impact on economic variables when examining the transmission of economic narratives and how they are disseminated.

One possible explanation for these observations could be that people tend to rely on the behaviour and opinions of others when making economic decisions that involve uncertainty, such as predicting future inflation rates. If a person perceives that their peers or social network have certain expectations about inflation, they may be more likely to conform to those expectations and adjust their own beliefs accordingly. As agents in the network interacted with each other, they exchanged information and affected each other's expectation decisions. This process resulted in increased propagation of a specific behaviour across the network as agents revise their expectations by taking into account a weighted average of their neighbours' expectation heuristic choices in conjunction with their own choices based on the heuristic switching framework. Hence, having an agent in a central position enables information to be disseminated more efficiently. In a highly connected network, information spreads even more quickly, and the influence of the agent with the highest centrality degree (i.e., the influencer) could be amplified. This might result in faster propagation of narratives compared to a network with a more dispersed structure.

Based on this reasoning, the findings of this study expand upon prior research that has investigated the influence of social networks on economic expectations and behaviour. For instance, Bargigli and Tedeschi (2014) demonstrated that agents may alter their expectations or behaviour as a result of the expectations or behaviour of those with whom they communicate, leading to herd behaviour and/or imitation. Meanwhile, Bailey et al. (2018) found that communication between agents is propagating shocks to expectations, and that this could be due to the spread of irrational sentiments as described in Akerlof and Shiller (2010). Moreover, the study's emphasis on the averaging effect of imitating expectations within the model framework aligns with previous research on the approach that investors, as heterogeneous interacting agents, form information networks to inform their investment decisions (Oldham, 2019). For example, Han and Yang (2013) showed that traders with informed neighbours may not generate their own information, as they can rely on their neighbours' instead. Furthermore, this study corroborates the results of previous research that has investigated the impact of network topologies on asset price dynamics. For example, Panchenko et al. (2013) demonstrated that network structures have an effect on asset price dynamics, affecting price stability, fluctuation amplitude, and statistical properties.

While this study has produced some significant findings, there are certain limitations that need to be taken into account. Firstly, the results are based on several strong assumptions regarding the model specifications. The DeGroot opinion model is a form of opinion aggregation in social networks that operates by averaging the opinions of all individuals in the network. The Heuristic Switching Model involves a type of averaging, as it assumes that the weights of the heuristics in the population are equivalent to the average switching probabilities across all agents. It seemed that the DeGroot model enforced this averaging effect of neighbour opinions. This may have resulted in weaker market sentiments and greater agglomeration of output and inflation in the centre of the distribution, as depicted in figures (10). This observation was consistent with the expected outcome, since a discrete set of homogeneous agents is incorporated under the assumption of symmetrical information.

Moreover, the simulation assumes that economic agents possess complete and accurate information, which is not always the case in reality. One way to incorporate incomplete and asymmetric information in an agent-based simulation is to introduce a random component in the perception of macroeconomic variables, as demonstrated by Schmitt (2021). In this setup, an agent's decision to follow its own discrete heuristic choice or the network's opinion could be discretely modelled using a fitness measure that considers the costs of acquiring information and the utility gained from the network's opinion. To simulate this decision-making process, an independent cascade model (e.g. Panchenko et al., 2013) with a threshold value for diverging opinions in its neighbourhood, or a heuristic switching approach based on attractivity value, could be used.

While the interpretation of heuristics as implicit narratives has been a useful framework for understanding the formation of inflation expectations in social networks, it is crucial to acknowledge the limitations of this approach. For instance, the notion that individuals rely on narratives to determine their expectations implies that they possess a coherent and consistent mental model of the economic environment in which they operate. However, this may not always be the case, given the complexity and uncertainty of real-world economic systems. To address this issue, future research could explore ways of translating the narratives of agents' beliefs about what is right or wrong into more concrete and measurable variables. For example, one could investigate whether individuals' trust in the central bank's strategy is influenced by their perceptions of the bank's track record, the state of the economy, or the opinions of their peers. By taking a more nuanced and multifaceted approach to the analysis of heuristics and narratives, researchers may be able to identify more reliable and accurate predictors of inflation expectations in social networks. Moreover, it is essential to recognise that trust in the central bank is not a static or isolated phenomenon but rather is shaped by a complex interplay of social and economic factors. For instance, an individual's probability of trusting the central bank may be influenced by the opinions of their neighbours, who in turn may be influenced by a variety of contextual factors, such as media coverage, political events, or economic shocks. To capture the dynamic and contextual nature of trust in the central bank, future research could adopt a more nuanced and sophisticated approach to social network analysis, such as by incorporating time-varying weights or dynamic edge formation rules.

In addition, a possible extension to the simulation would be to model an evolving network where the weights are updated over time based on the forecast error of the respective neighbours or the agent's own forecast error relative to that of its neighbours. New edges could be formed based on the performance of the agents. It would be interesting to investigate whether this would lead to network growth and a power-law distribution in line with the preferential attachment principle applied by the Barabási-Albert network (Barabási and Albert, 1999). These approaches could be further explored from the perspective of rational inattention or explicit conformity effects resulting from disagreements in the network.

One potential area of further investigation could be the role of persuasion within social networks and how they contribute to the formation of expectations. This could involve examining how social norms and group dynamics shape the attitudes and beliefs of individual agents within a network, and how these factors influence the expectations they hold. Another area of research could involve examining the impact of network structure on the transmission of information and the formation of expectations. For example, it would be valuable to investigate the effect of network topology on the speed and accuracy of information transmission, and how that in turn affects the stability of expectations. Finally, it would be valuable to examine the potential implications of these findings for policymakers and investigate the potential for social networks to be used as a tool for influencing expectations in a more favourable direction. For instance, policymakers could design and implement communication strategies aimed at shaping expectations through social networks, with the goal of promoting economic stability.

Although the interpretation of heuristics as implicit narratives has its flaws, it remains a valuable framework for understanding the formation of inflation expectations in social networks. By addressing the limitations of current approaches and adopting a more nuanced and multifaceted analysis of heuristics and narratives, researchers may be able to identify more reliable and accurate predictors of inflation expectations. Furthermore, examining the potential of social networks as a tool for influencing expectations in a more favourable direction could contribute to a more robust understanding of the relationship between social networks and economic behaviour. To this end, policymakers could design and implement communication strategies aimed at shaping expectations through social networks, with the ultimate goal of promoting economic stability.

7 Conclusion

The aim of this study was to examine how different network structures and behavioural strategies can affect the expectation formation process of economic agents under bounded rationality. My hypothesis was that the stability of expectations can be influenced by certain agents who are particularly well-connected to other agents within the network. Specifically, this study sought to explore the impact of higher levels of inter-connectivity between agents and agents with high degree centrality on expectations' stability. To achieve this goal, I developed a conceptual framework incorporating an additional network component in the process of expectation formation of bounded rational agents. The analysis demonstrated that an agent possessing a high degree centrality and propagating a specific behaviour or information narrative significantly can impact the simulation's entire outcome, particularly in relation to outliers. The study also found that the complexity of the network structure affects the expectation formation process by further enhancing the influence of the agent with high degree centrality.

The reduction in dispersion and outliers of the output gap and inflation rate distributions was evident under both complex and low complexity network structures, although with varying strengths. Therefore, the findings of this study suggests that the stability of expectations might be positive correlated with the overall degree centrality of a social network under certain circumstances.

In conclusion, this study emphasises the structural properties of the underlying network of economic agents. Moreover, the findings of this study have important implications for monetary policy. They emphasises the necessity for policymakers to consider the role of social networks in shaping expectations and the potential for monetary policy transmission through social networks. Policymakers might use this knowledge to develop more effective monetary policies that account for the impact of social networks. Overall, this research presents new avenues for future studies in the field of behavioural macroeconomics. By delving deeper into the impact of social networks on expectation formation and the macroeconomy, we might gain a better understanding of the complex dynamics at play in our intertwined world. I hope that this study will inspire further investigations and contribute to a growing body of knowledge in this field.

References

Akerlof, G. A. and Shiller, R. J. (2010). *Animal spirits: How human psychology drives the economy, and why it matters for global capitalism*. Princeton University Press, Princeton, N.J Woodstock.

Amato, J. D. and Laubach, T. (2003). Rule-of-thumb behaviour and monetary policy. *European Economic Review*, 47(5):791–831.

Andre, P., Haaland, I., Roth, C., and Wohlfart, J. (2021). Narratives about the Macroeconomy. *ECONtribute Discussion Papers Series*. Number: 127 Publisher: University of Bonn and University of Cologne, Germany.

Angelico, C., Marcucci, J., Miccoli, M., and Quarta, F. (2022). Can we measure inflation expectations using Twitter? *Journal of Econometrics*, 228(2):259–277.

Anufriev, M. and Hommes, C. (2012). Evolutionary Selection of Individual Expectations and Aggregate Outcomes in Asset Pricing Experiments. *American Economic Journal: Microeconomics*, 4(4):35–64.

Arifovic, J., Bullard, J., and Kostyshyna, O. (2013). Social Learning and Monetary Policy Rules. *The Economic Journal*, 123(567):38–76.

Assenza, T., Bao, T., Hommes, C., and Massaro, D. (2014). Experiments on Expectations in Macroeconomics and Finance. In Duffy, J., editor, *Experiments in Macroeconomics - Research in Experimental Economics*, volume 17, pages 11–70. Emerald Group Publishing Limited.

Assenza, T., Cardaci, A., Gatti, D. D., and Grazzini, J. (2018). Policy experiments in an agent-based model with credit networks. *Economics: The Open-Access, Open-Assessment E-Journal*, 12(2018-47):1–17.

Azzimonti, M. and Fernandes, M. (2022). Social media networks, fake news, and polarization. *European Journal of Political Economy*, page 102256.

Bailey, M., Cao, R., Kuchler, T., and Stroebel, J. (2018). The Economic Effects of Social Networks: Evidence from the Housing Market. *Journal of Political Economy*, 126(6):2224–2276.

Barabási, A.-L. and Albert, R. (1999). Emergence of Scaling in Random Networks. *Science*, 286(5439):509–512. Publisher: American Association for the Advancement of Science.

Bargigli, L. and Tedeschi, G. (2014). Interaction in agent-based economics: A survey on the network approach. *Physica A: Statistical Mechanics and its Applications*, 399:1–15.

Baumann, U., Darracq Paries, M., Westermann, T., Riggi, M., Bobeica, E., and Meyler, A ... Stockhammar, P. (2021). Inflation Expectations and Their Role in Eurosystem Forecasting. *Occasional paper series / European Central Bank*, 264.

Benhammada, S., Amblard, F., and Chikhi, S. (2021). An Agent-Based Model to Study Informational Cascades in Financial Markets. *New Generation Computing*, 39(2):409–436.

Biondi, Y. and Zhou, F. (2019). Interbank credit and the money manufacturing process: a systemic perspective on financial stability. *Journal of Economic Interaction and Coordination*, 14(3):437–468.

Blattner, T. S. and Margaritov, E. (2010). Towards a Robust Monetary Policy Rule for the Euro Area. *Working Paper Series*, No. 1210, European Central bank.

Branch, W. A. (2004). The Theory of Rationally Heterogeneous Expectations: Evidence from Survey Data on Inflation Expectations. *The Economic Journal*, 114(497):592–621.

Branch, W. A. and McGough, B. (2010). Dynamic predictor selection in a new Keynesian model with heterogeneous expectations. *Journal of Economic Dynamics and Control*, 34(8):1492–1508.

Brazier, A., Harrison, R., King, M., and Yates, T. (2008). The Danger of Inflating Expectations of Macroeconomic Stability: Heuristic Switching in an Overlapping-Generations Monetary Model. *International Journal of Central Banking*, 4(2):219–254. Publisher: International Journal of Central Banking.

Brock, W. A. and Hommes, C. H. (1997). A Rational Route to Randomness. *Econometrica*, 65(5):1059.

Brock, W. A. and Hommes, C. H. (1998). Heterogeneous beliefs and routes to chaos in a simple asset pricing model. *Journal of Economic Dynamics and Control*, 22(8-9):1235–1274.

Buechel, B., Hellmann, T., and Klößner, S. (2015). Opinion dynamics and wisdom under conformity. *Journal of Economic Dynamics and Control*, 52:240–257.

Carroll, C. D. (2003). Macroeconomic Expectations of Households and Professional Forecasters. *The Quarterly Journal of Economics*, 118(1):269–298.

Cassou, S. P. and Vázquez, J. (2014). Small-scale New Keynesian model features that can reproduce lead, lag and persistence patterns. *The B.E. Journal of Macroeconomics*, 14(1).

Chandrasekhar, A. G., Larreguy, H., and Xandri, J. P. (2020). Testing Models of Social Learning on Networks: Evidence From Two Experiments. *Econometrica*, 88(1):1–32.

Choi, S., Gale, D., and Kariv, S. (2008). Sequential equilibrium in monotone games: A theory-based analysis of experimental data. *Journal of Economic Theory*, 143(1):302–330.

Clarida, R., Gali, J., and Gertler, M. (2000). Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory*. *Quarterly Journal of Economics*, 115(1):147–180.

Clemente, G. P., Grassi, R., and Pederzoli, C. (2020). Networks and market-based measures of systemic risk: the European banking system in the aftermath of the financial crisis. *Journal of Economic Interaction and Coordination*, 15(1):159–181.

Corazzini, L., Pavesi, F., Petrovich, B., and Stanca, L. (2012). Influential listeners: An experiment on persuasion bias in social networks. *European Economic Review*, 56(6):1276–1288.

Dawid, H. and Delli Gatti, D. (2018). Agent-Based Macroeconomics. In *Handbook of Computational Economics*, volume 4, pages 63–156. Elsevier.

De Grauwe, P. (2011). Animal spirits and monetary policy. *Economic Theory*, 47(2):423–457.

De Grauwe, P. and Foresti, P. (2020). Animal Spirits and Fiscal Policy. *Journal of Economic Behavior & Organization*, 171:247–263.

De Grauwe, P. and Ji, Y. (2019). Inflation Targets and the Zero Lower Bound in a Behavioural Macroeconomic Model. *Economica*, 86(342):262–299.

De Grauwe, P. and Ji, Y. (2020). Structural reforms, animal spirits, and monetary policies. *European Economic Review*, 124:103395.

De Grauwe, P. and Ji, Y. (2022). On the use of current and forward-looking data in monetary policy: a behavioural macroeconomic approach. *Oxford Economic Papers*, page gpac024.

Degroot, M. H. (1974). Reaching a Consensus. *Journal of the American Statistical Association*, 69(345):118–121.

Flynn, J. P. and Sastry, K. (2022). The Macroeconomics of Narratives.

Franke, R. and Westerhoff, F. (2018). Taking Stock: A Rigorous Modelling of Animal Spirits in Macroeconomics. In Veneziani, R. and Zamparelli, L., editors, *Analytical Political Economy*, pages 5–38. John Wiley & Sons, Ltd, Oxford, UK.

Fuhrer, J. and Moore, G. (1995). Inflation Persistence. *The Quarterly Journal of Economics*, 110(1):127–159.

Gabaix, X. (2020). A Behavioral New Keynesian Model. *American Economic Review*, 110(8):2271–2327.

Galí, J. (2008). *Monetary policy, inflation, and the business cycle: an introduction to the new Keynesian framework*. Princeton University Press, Princeton, N.J. OCLC: ocn177826088.

Gigerenzer, G. and Selten, R., editors (2002). *Bounded rationality: the adaptive toolbox*. Dahlem workshop reports. MIT Press, Cambridge, Mass., 1. mit press paperback ed edition. Meeting Name: Dahlem Workshop.

Gorodnichenko, Y., Pham, T., and Talavera, O. (2021). Social media, sentiment and public opinions: Evidence from #Brexit and #USElection. *European Economic Review*, 136:103772.

Han, B. and Yang, L. (2013). Social Networks, Information Acquisition, and Asset Prices. *Management Science*, 59(6):1444–1457.

Hommes, C. (2011). The heterogeneous expectations hypothesis: Some evidence from the lab. *Journal of Economic Dynamics and Control*, 35(1):1–24.

Hommes, C. (2013). *Behavioral Rationality and Heterogeneous Expectations in Complex Economic Systems*. Cambridge University Press, Cambridge.

Hommes, C., Makarewicz, T., Massaro, D., and Smits, T. (2017). Genetic algorithm learning in a New Keynesian macroeconomic setup. *Journal of Evolutionary Economics*, 27(5):1133–1155.

Iori, G. and Mantegna, R. N. (2018). Empirical Analyses of Networks in Finance. In *Handbook of Computational Economics*, volume 4, pages 637–685. Elsevier.

Khashanah, K. and Alsulaiman, T. (2016). Network theory and behavioral finance in a heterogeneous market environment. *Complexity*, 21(S2):530–554.

Khashanah, K. and Alsulaiman, T. (2017). Connectivity, Information Jumps, and Market Stability: An Agent-Based Approach. *Complexity*, 2017:1–16.

Lamla, M. and Vinogradov, D. V. (2021). Is the word of a gentleman as good as his tweet? Policy communications of the Bank of England. *Working Paper Series in Economics*, No. 403, , Leuphana Universität Lüneburg, Institut für Volkswirtschaftslehre, Lüneburg.

Lengnick, M. and Wohltmann, H.-W. (2016). Optimal monetary policy in a new Keynesian model with animal spirits and financial markets. *Journal of Economic Dynamics and Control*, 64:148–165.

Luan, S., Reb, J., and Gigerenzer, G. (2019). Ecological Rationality: Fast-and-Frugal Heuristics for Managerial Decision Making under Uncertainty. *Academy of Management Journal*, 62(6):1735–1759.

Luarn, P., Yang, J.-C., and Chiu, Y.-P. (2014). The network effect on information dissemination on social network sites. *Computers in Human Behavior*, 37:1–8.

Macaulay, A. and Song, W. (2022). Narrative-Driven Fluctuations in Sentiment: Evidence Linking Traditional and Social Media. *SSRN Electronic Journal*.

Makarewicz, T. (2017). Contrarian Behavior, Information Networks and Heterogeneous Expectations in an Asset Pricing Model. *Computational Economics*, 50(2):231–279.

Manski, C. F. and McFadden, D., editors (1981). *Structural analysis of discrete data with econometric applications*. MIT Press, Cambridge, Mass.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. *Frontiers in econometrics*.

Müller, H., Schmidt, T., Rieger, J., Hufnagel, L. M., and Hornig, N. (2022). A German Inflation Narrative. *DoCMA Working Paper*, No. 9, TU Dortmund University, Dortmund Center for Data-based Media Analysis (DoCMA), Dortmund. Publisher: TU Dortmund.

Oldham, M. (2019). Understanding How Short-Termism and a Dynamic Investor Network Affects Investor Returns: An Agent-Based Perspective. *Complexity*, 2019:1–21.

Panchenko, V., Gerasymchuk, S., and Pavlov, O. V. (2013). Asset price dynamics with heterogeneous beliefs and local network interactions. *Journal of Economic Dynamics and Control*, 37(12):2623–2642.

Pfajfar, D. and Žakelj, B. (2014). Experimental evidence on inflation expectation formation. *Journal of Economic Dynamics and Control*, 44:147–168.

Pfajfar, D. and Žakelj, B. (2018). Inflation Expectations And Monetary Policy Design: Evidence From The Laboratory. *Macroeconomic Dynamics*, 22(4):1035–1075. Publisher: Cambridge University Press.

Proaño, C. R. and Lojak, B. (2020). Animal spirits, risk premia and monetary policy at the zero lower bound. *Journal of Economic Behavior & Organization*, 171:221–233.

Roos, M. W. M. and Reccius, M. (2021). Narratives in economics. *Ruhr Economic Papers*, No. 922. ISBN: 978-3-96973-068-3.

Schmitt, N. (2021). Heterogeneoues expectations and asset price dynamics. *Macroeconomic Dynamics*, 25(6):1538–1568.

Selten, R. (1998). Features of experimentally observed bounded rationality. *European Economic Review*, 42(3-5):413–436.

Shiller, R. J. (2017). Narrative Economics. *American Economic Review*, 107(4):967–1004.

Simon, H. A. (1957). *Models of man; social and rational.* Models of man; social and rational. Wiley, Oxford, England. Pages: xiv, 287.

Smets, F. and Wouters, R. (2003). An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area. *Journal of the European Economic Association*, 1(5):1123–1175.

Smets, F. and Wouters, R. (2007). Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach. *American Economic Review*, 97(3):586–606.

Steinbacher, M., Raddant, M., Karimi, F., Camacho Cuena, E., Alfarano, S., Iori, G., and Lux, T. (2021). Advances in the agent-based modeling of economic and social behavior. *SN Business & Economics*, 1(7):99.

Steinbacher, M., Steinbacher, M., and Steinbacher, M. (2014). Interaction-Based Approach to Economics and Finance. In Faggini, M. and Parziale, A., editors, *Complexity in Economics: Cutting Edge Research*, pages 161–203. Springer International Publishing, Cham. Series Title: New Economic Windows.