Connecting the Dots: How Social Networks Shape Expectations Through Economic Narratives

Rafael Kothe

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Bamberg Economic Research Group Bamberg University Feldkirchenstraße 21 D-96052 Bamberg Telefax: (0951) 863 5547 Telephone: (0951) 863 2687 felix.stuebben@uni-bamberg.de http://www.uni-bamberg.de/vwl/forschung/berg/

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Dr. Felix Stübben*

^{*} felix.stuebben@uni-bamberg.de

Connecting the Dots: How Social Networks Shape Expectations Through Economic Narratives

Rafael Kothe 1,2,3

¹Department of Economics^{*}. ²Bamberg Research Training Group on Bounded Rationality, Heterogeneity, and Network Effects^{*}. ³Bamberg Graduate School of Social Sciences^{*}. ^{*}University of Bamberg, Feldkirchenstr. 21, 96052, Bamberg, Germany.

Contributing authors: rafael.kothe@uni-bamberg.de;

Abstract

This paper investigates how social network and conformity dynamics shape the stability of inflation expectations and the dissemination of economic narratives. Using an agent-based macroeconomic simulation, I integrate a heuristic switching framework with an opinion dynamics mechanism to examine the impact of targeted narrative dissemination by highly central agents on expectation dispersion. The computational experiments reveal that when influential network actors transmit the central bank's inflation narrative, both inflation rate dispersion and the dispersion of expectations are substantially reduced. Conversely, when distorting narratives spread through these key nodes, it requires very high persuasion levels to significantly amplify instability. Moreover, impulse response analyses show that stronger social influence accelerates convergence toward rational expectations following shocks, thereby mitigating both the magnitude and persistence of deviations. However, heightened persuasion can also weaken the link between expectations and underlying fundamentals, as agents increasingly align with dominant narratives rather than economic signals. Overall, these findings underscore the dual role of social networks in monetary policy communication, capable of both anchoring expectations and amplifying destabilising narratives.

Keywords: Expectations, Economic Narratives, Network Effects, Behavioral Macroeconomics, Agent-Based Modeling, Monetary Policy Communication

JEL Classification: D84, D83, E52, E71, D85

"A man is always a teller of tales, he lives surrounded by his stories and the stories of others, he sees everything that happens to him through them; and he tries to live his life as if he were recounting it."

- Jean-Paul Sartre (2000), quoted in Robert J. Shiller (2020) "Narrative Economics: How Stories Go Viral and Drive Major Economic Events"

1 Introduction

Social network platforms have revolutionized the way information is shared and processed (Luarn et al. 2014; Bailey et al. 2018). The underlying networks represent the structure of social interactions and relationships and act as a critical conduit for transmitting economic information and narratives (Macaulay and Song 2023a,b). In this context, narratives are defined as coherent, contextually embedded stories that provide meaning to social phenomena. They influence individual and collective decision-making, shape expectations about the future, and drive macroeconomic behaviors (Akerlof and Shiller 2010; Beckert 2013, 2016; Tuckett and Tuckett 2011). Consequently, narratives emerging from social networks offer valuable insights into mechanisms such as inflation expectations and market dynamics, aligning with the broader literature on the role of narratives in economics (Shiller 2017; Flynn and Sastry 2024; Andre et al. 2024; Collier and Tuckett 2021; Roos and Reccius 2024).

In macroeconomics, such narratives transform abstract data into relatable and actionable insights by framing complex economic information (Shiller 2017, 2020). By simplifying complex economic information, narratives effectively influence public sentiment and market reactions (Roos and Reccius 2024). They also shape individuals' perceptions of inflation risks, interpretations of market signals, and adjustments to their economic behaviours (Akerlof and Snower 2016). Thus, narratives play a key role in how expectations spread through social networks, interacting dynamically with network structures and agent behaviour. Central banks leverage these narratives to shape inflation expectations and guide macroeconomic responses in ways similar to traditional monetary policy communication (Ter Ellen et al. 2022). By influencing household spending and inflation expectations, effective communication can further impact price momentum and market outcomes (see e.g., Baumann et al. 2021b; Coibion et al. 2020a, b, 2022). Moreover, empirical studies reveal evidence of narrative hysteresis - even transient shocks can trigger self-sustaining shifts in inflation expectations that persist over time, indicating that once a narrative goes viral, its impact on public sentiment and economic behavior may remain entrenched long after the initial trigger has faded (Flynn and Sastry 2025).

Previous research has extensively explored the relationship between first-order expectations (an agent's expectations) and higher-order expectations (expectations about others' expectations) (e.g. Coibion et al. 2021), as well as the role of heterogeneous expectations in economic models (Hommes 2013).¹ Models such as the heuristic switching framework focus on agents' perceptions of heuristic success in predicting outcomes but often place less emphasis on interaction effects or communication within networks (Lustenhouwer 2021; Proaño and Lojak 2020; Hommes and Lustenhouwer 2019a,b). Contributions from eco-physics have further examined opinion dynamics in social networks, including polarized opinions (Baumann et al. 2021a) and network effects on extremist opinion formation (Azzimonti and Fernandes 2023; Martins 2008). Although earlier studies often overlooked the complex interactions and communication dynamics significantly influencing expectation formation, particularly in agent-based models, more recent work has started to address these (Rengs and Scholz-Wäckerle

 $^{^{1}}$ For a comprehensive overview of state-of-the-art theories and modeling approaches, reference is made to Hommes (2013)



2019; Rengs et al. 2020; Dosi et al. 2010, 2009; Fagiolo and Roventini 2017). This highlights the need to further explore how network interactions shape expectation formation and their implications for monetary policy.

This study addresses these gaps by examining how network dynamics amplify narratives and their impact on the stability of macroeconomic expectations at individual and systemic levels. The objective is to enhance central bank communication strategies and provide a robust foundation for future empirical validation. To achieve this, this paper develops of a hybrid agent-based macroeconomic model that simultaneously captures individual bounded rationality - via a traditional heuristic switching framework Brock and Hommes (1997, 1998) - and network-driven belief updating through a DeGroot-type social learning mechanism Degroot (1974). Building on the behavioral New Keynesian framework established by De Grauwe (2011); De Grauwe and Ji (2020, 2023) and insights from prior experimental studies (Hommes 2011, 2013, 2021; Bao et al. 2021), the paper investigates the research question: "How do social networks shape the stability of macroeconomic expectations at both individual and systemic levels?". Unlike other hybrid approaches (e.g. Proaño and Lojak 2020; Anufriev et al. 2013: Arifovic et al. 2013: Assenza and Gatti 2013: Assenza and Delli Gatti 2019; Lengnick and Wohltmann 2016; Hommes and Lustenhouwer 2019a,b) that merge macroeconomic frameworks with agent-based techniques while focusing primarily on agent heterogeneity or market frictions, not accounting for social interactions at a spatial level, this approach extends the hybrid tradition by explicitly embedding network structures into expectation formation. This integrated approach allows for a novel analysis of how the dissemination of economic narratives through social networks influences macroeconomic expectations and systemic stability.

The findings indicate that strategically targeting central agents within social networks to disseminate the central bank's inflation narrative significantly enhances monetary policy effectiveness by reducing inflation variability and anchoring expectations. Conversely, when competing or distorting narratives spread through influential nodes, exceptionally high levels of persuasion are necessary to substantially amplify instability, resulting in heightened inflation volatility and an increased risk of deanchoring expectations. The simulations also consistently demonstrate that the (de-)stabilizing effects resulting from the dissemination of targeted or naive narratives persist even when the intervention is directed solely at agents with lower centrality. Additionally, the analysis reveals that network structure critically influences these dynamics - with different topologies exhibiting distinct patterns in the propagation of narratives and the resulting aggregate outcomes. Interestingly, impulse response analyses show that stronger social influence accelerates convergence towards rational expectations following shocks, reducing both the magnitude and persistence of deviations.

This paper is organized as follows: Section 2 reviews the literature on social networks, economic narratives, and expectation formation. Section 3 details the integrated agent-based model combining heuristic switching and social learning in a behavioral New Keynesian framework. Section 4 presents computational results on network effects on inflation expectations and policy effectiveness. Section 5 discusses the findings and the study's contributions. Section 6 concludes with policy implications.

2 Literature Review

This paper relates to four strands of the literature: First, it is primarily situated within the context of existing research on bounded rationality, social learning, and expectations. A significant part of the theoretical literature has focused on formalizing alternative approaches to the rational expectations assumption, describing the decision-making process of heterogeneous agents under bounded rationality. These approaches often assume that agents cannot 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 complex information and developing rational expectations. Empirical evidence from laboratory experiments and survey data supports these cognitive constraints (Branch 2004; Carroll 2003; Hommes 2011; Pfajfar and Žakelj 2014). Instead, people use heuristics when making decisions under uncertainty (Gigerenzer and Selten 2002; Luan et al. 2019). The heuristic switching framework used in this study is a popular method for incorporating bounded rationality in macroeconomic models, assuming that agents update their forecasts based on past mistakes (Brock and Hommes 1997, 1998; Branch and McGough 2010). This framework employs a discrete choice model, allowing agents to switch between different expectation heuristics based on their historical predictive accuracy (McFadden 1974; Manski and McFadden 1981). Similar approaches that merge macroeconomic frameworks with agent-based techniques are frequently used in business cycle models to incorporate heterogeneous expectations (see e.g. De Grauwe 2011; De Grauwe and Ji 2019, 2020, 2023; De Grauwe and Foresti 2020; Hommes 2013; Hommes et al. 2017; Proaño and Lojak 2020; Hommes and Lustenhouwer 2019a,b; Galanis et al. 2022), to study the efficiency of micro- and macroprudential measures (e.g. Assenza et al. 2018; Lengnick and Wohltmann 2016), or to analyze the impact of bounded rationality on monetary policy in empirically enriched New Keynesian models (e.g. De Grauwe and Foresti 2023; Gabaix 2020; Jang and Sacht 2022). Anufriev and Hommes (2012) highlighted that applying the heuristic switching framework in macroeconomic models can successfully replicate empirical data obtained in laboratory environments. Multiple other studies and laboratory experiments corroborate this notion, indicating that the expectation formation of economic agents can be modeled as an alternation of simple, heterogeneous forecasting heuristics (Assenza et al. 2014; Pfajfar and Zakelj 2014, 2018).

Second, this paper is situated within the context of Agent-Based Macroeconomics. Earlier macro agent-based models tended to rely on self-referential decision-making and abstract from spatial or networked structures (Dawid and Delli Gatti 2018; Steinbacher et al. 2014; Farmer and Foley 2009). However, a significant portion of more recent macro ABM research specifically addresses these limitations by incorporating detailed local interactions among agents. For instance, Rengs et al. (2020); Rengs and Scholz-Wäckerle (2019) underscore the critical role of localized interactions in driving macroeconomic dynamics by demonstrating how signaling effects (e.g., bandwagon, Veblen, and snob behaviors) and the co-evolutionary processes between consumption patterns and firm specialization influence innovation diffusion, income distribution, and economic stability. Similarly, evolutionary multi-agent frameworks developed by Dosi et al. (2010, 2009) illustrate that heterogeneous behaviors, adaptive learning, and

firm-level innovation can collectively give rise to emergent business cycles and growth patterns, thereby highlighting the relevance of spatial and network effects for aggregate outcomes. In contrast, there exists another strand of the literature - particularly in the study of financial markets and credit contagion - that leverages network structures explicitly to capture localized interactions, information cascades, and belief contagion (Panchenko et al. 2013; Han and Yang 2013; Khashanah and Alsulaiman 2016, 2017; Hatcher and Hellmann 2023; Bertella et al. 2021; Huang et al. 2023; Makarewicz 2017; Benhammada et al. 2021; Iori and Mantegna 2018; Oldham 2019; Biondi and Zhou 2019; Clemente et al. 2020). Indeed, earlier calls by Lux and Westerhoff (2009) and Farmer and Foley (2009) emphasized that ABMs can better capture the interplay of micro-level herding, belief contagion, and market fluctuations; insights that remain central to financial agent-based modeling. This paper contributes to the literature on Agent-Based Macroeconomics by extending the frameworks of De Grauwe (2011); De Grauwe and Ji (2020, 2023); Hommes and Lustenhouwer (2019a,b) through the explicit incorporation of network dynamics into expectation formation. Rather than neglecting local interactions, the proposed model embeds agents in various network structures and allows them to switch between different forecasting heuristics based on a discrete choice mechanism (Manski and McFadden 1981), thereby integrating the heuristic switching model (Brock and Hommes 1997, 1998) with the opinion dynamics framework of Degroot (1974). In doing so, the model updates agents' beliefs using a convex combination of the heuristic switching probability distribution and DeGroot's update rule, capturing both the agents' perception of the true state of the world and the influences of their network neighbors' forecasting choices. This approach more accurately reflects the interplay between individual belief formation and social influence than models that abstract from network structures, and it can be empirically validated using data from experimental studies and real-world observations (Hommes 2011, 2013, 2021; Bao et al. 2021).

Third, this paper relates to the broader literature on the role of social networks in disseminating information and the importance of narratives in shaping economic expectations (e.g., Bailey et al. 2018; Flynn and Sastry 2024; Andre et al. 2024; Gorodnichenko et al. 2021; Bargigli and Tedeschi 2014). These stories often spread virally within social networks, amplifying their impact (Shiller 2017; Beckert 2013, 2016; Tuckett and Nikolic 2017). Roos and Reccius (2024) emphasize the performative nature of narratives, showing how they guide agents' expectations and actions under uncertainty, a notion supported by Tuckett and Tuckett (2011) and MacKenzie (2008), who explore the self-fulfilling power of emotionally charged and model-driven stories. Central banks also leverage narratives to anchor inflation expectations and shape public sentiment, using them to frame policy objectives in relatable terms (Shiller 2020; Roos and Reccius 2024; MacKenzie 2008). Empirical studies further demonstrate how narratives propagate expectations through social networks by interacting with network structures to amplify or temper beliefs (Aral and Walker 2012; Tuckett and Taffler 2012). While heuristic-switching models account for some narrative-driven adaptation, they often overlook the explicit mechanisms by which narratives, rooted in "imagined futures" (Beckert and Bronk 2018), shape macroeconomic outcomes (e.g., Hommes 2013; Hommes and Lustenhouwer 2019a). This calls for deeper integration

of performative and narrative elements into macroeconomic theory. Recent studies on inflation rates have leveraged social network data to explore policy communication effects (Lamla and Vinogradov 2021), narrative monetary policy surprises (Ter Ellen et al. 2022), and the role of narratives in economics (Macaulay and Song 2023a). Tools such as text-based probability models have been employed to track inflation narrative dynamics and media sentiment (e.g., Müller et al. 2022; Angelico et al. 2022). For instance, Larsen et al. (2021) found that media significantly influence inflation expectations and information rigidities, while Beckers et al. (2017) showed that linguistic sentiment algorithms improve inflation forecasting precision. Similarly, Sharpe et al. (2023) demonstrated that the tonality of economic narratives serves as a predictive indicator for economic outcomes, particularly during periods of high uncertainty and growth anticipation.

Fourth, this paper also contributes to the policy-oriented research on central bank communication. The evolution and impact of central bank communication strategies have become crucial for monetary policy effectiveness and financial stability. Studies have shown that central bank communication can significantly influence market expectations and enhance the predictability of monetary policy decisions (Blinder et al. 2008; Woodford 2005). Best practices and strategic frameworks for central bank communication have been outlined by institutions like the International Monetary Fund (2022), emphasizing their role in achieving monetary policy objectives and maintaining financial stability. Research also explores the impact of central bank communication on financial stability (Born et al. 2014; Cieslak and Schrimpf 2019), highlighting the importance of clear and consistent communication during periods of unconventional policy. Furthermore, the integration of bounded rationality into New Keynesian models provides insights into how central bank communication strategies affect expectations and policy outcomes (Gabaix 2020). Finally, research on the influence of central bank announcements on public beliefs underscores the necessity of clear communication to manage expectations effectively (Lamla and Vinogradov 2019; Blinder et al. 2024; Dräger 2023).

3 Model

3.1 The Economy

The behavioral macroeconomic model proposed by De Grauwe (2011) and further developed by De Grauwe and Ji (2020, 2023) forms the foundation of this approach. This model extends the New Keynesian business cycle framework presented by Galí (2008) by incorporating heterogeneous forecasting rules.

The demand side of the economy is represented by the New Keynesian IS curve:

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

Here, x_t denotes the output gap, i_t the nominal interest rate, $\tilde{E}_t(x_{t+1})$ the expected output gap, and $\tilde{E}_t(\pi_{t+1})$ the expected inflation rate. The parameter a_2 represents the inverse elasticity of substitution of demand, and the tilde (\tilde{E}_t) indicates bounded rational expectations (BRE).

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

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

In this equation, b_2 represents the slope of the Phillips curve, indicating the extent to which inflation adjusts to changes in the output gap and how flexible firms are in their price-setting behavior. Following De Grauwe and Ji (2020, 2023), lagged output is included in the demand equation, and lagged inflation is included in the supply equation.

The central bank's response to fluctuations in the inflation rate and the output gap is modeled by the Taylor rule:

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

According to this equation, the central bank raises interest rates if the output gap widens or if observed inflation rises relative to the target inflation rate. The central bank also smooths the interest rate by considering the lagged interest rate (i_{t-1}) , measured by the coefficient c_3 .

Noise terms are added to equations (1), (2), and (3) to describe the exogenous shocks affecting the economy. These noise terms $(\epsilon_t^x, \epsilon_t^\pi, \text{ and } \epsilon_t^i)$ follow a white-noise process and are assumed to be normally distributed random variables with a zero mean and constant standard deviations $(\sigma^x, \sigma^\pi, \text{ and } \sigma^i)$, e.g. $\epsilon_t^x \sim N(0, \sigma^x)$ and $\epsilon_t^\pi \sim N(0, \sigma^\pi)$ and $\epsilon_t^\pi \sim N(0, \sigma^i)$.

3.2 Heterogeneous Expectations

The heuristic switching framework, rooted in Brock and Hommes (1997), captures how boundedly rational agents adapt their expectations by dynamically choosing forecasting heuristics based on past performance. These heuristics simplify decisionmaking under uncertainty, enabling agents to adjust flexibly to changing economic environments. Constrained by bounded rationality, agents rely on behavioral heuristic decision-making principles to form their expectations. The set of possible expectation heuristics is based on those employed in De Grauwe and Ji (2020, 2023). Agents in this framework choose between two primary heuristics. The first is target-based expectations, in which agents assume that the central bank will achieve its inflation target in the next period (i.e. they expect π^* to prevail at t+1) and that the output gap will move toward its natural level in the following period. The second is naive expectations, where agents forecast future outcomes by simply extrapolating from past observations. In case of inflation expectations, the Target-based expectations indicate trust in the central bank's credibility, while naive expectations serve as an alternative when policy guidance is viewed with skepticism. The degree of credibility of the central bank is thus defined as the share of inflation targeters in the total population of agents.

Agents who trust the announced inflation target π^* are therefore referred to as targeters. Consequently, these agents use the following heuristic to forecast:

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

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

Agents using naive (or static) expectations forecast the next period's value by simply employing the previous period's observation (De Grauwe and Ji 2020, 2023; Lengnick and Wohltmann 2016). Therefore, they use equation 6 as a forecasting rule:

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

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

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

Agent *i* will opt for $\tilde{E}_{i,t}^{\text{tar}}(k_{t+1})$ if its indicator function assumes the value 1 and for $\tilde{E}_{i,t}^{\text{stat}}(k_{t+1})$ otherwise. Considering $\omega_i^{k,\text{tar}}(t)$ and $\omega_i^{k,\text{stat}}(t)$ as the switching probabilities that agent *i* will opt for heuristic $j \in \{\text{tar}, \text{stat}\}$ to forecast variable $k_{t+1} \in \{\pi, x\}$ in period *t*, this indicator function can be formalized by:

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

The indicator matrix $\mathbb{I}_t^k = \{0, 1\}^{N \times 2}$ indicating the forecasting choice of all agents is shown in Appendix A.1.

The number of agents that follow each forecasting rule can now easily be defined by:

$$n_t^{k,\text{tar}} = \sum_{i=1}^N \lambda_i^{k,\text{tar}}(t) \tag{9}$$

$$n_t^{k,\text{stat}} = \sum_{i=1}^{N} |\lambda_i^{k,\text{tar}}(t) - 1|$$
(10)

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

$$w_t^{k,\text{tar}} = \frac{n_t^{k,\text{tar}}}{N} \tag{11}$$

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

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

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 $\tilde{E}_t^j(k_{t+1})$ with $j \in \{\tan, \operatorname{stat}\}$ and $k \in \{\pi, x\}$ to derive the market expectations (Arifovic et al. 2013; Brazier et al. 2008):

$$\tilde{E}_{t}(k_{t+1}) = w_{t}^{k, \text{tar}} E_{t}^{\text{tar}}(k_{t+1}) + w_{t}^{k, \text{stat}} E_{t}^{\text{stat}}(k_{t+1}) = w_{t}^{k, \text{tar}} k^{*} + w_{t}^{k, \text{stat}} k_{t-1}$$
(13)

Based on the share of agents given by Equations (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, 2023) and works as follows:

$$S_{t} = \begin{cases} w_{t}^{k,\text{stat}} - w_{t}^{k,\text{tar}} & \text{if } k_{t-1} > 0\\ -w_{t}^{k,\text{stat}} + w_{t}^{k,\text{tar}} & \text{if } k_{t-1} < 0 \end{cases}$$
(14)

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

3.3 Behavioral Heuristics and Switching Mechanisms

The selection of a heuristic is governed by a discrete-choice approach (McFadden 1974), where agents assess the historical predictive accuracy of each heuristic using the Mean Squared Forecast Error (MSFE), which has been applied in prior research (e.g. Branch and McGough 2010; De Grauwe and Ji 2020, 2023; Lengnick and Wohltmann 2016).

The attractiveness of heuristic $j \in \{\text{tar}, \text{stat}\}$ for variable $k \in \{\pi, x\}$ in period t is defined as:

$$A_t^{k,j} = -(k_{t-1} - \tilde{E}_{t-2}^j(k_{t-1}))^2 + \zeta A_{t-1}^{k,j}$$
(15)
with $k \in \{\pi, x\}$ and $j \in \{\text{tar}, \text{stat}\}$

where ζ is a memory parameter determining how much weight agents assign to past forecast errors (Franke and Westerhoff 2018). A higher ζ indicates longer memory, reinforcing persistence in heuristic choice.

The probability that an agent selects a specific forecasting heuristic j for variable k in period t is determined by the multinomial logit model (Branch and McGough 2010):

$$\beta_t^{k,j} = \frac{\exp\{\theta A_t^{k,j}\}}{\sum_{j'} \exp\{\theta A_t^{k,j'}\}}$$
(16)

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

where θ is the intensity of choice parameter, governing how strongly agents react to differences in performance. When θ is high, agents switch heuristics more frequently in response to performance differentials; when θ is low, agents are more inertial and less sensitive to past forecast errors.

This heuristic switching framework allows agents to dynamically adapt their expectations based on observed economic conditions. Unlike models assuming rational expectations, this approach better captures the heterogeneity observed in empirical inflation expectation surveys (Pfajfar and Žakelj 2014). Moreover, the framework aligns with evidence suggesting that households and firms frequently adjust their forecasting rules based on past forecast errors rather than forming fully rational expectations (Branch and McGough 2010).

Assuming $\beta_i^{k, \text{tar}}(t) = \beta^{k, \text{tar}}(t)$ and $\beta_i^{k, \text{stat}}(t) = \beta^{k, \text{stat}}(t) \forall i$, these represent the probability choices of agent *i* for heuristics *j*. Let the Switching Probabilities Matrix (SPM) be defined as \mathbb{B}_t^k . The SPM is provided in matrix notation in Appendix A.2 for reference.

3.4 Network Structure and Agent Connectivity

The agent population consists of N = 100 agents, embedded in different network structures reflecting key characteristics of real-world interactions. The scale-free network, based on preferential attachment (Barabási and Albert 1999), is initialized with 100 nodes and 1275 edges, featuring a power-law degree distribution, low clustering, and short path lengths. These networks, observed in systems like the World Wide Web and social networks (Barabási 2009), are dominated by a few highly connected "hubs" (i.e., agents with high degree centrality, where the number of connections determines centrality) that play a disproportionate role in information dissemination (Thurner et al. 2018, pp. 174ff). In the context of inflation dynamics, these hubs can amplify stabilizing or destabilizing narratives, disproportionately influencing aggregate expectations (Gabaix 2016).

The small-world network (Watts and Strogatz 1998), initialized with 1473 edges, features high clustering and short path lengths. These properties enable efficient information flow while maintaining local coherence, making them well-suited for modeling

localized economic interactions such as household consumption or firm-level pricesetting (Easaw and Mossay 2015; Jackson et al. 2008). Small-world networks capture how localized shocks propagate to the macro level, balancing local and global influences (Strogatz 2001; Watts 1999).

The random network, based on the Erdős–Rényi framework (Erdos et al. 1960), is initialized with 1200 edges, featuring a Poisson degree distribution, low clustering, and short path lengths. It serves as a baseline for evaluating the effects of network heterogeneity on expectation dynamics. Lastly, the regular network, initialized with 3000 edges for computational efficiency, exhibits a fixed degree distribution, high clustering, and long path lengths, providing a contrast to the more dynamic scale-free and small-world networks (Newman 2003).

By simulating heterogeneous pathways of narrative dissemination, belief updating, and systemic stability, the model evaluates how differences in agent connectivity and information flow influence the resilience of inflation expectations under varying economic scenarios. A stylized overview of the different network types used and common network properties is illustrated in table 1:

Table 1: Comparison of Different Network Types with 16 Nodes Each. The table illustrates four distinct graph types - regular, random, small-world, and scale-free networks - each comprising 16 nodes. It highlights the differences in degree distribution, clustering coefficient, path length, and randomness. This tabular representation was adapted from Anderson and Dragićević (2020).



3.5 Social Influence and Belief Updating

Individuals, due to cognitive limitations, partially rely on information from their social network when making decisions under uncertainty (Azzimonti and Fernandes 2023). This phenomenon, known as informational social influence, can be effectively illustrated using the DeGroot Model (Buechel et al. 2015). The DeGroot model (Degroot 1974) represents how agents update their beliefs through interactions with their network neighbors, combining their own opinions with those of their peers. Experimental and empirical evidence suggests that individuals tend to adhere to this heuristic 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 neighbors in the previous period. Hence, agents update their opinions quasi-naively to a probability distribution that better fits the decisions made in their network vicinity.

All networks can be characterized by a row-stochastic $n \times n$ matrix denoted by

$$\mathbb{T} = (g_{ij})_{i,j=1}^n,$$

where for all $i, j \in N$, we have $g_{ij} \geq 0$ and $\sum_{j=1}^{n} g_{ij} = 1$. Here, g_{ij} represents the weight that agent *i* assigns to agent *j*'s current belief when updating their own belief in the next period. This matrix, which is herein called Trust Matrix (TM), encapsulates the network topology and the intensity of trust among agents.

Assuming symmetric trust (i.e., $g_{ij} = g_{ji}$), reflecting reciprocal confidence between agents, the TM is defined explicitly as:

$$\mathbb{T} = \begin{vmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ g_{n1} & g_{n2} & \cdots & g_{nn} \end{vmatrix} .$$
(17)

The row-stochastic property ensures that each row sums to 1, which enables a clear probabilistic interpretation of the trust levels: each agent distributes a total weight of 1 across all other agents' beliefs. This structure is crucial for modeling how information and influence propagate through the network.

The social influence of neighbors' decisions is measured by a matrix derived from the inner product of this TM (17) and the Indicator Matrix (IM) provided in Appendix A.1 for variable k from period t - 1. The resulting Conformity Probabilities Matrix (CPM) for variable k in period t is then given by (see Appendix A.3 for details):

$$CPM_t^k = \mathbb{C}_t^k = \mathbb{T} \cdot \mathbb{I}_{t-1}^k \tag{18}$$

In addition, agents' individual past forecasting performance is captured by the discrete-choice-based model, yielding the Switching Probabilities Matrix given in Appendix A.2. The core part of the model is a convex combination of these two probability distributions. The probability distributions over a discrete set of alternatives are

weighted by a persuasion parameter and additively combined to create the weighted probabilities matrix (wPM):

$$wPM_t^k = \Omega_t^k = \chi \cdot \mathbb{C}_t^k + (1 - \chi) \cdot \mathbb{B}_t^k.$$
⁽¹⁹⁾

Here, each element $\omega_i^{k,j}(t)$ of wPM_t^k represents the probability that agent *i* opts for heuristic $j \in \{tar, stat\}$ to forecast the variable $k_{t+1} \in \{\pi, x\}$ in period *t*, as given mathematically by:

$$\omega_i^{k,j}(t) = \chi \cdot \left(\sum_{l=1}^n g_{il} \lambda_l^{k,j}(t-1)\right) + (1-\chi) \cdot \left(\frac{\exp\{\theta A_i^{k,j}(t)\}}{\sum_{j'} \exp\{\theta A_i^{k,j'}(t)\}}\right)$$
(20)

This formulation consists of two primary components: The first term $\sum_{l=1}^{n} g_{il} \lambda_l^{k,j}(t-1)$ (weighted by χ) captures the social influence mechanism based on DeGroot learning (Degroot 1974). Each agent *i* assigns a weight g_{il} to the forecast of network neighbor *l*, reflecting their level of trust. In the limiting case where $\chi = 1$, the agent completely follows the network, effectively dismissing the impact of its own historical performance. The multinomial logit component in the second term (weighted by $1 - \chi$) quantifies the probability of selecting heuristic *j* based on its past performance, as measured by the Mean Squared Forecast Error. The parameter θ , representing the intensity of choice, determines the sensitivity to forecast errors. When $\chi = 0$, the agent disregards social influence entirely and bases its decision solely on past forecasting accuracy.

The persuasion parameter χ serves as a convex combination weight between individual learning and network-driven updates. Specifically, when $\chi = 0$, agents base their heuristic switching exclusively on their own past forecasting performance, thereby acting independently. In contrast, when $\chi = 1$, agents fully incorporate the opinions of their network neighbors, resulting in a completely network-driven belief updating process. For intermediate values, $0 < \chi < 1$, the model captures a integrated environment in which agents blend self-learning with social influence. This integration of the heuristic switching model with the DeGroot opinion dynamics model within a macroeconomic context, particularly considering various network structures, provides a robust framework for analyzing expectation formation. It offers a comprehensive mechanism to investigate the interplay between personal adaptation and network effects in expectation formation and the transmission of monetary policy. This approach was further inspired by frameworks like Azzimonti and Fernandes (2023), which model information exchange within synthetic networks, and Easaw and Mossay (2015), which explore social learning through localized interactions where households acquire knowledge from proximate peers to shape their expectations.

The calculation of the weighted probabilities matrix is provided in Appendix A.4 for reference. The solution of the model is illustrated in Appendix B.1.

3.6 Simulation Framework and Algorithmic Implementation

In this subsection, the computational framework for simulating the behavioral macroeconomic model presented in section 3. The simulation is structured in three interconnected layers. First, Algorithm 1 details the micro-level decision process of individual agents. Here, each agent computes forecast errors based on the discrepancy between the previous observation and an earlier forecast, updates the attractiveness of alternative heuristics via a memory parameter, and calculates switching probabilities using a multinomial logit formulation. In addition, agents incorporate social influence - quantified as a weighted sum of neighboring agents' previous choices - to determine a combined probability for selecting either a target-based or a naive forecasting heuristic.

Secondly and building on these micro-foundations, the overall simulation is divided into two main components, as detailed in Algorithms2 (Parts I and II). In Part I, the simulation iterates over a predetermined time horizon where, for each period and for each macroeconomic variable (inflation and output gap), agents update their heuristic attractiveness based on historical forecast errors. They then compute individual switching probabilities and integrate these with social influence to form a weighted probability for each forecasting alternative. Part I, therefore, emphasizes the dynamics of expectation formation and the evolution of social influence over time.

Part II of Algorithm 2 advances the analysis by aggregating the micro-level decisions through matrix-based computations. In this stage, the Switching Probabilities Matrix - constructed from agents' individual switching probabilities - is combined with the Conformity Probabilities Matrix, which derives from the network's Trust Matrix and the indicator matrices reflecting previous heuristic choices. The resulting weighted probabilities matrix, parameterized by the persuasion weight, consolidates individual behaviors into aggregate weights. These weights are then used to form market expectations, which are subsequently integrated into standard macroeconomic updating mechanisms via the New Keynesian Phillips Curve, the IS curve, and the Taylor rule. This systematic updating process yields the time series for key macroeconomic variables such as inflation, output gap, and nominal interest rates.

Together, these algorithms provide a transparent and rigorous depiction of how individual behavioral processes - captured in Algorithm 1 - are aggregated via network interactions and matrix computations in Algorithm 2 (Parts I and II), ultimately generating aggregate macroeconomic dynamics. This integrated approach not only facilitates reproducibility but also offers insights into the interplay between microlevel bounded rationality and social network effects in expectation formation, thereby enhancing our understanding of the individual decision-making processes involved in heterogeneous forecasting strategies and the systemic stabilization mechanisms that emerge from network dynamics.

Algorithm 1 Single Agent Expectation Formation Process

Require: Agent *i*'s information at time *t*:

- Previous observation k_{t-1} and forecast $E_{t-2}^{j}(k_{t-1})$ for each heuristic $j \in$ $\{$ tar,stat $\}.$
- Previous attractiveness $A_{t-1}^{k,j}$ for each heuristic.
- Parameters: memory ζ , intensity θ , persuasion weight χ .
- For each neighbor $l \in N(i)$: trust weight g_{il} and past choice indicator $\lambda_l^{k,j}(t-1)$.
- Target value k^* (e.g. π^* for inflation or 0 for output).

Ensure: Agent *i*'s forecast $E_{i,t}(k_{t+1})$ for variable k.

1: for all $j \in \{ tar, stat \}$ do

- Compute forecast error: error^j $\leftarrow k_{t-1} E_{t-2}^{j}(k_{t-1})$. 2:
- Update attractiveness: 3:

$$A_t^{k,j} \leftarrow -\left(\operatorname{error}^j\right)^2 + \zeta A_{t-1}^{k,j}$$

Compute switching probability (individual component): 4:

$$\beta_t^{k,j} \leftarrow \frac{\exp\{\theta \, A_t^{k,j}\}}{\exp\{\theta \, A_t^{k,\text{tar}}\} + \exp\{\theta \, A_t^{k,\text{stat}}\}}$$

5: end for

6: Compute social influence for each heuristic:

$$S_i^{k,j}(t) \leftarrow \sum_{l \in N(i)} g_{il} \lambda_l^{k,j}(t-1)$$

7: Combine individual and social components:

$$\omega_i^{k,j}(t) \leftarrow \chi \, S_i^{k,j}(t) + (1-\chi) \, \beta_t^{k,j}, \quad j \in \{ \text{tar}, \text{stat} \}$$

- s: Normalize $\omega_i^{k,j}(t)$ so that $\omega_i^{k,\text{tar}}(t) + \omega_i^{k,\text{stat}}(t) = 1$. 9: Randomly choose heuristic j^* using the probabilities $\omega_i^{k,j}(t)$.
- 10: **if** $j^* = \tan$ **then**
- Set forecast: $E_{i,t}(k_{t+1}) \leftarrow k^*$. 11:
- 12: **else**
- Set forecast: $E_{i,t}(k_{t+1}) \leftarrow k_{t-1}$. 13:
- 14: end if
- 15: return $E_{i,t}(k_{t+1})$.

Algorithm 2 Overall Model Simulation Process (Part I: Expectation Formation and Social Influence)

Require: Model parameters and initial conditions

- Number of agents N and simulation horizon T.
- Model parameters: a_1 , a_2 , b_1 , b_2 , c_1 , c_2 , c_3 , π^* , ζ , θ , χ , and noise standard deviations σ^x , σ^{π} , σ^i .
- Initial macro variables: x_0, π_0, i_0 .
- Initial expectation forecasts $\tilde{E}_{-1}^{j}(k)$ for $k \in \{x, \pi\}$ and $j \in \{\text{tar}, \text{stat}\}$.
- Network structure to generate the Trust Matrix \mathbb{T} , with elements g_{ij} .
- Initial indicator matrices $\mathbb{I}_0^k \in \{0,1\}^{N \times 2}$ for $k \in \{x,\pi\}$.

1: Initialize:

- 2: Generate network and compute Trust Matrix $\mathbb T.$
- Set initial indicator matrices I^π₀, I^x₀ (e.g., random assignment between target and naive).
- 4: Set x_0, π_0, i_0 .
- 5: for t = 1 to T do
- 6: for all $k \in \{x, \pi\}$ do

7: for all agents $i = 1, \ldots, N$ do

- 8: for all $j \in \{tar, stat\}$ do
- 9: Compute forecast error:

$$\operatorname{error}_{i}^{j} \leftarrow k_{t-1} - \tilde{E}_{t-2}^{j}(k_{t-1})$$

10:

Update attractiveness:

$$A_i^{k,j}(t) \leftarrow -\left(\operatorname{error}_i^j\right)^2 + \zeta A_i^{k,j}(t-1)$$

11: Compute individual switching probability:

$$\beta_i^{k,j}(t) \leftarrow \frac{\exp\{\theta \, A_i^{k,j}(t)\}}{\exp\{\theta \, A_i^{k,\mathrm{tar}}(t)\} + \exp\{\theta \, A_i^{k,\mathrm{stat}}(t)\}}$$

14: for all agents $i = 1, \ldots, N$ do

15: for all $j \in \{ tar, stat \}$ do

Compute social influence component:

$$S_i^{k,j}(t) \leftarrow \sum_{l=1}^N g_{il} \,\lambda_l^{k,j}(t-1)$$

17:

16:

$$\omega_i^{k,j}(t) \leftarrow \chi \, S_i^{k,j}(t) + (1-\chi) \, \beta_i^{k,j}(t)$$

15

Combine individual and social components:

 18:
 end for

 19:
 end for

Algo Macr	rithm 2 Overall Model Simulation Process (Part II: Matrix Aggregation and o Updates)				
20:	Form the following matrices:				
21:	Construct the Switching Probabilities Matrix \mathbb{B}_{t}^{k} from $\{\beta_{i}^{k,j}(t)\}$.				
22:	Compute the Conformity Probabilities Matrix:				
	$\mathbb{C}^k_t \gets \mathbb{T} \cdot \mathbb{I}^k_{t-1}$				
23:	Compute the Weighted Probabilities Matrix:				
	$\Omega_t^k \leftarrow \chi \mathbb{C}_t^k + (1 - \chi) \mathbb{B}_t^k$				
24:	for all agents $i = 1, \ldots, N$ do				
25:	Draw a random outcome from $\{tar, stat\}$ using probabilities from the <i>i</i> th row of Ω^k .				
26:	Set indicator:				
	$\lambda_i^{k,\text{tar}}(t) = \begin{cases} 1, & \text{if target heuristic is chosen} \\ 0, & \text{otherwise} \end{cases} \text{and } \lambda_i^{k,\text{stat}}(t) = 1 - \lambda_i^{k,\text{tar}}(t).$				
27:	end for				
28:	Update indicator matrix \mathbb{I}_t^k accordingly.				
29:	Compute aggregate weights:				
	$w_t^{k, \text{tar}} \leftarrow \frac{1}{N} \sum_{i=1}^N \lambda_i^{k, \text{tar}}(t), w_t^{k, \text{stat}} \leftarrow 1 - w_t^{k, \text{tar}}.$				
30:	Form market expectations:				
	$\tilde{E}_t(k_{t+1}) \leftarrow w_t^{k, \text{tar}} k^* + w_t^{k, \text{stat}} k_{t-1},$				
	where k^* is π^* for inflation and 0 for output gap.				
31:	end for				
32:	Update Macro Variables:				

33: Update output gap using the New Keynesian IS curve:

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

34: Update inflation using the New Keynesian Phillips curve:

$$\pi_t \leftarrow b_1 \tilde{E}_t(\pi_{t+1}) + (1-b_1)\pi_{t-1} + b_2 x_t + \epsilon_t^{\pi}.$$

35: Update nominal interest rate via the Taylor rule:

$$i_t \leftarrow (1-c_3)[c_1(\pi_t - \pi^*) + c_2 x_t] + c_3 i_{t-1} + \epsilon_t^i.$$

36: Generate noise terms ϵ_t^x , ϵ_t^{π} , ϵ_t^i as Hedependent draws from $N(0, \sigma^x)$, $N(0, \sigma^{\pi})$, $N(0, \sigma^i)$, respectively.

37: end for

38: **return** Time series of x_t , π_t , i_t and the evolution of indicator matrices \mathbb{I}_t^k , for $k \in \{x, \pi\}$.

4 Computational Results

4.1 Numerical Approach and Parameter Calibration

Building upon the agent-based model with heterogeneous expectations and network structures, this section presents the computational results from Monte Carlo simulations detailed in Section 3.6 designed to analyse the impact of social influence on inflation expectations and market sentiment, guided by the parameter calibration outlined in Table 2 and the network topologies described in Section 3.4.

Behavioral economic models incorporating evolutionary switching between heterogeneous expectations are inherently complex, often precluding analytical solutions due to their non-linear dynamics (Hommes 2013).² Consequently, this study employs an agent-based Monte Carlo simulation framework to capture local interactions within a heterogeneous expectations environment under bounded rationality. At the outset of each simulation, agents are randomly assigned to follow either the target-based or naive expectation heuristic with equal probability (i.e., a 50:50 split), thereby ensuring an initially balanced heterogeneity in forecasting behavior. To mitigate the influence of transient dynamics, a burn-in period of 30 periods is implemented, during which no data are recorded. This approach ensures that the statistical analysis is not biased by initial conditions. Each simulation run spans 200 periods, with economic shocks modeled as normally distributed random variables with a mean of zero and standard deviations of $\sigma^x = 0.5$, $\sigma^{\pi} = 0.5$, and $\sigma^i = 0.5$. To ensure statistical robustness, results are averaged across multiple independent Monte Carlo iterations.

For the agent-based simulations, the default network structure is a scale-free Barabási-Albert network, which reflects real-world financial and social network properties with preferential attachment. This ensures that a small number of highly connected agents play a dominant role in expectation propagation. For sensitivity analysis, simulations were also conducted across four alternative network structures: (i) Scale-free (Barabási-Albert) network with 100 nodes and 1275 edges, (ii) Small-world network with 1473 edges, (iii) Random (Erdős-Rényi) network with 1200 edges, and (iv) Regular lattice network with 3000 edges. These variations allow for assessing the robustness of results across different interaction topologies.

²For an in-depth discussion on the stability conditions of behavioral models, refer to De Grauwe and Ji (2020) and Hommes and Lustenhouwer (2019a).

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Table 2 outlines the parameters used, which are largely consistent with those in De Grauwe and Ji (2020, 2023).

	Calibration
Parameter	Description
$a_1 = 0.5$	Coefficient of expected output in IS equation (Smets and Wouters 2003)
$a_2 = 0.2$	Inverse elasticity of substitution (Clarida et al. 2000)
$b_1 = 0.5$	Coefficient of expected inflation in PC equation (Smets and Wouters 2003)
$b_2 = 0.05$	Phillips curve coefficient of the output gap (De Grauwe and Ji 2023)
$c_1 = 1.5$	Interest rate control parameter for inflation (Blattner and Margaritov 2010)
$c_2 = 0.5$	Interest rate control parameter for output (Blattner and Margaritov 2010)
$c_3 = 0.5$	Interest smoothing parameter in Taylor equation (Blattner and Margaritov 2010)
$\pi^* = 0$	Inflation target (De Grauwe and Ji 2023)
$\sigma^x = 0.5$	Standard deviation of the output gap (De Grauwe and Ji 2023)
$\sigma^{\pi} = 0.5$	Standard deviation of the inflation rate (De Grauwe and Ji 2023)
$\sigma^i = 0.5$	Standard deviation of the nominal interest rate (De Grauwe and Ji 2023)
$\phi = 2$	Intensity of Choice (De Grauwe and Ji 2023)
$\zeta = 0.5$	Memory Parameter (De Grauwe and Ji 2023)
$\chi \in [0,1]$	Persuasion Parameter (Own calibration)

Table 2: Parameter values of the calibrated model.

Figure 1 presents the time series of the inflation rate, the corresponding market expectations, and the forecast errors from a representative simulation run with $\chi = 0.5$ over a simulation length of 200 periods.



Fig. 1: Inflation, Market Expectations, and Forecast Errors. The top panel shows the evolution of inflation, the middle panel displays market expectations, and the inset highlights forecast errors

4.2 Behavioral Interventions and Market Sentiment Dispersion

To analyze agent susceptibility to network effects, computational experiments were conducted, defining dispersion as the standard deviation of variables (e.g., inflation rate, market sentiment). These experiments introduced distinct behavioral strategies: agents with degree centrality ranks (1st, 5th, 10th, and 25th) adopted either targeted or naive inflation expectations. The targeted strategy reflects a central bank's deliberate inflation narrative via highly central nodes, while the naive strategy illustrates the impact of distorting narratives. Agents updated expectations using a convex combination of heuristic-based forecasts and the weighted average of neighbors' expectations, modulated by the persuasion parameter χ , which determines the influence of social interactions. Highly connected agents thus significantly shape overall market expectations. Following Equation 20 in Section 3.5, agent *i* updates its forecast as:

$$\omega_i^{k,j}(t) = \chi \cdot \left(\sum_{l=1}^n g_{il} \lambda_l^{k,j}(t-1) \right) + (1-\chi) \cdot \left(\frac{\exp\{\theta A_i^{k,j}(t)\}}{\sum_{j'} \exp\{\theta A_i^{k,j'}(t)\}} \right)$$

where $E_H(\pi_{i,t+1})$ is the heuristic forecast, w_{ij} is the trust weight for neighbor j, and N(i) denotes the set of neighbors. For the main simulations, the Barabási-Albert scale-free network is employed.

Figures 2 and 3 illustrate the impact of behavioral interventions on the mean share of inflation targeters and naive agents - grouped by degree centrality - as the persuasion parameter (χ) varies. When $\chi \neq 0$, significant differences emerge both within and across centrality groups. Under the targeted intervention, even agents with lower centrality adopt target-based expectations more frequently as social influence strengthens (see Figure 2). The nested Heuristic Switching Model ($\chi = 0$) consistently shows the lowest share of targeters, whereas the nested DeGroot model ($\chi = 1$) achieves the highest, confirming that full network-based updating drives stronger convergence. For intermediate persuasion levels ($\chi = 0.3, 0.5, 0.7$), the mean share of targeters increases steadily with centrality - particularly between the 1st and 5th ranks - but this effect is less pronounced for agents ranked below 10th, indicating that highly central agents are more responsive to targeted narratives. In contrast, in the naive intervention scenario (Figure 3), the share of naive expectations increases significantly at $\chi = 1$ under the nested DeGroot model - exceeding even the effect observed under targeted interventions. For intermediate χ values (0.3, 0.5, 0.7), the increase in naive expectations is modest and shows little sensitivity to centrality, suggesting a uniformly destabilizing influence across the network.

Compared to targeted interventions, naive interventions exhibit smaller effect sizes and weaker differentiation across centrality ranks. While targeted interventions show pronounced increases in inflation targeters, particularly among highly central agents, naive interventions result in more evenly distributed effects. Notably, as χ rises, the share of naive expectations declines in the benchmark, whereas inflation targeters consistently increase.

Figures 4 and 5 illustrate the distribution and dispersion of market sentiment - calculated from the sentiment index (ranging from -1 for purely deflationary to 1 for purely inflationary expectations) as defined in equation 14 - across 500 Monte



Fig. 2: Average Share of Targeters in the Benchmark and under Targeted Intervention across Centrality Ranks (1st, 5th, 10th, 25th) for Persuasion Values (chi) varied in discrete steps (0, 0.3, 0.5, 0.7, 1). Error bars indicate variability over 500 simulation iterations, each lasting 200 periods



Fig. 3: Average Share of Naive Agents in the Benchmark and under Naive Intervention across Centrality Ranks (1st, 5th, 10th, 25th) for Persuasion Values (chi) varied in discrete steps (0, 0.3, 0.5, 0.7, 1). Error bars indicate variability over 500 simulation iterations, each lasting 200 periods

Carlo iterations. The sentiment index reflects the direction and degree of polarization or consensus in agents' inflation expectations during each simulation run. A lower mean dispersion indicates that most agents' inflation expectations are closely

aligned, whether leaning toward inflation or deflation, resulting in a relatively narrow spread (high cohesion) of sentiment values over time. Conversely, a higher mean dispersion (e.g., 0.8) suggests that sentiment indices are more widely dispersed and volatile, implying greater polarization and less anchored expectations. This increased divergence amplifies overall uncertainty in market expectations.

For targeted interventions (Figure 4), the overall trend shows an increase in the cohesion of market sentiment as persuasion levels rise, while the behavioral target intervention itself appears to have only a negligible effect (at least within the nested HSM and the integrated model) on market sentiments (see Figure 4 for reference). However, in the absence of targeted anchoring, the nested DeGroot Model exhibits a counterintuitive uptick in dispersion, with extreme persuasion ($\chi = 1$) seemingly increasing heterogeneity among agents. In contrast, the targeted intervention consistently maintains lower dispersion even at high persuasion levels, even for subordinate centrality ranks. This suggests that targeted messaging effectively narrows the range of sentiment, provided the agents' susceptibility to persuasion within the network is sufficiently high.

In contrast, the naive intervention (Figure 5) exhibits a somewhat different pattern. While there is a decline in sentiment dispersion as persuasion increases - similar to the trend observed in the targeted case - the naive intervention appears to have minimal to no impact, particularly within the nested Heuristic Switching Model and the integrated model. However, in the nested DeGroot Model, the standard deviation rises at high persuasion levels and consistently remains elevated in the behavioral intervention scenarios, even for agents with lower centrality ranks.



Fig. 4: Dispersion of Inflation Market Sentiments in the Benchmark and under Targeted Intervention across Centrality Ranks (1st, 5th, 10th, 25th) for Persuasion Values (chi) varied in discrete steps (0, 0.3, 0.5, 0.7, 1). Box plots show the average standard deviation of the sentiment index resulting from 500 Monte Carlo iterations each with 200 periods



Fig. 5: Dispersion of Inflation Market Sentiments in the Benchmark and under Naive Intervention across Centrality Ranks (1st, 5th, 10th, 25th) for Persuasion Values (chi) varied in discrete steps (0, 0.3, 0.5, 0.7, 1). Box plots show the average standard deviation of the sentiment index resulting from 500 Monte Carlo iterations each with 200 periods

4.3 Impact of Behavioral Interventions on Inflation Rate Dispersion

The analysis of behavioral interventions reveals a significant modulation of inflation dispersion, as quantified by the standard deviation of the inflation rate. Figures 6 and 7 present the variability of inflation under targeted and naive narrative interventions, with error bars capturing the distribution of standard deviations.

Figure 6 demonstrates that, under the target intervention scenario, the standard deviation of inflation consistently declines as the persuasion parameter (χ) increases, with the most substantial reductions observed among agents with high degree centrality - particularly between the 1st and 5th ranks. This reduction indicates that when agents receive a targeted narrative aligned with the central bank's inflation target, their inflation expectations converge, leading to more stable inflation outcomes. In particular, under the nested DeGroot model ($\chi = 1$), where agents fully rely on network-based belief updating, the stabilization effect is most pronounced.

In contrast, the naive intervention (Figure 7) demonstrates that only under the nested DeGroot model does a distorting narrative notably increase the standard deviation of the inflation rate - indicating that strong conformity pressures are necessary to significantly destabilize the market. In both the nested Heuristic Switching Model (HSM) and the integrated model at intermediate persuasion levels ($\chi = 0.3$ and $\chi = 0.5$), the standard deviation remains relatively constant across different degree centrality ranks. This suggests that with moderate social influence, a naive narrative



Fig. 6: Average Inflation Dispersion in the Benchmark and under Target Intervention across Centrality Ranks (1st, 5th, 10th, 25th) for Persuasion Values (chi) varied in discrete steps (0, 0.3, 0.5, 0.7, 1). Error bars indicate variability over 500 simulation iterations, each lasting 200 periods

does not substantially affect inflation dispersion. However, when agents rely entirely on network-based belief updating (i.e., $\chi = 1$ under the nested DeGroot model), a marked increase in dispersion is observed. Moreover, even among intermediate persuasion levels ($\chi = 0.3$, $\chi = 0.5$, and $\chi = 0.7$), subtle variations across centrality ranks appear, highlighting that the destabilizing impact of a naive narrative is sensitive to both the level of persuasion and agents' network positions.

Table 3 presents the estimated effects of behavioral interventions on the standard deviation of the inflation rate. The effect sizes are reported as Cohen's d (a standard-ized measure of the magnitude of the difference between the intervention and baseline scenarios) along with the corresponding t-statistics (with negative values indicating a reduction in the standard deviation relative to the benchmark) and the post-hoc statistical power based on 500 simulation iterations.

For the targeted intervention, substantial reductions in the standard deviation of the inflation rate are observed at moderate to high levels of the persuasion parameter $(\chi = 0.3, \chi = 0.5, \text{ and } \chi = 0.7)$. Notably, even agents with lower degree centrality (Rank 25) show statistically significant reductions - albeit with smaller effect sizes compared to more central agents. This finding implies that targeted dissemination of the central bank's inflation narrative can stabilize inflation outcomes across the network, benefiting even those agents who are less influential.

In contrast, the naive intervention displays a different pattern. At lower persuasion levels ($\chi \leq 0.7$), the effects on the standard deviation of inflation are minimal and statistically weak. However, when the persuasion parameter reaches its maximum value ($\chi = 1$), there is a marked increase in the standard deviation of the inflation rate. This increase is especially pronounced among agents with high degree centrality, but it also affects agents with lower centrality. This counterintuitive outcome - that a naive

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Fig. 7: Average Inflation Dispersion in the Benchmark and under Naive Intervention across Centrality Ranks (1st, 5th, 10th, 25th) for Persuasion Values (chi) varied in discrete steps (0, 0.3, 0.5, 0.7, 1). Error bars indicate variability over 500 simulation iterations, each lasting 200 periods

(or distorting) narrative can significantly destabilize inflation when social influence is very strong - underscores the potential risk such narratives pose to market stability when agents are highly susceptible to peer influence.

		Target Intervention		Naive Intervention	
Persuasion	Centrality Target	Est. Effect	Post-hoc Power	Est. Effect	Post-hoc Power
0	Rank 1	0.1833^{**}	0.825	0.0094	0.053
		(-2.8977)		(0.148)	
	Rank 5	0.1837^{**}	0.827	0.0092	0.052
		(-2.9047)		(0.146)	
	Rank 10	0.1827^{**}	0.823	0.0094	0.053
		(-2.8893)		(0.149)	
	Rank 25	0.1829^{**}	0.824	0.0093	0.052
		(-2.8920)		(0.147)	
0.3	Rank 1	0.3188^{***}	0.999	0.0295	0.075
		(-5.0406)		(0.466)	
	Rank 5	0.2607^{***}	0.985	0.0273	0.072
		(-4.1217)		(0.432)	
	Rank 10	0.1967^{**}	0.874	0.0241	0.067
		(-3.1105)		(0.382)	
	Rank 25	$\boldsymbol{0.1356}^{*}$	0.572	0.0198	0.061
		(-2.1443)		(0.313)	
0.5	Rank 1	0.4043^{***}	1.000	0.0646	0.175
		(-6.3925)		(1.021)	
	Rank 5	0.2776^{***}	0.992	0.0609	0.161
		(-4.3898)		(0.963)	
	Rank 10	$\boldsymbol{0.1499}^{*}$	0.658	0.0479	0.118
		(-2.3697)		(0.758)	
	Rank 25	0.0315	0.079	0.0381	0.092
		(-0.4975)		(0.602)	
0.7	Rank 1	0.4418^{***}	1.000	0.1548^{*}	0.686
		(-6.9853)		(2.447)	
	Rank 5	0.2048^{stst}	0.899	$\boldsymbol{0.1296}^{*}$	0.535
		(-3.2375)		(2.049)	
	Rank 10	0.0165	0.058	0.1135	0.434
		(0.261)		(1.795)	
	Rank 25	0.2054^{**}	0.901	0.0864	0.276
		(3.248)		(1.366)	
1.0	Rank 1	0.8460^{***}	1.000	1.0544^{***}	1.000
		(-13.375)		(16.672)	
	Rank 5	0.5388^{***}	1.000	0.9696^{***}	1.000
		(-8.5185)		(15.331)	
	Rank 10	0.1858^{**}	0.835	0.7502^{***}	1.000
		(-2.9372)		(11.862)	
	Rank 25	0.0806	0.247	0.7502^{***}	1.000
		(-1.275)		(11.862)	
Iterations		500 2!		500	

Table 3: Estimated effect of varying persuasion parameter levels (χ) on the standard deviation of inflation, measured by T-test differences relative to a baseline.

Notes: The column Est. Effect reports Cohen's d, a standardized measure of the magnitude of the difference in inflation rate dispersion between intervention and benchmark scenarios. While Cohen's d is always positive, the direction of the effect is indicated by the sign of the t-statistic (reported in parentheses); negative t-statistics denote reduced inflation rate dispersion under intervention relative to the benchmark, and positive values denote increased dispersion. Post-hoc Power indicates the approximate probability of detecting an effect of this magnitude at the 5% significance level given 500 independent simulation runs (Monte Carlo iterations). Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10.

4.4 Dynamic Responses and Impulse Response Analysis

To analyze the dynamic response of the model under rational expectations to an exogenous price shock compared to the behavioral counterpart, the method of undetermined coefficients was employed. This involves guessing the functional forms of the solutions and solving for the coefficients to derive clear expressions for the endogenous variables. The solutions for inflation π_t and output gap x_t are linear functions of the exogenous shocks ϵ_t^x , ϵ_t^π , and ϵ_t^i are assumed to be of the form:

$$\pi_t = \psi_\pi^x \epsilon_t^x + \psi_\pi^\pi \epsilon_t^\pi + \psi_\pi^i \epsilon_t^i$$
$$x_t = \psi_x^x \epsilon_t^x + \psi_x^\pi \epsilon_t^\pi + \psi_x^i \epsilon_t^i$$

where ψ_{π}^{x} , ψ_{π}^{π} , ψ_{x}^{i} , ψ_{x}^{x} , ψ_{x}^{π} , and ψ_{x}^{i} are the undetermined coefficients. These forms are substituted into the IS curve, the Phillips Curve, and the Taylor rule. By equating the coefficients of the corresponding shocks, a system of equations for the undetermined coefficients is derived and solved for their values. Applying this method to the NK model specified in section 3 with assumed rational expectations, the coefficients relating output and inflation to an exogenous price shock in period t = 45 are derived as follows:

$$\psi_{\pi}^{\pi} = \frac{1}{1 + a_2 c_1 b_2} \qquad \qquad \psi_{x}^{\pi} = \frac{-a_2 c_1}{1 + a_2 c_1 b_2}$$

The detailed derivation of these coefficients is provided in Appendix B.2.

Using these coefficients, the dynamic effects of a one-period price shock, sized at twice the standard deviation of inflation, occurring in period t = 45, are visualized. The IRF for the behavioral model is calculated as the difference between the shocked and baseline trajectories (Lengnick and Wohltmann 2016):

$$IRF(z) = z_t^s - z_t^b \tag{21}$$

where z_t^s is the time series after the shock, and z_t^b is the baseline time series without the shock both based on 1,000 Monte Carlo simulation iterations.

Figure 8(a) shows the dynamic response of inflation to a one-period price shock at t = 45. When the persuasion parameter (χ) is low (e.g., $\chi = 0$ and $\chi = 0.3$), the inflation response is both larger in magnitude and more persistent over time, suggesting that, in the absence of strong social influence, agents rely predominantly on their individual heuristics, delaying convergence to the rational expectations (RE) benchmark. As χ increases (e.g., $\chi = 0.5$, $\chi = 0.7$, and $\chi = 1$), the inflation response becomes noticeably more muted and declines more rapidly, indicating that higher social influence accelerates convergence toward the RE solution. The results imply that stronger network-based belief updating promotes faster alignment of inflation expectations, thus reducing the overall dispersion.

Figure 8(b) depicts the corresponding response of market expectations to the same shock. A similar trend is evident: at low χ levels, market expectations exhibit a pronounced and prolonged deviation from the RE benchmark, reflecting heavy reliance

on individual heuristics. In contrast, as χ increases, the adjustment in market expectations becomes more rapid and the deviations diminish, illustrating that enhanced social influence helps synchronize agents' forecasts.

This pattern highlights an important and intuitive result: stronger social influence facilitates quicker consensus among agents, thereby reducing deviations from rational expectations. Interestingly, the differences between intermediate and high persuasion levels ($\chi = 0.5, 0.7, 1$) are subtle but notable - while increasing persuasion from moderate to high levels still improves convergence speed, the incremental gains diminish at higher values of χ .



(a) Impulse Response of Inflation to a One- (b) Impulse Response of Market Expectations Period Price Shock at t = 45 (RE and to a One-Period Price Shock at t = 45 (RE Persuasion Values: 0, 0.3, 0.5, 0.7, 1) and Persuasion Values: 0, 0.3, 0.5, 0.7, 1)

Fig. 8: Overall Impulse Response Analysis based on 1,000 Monte Carlo simulation iterations. Panel (a) shows the response of inflation while panel (b) depicts the reaction of market expectations.

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4.5 Sensitivity Analysis and Robustness Check

The sensitivity analysis provides further evidence that increasing the persuasion parameter, χ , exerts a stabilizing influence on inflation dynamics. Notably, this analysis was conducted under the rationale of the behavioral intervention in which the central bank's inflation target is actively disseminated among agents. As illustrated in Figures 9 to 12, the average dispersion of the inflation rate - measured as the standard deviation across simulation runs - declines consistently with higher χ values. This stabilizing effect is evident across multiple network structures. In both scale-free (Albert–Barabási; Figure 9) and small-world (Watts–Strogatz; Figure 10) networks, agent centrality significantly modulates the reduction in inflation dispersion, indicating that highly central agents contribute disproportionately to the stabilization effect. In contrast, random (Figure 11) and regular networks (Figure 12) exhibit negligible centrality effects, with the greatest reduction in standard deviation observed in regular networks. Overall, these results underscore that both the network structure and the degree of persuasion play crucial roles in shaping inflation dynamics. In particular, scale-free and small-world networks demonstrate pronounced sensitivity to persuasion, with central agents acting as key conduits for information dissemination and belief updating, while random and regular networks display a more uniform behavior, suggesting a less pronounced influence of individual agents in these settings.

The sensitivity analysis was also conducted on the mean inflation rates, averaged over 250 Monte Carlo iterations. The findings indicate that as the persuasion parameter increased, the inflation rates converged to a steady-state value of zero, with progressively narrower confidence intervals. However, no significant differences were observed across targeted centrality ranks or between different network structures. Although these results are not included in the main text or abstract, they are available upon request.



Fig. 9: Sensitivity of Inflation Dispersion to Persuasion in a Scale-Free Network across Centrality Ranks (1st, 5th, 10th, 25th) The x-axis shows χ , and the y-axis shows the average standard deviation of inflation. Results are averaged over 250 simulations



Fig. 10: Sensitivity of Inflation Dispersion to Persuasion in a Small-World Network across Centrality Ranks (1st, 5th, 10th, 25th) The x-axis shows χ , and the y-axis shows the average standard deviation of inflation. Results are averaged over 250 simulations



Fig. 11: Sensitivity of Inflation Dispersion to Persuasion in a Random Network across Centrality Ranks (1st, 5th, 10th, 25th) The x-axis shows χ , and the y-axis shows the average standard deviation of inflation. Results are averaged over 250 simulations



Fig. 12: Sensitivity of Inflation Dispersion to Persuasion in a Regular Network across Centrality Ranks (1st, 5th, 10th, 25th) The x-axis shows χ , and the y-axis shows the average standard deviation of inflation. Results are averaged over 250 simulations

Complementary to the analysis of inflation rate dispersion, we examine the sensitivity of the correlation between realized inflation and market sentiment to variations in χ . Recall that the sentiment index - ranging from -1 (purely deflationary) to 1 (purely inflationary expectations) - captures both the direction and degree of polarization or consensus among agents. A higher correlation between inflation and sentiment indicates that agents' expectations are more closely anchored to actual inflation outcomes.

Figure 13 presents the correlation coefficients between realized inflation and market sentiment across different values of χ , averaged over 500 Monte Carlo iterations (each spanning 200 simulation periods) for the Albert–Barabási network. As χ increases, the correlation weakens, suggesting that higher persuasion levels diminish the alignment of agents' expectations with realized inflation. This trend is particularly pronounced in the Albert–Barabási network, where the correlation even turns negative when targeting the most central node with the behavioral target intervention.

A similar trend is observed in the Watts–Strogatz small-world network, as shown in Figure 14. Here, the correlation decreases with increasing χ , but the differences among agents at the 5th, 10th, and 25th centrality ranks remain negligible. However, a pronounced divergence emerges between the 1st and 5th ranks, indicating that the most central agents are more susceptible to persuasion, leading to a stronger divergence in their expectations relative to less central agents.

In contrast, the random network, depicted in Figure 15, exhibits a muted response in the correlation between inflation and sentiment as χ increases. The uniformity in influence across agents ensures negligible differences across centrality ranks, aligning with theoretical expectations about the even distribution of influence in random networks. This homogeneity results in a more consistent response to changes in persuasion, reflecting the network's structural properties.

Interestingly, the regular network, as shown in Figure 16, demonstrates a strong responsiveness of the inflation–sentiment correlation to increasing persuasion as well. At higher χ levels, the correlation even turns negative, indicating a collective divergence between realized inflation and market sentiment. This behavior is reminiscent of the dynamics observed in the Albert–Barabási scale-free network (Figure 13), where the correlation also becomes negative at high persuasion levels, particularly when targeting the most central node with the behavioral target intervention. Unlike the scale-free and small-world networks, however, no significant differences emerge across centrality ranks in the regular graph. This uniformity underscores the homogeneous structure of regular networks, where all agents exert similar influence, leading to a network-wide shift in expectation formation as persuasion intensifies.



Fig. 13: Correlation between Realized Inflation and Sentiment Index in a Scale-Free Network across Persuasion Values for Centrality Ranks (1st, 5th, 10th, 25th). The x-axis shows χ , and the y-axis shows the average correlation coefficients. Results are averaged over 250 simulations



Fig. 14: Correlation between Realized Inflation and Sentiment Index in a Small-World Network across Persuasion Values for Centrality Ranks (1st, 5th, 10th, 25th). The x-axis shows χ , and the y-axis shows the average correlation coefficients. Results are averaged over 250 simulations



Fig. 15: Correlation between Realized Inflation and Sentiment Index in a Random Network across Persuasion Values for Centrality Ranks (1st, 5th, 10th, 25th). The x-axis shows χ , and the y-axis shows the average correlation coefficients. Results are averaged over 250 simulations



Fig. 16: Correlation between Realized Inflation and Sentiment Index in a Regular Network across Persuasion Values for Centrality Ranks (1st, 5th, 10th, 25th). The x-axis shows χ , and the y-axis shows the average correlation coefficients. Results are averaged over 250 simulations

5 Discussion

The computational results presented in the preceding section revealed a significant role for social networks and narrative dissemination in shaping inflation expectations and policy effectiveness. In this framework, individual forecasting heuristics - whether target-based or naive - act as explicit narratives that agents update through peer interactions and individual decision-making. The analysis robustly demonstrates that these network effects are crucial for disseminating information essential for interpreting economic developments and news (Shiller 2017; Andre et al. 2024; Roos and Reccius 2024).

This section discusses the key findings in detail, such as the impact of targeted interventions in reducing inflation dispersion (see Figure 6), the dual influence of persuasion (χ) within social networks. These results are contextualized within the broader literature, emphasizing the study's contributions and implications.

A central contribution of this study is the introduction of an an integrated agentbased macroeconomic model that combines behavioural heuristics with network effect, formally characterized by intermediate persuasion levels ($\chi = 0.3, 0.5, \text{ and } 0.7$). In contrast to other hybrid approaches merging macroeconomic frameworks with agentbased techniques, this approach explicitly embeds network structures into expectation formation and emphasizes how agents update their beliefs through peer interactions and conformity dynamics inherent in network structures. By integrating individual learning mechanisms with social influence dynamics, this model not only enhances empirical relevance but also provides a more realistic representation of agents' decisionmaking processes. In contrast to the nested heuristic switching model ($\chi = 0$) or the fully network-dependent DeGroot model ($\chi = 1$), the integrated framework captures a spectrum of behaviors where agents are partially driven by their own forecasting performance and partially by the influence of their peers.

In the benchmark scenario, where no behavioral intervention is applied, the natural propagation of narratives results in a decline in the share of naive expectations and a steady increase in target-based expectations as the persuasion parameter (χ) rises. In the intervention scenarios, the integrated model reveals that the mean share of targetbased expectations grows consistently with degree centrality when the central bank's target narrative is explicitly disseminated. This is accompanied by a marked reduction in inflation dispersion as χ increases, reflecting a strong convergence toward the central bank's inflation target. Notably, the effectiveness of propagating the central bank's target narrative contrasts sharply with that of a naive expectations narrative. While even moderate levels of social influence are sufficient for the target narrative to stabilize inflation variability, a distorting naive narrative requires very high persuasion levels (i.e., $\chi = 1$) to significantly amplify instability. In essence, the benchmark scenario demonstrates that target-based messaging naturally fosters stability under moderate social influence, whereas a naive narrative must rely on near-total network dependence to induce substantial instability, particularly among highly central agents. Further supporting these findings, the impulse response functions indicate that as the persuasion parameter (χ) increases, both inflation and market expectations converge more rapidly toward the rational expectations benchmark. This finding is consistent with opinion dynamics studies (e.g., Degroot (1974); Hegselmann and Krause (2002)),

which demonstrate that enhanced connectivity and social influence accelerate consensus formation. In effect, stronger social influence emerges as a powerful mechanism for realigning macroeconomic expectations following shocks.

Building on these findings, the observed decline in the standard deviation of inflation, alongside the weakening correlation between inflation and market sentiment as χ increases, highlights a dual effect of heightened persuasive dynamics. On one hand, stronger persuasive forces facilitate a convergence of agents' expectations around influential, highly central actors who disseminate prevailing narratives. This convergence fosters stabilization in inflation outcomes, measurable by reduced dispersion of inflation rates. On the other hand, this stabilization effect simultaneously introduces the risk of expectations becoming increasingly decoupled from economic fundamentals, evident from a decline in the correlation between inflation and market sentiment. Such decoupling suggests that while behavioral interventions anchored by central agents can effectively reduce the inflation variability, they may inadvertently detach inflation expectations from reality, potentially distorting economic decision-making. Moreover, this dual role of central agents - as both stabilizers and potential amplifiers - parallels findings from social contagion research in financial markets, indicating that narrative dominance can either promote uniformity and stability or, conversely, exacerbate market segmentation and belief polarization.

The model's predictions align with existing literature on social contagion and belief polarization, suggesting that the dynamics observed in the simulations reflect realworld phenomena. Prior research demonstrates that agents' forecasts are not formed in isolation but are continuously adjusted based on the behavior of others, which can lead to herd behavior and the amplification of shocks (Bargigli and Tedeschi 2014; Bailey et al. 2018). This reliance on social information is evident in economic decision-making under uncertainty, where individuals often depend on heuristic decision-making, imitation, and conformity biases influenced by social networks and expert guidance (Friedkin 1990; Llano-González 2012; Charness et al. 2013). If a person perceives that their peers have certain expectations about inflation or stock prices, they are likely to conform and adjust their beliefs accordingly (Arrondel et al. 2022). Furthermore, the observed decline in the correlation between inflation and market sentiment at higher persuasion levels suggests a potential decoupling of expectations from economic fundamentals - a phenomenon with clear parallels in opinion dynamics research, where strong social influence can sustain beliefs even in the face of contradictory evidence (Llano-González 2012). When network interactions, including exposure to filter bubbles or automated actors (bots), propagate specific narratives or misinformation about inflation determinants, agents may disproportionately conform, causing temporary economic shocks to be perceived as persistent (Flynn and Sastry 2025). Consequently, price and wage adjustments may diverge from underlying fundamentals, weakening central bank credibility and potentially initiating self-reinforcing cycles of inflation expectation variability. This model captures these phenomena by combining heuristic switching with a network-based belief updating mechanism, where the influence of social interactions is modulated by the persuasion parameter (χ). The averaging effects emerging from network interactions are consistent with empirical findings on

how investors rely on information shared within their social networks to guide decisionmaking (Oldham 2019; Ivković and Weisbenner 2007). Moreover, the model reveals that social learning can simultaneously foster convergence in expectations and maintain persistent biases, depending on the underlying network structure and the nature of information distributed among agents (Hong et al. 2004; Han and Yang 2013). Additionally, this model provides a framework to analyze how social contagion and conformity biases (Corazzini et al. 2012) prevalent in social networks contribute to the formation and potential polarization or fragmentation of macroeconomic expectations (Corazzini et al. 2012; Degroot 1974; Hegselmann and Krause 2002). Finally, recent research incorporating heterogeneous activity levels into opinion dynamics models demonstrates that differences in individuals' frequency of interactions can significantly influence the speed and nature of expectation convergence (Li and Porter 2023). Such heterogeneity tends to slow down the consensus process, leading to more fragmented belief distributions, thereby underscoring the importance of individual engagement levels on collective belief updating. This model explicitly captures heterogeneity in two distinct ways: first, through agents' heterogeneous forecasting strategies - targetbased versus naive heuristics - that dynamically evolve based on past performance; and second, through structural heterogeneity due to varying network positions (degree centrality), which differentially amplify individual influence. In general, this approach can be extended to any social opinion dynamics model that outputs a probability distribution over a discrete set of options. By combining it via a convex combination with the heuristic switching framework, localized interactions are captured while preserving the individual decision-making process.

While this study provides valuable insights, it also has limitations. The assumption that agents hold coherent and consistent narratives oversimplies the complexity of individual decision-making. Research by Coibion and Gorodnichenko (2015) has already highlighted the role of information rigidity and its effects on expectation formation, suggesting that individual cognitive biases significantly impact inflation expectations. Additionally, studies by Dräger and Lamla (2017) have shown that imperfect information and consumer inflation expectations are influenced by the mode of information delivery and personal experiences. Future research could explore more granular models that incorporate cognitive biases and varying levels of information rigidity. Incorporating incomplete and asymmetric information could provide insights into the speed and accuracy of information transmission and its impact on expectation stability. My model could be extended to account for dynamic changes in social influence and trust, which are crucial for understanding how macroeconomic expectations evolve in response to external shocks. To better capture this dynamic nature, future simulations could model evolving networks where weights adjust over time based on factors such as the forecast error of the central bank or individual agents relative to their neighbors.

6 Concluding Remarks

Overall, this study advances our understanding of expectation formation by explicitly capturing both the individual decision-making processes involved in heterogeneous forecasting strategies and the systemic stabilization mechanisms that emerge from network dynamics. At the individual level, social networks shape macroeconomic expectations by influencing agents' heuristic switching through differential peer pressures - agents update their forecasts based both on their own past performance and on the opinions of influential neighbors, as reflected by the persuasion parameter (χ). In turn, at the systemic level, the aggregation of these heterogeneous interactions yields convergence patterns that can either stabilize or destabilize overall inflation outcomes. In particular, agents with high degree centrality wield disproportionate influence: when they propagate a credible, policy-consistent narrative, they foster rapid convergence and reduce market volatility; conversely, if distorting narratives predominate among central agents, expectations may de-anchor, exacerbating systemic instability.

These findings have significant implications for monetary policy. By examining how social networks influence economic behavior and expectations, this study highlights the potential of leveraging network structures for effective policy transmission. Targeting influential agents and crafting clear, consistent narratives can enable central banks to disseminate critical economic messages more efficiently - enhancing central bank communication and forward guidance to stabilize economic expectations and reduce market volatility. At the same time, policymakers must remain mindful of the hazards posed by alternative narratives, which can trigger negative feedback loops and undermine policy credibility. Ultimately, effective monetary policy must balance the use of social networks to harness positive peer influence while mitigating the risks associated with distorting information.

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Declarations

Declaration of interests

I have nothing to declare.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used the service of OpenAI's ChatGPT in the writing process to improve the readability and language of the manuscript. After using this service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Data availability

The datasets generated and analyzed during the current study are not publicly available due to their proprietary nature but are available from the corresponding author upon reasonable request.

Materials availability

The materials used in this study, including any supplementary files or additional documentation, are not publicly available but can be provided by the corresponding author upon reasonable request.

Code availability

The code used to generate the results and perform the analyses in this study is not publicly available but is available from the corresponding author upon reasonable request.

Appendix A Matrices

A.1 Indicator Matrix

The indicator matrix, $\mathbb{I}_t^k \in \{0, 1\}^{n \times 2}$, represents the forecasting decisions of all agents at time t for variable $k \in \{\pi, x\}$. Each row corresponds to an individual agent, while the two columns represent the two forecasting heuristics: target-based and static (naive). Specifically, it is defined as:

$$\mathbb{I}_{t}^{k} = \begin{bmatrix} \lambda_{1}^{k, \text{tar}}(t) & |\lambda_{1}^{k, \text{tar}}(t) - 1| \\ \lambda_{2}^{k, \text{tar}}(t) & |\lambda_{2}^{k, \text{tar}}(t) - 1| \\ \vdots & \vdots \\ \lambda_{n}^{k, \text{tar}}(t) & |\lambda_{n}^{k, \text{tar}}(t) - 1| \end{bmatrix} = (\lambda_{i}^{k}(t))_{i=1, \dots, n; k \in \{\pi, x\}} :$$
(A1)

Here, $\lambda_i^{k, \text{tar}}(t)$ denotes the forecasting decision of agent *i* for variable *k*: it equals 1 if the agent selects the target-based heuristic, and 0 otherwise. Consequently, $\left|\lambda_i^{k, \text{tar}}(t) - 1\right|$ equals 1 when the agent does not choose the target-based heuristic (i.e., when the static, or naive, heuristic is adopted). This formulation ensures that each agent's decision is fully captured by the two columns of \mathbb{I}_t^k .

A.2 Switching Probabilities Matrix (SPM)

The Switching Probabilities Matrix, denoted as \mathbb{B}_t^k , captures the probabilities that agents switch between forecasting heuristics at time t for variable k. Each row corresponds to an agent, and the two columns correspond to the two heuristics: target-based (tar) and static (stat). We assume that all agents share the same switching probability distribution:

$$\beta_i^{k,j}(t) = \beta^{k,j}(t) \quad \forall i,$$

and define:

$$\mathbb{B}_{t}^{k} = \begin{bmatrix} \beta_{1}^{k,tar}(t) \ \beta_{1}^{k,stat}(t) \\ \beta_{2}^{k,tar}(t) \ \beta_{2}^{k,stat}(t) \\ \vdots \\ \vdots \\ \beta_{n}^{k,tar}(t) \ \beta_{n}^{k,stat}(t) \end{bmatrix} = (\beta_{i}^{k,j}(t))_{i=1,\dots,n;k\in\{\pi,x\};j\in\{tar,stat\}}$$
(A2)

A.3 Conformity Probability Matrix

The Conformity Probability Matrix, denoted as \mathbb{C}_t^k , reflects the influence of social interactions on agents' forecasting decisions. It is computed as the product of the Trust Matrix and the Indicator Matrix from the previous period:

$$CPM_t^k = \mathbb{C}_t^k = \mathbb{T} \cdot \mathbb{I}_{t-1}^k \tag{A3}$$

$$= \begin{bmatrix} g_{11}\lambda_1^{k,tar}(t-1) + g_{12}\lambda_2^{k,tar}(t-1) + \dots + g_{1n}\lambda_n^{k,tar}(t-1) & A_{11}\lambda_1^{k,stat}(t-1) + \dots \\ \vdots & \vdots & \vdots \\ g_{n1}\lambda_1^{k,tar}(t-1) + g_{n2}\lambda_2^{k,tar}(t-1) + \dots + g_{nn}\lambda_n^{k,tar}(t-1) & \vdots & \end{bmatrix}$$
(A4)

$$CPM_{t}^{k} = \begin{bmatrix} \zeta_{1}^{k,tar}(t) \ \zeta_{1}^{k,stat}(t) \\ \zeta_{2}^{k,tar}(t) \ \zeta_{2}^{k,stat}(t) \\ \vdots \\ \zeta_{n}^{k,tar}(t) \ \zeta_{n}^{k,stat}(t) \end{bmatrix} = (\zeta_{i}^{k,j}(t))_{i=1,..,n;k\in\{\pi,x\};j\in\{tar,stat\}}$$
(A5)
$$\mathbb{C}_{t}^{k} = \mathbb{T} \cdot \mathbb{I}_{t-1}^{k}.$$

Each element $\zeta_i^{k,j}(t)$ in \mathbb{C}_t^k represents the aggregate influence from all of agent *i*'s neighbors on the likelihood of adopting heuristic *j* for variable *k* at time *t*.

A.4 Weighted Probability Matrix

The Weighted Probability Matrix, denoted as Ω_t^k , integrates two distinct models: the individual-based switching probabilities from the SPM and the network-based conformity effects from the CPM. This integration is achieved via a convex combination, governed by the persuasion parameter χ , ranging between 0 and 1, which modulates the balance between an agent's personal forecasting performance and the influence of their social network:

$$\Omega_t^k = \chi \, \mathbb{C}_t^k + (1 - \chi) \, \mathbb{B}_t^k. \tag{A6}$$

Element-wise, this is expressed as: with

$$\omega_i^{k,j}(t) = \chi \cdot \zeta_i^{k,j}(t) + (1-\chi) \cdot \beta_i^{k,j}(t), \tag{A7}$$

e.g.

$$\begin{bmatrix} \chi * \zeta_1^{k,tar}(t) + (1-\chi) * \beta_1^{k,tar}(t) & \chi * \zeta_1^{k,stat}(t) + (1-\chi) * \beta_1^{k,stat}(t) \\ \chi * \zeta_2^{k,tar}(t) + (1-\chi) * \beta_2^{k,tar}(t) & \chi * \zeta_2^{k,stat}(t) + (1-\chi) * \beta_2^{k,stat}(t) \\ \vdots & \vdots \\ \chi * \zeta_n^{k,tar}(t) + (1-\chi) * \beta_n^{k,tar}(t) & \chi * \zeta_n^{k,stat}(t) + (1-\chi) * \beta_n^{k,stat}(t) \end{bmatrix}$$
(A8)

$$= \begin{bmatrix} \omega_{1}^{k,tar}(t) & \omega_{1}^{k,stat}(t) \\ \omega_{2}^{k,tar}(t) & \omega_{2}^{k,stat}(t) \\ \vdots & \vdots \\ \omega_{n}^{k,tar}(t) & \omega_{n}^{k,stat}(t) \end{bmatrix} = (\omega_{i}^{k,j}(t))_{i=1,..,n;k\in\{\pi,x\};j\in\{tar,stat\}}$$
(A9)

where $\omega_i^{k,j}(t)$ is the effective switching probability for agent *i* to select heuristic *j* for variable *k* at time *t*. A higher χ value indicates greater reliance on social influence, whereas a lower χ reflects a higher confidence in individual judgment.

Appendix B Analytical Solutions

B.1 Solution of the behavioural model

The solution of the behavioural model is 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:

$$\underbrace{ \begin{bmatrix} 1 + a_2 c_2 (1 - c_3) & a_2 c_1 (1 - c_3) \\ -b_2 & 1 \end{bmatrix}}_{\mathbf{A}} \underbrace{ \begin{bmatrix} x_t \\ \pi_t \end{bmatrix}}_{\mathbb{Z}_t} = \\ \underbrace{ \begin{bmatrix} 1 + a_1 w_{x,t}^{stat} - a_1 & w_{\pi,t}^{stat} \\ 0 & 1 + b_1 w_{\pi,t}^{stat} - b_1 \end{bmatrix}}_{\mathbf{B}_t} \underbrace{ \begin{bmatrix} x_{t-1} \\ \pi_{t-1} \end{bmatrix}}_{\mathbb{Z}_{t-1}} + \\ + \underbrace{ \begin{bmatrix} a_2 w_{\pi,t}^{stat} - a_2 c_1 (c_3 - 1) \\ b_1 w_{\pi,t}^{tar} \end{bmatrix}}_{\mathbf{a}} \pi^* + \underbrace{ \begin{bmatrix} -a_2 c_3 \\ 0 \end{bmatrix}}_{\mathbf{b}} i_{t-1} + \underbrace{ \begin{bmatrix} -a_2 \epsilon_t^i + \epsilon_t^x \\ \epsilon_t^\pi \end{bmatrix}}_{\mathcal{E}_t}$$

i.e.

$$\mathbb{A}\mathbb{Z}_{ ext{t}} = \mathbb{B}_{ ext{t}}\mathbb{Z}_{ ext{t}-1} + \mathrm{a}\pi^* + \mathrm{b}i_{t-1} + arepsilon_t$$

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

$$\mathbb{Z}_{t} = \mathbb{A}^{-1}[\mathbb{B}_{t}\mathbb{Z}_{t-1} + a\pi^{*} + bi_{t-1} + \varepsilon_{t}]$$
(B10)

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)

B.2 Deriving impulse responses using the 'Method of Undetermined Coefficients'

The demand side of the economy is represented by the New Keynesian IS curve:

$$x_t = a_1 \tilde{E}_t(x_{t+1}) + (1 - a_1) x_{t-1} - a_2(i_t - \tilde{E}_t(\pi_{t+1})) + \epsilon_t^x$$
(B11)

The supply side of the economy is described by the New Keynesian Phillips curve (NKPC):

$$\pi_t = b_1 \tilde{E}_t(\pi_{t+1}) + (1 - b_1)\pi_{t-1} + b_2 x_t + \epsilon_t^{\pi}$$
(B12)

The central bank's response is modeled by the Taylor rule:

$$i_t = (1 - c_3)[c_1(\pi_t - \pi^*) + c_2 x_t] + c_3 i_{t-1} + \epsilon_t^i$$
(B13)

We assume that ϵ_t^x , ϵ_t^{π} , and ϵ_t^i follow a white-noise process, i.e.

$$\begin{aligned} \epsilon_t^x &= \zeta_t \\ \epsilon_t^\pi &= \eta_t \\ \epsilon_t^i &= \xi_t \end{aligned} \tag{B14}$$

We make the following guesses for the solutions of π_t and x_t :

$$\pi_t = \psi_\pi^x \epsilon_t^x + \psi_\pi^\pi \epsilon_\pi^\pi + \psi_\pi^i \epsilon_t^i$$

$$x_t = \psi_x^x \epsilon_t^x + \psi_\pi^\pi \epsilon_t^\pi + \psi_x^i \epsilon_t^i$$
(B15)

To determine the values of ψ_{π}^{x} , ψ_{π}^{π} , ψ_{π}^{i} , ψ_{x}^{x} , ψ_{x}^{π} , and ψ_{x}^{i} we substitute the guesses and the random walk processes back into the IS Equation:

$$\psi_x^x \epsilon_t^x + \psi_x^\pi \epsilon_t^\pi + \psi_x^i \epsilon_t^i = a_1 E_t (\psi_x^x \zeta_{t+1} + \psi_x^\pi \eta_{t+1} + \psi_x^i \xi_{t+1}) + (1 - a_1) x_{t-1} - a_2 \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_x^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t + \xi_t) + (1 - a_t) x_{t-1} - a_t \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_x^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t) + (1 - a_t) x_{t-1} - a_t \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_x^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t) + (1 - a_t) x_{t-1} - a_t \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_x^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t) + (1 - a_t) x_{t-1} - a_t \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_x^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t) + (1 - a_t) x_{t-1} - a_t \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_x^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t) + (1 - a_t) x_{t-1} - a_t \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_\pi^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t) + (1 - a_t) x_{t-1} - a_t \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_\pi^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t) + (1 - a_t) x_{t-1} - a_t \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_\pi^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t) + (1 - a_t) x_{t-1} - a_t \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_\pi^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t) + (1 - a_t) x_{t-1} - a_t \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_\pi^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t) + (1 - a_t) x_{t-1} - a_t \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_\pi^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t) + (1 - a_t) x_{t-1} - a_t \left(i_t - E_t (\psi_x^\pi \zeta_{t+1} + \psi_\pi^\pi \eta_{t+1} + \psi_\pi^i \xi_{t+1}) \right) + \epsilon_t^x (\xi_t) + \epsilon_t^x (\xi_t) + (1 - a_t) x_{t-1} + \epsilon_t^x (\xi_t) + \epsilon_t^x$$

Given that $E_t \zeta_{t+1} = E_t \eta_{t+1} = E_t \xi_{t+1} = 0$, this simplifies to:

$$\psi_x^x \epsilon_t^x + \psi_x^\pi \epsilon_t^\pi + \psi_x^i \epsilon_t^i = -a_2(c_1 \pi_t + c_2 x_t + \epsilon_t^i) + \epsilon_t^x$$

Collect terms involving ϵ_t^x , ϵ_t^{π} , and ϵ_t^i to solve for the coefficients yields:

• For ϵ_t^x :

$$\psi_x^x = -a_2c_2\psi_x^x + 1$$

• For ϵ_t^{π} :

$$\psi_x^{\pi} = -a_2 c_1 \psi_{\pi}^{\pi}$$

• For ϵ_t^i :

$$\psi_x^i = -a_2 c_2 \psi_x^i + 1$$

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Substituting the guesses and the random walk processes back into the NK Phillips Curve yields:

$$\psi_{\pi}^{x}\epsilon_{t}^{x} + \psi_{\pi}^{\pi}\epsilon_{t}^{\pi} + \psi_{\pi}^{i}\epsilon_{t}^{i} = b_{1}E_{t}(\psi_{\pi}^{x}\zeta_{t+1} + \psi_{\pi}^{\pi}\eta_{t+1} + \psi_{\pi}^{i}\xi_{t+1}) + b_{2}(\psi_{x}^{x}\epsilon_{t}^{x} + \psi_{\pi}^{\pi}\epsilon_{t}^{\pi} + \psi_{x}^{i}\epsilon_{t}^{i}) + \epsilon_{t}^{\pi}\psi_{\pi}^{x}\epsilon_{t}^{x} + \psi_{\pi}^{x}\epsilon_{t}^{x} + \psi_{\pi}^$$

Given that $E_t\zeta_{t+1} = E_t\eta_{t+1} = E_t\xi_{t+1} = 0$, this simplifies to:

$$\psi_{\pi}^{x}\epsilon_{t}^{x} + \psi_{\pi}^{\pi}\epsilon_{t}^{\pi} + \psi_{\pi}^{i}\epsilon_{t}^{i} = b_{2}(\psi_{x}^{x}\epsilon_{t}^{x} + \psi_{x}^{\pi}\epsilon_{t}^{\pi} + \psi_{x}^{i}\epsilon_{t}^{i}) + \epsilon_{t}^{\pi}$$

Collect terms involving ϵ_t^x , ϵ_t^{π} , and ϵ_t^i to solve for the coefficients yields:

- For ϵ_t^x :
- For ϵ_t^{π} :

$$\psi_{\pi}^{\pi} = b_2 \psi_x^{\pi} + 1$$

 $\psi_{\pi}^{x} = b_{2}\psi_{x}^{x}$

• For ϵ_t^i :

$$\psi^i_{\pi} = b_2 \psi^i_x$$

To solve for the coefficients ψ_x^x , ψ_x^π , ψ_x^π , ψ_π^x , ψ_π^π , and ψ_π^i , we equate the corresponding coefficients from the IS equation and the NK Phillips Curve.

For ϵ_t^x : From the IS equation:

 $\psi_x^x = -a_2 c_2 \psi_x^x + 1$

 $\psi_{\pi}^x = b_2 \psi_x^x$

From the NK Phillips Curve:

Substitute $\psi_{\pi}^{x} = b_{2}\psi_{x}^{x}$ into the IS equation:

$$\psi_x^x = -a_2 c_2 \psi_x^x + 1$$

$$\psi_x^x (1 + a_2 c_2) = 1$$

$$\psi_x^x = \frac{1}{1 + a_2 c_2}$$
(B16)

$$\psi_{\pi}^{x} = b_{2}\psi_{x}^{x} = \frac{b_{2}}{1 + a_{2}c_{2}}$$
(B17)

For ϵ_t^{π} : From the IS equation:

 $\psi^{\pi}_{x} = -a_{2}c_{1}\psi^{\pi}_{\pi}$ From the NK Phillips Curve: $\psi^{\pi}_{\pi} = b_{2}\psi^{\pi}_{x} + 1$

Substitute $\psi_{\pi}^{\pi} = b_2 \psi_x^{\pi} + 1$ into the IS equation:

$$\psi_x^{\pi} = -a_2 c_1 (b_2 \psi_x^{\pi} + 1)$$

$$\psi_x^{\pi} (1 + a_2 c_1 b_2) = -a_2 c_1$$

$$\psi_x^{\pi} = \frac{-a_2 c_1}{1 + a_2 c_1 b_2}$$
(B18)

$$\psi_{\pi}^{\pi} = b_2 \psi_x^{\pi} + 1 = \frac{1}{1 + a_2 c_1 b_2} \tag{B19}$$

For ϵ_t^i From the IS equation:

$$\psi_x^i = -a_2 c_2 \psi_x^i + 1$$

From the NK Phillips Curve:

$$\psi^i_{\pi} = b_2 \psi^i_x$$

Substitute $\psi^i_{\pi} = b_2 \psi^i_x$ into the IS equation:

$$\psi_x^i (1 + a_2 c_2) = 1$$

$$\psi_x^i = \frac{1}{1 + a_2 c_2}$$
(B20)

$$\psi_{\pi}^{i} = b_{2}\psi_{x}^{i} = \frac{b_{2}}{1 + a_{2}c_{2}} \tag{B21}$$

To summarize, the coefficients are:

$$\begin{split} \psi_{\pi}^{x} &= \frac{b_{2}}{1 + a_{2}c_{2}} \\ \psi_{x}^{x} &= \frac{1}{1 + a_{2}c_{2}} \\ \psi_{\pi}^{\pi} &= \frac{1}{1 + a_{2}c_{1}b_{2}} \\ \psi_{\pi}^{\pi} &= \frac{-a_{2}c_{1}}{1 + a_{2}c_{1}b_{2}} \\ \psi_{\pi}^{i} &= \frac{b_{2}}{1 + a_{2}c_{2}} \\ \psi_{x}^{i} &= \frac{1}{1 + a_{2}c_{2}} \end{split}$$

To derive the impulse response functions for a one-period shock to inflation, we proceed as follows:

1. Consider a one-period shock to inflation ϵ_t^{π} , e.g. $\eta_t = 1$. This means $\epsilon_t^{\pi} = 1$ at t = 0 and $\epsilon_t^{\pi} = 0$ for t > 0.

2. At t = 0, the shock affects π_0 and x_0 directly. Using the coefficients ψ_{π}^{π} and ψ_{x}^{π} :

$$\pi_0 = \psi_\pi^\pi \epsilon_0^\pi = \frac{1}{1 + a_2 c_1 b_2} \cdot 1$$
$$x_0 = \psi_x^\pi \epsilon_0^\pi = \frac{-a_2 c_1}{1 + a_2 c_1 b_2} \cdot 1$$

- 3. For t > 0, the shock ϵ_t^{π} returns to 0, but the model's dynamics will cause π_t and x_t to adjust over time based on the previous periods' values and the model's parameters.
- 4. Use the model equations to find the values in subsequent periods. Recall the equations:

$$x_{t} = a_{1}\tilde{E}_{t}(x_{t+1}) + (1 - a_{1})x_{t-1} - a_{2}(i_{t} - \tilde{E}_{t}(\pi_{t+1})) + \epsilon_{t}^{x}$$
$$\pi_{t} = b_{1}\tilde{E}_{t}(\pi_{t+1}) + (1 - b_{1})\pi_{t-1} + b_{2}x_{t} + \epsilon_{t}^{\pi}$$
$$i_{t} = (1 - c_{3})[c_{1}(\pi_{t} - \pi^{*}) + c_{2}x_{t}] + c_{3}i_{t-1} + \epsilon_{t}^{i}$$

Given that $\epsilon_t^{\pi} = 0$ for t > 0, the impulse response will depend on the dynamics set in motion by the initial shock at t = 0.

5. For t = 1:

$$\begin{aligned} \pi_1 &= b_1 E_1(\pi_2) + b_2 x_1 \\ x_1 &= E_1(x_2) - a_2(i_1 - E_1(\pi_2)) \\ i_1 &= (1 - c_3) [c_1(\pi_1 - \pi^*) + c_2 x_1] + c_3 i_{t-1} \end{aligned}$$

Given that $E_1(\pi_2)$ and $E_1(x_2)$ are the expected values based on the initial shock, use the known values of π_0 and x_0 to solve recursively for π_1 and x_1 .

6. Repeat this process for t = 2, 3, ..., using the coefficients and recursive relationships to trace out the path of π_t and x_t .

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