The Expectations of Others*

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Abstract

Based on a framework of memory and recall that accounts for social networks, we provide conditions under which social networks can amplify expectations. We provide evidence for several predictions of the model using a novel dataset on inflation expectations and social network connections: Inflation expectations in the social network are statistically significantly, positively associated with individual inflation expectations; the relationship is stronger for groups that share common demographic characteristics, such as gender, income or political affiliation; an instrumental variables approach further establishes causality of these results. Our estimates imply that the influence of the social network overall amplifies but does not destabilize beliefs.

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1 Introduction

Inflation expectations are shown to matter for economic decision-making (see, for instance, Coibion et al. (2019a), Coibion et al. (2019b), and Hajdini et al. (2022b)). Because there are many ways in which these expectations depart from rationality, a large literature aims to understand – primarily in the domain of consumer expectations – the expectations formation processes and their implications for macro dynamics.[1] Specifically, the behavioral literature has shown that consumers may use availability heuristics to form expectations (Tversky and Kahneman (1973)), implying that they find events that are more salient or easier to recall to be more likely.[2] Recent work by da Silveira and Woodford (2019) and Bordalo et al. (2023) has focused on understanding the role of memory in belief formation.[3]

We contribute to current literature by showing – through the lens of inflation expectations – that social comparison can play a complementary, important role in the process of belief formation, as postulated in Festinger (1954). In his original work, Festinger (1954) evaluated the hypothesis in various experimental social contexts that "people evaluate their opinions and abilities by comparison respectively with the opinions and abilities of others." We formalize this point theoretically and show that there is a role for the opinions and abilities of others. In the same work, Festinger (1954) claimed that "The tendency to compare oneself with some other specific person decreases as the difference between his opinion or ability and one's own increases." Our framework likewise formalizes this role of social similarity for the context of expectations: While individual experiences are heterogeneous and volatile, social comparison may contribute to more homogeneous inflation expectations and could make other consumers' expectations useful.

We provide strong empirical evidence for the relevance of social comparison in the process of belief formation. We do so on the basis of a novel dataset that merges a uniquely dense survey of inflation expectations for nearly 2 million US consumers across counties in the US with information on the social network connections of individuals in a county with other counties in the US (see e.g. Bailey et al. (2018a)). Exploiting cross-sectional and time variation while taking into account

[1] See, for instance, Coibion and Gorodnichenko (2015a), Gabaix (2020), Kohlhas and Walther (2021), L'Huillier et al. (2021), among many others.

[2] See, for example, Carroll (2003).

[3] Implications of memory and its limits on economic behavior have been also studied in Dow (1991), Mullainathan (2002), Gennaioli and Shleifer (2010), among others.

local inflation expectations and time-fixed effects, a clear finding emerges: The inflation expectations of others matter when individuals form their own inflation expectations. An appropriate instrumentation strategy ensures we can interpret this finding causally and also, as immune to the endogeneity concerns embodied by the reflection problem (Manski (1993)). Moreover, using data on demographic characteristics, inflation expectations of an individual's social network turn out to matter more if the network contains people of the same demographic group, in short: if social similarity is high. These results indicate that Festinger (1954)'s original hypothesis matters in the context of belief formation.

Our theoretical analysis develops the idea of social comparison in Festinger (1954) for the formation of economic expectations by embedding it into the framework of memory and similarity of recall in Bordalo et al. (2023). While we implement the idea in the framework of Bordalo et al. (2023), it can broadly be implemented in any other behavioral frameworks. In the work of Bordalo et al. (2023), individuals recall hypothesis k by drawing experiences stored in their memory database with some recall probability. A similarity function that measures the intensity of resemblance between an experience and hypothesis k is at the core of the recall probability of hypothesis k.[4] Individuals randomly draw experiences from their memory dataset, and the number of times that the individual successfully recalls events aligned with hypothesis k is governed by a binomial distribution with probability equal to the recall probability of k. This number of successful draws then determines this individual's subjective likelihood that hypothesis k occurs.

We extend this framework of Bordalo et al. (2023) and allow for social comparison to affect probability assessments by explicitly extending the memory database to include the experiences retrievable from one's social network. When disciplining recall probabilities, we assume that individuals divide their attention between their own experiences and experiences shared through the social network. Similarly, we assume that any individual assigns her attention among the experiences shared by the various members of her network. Finally, we allow for the similarity function to depend on the number of demographic characteristics that an individual shares with each member of the network.

The model analysis yields three predictions for the formation of inflation expectations in the

[4] The similarity function is assumed to be fairly generic. As a result, the implications of our framework would continue to apply if the similarity function depends on variables that speak to other behavioral biases of expectations formation processes.

presence of social networks. First, social networks matter for expectations if individuals pay attention to experiences shared by members of their social network. In particular, social interaction generates amplification if shared experiences are relatively more relevant than irrelevant for a high-inflation scenario. Second, in inflationary environments, networks of common demographics amplify expectations if they increase similarity between shared experiences and the scenario of high inflation. Moreover, the likelihood that social interaction amplifies inflation expectations is higher if people are more attentive to individuals with whom they share a larger number of demographics, given that similarity of experiences shared through the social network with a scenario of high inflation is increasing in common demographics. Third, idiosyncratic county-level inflationary disturbances can destabilize inflation expectations if aggregate attention to experiences retrieved from the memory database of the social network exceeds aggregate attention to experiences retrieved from the personal memory database.

These predictions find strong empirical support from a novel dataset. This dataset derives from a merger of a uniquely dense survey of inflation expectations for nearly 2 million US consumers across counties in the US with data on the social networks of individuals across counties (see e.g. Bailey et al. (2018a)). The combination of these two datasets allows us to observe the inflation expectations of an individual in a county, the average probability that this individual is connected to an individual in another county in the US (based on Facebook friendships between counties), and the inflation expectations of individuals in other counties. We use these data, first, to construct a measure of an individual's exposure to inflation expectations in other counties. We assume that the average social connection of an individual in a given county captures this exposure, a measure of the network weight that has been shown to be relevant in other applications such as in Kuchler et al. (2022). Given these weights, we compute network-weighted inflation expectations of expectations based on all respondents in the other counties, as we well as for sets of individuals with similar demographic groups only (based on gender, income, and political party). Second, we compute average inflation expectations within a given county, excluding those of the individual under consideration in the given county.

Strong evidence – in the spirit of Festinger (1954) – emerges from several regression specifications that experiences of individuals in geographically distant, but socially connected counties matter for the formation of inflation expectations. First, an increase of 1 percentage points of the network-weighted inflation expectations in other counties is associated with a rise of 0.29 percentage points in an individual's inflation expectations, after filtering out county fixed effects and the average inflation expectation of the county. Second, a one-percentage-point increase of network-weighted inflation expectations of individuals with the same reported gender that live in other counties is associated with increased inflation expectations of 0.754 percentage points. This larger coefficient estimate compared to the first regression result suggests that individuals pay relatively more attention to the experiences of people in the same demographic group.[5]

While these results take into account unobserved factors through detailed fixed effects, variation may still be endogenous. For example, expectations might be affected by common shocks or other concerns such as described by the reflection problem (Manski (1993)).[6] Construction of an exogenous shock at the county-time level allows us to address such concerns of endogeneity. The idea is simple: Gas prices are relevant for the formation of inflation expectations (Coibion and Gorodnichenko (2015b)); the relevance of gas prices varies across cities, depending on the importance of gas use. We can thus use a shift-share approach exploiting different commuting shares by car across counties (and hence gas use) to obtain county-time specific exogenous shocks to gas prices after filtering out any common time variation from the shift-share measures. By then showing that a network-weighted measure of these exogenous, county-specific shocks has a strong and statistically significant effect on individual inflation expectations, we can give a causal interpretation to the importance of social networks for the formation of inflation expectations. Going one step further, we can also establish causality in the relationship between the beliefs embedded in an individual's social network and the formation of individual inflation expectations. To do so, we use this measure of network-weighted gas use as a instrumental variable in a regression of individual inflation expectations on network-weighted inflation expectations. The coefficient on the network's expectations is higher than in the case of the above OLS specification and statistically

[5]Notably, this result is obtained after controlling for the average inflation rate in one's own county and county-time fixed effects: Such county-time fixed effects filter out any common variation at the county level, including possible confounding network effects and the effects of other shocks affecting the area.

[6]We prove that the reflection problem induces a bias in the estimated effects of social networks on inflation expectations *only* if the network truly matters for expectations. By contrast, if the social network is in fact irrelevant for inflation expectations, then the reflection problem disappears. As a result, it must be that any non-zero empirical correlation between individual expectations and the expectations of the network indicates relevance of social networks for inflation expectations. Our reduced-form OLS results show presence of a significantly positive correlation between individual inflation expectations and the expectations of others, implying that the network matters for expectations formation. While an OLS coefficient that is different from zero is sufficient to show that the network matters, we rely on an IV approach to quantify the importance of the network for inflation expectations.

different from zero.

Clearly, social interaction matters for the formation of expectations. But what are the stability properties of social networks implied by these estimates, following a one-time idiosyncratic county-level shock to inflation expectations?[7] For example, if individuals pay too much attention to the experiences in their network instead of their own experiences, the social network might render beliefs unstable. We derive conditions for instability which show that our empirical findings still indicate stability. Likewise, while the results based on the instrumental variables approach present a higher coefficient estimate, they still imply stability. At the same time, the higher point estimate implies stronger amplification of possibly salient price changes. These findings overall indicate that variation coming from salient prices, that individuals discuss more, can exacerbate inflation expectations significantly. These findings also indicate that policy makers should identify those informational shocks that transmit strongly through the network to control unstable movements in inflation expectations.

In the literature, many studies have shown how *individual* characteristics and experiences affect the process of expectations formation. For example, Malmendier and Nagel (2016) find that past individual experiences influence their reported inflation expectations. D'Acunto et al. (2021) find that shopping experiences matter for expectations formation. Kuchler and Zafar (2019) show how individuals extrapolate from recent personal experiences when forming expectations about aggregate economic outcomes. More generally, Hajdini et al. (2022a) show that demographic characteristics, such as gender, income, political affiliation, and the like, matter for the formation of expectations. These findings relate to a theoretical literature which argues that individuals use simple rules, or heuristics, in the formation of beliefs. This literature goes back most prominently to Kahneman and Tversky (1972). It has recently been refined using the diagnostic expectation model (Bordalo et al. (2018), Bordalo et al. (2019), L'Huillier et al. (2021)), as well as through the idea of memory in the expectation formation process (da Silveira and Woodford (2019), Bordalo et al. (2023)). As posited by Festinger (1954), *social* interaction can help to further discipline the formation of expectations. While it has been shown that social experiences matter in other contexts, such as the pandemic (Kuchler et al. (2022)), we highlight both theoretically and empirically the

[7] The implications of idiosyncratic shocks have been studied in other contexts; for instance, Gabaix (2011) has shown that idiosyncratic firm-level shocks can explain an important part of aggregate fluctuations.

role that social experiences play in disciplining the expectations formation process of individuals.

Our analysis also broadly relates to a growing literature that studies the effects of interactions through social networks on economic decision-making. For example, Bailey et al. (2018b) studies the role of social networks in shaping decisions about housing. They find that individuals whose geographically distant friends experienced larger house price increases are more likely to transition from renting to owning. We contribute to this literature in the domain of expectations by showing that social networks can affect individuals' inflation expectations. Analyzing the economic effects of social interactions on inflation expectations is fundamentally challenging because of the absence of high-quality data on social networks that can be linked to a representative survey of inflation expectations – a challenge our analysis overcomes.

The remainder of the paper is organized as follows. Section 2 presents a model of inflation expectations and social networks. Section 3 presents the data that we use in this paper. Section 4 presents the main empirical results. Section 5 applies an instrumental variable strategy to the empirical analysis and and discusses stability implications of social networks for inflation expectations. Finally, Section 6 concludes.

2 Theoretical Framework

In this section, we extend the memory and recall model of Bordalo et al. (2022) and Bordalo et al. (2023) by incorporating the feature of social interaction. We start off by describing a baseline setting in which individuals in the economy do not socially interact with one another (similar to Bordalo et al. (2022) and Bordalo et al. (2023)). We then allow for individuals to socially interact and exchange experiences with one another, and derive a number of testable implications.

2.1 Baseline: No Social Interaction

Consider some individual j, who has stored a set of *personal* experiences in her memory database E_j of size $|E_j|$. For simplicity, we split the set of experiences of j into three mutually exclusive subsets containing high inflation experiences, E_j^H, low inflation experiences, E_j^L, and experiences that are irrelevant to high or low inflation experiences, E_j^O. We would like to asses the probability that individual j recalls experiences that are similar to a particular hypothesis $k \in K = \{H, L\}$, where H denotes the hypothesis of high inflation and L that of low inflation. To assess the probability of recall, we define a similarity function between two events $u_j \in E_j$ and $v_j \in E_j$, that is, $S_j(u_j,v_j) : E_j \times E_j \rightarrow \begin{bmatrix} 0 & \bar{S}_j \end{bmatrix}$, that quantifies the similarity between individual j's experience u_j and v_j. The similarity between any two experiences u_j and v_j increases in the number of shared features between the two experiences, and the highest value of similarity, $\bar{S}_j$, is achieved when $u_j = v_j$. We purposefully abstract from providing a particular functional form for S_j to warrant generality of our results.[8]

The similarity between an experience e_j and a subset of experiences, $A \subset E_j$, is given by

$$S_j(e_j, A) = \sum_{u_j \in A} \frac{S_j(e_j,u_j)}{|A|} \tag{1}$$

and the probability $r(e_j,k)$ that individual j recalls experience e_j when cued with hypothesis k is given by the similarity between e_j and event k as a share of the total similarity between all the experiences in the memory database and hypothesis k:

$$r(e_j,k) = \frac{S_j(e_j,k)}{\sum_{e \in E_j} S(u,k)} \tag{2}$$

Next, the probability that individual j recalls experiences similar to hypothesis $k \in K$ is given by the total similarity between experiences related to k and hypothesis k as a share of the total similarity between all the experiences in the memory database and hypothesis k, that is,

$$r_j(k) = \frac{\sum_{e \in E_j^k} S_j(e,k)}{\sum_{e \in E_j^H} S_j(e,k) + \sum_{e \in E_j^L} S_j(e,k) + \sum_{e \in E_j^O} S_j(e,k)} \tag{3}$$

It is important to note that an enlargement of experiences related to k leads to a higher recall probability of hypothesis k, but experiences unrelated to k imply interference for $r_j(k)$.

2.2 Social Interaction

Now suppose that individual j socially interacts with other individuals $i \in \{1,2,...,j-1,j+1,...,N_j+1\}$, such that every individual i shares experiences with j. N_j denotes the total number of individuals that j interacts with. We denote the set of experiences that individual i shares with individual j by $E_{i \rightarrow j}$ (without putting any restrictions on the flow of information in the reverse direction).

[8] Relatedly, the functional form of similarity can very well be unique to individual j, and depend on her behavioral characteristics, cognitive abilities, etc.

Experiences shared by individual i are categorized into three mutually exclusive subsets: high inflation experiences, $E^H_{i\to j}$, low inflation experiences, $E^L_{i\to j}$, and irrelevant experiences to high or low inflation, $E^O_{i\to j}$.

We assume that, when interacting with others, individual j's assessment of similarity between k-related experiences shared by any individual i and any hypothesis k is conditional on the share of common demographic characteristics between j and i, θ_{ji}. Therefore, the similarity between any experience $e \in E_{i\to j}$ and hypothesis k is given by $S_j(e,k \mid \theta_{ji})$. This assumption allows for a heterogeneous function to judge similarity between a given hypothesis and experiences shared by others. Using common demographic characteristics is a natural way to do so, given the growing empirical evidence that shows that individuals with common demographic characteristics, such as gender and age group, share similar experiences in terms of inflation (see, for instance, Malmendier and Nagel (2016), D'Acunto et al. (2021), Hajdini et al. (2022a), and Pedemonte et al. (2023), among others).

When computing recall probabilities, we assume that individual j assigns weight $\gamma_j \in [0,1]$ to her own experiences and weight $(1-\gamma_j)$ to everyone else's experiences. We further assume that she assigns weight $\omega_{ji} \in [0,1]$ to experiences shared by individual i, for any $i \in \{1,2,...,j-1,j+1,...,N_j+1\}$, such that $\sum_i \omega_{ji} = 1$.

We let $\hat{r}_j(k)$ denote individual j's probability of recalling experiences linked to hypothesis $k \in \{H,L\}$ when she socially interacts with others. Such recall probability is given by:

$$\hat{r}_j(k) = \frac{\gamma_j \sum_{e\in E^k_j} S_j(e,k) + (1-\gamma_j)\sum_i \omega_{ji} \sum_{e\in E^k_{i\to j}} S_j(e,k \mid \theta_{ji})}{\gamma_j \sum_{e\in E_j} S_j(e,k) + (1-\gamma_j)\sum_i \omega_{ji} \sum_{e\in E_{i\to j}} S_j(e,k \mid \theta_{ji})} \tag{4}$$

where $\sum_{e\in E_j} S_j(e,k) = \sum_{e\in E^H_j} S_j(e,k) + \sum_{e\in E^L_j} S_j(e,k) + \sum_{e\in E^O_j} S_j(e,k)$ and $\sum_{e\in E_{i\to j}} S_j(e,k \mid \theta_{ji}) = \sum_{e\in E^H_{i\to j}} S_j(e,k \mid \theta_{ji}) + \sum_{e\in E^L_{i\to j}} S_j(e,k \mid \theta_{ji}) + \sum_{e\in E^O_{i\to j}} S_j(e,k \mid \theta_{ji})$.

To understand whether social interaction amplifies or mitigates the recall probability of events pertaining to hypothesis k, we derive conditions under which the recall probability under social interaction, $\hat{r}_j(k)$, is higher than the recall probability when social interaction is absent, $r_j(k)$. To do this, we compute the difference between $\hat{r}_j(k)$ and $r_j(k)$, that is,

$$\hat{r}_j(k) - r_j(k) = \frac{\gamma_j \sum_{e \in E_j^k} S_j(e,k) + (1-\gamma_j) \sum_i \omega_{ji} \sum_{e \in E_{i \to j}^k} S_j(e,k \mid \theta_{ji})}{\gamma_j \sum_{u \in E_j} S_j(u,k) + (1-\gamma_j) \sum_i \omega_{ji} \sum_{u \in E_{i \to j}} S_j(u,k \mid \theta_{ji})} - \frac{\sum_{e \in E_j^k} S_j(e,k)}{\sum_{u \in E_j} S_j(u,k)} \tag{5}$$

Proposition 1 provides conditions for social interaction to be relevant for recall probabilities and for social interaction to increase the recall probability of hypothesis k.

Proposition 1. *The following statements are true:*

1. *If individual j allocates no attention to experiences shared by others, that is, $\gamma_j = 1$, then social interaction has no affect on recall probabilities.*
2. *Suppose that j assigns some weight to the experiences shared by others, that is, $\gamma_j \in [0,1)$. Then, social interaction increases the recall probability of hypothesis k if the total similarity of k-relevant shared experiences relative to that of k-relevant own experiences* exceeds *the aggregate similarity of k-irrelevant shared experiences relative to that of k-irrelevant own experiences:*

$$\underbrace{\frac{\sum_i \omega_{ji} \sum_{e \in E_{i \to j}^k} S_j(e,k \mid \theta_{ji})}{\sum_{e \in E_j^k} S_j(e,k)}}_{\textit{relative relevance}} > \underbrace{\frac{\sum_i \omega_{ji} \left(\sum_{u \in E_{i \to j}^{K \setminus k}} S_j(u,k \mid \theta_{ji}) + \sum_{u \in E_{i \to j}^O} S_j(u,k \mid \theta_{ji}) \right)}{\sum_{u \in E_j}^{K \setminus k} S_j(u,k) + \sum_{u \in E_j^k} S_j(u,k)}}_{\textit{relative irrelevance}} \tag{6}$$

Proof. See Appendix D.1. □

We call the term on the left-hand side of inequality (6) *relative relevance* and the term to the right-hand side *relative irrelevance*. Then, in order for social interaction to amplify the recall probability of events related to hypothesis k, relative relevance has to exceed relative irrelevance. By the same argument, social interaction interferes with the recall probability of events linked to hypothesis k if relative irrelevance surpasses relative relevance.

Corollary 1 considers two extreme cases of Proposition 1: first, when any individual i shares with individual j only experiences that relate to hypothesis k; and second, when any individual i shares with individual j only experiences that do not relate to hypothesis k.

Corollary 1. *Consider the environment described in Proposition 1. Then, the following statements are true:*

1. *Suppose that any individual i shares with j experiences that only relate to hypothesis k. Then, social interaction amplifies individual j's recall probability of k.*

2. *Next, suppose that all individuals i share experiences that do not relate to hypothesis k. Then, social interaction interferes with individual j's recall probability of k.*

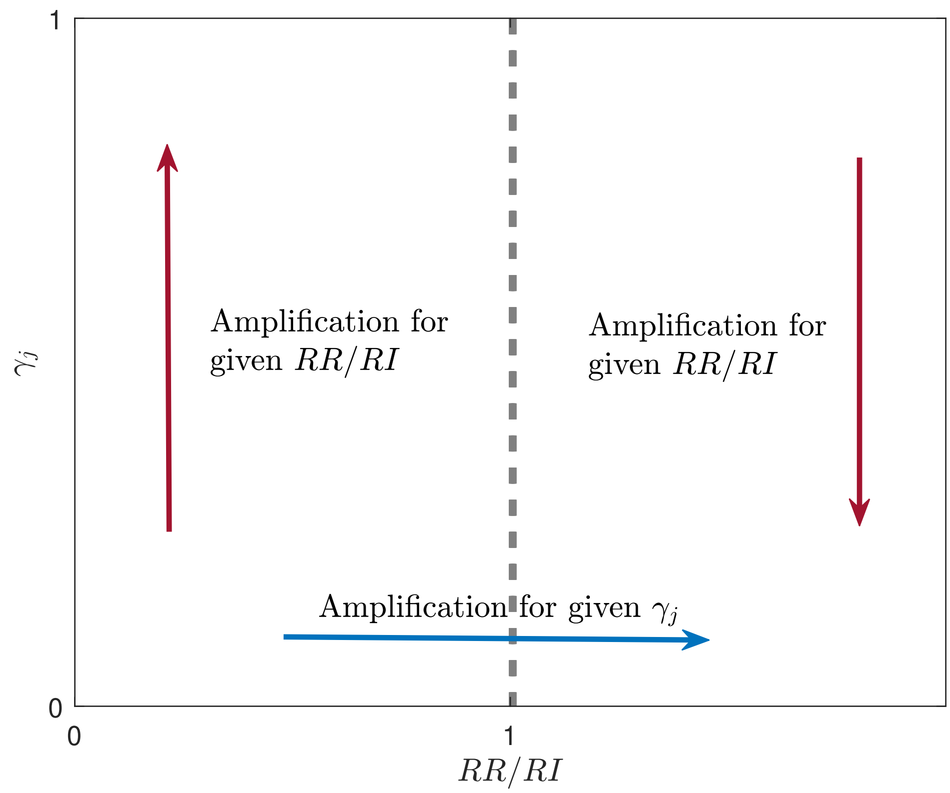
Proof. See Appendix D.2. □

Proposition 2 shows the implications that a change in attention to shared experiences has on the probability of recall, in the *presence* of social interaction. In particular, if social interaction gives rise to a higher recall probability, then an increase in the attention to others' experiences will amplify the recall probability even more.

Proposition 2. *If the condition in (6) holds true, then an increase in attention to shared experiences, that is, $(1-\gamma_j)$, intensifies the increase in the recall probability induced by social interaction.*

Proof. See Appendix D.3. □

Figure 1: Visual summary of the main theoretical results



Note: Summary of the direction of amplification for the recall probability related with hypothesis k, for any $\gamma_j \in [0,1)$ and $RR/RI =$ relative relevance/relative irrelevance. Arrows in red indicate the direction of amplification for the recall probability as γ_j changes, for a given RR/RI; arrow in blue indicates the direction of amplification for the recall probability as RR/RI changes, for a given γ_j. Left-hand side: relative relevance $>$ relative irrelevance; right-hand side: relative relevance $<$ relative irrelevance; dashed gray line: relative relevance $=$ relative irrelevance.

Figure 1 visually summarises the main theoretical results of Propositions 1, 2, and Corollary 1. Consider a social network where experiences are shared whose aggregate relative relevance exceeds relative irrelevance with hypothesis k. Then, paying more attention to the social network means social interaction will intensify the recall probability of such a hypothesis. However, when aggregate relative relevance is lower than relative irrelevance with hypothesis k, then paying more attention to the social network means social interaction will dampen the recall probability of such a hypothesis.

What about paying more attention to a specific individual? The effects that weights ω_{ji} have on the implications of social interaction on recall probabilities are not trivial to analyze. Proposition 3 provides a condition for which a change in the weight assigned to experiences shared by a particular individual facilitates the occurrence of inequality in (6).

Proposition 3. *Suppose that individual j allocates more attention to experiences shared by individual l at the expense of attention allocated to experiences shared by individual q, that is, suppose that ω_{jl} increases, ω_{jq} decreases, and all the other weights remain the same. Then, social interaction is more likely to amplify the recall probability of hypothesis k if individual l adds more relative relevance than relative irrelevance for this hypothesis, when compared with individual q:*

$$\underbrace{\frac{\sum_{e \in E^k_{l\to j}} S_j(e,k \mid \theta_{jl}) - \sum_{e \in E^k_{q\to j}} S_j(e,k \mid \theta_{jq})}{\sum_{e \in E^k_j} S_j(e,k)}}_{\textit{marginal relative relevance}} > \underbrace{\frac{\sum_{e \in E^{k^-}_{l\to j}} S_j(e,k \mid \theta_{jl}) - \sum_{e \in E^{k^-}_{q\to j}} S_j(e,k \mid \theta_{jq})}{\sum_{e \in E^{K\setminus k}_j} S_j(e,k) + \sum_{e \in E^O_j} S_j(e,k)}}_{\textit{marginal relative irrelevance}} \tag{7}$$

where $k^- = \{K \setminus k, O\}$, and $\sum_{e \in E^{k^-}_{i\to j}} S_j(e,k \mid \theta_{ji}) = \sum_{e \in E^{K\setminus k}_{i\to j}} S_j(e,k \mid \theta_{ji}) + \sum_{e \in E^O_{i\to j}} S_j(e,k \mid \theta_{ji})$ for any $i \in \{l,q\}$.

Proof. See Appendix D.4. □

We refer to the term in the left-hand side of condition (7) as marginal relative relevance and to the term in the right-hand side as marginal relative irrelevance. Proposition 3 shows that if the marginal relative relevance exceeds the marginal relative irrelevance, that is, if individual j is more attentive to individuals who share experiences with relative relevance for hypothesis k while shifting attention away from individuals who share experiences with relative irrelevance, then social interaction is more probable to amplify the recall probability of hypothesis k.

Finally, we turn to the effects that common demographic factors have on the recall probability of hypothesis k in Corollary 2. For simplicity purposes, we assume that the number of common demographic factors *only* affects the similarity between hypothesis k and shared events that belong to the hypothesis k subset of experiences.

Corollary 2. *Suppose that $S_j(e,k \mid \theta_{ji})$ is increasing in θ_{ji} for any $e \in E^k_{i\to j}$, but $S_j(e,k \mid \theta_{ji}) = S_j(e,k)$ for any $e \in E^{k^-}_{i\to j}$. Social interaction is more likely to propagate the recall probability of hypothesis k if individual j allocates more attention to an individual with whom she shares more demographic factors and less attention to a person with whom she shares fewer demographics.*

Proof. It follows directly from Proposition 3. □

To illustrate Corollary 2, suppose that the only demographic factor affecting the similarity function is gender, thus $\theta_{ji} \in \{0,1\}$. Further, let's assume that individual j is a female. Corollary 2 implies that, given experiences $E^k_{i\to j}$, $\sum_{e\in E^k_{i\to j}} S_j(e,k \mid 1) > \sum_{e\in E^k_{i\to j}} S_j(e,k \mid 0)$, for any $i \in \{l,q\}$. This implies that

$$\underbrace{\frac{\sum_{e\in E^k_{l\to j}} S_j(e,k \mid 1) - \sum_{e\in E^k_{q\to j}} S_j(e,k \mid 0)}{\sum_{e\in E^k_j} S_j(e,k)}}_{MRR \text{ if more attention to another female, less to a male}} > \underbrace{\frac{\sum_{e\in E^k_{l\to j}} S_j(e,k \mid 0) - \sum_{e\in E^k_{q\to j}} S_j(e,k \mid 1)}{\sum_{e\in E^k_j} S_j(e,k)}}_{MRR \text{ if more attention to a male, less to another female}}$$

where MRR denotes marginal relative relevance. Given that gender does not affect the right-hand side of condition (7), Corollary 2 implies that social interaction facilitates the amplification of recall probabilities if individual j interacts more intensively with individuals that share the same gender as her and less so with with individuals of the opposite gender.

2.3 Implications for Stability

Can shocks that are idiosyncratic to an individual destabilize recall? In the following, we assess the role of social networks for the stability of recall probability of hypothesis k, given an idiosyncratic shock to the recall probability of a member of the network. We focus on a social network of two individuals, and assume, for simplicity, that the two individuals have a common similarity function and that each individual shares all of their personal experiences with the other peer.

Let x_j be the aggregate similarity of the personal experiences of individual j from set E^k_j with hypothesis k, for any $j \in \{1,2\}$:

$$x_j = \sum_{e\in E^k_j} S_j(e,k) = \sum_{e\in E^k_{j\to i}} S_i(e,k) \tag{8}$$

where the second equality follows from the assumption that the two individuals share a common similarity function. Let y_j be the aggregate similarity of the personal experiences of individual j from sets $E^{K\setminus k}_j$ and E^O_j with hypothesis k, for any $j \in \{1,2\}$:

$$y_j = \gamma_j z_j + (1-\gamma_j) z_i \tag{9}$$

with

$$z_j = \left(\sum_{e \in E_j^{K \setminus k}} S_j(e,k) + \sum_{e \in E_j^O} S_j(e,k) \right) = \left(\sum_{e \in E_{j \to i}^{K \setminus k}} S_i(e,k) + \sum_{e \in E_{j \to i}^O} S_i(e,k) \right) \tag{10}$$

where the second equality follows from the assumption that the two individuals rely on the same similarity function.[9] Then, the recall probabilities of hypothesis k are given by

$$\hat{r}_1(k) = \frac{\gamma_1 x_1 + (1-\gamma_1)x_2}{\gamma_1 x_1 + (1-\gamma_1)x_2 + y_1}$$

$$\hat{r}_2(k) = \frac{\gamma_2 x_2 + (1-\gamma_2)x_1}{\gamma_2 x_2 + (1-\gamma_2)x_1 + y_2}$$

Individual 2 has an effect on the recall probability of individual 1 through x_2, and individual 1 has an effect on the recall probability of individual 2 through x_1. Hence, for given x_2, y_1 and y_2, we have $\hat{r}_2(k) = f(\hat{r}_1(k) \mid x_2, y_1, y_2)$. Similarly, for given x_1, y_1, and y_2 we have $\hat{r}_1(k) = g(\hat{r}_2(k) \mid x_1, y_1, y_2)$. It is straightforward to show that, for any $j \in \{1,2\}$ and $i \neq j$,[10]

$$\hat{r}_j(k) = \max\left[0, \frac{a_j \hat{r}_i(k) + b_j}{c_j \hat{r}_i(k) + d_j}\right] \tag{11}$$

where $a_j = (1-\gamma_j)y_i + (1-\gamma_1-\gamma_2)x_j$; $b_j = (\gamma_1+\gamma_2-1)x_j$; $c_j = a_j - \gamma_i y_j$; and $d_j = b_j + \gamma_i y_j$. The max operator captures the fact that the recall probabilities cannot be negative.

From here, it is trivial to see that, generally, there exist *three* equilibria: i) $\hat{r}_1^*(k) = \hat{r}_2^*(k) = 0$; ii) $0 < \hat{r}_1^{**}(k), \hat{r}_2^{**}(k) < 1$; and iii) $\hat{r}_1^{***}(k) = \hat{r}_2^{***}(k) = 1$.[11] However, two equilibria occur under special circumstances: for $\hat{r}_1^*(k) = \hat{r}_2^*(k) = 0$ it must be that $x_1 = x_2 = 0$, and for $\hat{r}_1^*(k) = \hat{r}_2^*(k) = 1$ it must be that $y_1 = y_2 = 0$. For this reason, we remain primarily focused on the more likely equilibrium with $0 < \hat{r}_1^*(k), \hat{r}_2^*(k) < 1$. Proposition 4 shows that this particular equilibrium is stable only if the aggregate attention paid to personal experiences is larger than the aggregate attention we pay to experiences shared through the network.

Proposition 4. *Consider the setting above and assume that $x_i, y_j > 0$, for any $i,j \in \{1,2\}$, implying that there is a unique equilibrium with $0 < \hat{r}_1^*(k), \hat{r}_2^*(k) < 1$. Perturbating $\hat{r}_1(k)$ or $\hat{r}_2(k)$ away from this equi-*

[9] We note that $x_j, y_j \geq 0$ for any $j \in \{1,2\}$ since by assumption, for any experience, $S_j(e,k) \geq 0$.

[10] See Appendix A for details.

[11] As shown in Appendix A and visualized in Figure 2, in the case of $\gamma_1 + \gamma_2 > 1$, the equilibria are $(\hat{r}_1^{**}(k), \hat{r}_1^{**}(k))$ and $(\hat{r}_1^{***}(k), \hat{r}_1^{***}(k))$, whereas in the case of $\gamma_1 + \gamma_2 < 1$ all three are equilibria.

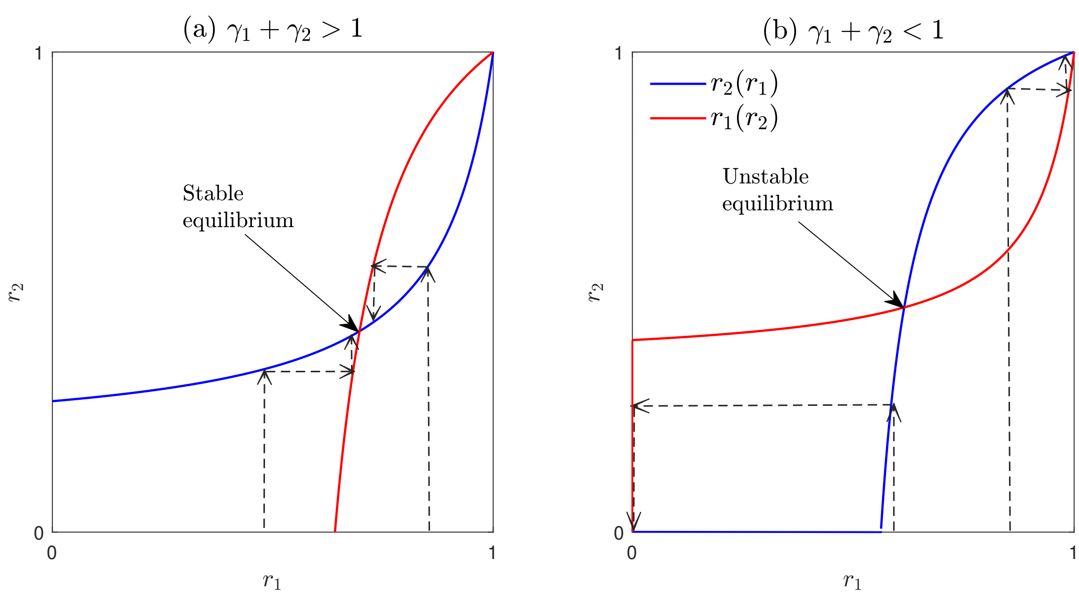
librium yields two outcomes in terms of equilibrium stability:

- *If $\gamma_1 + \gamma_2 > 1$, then recall probabilities converge back to the equilibrium above.*
- *If $\gamma_1 + \gamma_2 < 1$, then recall probabilities diverge away from the equilibrium above towards either $\hat{r}_1(k) = \hat{r}_2(k) = 0$ or $\hat{r}_1(k) = \hat{r}_2(k) = 1$.*

Proof. See Appendix D.5. □

Proposition 4 shows that if the aggregate attention paid to the social network exceeds the aggregate attention to own experiences, then an incremental positive shock to the recall probability of one person will push $\hat{r}_1(k)$ and $\hat{r}_2(k)$ towards 1, whereas a small negative shock to an individual recall probability will converge $\hat{r}_1(k)$ and $\hat{r}_2(k)$ towards 0. On the contrary, if the aggregate attention paid to the social network does not surpass aggregate attention to own experiences, then a shock to an individual recall probability cannot pull away recall probabilities away from their equilibrium. Figure 2 visualizes the stability properties of this equilibrium for both cases.

Figure 2: Equilibrium stability



Note: Panel (a) exhibits the stability of recall probabilities when aggregate attention to the social network is lower than aggregate attention to own experiences; panel (b) presents the stability of recall probabilities when aggregate attention to the social network exceeds aggregate attention to personal experiences.

An example illustrates the intuition. Without loss of generality, suppose that there is an idiosyncratic *one-time* shock to the recall probability of individual 1 for high inflation ($k = H$) because individual 1 is experiencing higher gas prices in her location. This information is shared with the social network via Facebook, the network pays excessive attention to this network information, by, e.g., re-posting it on Facebook, the information feeds back to individual 1 (the originator), and the chain repeats itself until everyone in the social network recalls high inflation events almost with certainty, that is, $\hat{r}_1(H), \hat{r}_2(H) \to 1$. By contrast, suppose that the network's attention to the information shared by individual 1 does not exceed attention to own experiences (e.g., there is little re-posting of such information on social media), so the likelihood that the information comes back to the originator is very low and thus $(\hat{r}_1(H), \hat{r}_2(H)) \to (\hat{r}_1^{**}(H), \hat{r}_2^{**}(H))$.

Corollary 3 provides stability outcomes for the special cases when one individual in our two-person network pays full attention to own experiences versus when one individual pays full attention to the other's experiences.

Corollary 3. *Consider the case when there is a unique equilibrium,* $(\hat{r}_1^{**}(k), \hat{r}_2^{**}(k))$. *Then, one individual paying full attention to own experiences is sufficient for the equilibrium to be stable, whereas one individual paying no attention to own experiences is sufficient for the equilibrium to be unstable.*

Proof. Follows directly from Proposition 4. □

2.4 Testable Implications for Inflation Expectations

We now link recall probabilities with the focal object of the current paper: inflation expectations. Consistent with our two hypotheses of interest studied above, inflation can be in either one of two regimes: a high regime (H) with inflation equal to $\bar{\pi}^H$ and a low regime (L) with inflation equal to $\bar{\pi}^L$. We assume that the presence of the two regimes and inflation levels associated with each regime are common knowledge. However, distinct experiences and, as a result, distinct probabilities of recall lead to heterogenenous perceived probabilities assigned to each one of the two events, that is, to high and low inflation events, which further implies heterogeneous inflation expectations.

We formalize this link between experiences and perceived probabilities of a hypothesis as follows: Given probabilities of recall, individual j will draw with replacement T_j events from her set of experiences, $E_j \cup E_{1\to j} \cup ... \cup E_{j-1\to j} \cup E_{j+1\to j} ... \cup E_{N_j+1\to j}$. Let $R_j(k)$ be the number of times that j successfully recalls events aligned with hypothesis $k \in \{H, L\}$, that is, $R_j(k)$ has a binomial distribution $R_j(k) \sim Bin(T_j, \hat{r}_j(k))$. From here, individual j's *perceived* probability that regime k will realize is $p_j(k) = \frac{R_j(k)}{R_j(H)+R_j(L)}$ for any $k \in \{H, L\}$.

Therefore, individual j's expected inflation is given by

$$\mathbb{E}_j \pi = p_j(H)\bar{\pi}^H + (1 - p_j(H))\bar{\pi}^L = p_j(H)(\bar{\pi}^H - \bar{\pi}^L) + \bar{\pi}^L \tag{12}$$

where $p_j(H)$ is the source of heterogeneous expectations, and it is through that variable that social interaction affects inflation expectations. More specifically, Proposition 5 shows that social interaction propagates inflation expectations whenever it amplifies the recall probability of events linked to the hypothesis of high inflation. The intuition behind this result is that an increase in $\hat{r}_j(H)$ increases, on average, the odds of successful recalls of experiences aligned with hypothesis H, that is, $R_j(H)$. An increase in the latter raises the probability that individual j assigns to the high inflation regime, and therefore, her inflation expectations as shown in equation (12).

Proposition 5. *All else equal, if social interaction amplifies (respectively, mitigates) the recall probability for events related to the high regime for inflation, then it will lead to an increase (respectively, decrease) in inflation expectations on average.*

Proof. See Appendix D.6. □

A direct, important implication of Proposition 5 is that the stability properties for the recall probability translate into the same stability properties for inflation expectations. As a result, if the aggregate attention paid to the social network exceeds the aggregate attention to own experiences, then a small perturbation to the recall probability of one person will push $\hat{r}_1(H)$ and $\hat{r}_1(H)$ towards 0 or 1, with expectations converging towards $\mathbb{E}_1\pi = \mathbb{E}_2\pi \in \{\bar{\pi}^L, \bar{\pi}^H\}$. On the contrary, if the aggregate attention paid to the social network does not surpass aggregate attention to own experiences, then a shock to an individual recall probability cannot pull away recall probabilities away from their equilibrium, $\mathbb{E}_j\pi = p_j^{**}(H)(\bar{\pi}^H - \bar{\pi}^L) + \bar{\pi}^L$, where $p_j^{**}(H)$ is the (average) perceived probability of the high regime associated with $r_j^{**}(H)$.

The following summarizes three main testable implications of social interaction for the formation of inflation expectations:

1. Social interaction has an effect on inflation expectations if people pay attention to experiences shared by others.
2. In inflationary environments, networks of common demographics propagate expectations if they increase similarity between shared experiences and the event of high inflation.
3. Idiosyncratic shocks can destabilize inflation expectations if aggregate attention to experiences of the social network exceeds aggregate attention to personal experiences.

Our theoretical framework provides additional implications: First, social interaction increases inflation expectations if the relative relevance of shared experiences with the high inflation hypothesis exceeds the relative irrelevance of shared experiences with that same hypothesis. Second, if the relative relevance of shared experiences with the high inflation regime exceeds their relative irrelevance, then attributing more attention to the experiences of the social network and less attention to own experiences further increases inflation expectations. By contrast, if the relative irrelevance of shared experiences with the high inflation regime exceeds their relative relevance, then attributing more attention to the experiences of the social network and less attention to own experiences mitigates inflation expectations. Third, if the similarity between shared experiences and high inflation is increasing in common demographics, then the likelihood that social interaction propagates inflation expectations is higher if people are more attentive to individuals with whom they share a larger number of demographics.

3 Data

In order to gauge the extent to which the expectations of others who live in other regions affect expectations of individuals in a given region, we construct a novel dataset. This data set combines dense survey data on US consumers' inflation expectations with a map of the social network, based off Facebook connections.

Data on consumer inflation expectations come from the Indirect Consumers Inflation Expectation (ICIE) survey, developed by Morning Consult and the Center for Inflation Research of the Federal Reserve Bank of Cleveland. These data contain weekly measures of consumer inflation expectations, precise information of the geographic location of each consumer, and their demographic characteristics. Of note, the ICIE survey uses an approach of measuring inflation expectations the differs from the conventional approach (Hajdini et al. (2022c), Hajdini et al. (2022a)). Instead of asking directly for aggregate inflation expectations, it takes an indirect utility approach and elicits the change in income that would compensate respondents for the expected change in prices. The survey is nationally representative of the US, with 20,000 observations every week. Hajdini et al. (2022a) show that this measure has very good properties in terms of how it measures consumers expectations and how it relates to other common measures.

The granularity of our analysis requires a large enough sample size of respondents at the county level – our unit of analysis geographically – to obtain statistical significance. Without loss of generality, this requirement leads us to use a monthly frequency as time unit. The main variables of interest which the survey records include the identity of counties, gender (Male-Female), income brackets (less than 50k, between 50k and 100k and over 100k), age (18-34, 35-44, 45-64, 65+), and political party (Democrat, Republican or Independent). Hajdini et al. (2022a) discuss how expectations of some of these groups behave in the time series.

Data on social connections at the county-level come from The Social Connectedness Index Database. The Social Connectedness Index (SCI) was first proposed by Bailey et al. (2018a) and measures the social connectedness between different regions of the United States as of April 2016. It is based on friendship links on Facebook, the global online social networking service. Specifically, the Social Connectedness Index measures the relative probability that two individuals across two counties in the US are friends with each other on Facebook. It also contains information on the social relationship between every US county and foreign countries. Given Facebook's scale as well as the relative representativeness of Facebook's user body, these data provide a comprehensive measure of friendship networks at a national level.

We use the SCI for the year 2016 and hold those weights constant across the sample. Several properties of the data are convenient for our analysis. The SCI was sampled prior to the pandemic and the inflation surge in 2021, a period marked by low and stable inflation. Consequently, our measure of social connectedness is unlikely to be influenced by changes in inflation expectations after 2020. Our analysis assumes that social networks in 2016 are correlated with the networks after 2020, which is reasonable given the stability of Facebook connections over time.

At the heart of our analysis lies a county-level measure of exposure to inflation expectations in socially connected counties. To construct this measure, we build on the Social Connectedness

Index between two locations i and j,

$$SCI_{i,j} = \frac{\text{FB Connections}_{i,j}}{\text{FB Users}_i \times \text{FB Users}_j},$$

where FB Connections$_{i,j}$ denotes the total number of Facebook friendship connections between individuals in counties i and j and FB Users$_i$, FB Users$_j$ denote the number of users in each location. Intuitively, if the SCI is twice as large, a given Facebook user in location i is about twice as likely to be connected with a given Facebook user in location j.

We normalize the SCI by county and use it to weight up the expectations of others in connected counties. That is, we define bilateral social connectedness weights of county c with county k as follows:

$$\omega_{ck} = \frac{SCI_{ck}}{\sum\limits_{k} SCI_{ck}}$$

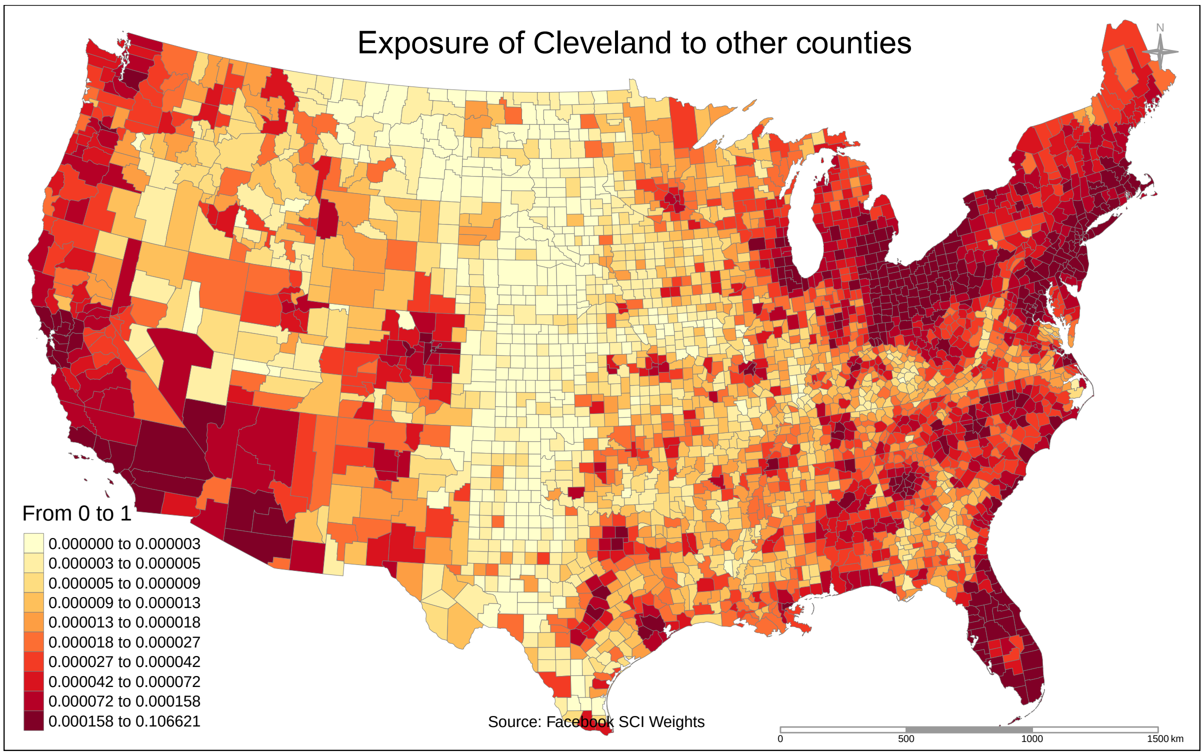
These weights ω_{ck} are at the center of the analysis and we use them to construct expectations $\pi_{ct}^{e,others}$ of others:

$$\pi_{ct}^{e,others} = \sum_{k \neq c} \omega_{ck} \pi_{kt}^{e}$$

where π_{kt}^{e} denote the average expectations of individuals in county k at time t. Our measure implies that a county c will be more exposed to information in county k if many users of county k have Facebook friendships with users in county c. Subsequently, we also compute more specific subindices for specific groups, such as men or women only.

To provide a concrete example, consider the social connectedness of Cuyahoga County, where Cleveland, OH is located, with other counties across the United States. Figure 9 illustrates this social connectedness through a heat map depicting the weights (ω_{ck}) for $c = Cleveland$. In Appendix E, we present similar maps for other counties. The color scheme ranges from light yellow to red, with red depicting counties that hold greater social significance for Cleveland. We observe three distinct patterns. Firstly, as expected, geography plays a significant role, with Cleveland showing stronger connections to nearby counties. Secondly, interestingly, we also observe robust social links with more distant counties. For instance, individuals residing in Hillsborough, Florida (Tampa) and Clark County, Nevada (Las Vegas) hold importance for Cleveland individuals. Thirdly, there is substantial heterogeneity in social connectedness. Even neighboring counties show varying degrees of influence on Cleveland. This is the kind of variability that we exploit in the paper.

Figure 3: Social Connectedness of Cleveland to Other Counties ($\omega_{c=Cleveland,k}$)



Note: The yellow-to-red color scale represents the degree to which Cleveland is socially connected to other counties, based on $\omega_{Cleveland,k}$. Red indicates higher $\omega_{Cleveland,k}$. Source: Social Connectedness Index

In reverse, we also present consider the social connectedness of other counties to Cuyahoga County, Ohio. The heat map in Figure 5 shows the weights ω_{ck} for $k = Cleveland$. Note that this weights do not add up to one. Again, as in the illustration above, three patterns emerge: geography plays an important role; counties far away are also socially connected to Cleveland; and there is substantial heterogeneity in connectedness. Relative to before, an asymmetry in connectedness stands out, a general feature of the data which the analysis will subsequently exploit.

4 Empirical analysis

4.1 Overview of Empirical Challenges and Strategy

In this section, we examine whether consumers incorporate information from their social networks when forming expectations. To assess this, we employ county averages of social connectedness to gauge the impact of interconnected counties on inflation expectations at either the county or individual level. By leveraging the Social Connectedness Index (SCI) and the ICIE data, we create a metric that captures the level of social connectedness between counties. Subsequently, our analysis utilizes this metric to underscore the significance of social connections in relation to the main predictions of our model.

Understanding the role of social networks for shaping inflation expectations comes with several challenges. First, social networks might be spuriously correlated with other networks. For example, nearby counties are more likely to be socially connected, but at the same time, they might also be connected by trade relationships. Second, even if social networks play a role for inflation expectations, our quantitative estimates could be affected by endogeneity concerns such the Manski (1993) reflection problem. It is important to highlight that the reflection problem induces a bias in the estimated effects of social networks on inflation expectations *only* if the network matters for expectations. By contrast, if the expectations of the social networks are, in reality, irrelevant for individual expectations, then the Manski (1993) reflection problem disappears. We prove this in Appendix B. Specifically, we analytically compute the degree of bias in the OLS estimate of the effect of the expectations of others on individual expectations, stemming from the reflection problem. Importantly, we show that, generally, the only case when the bias induced by the reflection problem disappears is when the true effect of the expectations of others on individual expectations is absent. As a result, it must be that any non-zero empirical correlation between individual expectations and the expectations of others indicates relevance of social networks for inflation expectations.

Our analysis utilizes different approaches that overcome such challenges. As a first step, we establish that the network matters *per se*, both at the individual and at the county level. We interpret this finding as a stylized fact indicating that there is a correlation in the inflation expectations of counties that are connected by social networks.[12] As a second step, once we have established that the network matters in the first place, we employ several empirical strategies to identify whether information is transmitted through social networks or other networks that may spuriously correlate with social networks. One way to do so lies in exploiting the asymmetric nature of the social network. Finally, we use demographic characteristics of individuals to construct county $\times$ demographic $\times$ year networks which allows for the inclusion of county-time fixed effects. These fixed effects absorb any variability that affects all demographic groups in a county equally, dispelling concerns about spatial spillovers, trade relationships, or demand spillovers from nearby regions, among other confounding factors.

As a third step to address the challenges of analyzing expectations in social networks, we apply an instrumental variables approach that addresses any remaining endogeneity concerns including those embodied by the reflection problem. To do so we obtain exogenous cross-sectional variation in inflation expectations from a shift-share approach that combines national changes in gas prices and the county-level variation in the share of drivers.

Across all of these strategies, we find strong evidence supporting the hypothesis that social networks are important in determining individuals' inflation expectations.

4.2 The Unconditional Influence of Expectations of Others

Our analysis starts off by showing that the first prediction of the model holds in the data: Inflation expectations are correlated with expectations in other counties linked through the social network even after taking into account detailed fixed effects. This result holds at the county level and also at the individual level.

4.2.1 County-Level Evidence

At the county level, we find strong, consistent evidence for the importance of the social network for the expectations formation process. We obtain these results from estimating variants of the following equation:

[12] Note that concerns of endogeneity as embodied by the reflection problem (Manski (1993)) arise only as a quantitative concern, relevant only if the network matters in the first place. Therefore, before addressing the reflection problem, we establish that there is evidence that individuals' inflation expectations are affected by the expectations of individuals in socially connected counties in the first place.

$$\pi^e_{c,t} = \alpha_c + \gamma_t + \beta \sum_{k \neq c} \omega_{ck} \pi^e_{kt} + \varepsilon_{c,t} \tag{13}$$

where $\pi^e_{c,t}$ denotes the average inflation expectations in county c in month t. Weights ω_{ck} capture the linkages in the social network between county c and county k. α_c denotes a county fixed effect, γ_t denotes time fixed effect. The coefficient β is our main coefficient of interest. It captures the relationship between inflation expectations, $\pi^e_{c,t}$, and inflation expectations in the social network, $\sum_{k \neq c} \omega_{ck} \pi^e_{kt}$. All estimated specifications of equation 13 cluster standard errors at the county level.

Various combinations of the fixed effects, conditioning the sample to counties with more than 10 observations, and weighting by the number of responses per period make up our specifications. Table 1 lists the different specifications and associated estimates of β across its columns. Column 1 presents a baseline without county and time fixed effects. Our preferred specification is Column 6. This specification includes county and time-fixed effects. It shows a positive relationship between local inflation expectations and inflation expectations in counties connected through the social network. Specifically, a 10 percentage point increase in network-weighted inflation expectations in other counties is statistically significantly associated with an increase of 0.38 percentage points in a county's inflation expectations. This result suggests that the expectations of others generally matter when individuals form expectations.

Table 1: Network Effect at the County Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Expectations of Others	0.670***	0.306***	0.055***	0.318***	0.043**	0.035**	0.041**
	(0.018)	(0.018)	(0.020)	(0.017)	(0.018)	(0.018)	(0.018)
Average Expectations					0.997***		
					(0.036)		
Sample	N>10	All	All	All	All	All	N>10
Weights	Yes	No	No	No	No	No	Yes
County FE	No	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	No	No	Yes	Yes
Observations	24,255	60,055	60,065	60,015	60,015	60,015	24,070
R-squared	0.151	0.009	0.026	0.150	0.167	0.167	0.441

Note: The Table shows the results of regression (13), where the dependant $\pi^e_{c,t}$ is the average inflation expectation of a county c at time t. Column (1) uses only counties at times where they have at least 10 observations ($N > 10$) and weights the regression by the number of answers in each period (*Weights = Yes*). Standard errors are clustered at the county level.

Estimating all other specifications (Columns 1 through 7) confirms this finding. Across specifications, beliefs in the network turn out to matter when individuals form expectations. One notable feature of these results is that with only a county fixed effect, a 1 percentage point increase in inflation expectation of the network increases county inflation expectations by 0.318 percentage points (Column 4). This coefficient is 10 times larger than in Column 6 which includes both county and time fixed effects. The reason for this difference is that a time fixed effect (which is the only fixed effect included in Column 3) filters out a lot of variation from the data and all counties share similar connections with "partner" counties. Including instead a time-varying macro variable, aggregate inflation, as a proxy for a time fixed effect produces a similar effect as Column 5 shows.

A further issue associated with the inclusion of time fixed effects is that our main control is the dependent variable for the other observations. Therefore, the time fixed effect contains that exact same variation, so in a way the analysis controls for the same variable twice, which results in a significantly lower coefficient estimate. Next, we exploit individual-level variation to better take into account various aspects of time variation.

4.2.2 Individual-Level Evidence

Exploiting the granularity of the expectations data at the individual level, the analysis can provide-further evidence for the first prediction of the model. Exploiting individual-level data is beneficial because it allows us to include county-time fixed effects to filter out time-varying county characteristics, such as county average changes in expectations or spillovers from nearby counties.

Formally, we estimate:

$$\pi^e_{ict} = \beta_0 + \beta_1 \pi^e_{-i,ct} + \beta_2 \sum_{k \neq c} \omega_{ck} \pi^e_{kt} + \varepsilon_{ict}, \tag{14}$$

where π^e_{ict} denotes the inflation expectations of i, located in county c at time t. $\pi^e_{-i,ct}$ denotes the "leave-out" average inflation expectations of county c which exclude the expectations of individual i from the calculation of county average. All regressions are weighted by the number of respondents in a county in a given period of time.

Again, we find clear support for the first, general prediction of the model – the expectations of others are associated with individual inflation expectations. Table 2 reports the results, with the first row displaying the coefficient associated with the network-weighted inflation expectations of other counties, and the second row displaying the coefficient for county "leave-out" inflation expectations. The OLS estimates in Column 1 show that the elasticity of inflation expectations of an individual with respect to inflation expectations in other counties is 0.22. The inclusion of time fixed effects which absorb time variation in inflation common to all counties leaves this result unchanged, with a coefficient of 0.175. Likewise, the inclusion of county fixed effects which capture characteristics of the county that are correlated with the network and invariant over time also leaves this result unchanged, with a coefficient of 0.289. Including both county and time effects again implies a statistically significant coefficient (Column 4). Now, an increase of 10 percentage points in the inflation expectations of others leads to an increase of 0.44 percentage points in an individual's inflation expectations.

Table 2: Network Effect on Inflation Expectations: Individual-Level Analysis

	(1)	(2)	(3)	(4)
Expectations of Others	0.221***	0.175***	0.290***	0.044**
	(0.041)	(0.048)	(0.071)	(0.017)
County Inflation Expectations	0.730***	0.711***	0.576***	0.529***
	(0.046)	(0.042)	(0.059)	(0.053)
Time Fe	No	Yes	No	Yes
County FE	No	No	Yes	Yes
Observations	1,624,780	1,624,780	1,624,780	1,624,780
R-squared	0.016	0.016	0.017	0.017

Note: The Table shows the results of regression (14), where the dependant π^e_{ict} is the inflation expectation of individual i that answers from county c at time t. Regressions are weighted by the number of answers in a county in each period. Standard errors are clustered at the county level.

Both this set of estimate and those from above at the county level consistently provide evidence in line with the first prediction of the theoretical model: When forming expectations, consumers are generally attentive to experiences shared through their social networks.

At this stage, we have established the general relevance of the social network for inflation expectations. However, social networks might correlate with other networks that might spuriously also explain the connections. Notably, counties nearby are socially connected and, at the same time, are connected by trade relationships due to proximity in space. In the next section, we address this challenge by combining the network with demographic characteristics which allows to control for county-by-time fixed effects. This exercise also naturally tests the second and third predictions of the model.

4.3 Demographic Similarity in the Social Network

In line with the second and third predictions of the model, this subsection shows that the impact of social interaction on inflation expectations varies depending on the degree of *demographic similarity* between the individuals in the network. This finding segues with the original intuition in Festinger (1954) that people may be more likely to pay attention to the expectations of groups that share similar characteristics with them.

To arrive at this result, we construct exposure to inflation expectations of similar groups in distant counties. In particular, we define such exposure as:

$$\sum_{k \neq c} \omega_{ck} \pi^e_{d,k,t}$$

where $\pi^e_{d,k,t}$ denotes the average inflation expectation of the demographic group d of individual i. The demographic characteristics that we consider include gender (male, female), political affiliation (democrats, republicans, independents), income (less than 50k, betweek 50k and 100k, over 100k), and age (18-34, 34-44, 45-64, 65+).

We then estimate the following specification:

$$\pi^e_{ict} = \beta_0 + \beta_1 \pi^e_{ct} + \beta_2 \sum_{k \neq c} \omega_{ck} \pi^e_{d,k,t} + \gamma_{ct} + \varepsilon_{ict} \tag{15}$$

which represents a direct test of the model predictions 2 and 3. If the similarity between individuals matters for the transmission of inflation expectations, then we expect a positive estimate coefficient β_2.

Note that an additional advantage of combining the SCI weights with information on demographics is that we can include county-time fixed effects. The main concern which this inclusion addresses is that counties connected by social ties are exposed to common regional shocks. For example, San Francisco and LA are connected socially and, at the same time, there are common shocks in California that affect inflation expectations in both places. Hence, even if they were not connected by the social networks, we would expect their inflation expectations to co-move. The county-time fixed effects control for any such common regional shock in California and even shocks in the county itself. The identifying variation comes from comparing inflation expectations of individuals that live in the same county, connected to the same other counties, but that have absorbed different experiences of others because they belong to different demographic groups. Standard errors are clustered at the county-level.

Our analysis sets out by illustrating the importance of demographic similarity through the lens of gender. This particular similarity feature has the appeal that unlike other demographics – evaluated subsequently – it does not depend on people choices, as political affiliation. In the case of gender, variation stems from demographic characteristics rather than reflecting possibly endogenous choices.

Table 3: Network Effect by Gender

	(1)	(2)	(3)	(4)	(5)	(6)
$Network - Gender$	0.293***	0.326***	0.321***	0.357***	0.411***	0.754***
	(0.036)	(0.032)	(0.055)	(0.054)	(0.056)	(0.099)
$Inf - County$	0.669***	0.658***	0.596***	0.584***	0.528***	0.211***
	(0.036)	(0.028)	(0.041)	(0.036)	(0.025)	(0.061)
County FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes	Yes
State-Time FE	No	No	No	No	Yes	No
County-Time FE	No	No	No	No	No	Yes
Observations	1,612,884	1,612,884	1,612,884	1,612,884	1,612,884	1,612,884
R-squared	0.025	0.025	0.026	0.026	0.026	0.028

Note: The Table shows the results of regression (15), where the dependant π^e_{ict} is the inflation expectation of individual i that answers from county c at time t. The network is defined as all the answers that are for individuals from the same gender in other counties. $Inf - County$ is the average of answers from respondents with the same gender in her/his own county. Regressions are weighted by the number of answers in a county in each period. Standard errors are clustered at the county level and time level.

Gender similarity plays an important amplifying role for social interaction in the process of belief formation: The effect of the network turns out to be significant and relevant in terms of the size of the coefficient as Table 3 shows. A one percentage point increase in the inflation expectations of the gender specific network increases own-inflation expectations between 0.293 and 0.754 percentage points. Notably, after additionally filtering out granular time, state-time, county and county-time fixed effects, the coefficient is always statistically significant and bigger than in the absence of fixed effects.

Further strong evidence for the importance of similarity within demographic groups emerges when the analysis explicitly includes a measure of *dissimilarity*, or interference, as in Corollary 2. To do so, we estimate regression (15), but we include the network-weighted expectations of the other, omitted demographic group as a control. In particular, two results emerge: First, *dissimilarity* of others – denoted by "Network-Other Gender" in the Table – has a very small and negative effect on the formation of inflation expectations. In particular, once we include a county fixed effect, the coefficient is insignificant; with a time fixed effect that subsumes most of the common variation the coefficient is significant, but less than a third of the similarity effect. Second, the effect of (dis)similarity of beliefs in the respondent's own county, captured by "County-Gender" and "County-Other Gender", also aligns with theory after inclusion of county and time fixed effects: Again, own-demographics bear a positive, statistically significant sign while other-demographics bear a smaller and possibly negative, statistically significant sign.

Table 4: Effect of Network from Own and Other Gender

	(1)	(2)	(3)	(4)	(5)
Network-Gender	0.309***	0.275***	0.339***	0.204***	0.363***
	(0.037)	(0.020)	(0.054)	(0.029)	(0.049)
Network-Other Gender	-0.065***	-0.100**	-0.011	-0.148***	
	(0.025)	(0.040)	(0.031)	(0.032)	
County-Gender	0.664***	0.653***	0.588***	0.566***	0.610***
	(0.034)	(0.031)	(0.040)	(0.040)	(0.030)
County-Other Gender	0.028***	0.021**	-0.045***	-0.065***	
	(0.009)	(0.010)	(0.012)	(0.016)	
Network					-0.247***
					(0.041)
County					-0.073***
					(0.049)
County FE	No	No	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes
Observations	1,571,662	1,571,662	1,571,662	1,571,662	1,612,884
R-squared	0.025	0.025	0.025	0.026	0.024

Note: The Table shows the results of regression (15), where the dependant π^e_{ict} is the inflation expectation of individual i that answers from county c at time t. The network is defined as all the answers that are for individuals from the same gender in other counties. $Network - OtherGender$ is the network from respondents of the other gender. $Inf - County$ is the average of answers from respondents with the same gender in her/his own county. $County - OtherGender$ are the answers from people of the other gender in the same county. Regressions are weighted by the number of answers in a county in each period. Standard errors are clustered at the county level and time level.

These results provide powerful evidence for the second and third predictions of the theoretical model: Interaction with individuals with whom one shares a common demographic feature creates an amplifying effect of social interconnectedness on inflation expectations. At the same time, interaction with individuals with whom one does not share a common feature creates an interfering effect on inflation expectations.

Analysis of the remaining demographic characteristics – age, income and political choice – all affirm the finding of strong network effects for the process of belief formation. As Table 5 shows, all of these factors individually, but also in a joint specification, clearly bear a significant relation on beliefs through the network on top of the effect due to local beliefs. People use information from their available network to form expectations even when the analysis takes into account common trends (time fixed effects) or local information (average of the county). The social component of expectations formation matters.

Table 5: Network and Individual Demographic Characteristics

	(1)	(2)	(3)	(4)	(5)
Network-Age	0.304***				0.357***
	(0.033)				(0.036)
County-Age	0.582***				0.513***
	(0.033)				(0.031)
Network-Income		0.144***			0.145**
		(0.038)			(0.057)
County-Income		0.619***			0.521***
		(0.032)			(0.027)
Network-Politics			0.174***		0.149***
			(0.038)		(0.035)
County-Politics			0.555***		0.459***
			(0.028)		(0.023)
Network-Gender				0.363***	0.356***
				(0.049)	(0.057)
County-Gender				0.610***	0.505***
				(0.030)	(0.026)
Network	-0.155***	-0.085**	-0.083***	-0.247***	-0.711***
	(0.016)	(0.037)	(0.024)	(0.041)	(0.063)
County	-0.031	-0.076	-0.013	-0.073	-1.429***
	(0.043)	(0.052)	(0.051)	(0.049)	(0.073)
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1,589,828	1,603,436	1,600,553	1,612,884	1,563,804
R-squared	0.031	0.025	0.023	0.026	0.049

Note: The Table shows the results of regression (15), where the dependant π^e_{ict} is the inflation expectation of individual i that answers from county c at time t. The network is defined as all the answers that are for individuals from the same demographic group in other counties, as described in the first column. *Network* is the network built with all the demographic groups from other counties and *County* is the average of the own county built with all the demographic groups. Regressions are weighted by the number of answers in a county in each period. Standard errors are clustered at the county level and time level.

5 Shocks to the Network

In order to address any remaining concerns in terms of identification, in this section we apply an instrumental variable strategy. We follow Hajdini et al. (2022a) and utilize a shift-share approach that combines cross-county variations in the proportion of individuals who use cars at a specific time and monthly fluctuations in national gas prices. The underlying idea is that areas with a higher intensity of car usage will experience a more pronounced impact of national gas price shocks, creating exogenous, county-specific variation.

First, we show as a first stage that the shift-share instrument affects local inflation expectations.

We estimate

$$\pi^e_{i,t} = \alpha_{c(i)} + \gamma_t + \beta P_{gas,t} \times Comm_{c(i)} + \varepsilon_{i,t},$$

where $\pi^e_{i,t}$ denotes the inflation expectations of individual i at time t. $P_{gas,t}$ denotes the average national price of regular gas according to the U.S. Energy Information Administration.[13] $Comm_{c(i)}$ denotes the share of people that use their own car to commute according to the ACS. $\alpha_{c(i)}$ denotes a county fixed effect and γ_t a time fixed effect. We estimate this regression specification for the period of March 2021 through January 2023. Table 6 reports the results. Across specifications, we observe a positive, highly statistically significant effect of the instrument on inflation expectations. A dollar increase in the price of gas increases the individual-level inflation expectations between 1.821 and 2.217 percentage points in a county where everybody uses their car to commute, compared to a counterfactual county where nobody uses a car to commute.

Table 6: Cross-sectional Effect of Gas Price on Expectations

	(1)	(2)	(3)	(4)	(5)
$P_{gas,t}$	0.426	0.305			
	(0.272)	(0.234)			
$Comm_{c(i)}$	-3.221***		-4.383***		
	(0.900)		(1.020)		
$P_{gas,t} \times Comm_{c(i)}$	1.821***	1.899***	2.104***	2.127***	1.875***
	(0.316)	(0.276)	(0.340)	(0.323)	(0.269)
County FE	No	Yes	No	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
State-Time FE	No	No	No	No	Yes
Observations	1,041,743	1,041,743	1,041,743	1,041,743	1,041,743
R-squared	0.007	0.013	0.011	0.017	0.019

Note: This table shows results from estimating the first-stage specification $\pi^e_{i,t} = \alpha_{c(i)} + \gamma_t + \beta P_{gas,t} \times Comm_{c(i)} + \varepsilon_{i,t}$, where $\pi^e_{i,t}$ denotes the inflation expectations of individual i at time t; $P_{gas,t}$ denotes the average national price of regular gas; $Comm_{c(i)}$ denotes the share of people that use their own car to commute according to the ACS; and $\alpha_{c(i)}$ and γ_t are county and time fixed effects.

Second, we exploit the exogenous within-time cross-sectional, county-specific variation em-

[13] We use the national gas price assuming that local county-level shocks in the cross section are less likely to influence US demand for gas, and therefore price. This also applies to local policies that can jointly influence expectations and local gas price. We rely on the fact that, as gas is very tradeable, its price correlates across regions following aggregate gas price shocks.

bodied in the above specification to show two results: On the one hand, the exogenous local variation of gas prices in other counties causally matters for individual inflation expectations in a given county. That is, the information transmitted through the social network *causally* matters for the formation of individual inflation expectations. On the other hand, inflation expectations in other counties – transmitted through the social network – likewise *causally* matter for the formation of individual inflation expectations.

To arrive at these insights, we construct the variable $Gas\_effect_{c,t} = \widehat{\beta} P_{gas,t} \times Comm_{c(i)}$, that contains county-time variation. Then, using the network linkages, we estimate regression specifications of the type:

$$\pi^e_{ict} = \alpha_c + \gamma_t + \beta_1 \pi^e_{-i,ct} + \beta_2 \sum_{k \neq c} \omega_{ck} Gas\_effect_{k,t} + \varepsilon_{ict}, \tag{16}$$

While time fixed effects have already been filtered out from the measure $Gas\_effect_{c,t}$, we nonetheless include a time fixed effect γ_t in some specifications. Overall, the specifications we estimate show whether or not information embedded in local gas prices in *other* counties *causally* affects individual expectations in a given county.

To apply the instrument to inflation expectations, we instrument the weighted inflation expectation with the weighted $Gas\_effect_{c,t}$. That is, we estimate the following specification:

$$\pi^e_{i,c,t} = \alpha_{c(i)} + \beta_1 \pi^e_{-i,ct} + \beta_2 \sum_{k \neq c} \omega_{ck} \pi^e_{kt} + \varepsilon_{i,t},$$

where inflation expectations of others have been instrumented by the respective $Gas\_effect_{c,t}$ measure.

Table 7: Exogenous Variation and Network Effect

	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{k\neq c}\omega_{ck}Gas\_effect_{c,t}$	0.784***	0.948***	1.269***	2.952***		
	(0.023)	(0.028)	(0.137)	(0.750)		
$\sum_{k\neq c}\omega_{ck}\pi^e_{kt}$					0.326***	0.676***
					(0.007)	(0.023)
$\pi^e_{-i,ct}$	0.494***	0.328***	0.466***	0.282***	0.380***	0.283***
	(0.008)	(0.007)	(0.009)	(0.007)	(0.011)	(0.008)
Time FE	No	No	Yes	Yes	No	No
County FE	No	Yes	No	Yes	Yes	Yes
Regression	OLS	OLS	OLS	OLS	OLS	IV
F-Test	-	-	-	-	-	11497
Observations	1,624,780	1,624,780	1,624,780	1,624,780	1,624,780	1,624,780
R-squared	0.027	0.034	0.028	0.036	0.032	0.011

Note: This table shows results from estimating two specifications. First, $\pi^e_{ict} = \alpha_c + \gamma_t + \beta_1\pi^e_{-i,ct} + \beta_2\sum_{k\neq c}\omega_{ck}Gas\_effect_{k,t} + \varepsilon_{ict}$, and second, $\pi^e_{i,c,t} = \alpha_c + \beta_1\pi^e_{-i,ct} + \beta_2\sum_{k\neq c}\omega_{ck}\pi^e_{kt} + \varepsilon_{i,t}$, where π^e_{ict} denotes the inflation expectations of individual i in county c at time t; $\pi^e_{-i,ct}$ inflation expectations of county c at time t excluding individual i; and π^e_{kt} county k inflation expectations at time t; $Gas\_effect_{k,t}$ denotes the gas effect variable constructed as described in the text; and α_c and γ_t are county and time fixed effects.

Two findings with a causal interpretation emerge: First, the variation captured by the gas effect variable has a significant effect on inflation expectations when propagated through the network. Table 7 shows this result in its first 4 columns. This effect is significant even after controlling for county-specific variation, as columns 2 and 4 indicate. Second, when we apply the instrumental variables approach, the coefficient estimate on the inflation expectations of others increases compared to the coefficient estimate from the OLS regression. This result could indicate that when inflation expectations are affected by certain salient prices, such as gas, the transmission to the network might be stronger. This finding aligns with the result that consumers pay more attention to gas prices than other goods, as shown in Coibion and Gorodnichenko (2015b).

5.1 Implications for Stability

A natural question arises in the context of our empirical results: Are social networks a stabilizing force for the formation of inflation expectations? Our empirical findings suggest that social networks are not associated with unstable propagation of shared experiences. This conclusion can be derived from our generic regression specification:

$$\pi_t^e = \boldsymbol{\alpha} + \beta \Omega \pi_t^e + \boldsymbol{\varepsilon}_t, \tag{17}$$

where $\pi_t^e = \begin{bmatrix} \pi_{1t}^e & \pi_{2t}^e & \dots & \pi_{Nt}^e \end{bmatrix}'$ embeds inflation expectations in county 1 through county N; $\boldsymbol{\varepsilon}_t = \begin{bmatrix} \varepsilon_{1t} & \dots & \varepsilon_{Nt} \end{bmatrix}'$ denotes a set of county-specific shocks to inflation expectations such that $\varepsilon_{nt} \sim i.i.d.\mathcal{N}(0, \sigma_n^2)$ for any $n \in \{1, 2, ..., N\}$; $\boldsymbol{\alpha} = \begin{bmatrix} \alpha_1 & \dots & \alpha_N \end{bmatrix}'$ denotes a vector of constants (county fixed effects); β denotes a scalar; and Ω is a $N \times N$ matrix with 0-diagonal and with row elements summing 1.

We explore the propagation of a one-time county n-specific shock in period t through the social network, that is, $\varepsilon_{nt} \neq 0$ for some $n \in \{1, 2, ..., N\}$ while $\varepsilon_{-nt} = 0$ and $\varepsilon_{t+k} = \mathbf{0}_{N\times 1}$ for any $k \geq 1$. Within period t, the following can be thought to happen: First, ε_{nt} will have a direct, immediate effect on $\pi_{nt}^e = \alpha_n + \varepsilon_{nt}$. Second, π_{nt}^e will affect the expectations in the other counties by propagation through the network. Appendix C provides a thorough description of the feedback loop taking place within period t through social networks, showing that county-level inflation expectations converge to finite values when $\beta \in (-1, 1)$ but become explosive otherwise, that is,

$$\pi_t^e = \begin{cases} (I - \beta\Omega)^{-1}\boldsymbol{\alpha} & \text{if } \mid \beta \mid < 1 \\ \pm\infty & \text{otherwise} \end{cases} \tag{18}$$

A one-time county-specific shock to inflation expectations can de-stabilize inflation expectations in all the other counties only if $\mid \beta \mid \geq 1$.

Empirically, which scenario are we in? Focusing on the IV empirical results in column (6) of Table 7, our estimate of β is given by $\hat{\beta} = \frac{\hat{\beta}_2}{1-\hat{\beta}_1} = 0.943 < 1$, implying that social networks have not had a de-stabilizing effect on expectations.[14] However, we note that even though $\hat{\beta} < 1$, it is quite close to the instability threshold of 1, suggesting that variation in inflation expectations that is due to county-level movements in consumers' exposure to price changes in salient goods, such as gas, can have large spillover effects on expectations through social networks. As suggested in

[14] Since $\pi_{-i,c,t}^e \approx \pi_{ct}^e$, from equation (18) we have that $\pi_{ct}^e = \alpha_c + \beta_1 \pi_{ct}^e + \beta_2 \sum_{k \neq c} \omega_{ck} \pi_{kt}^e + \varepsilon_{ct}$. Therefore, the equivalent of β in (16) is $\beta_2/(1-\beta_1)$.

Coibion et al. (2020c), effective communication from policy makers that emphasizes inflation as a broad rather than a goods-specific or local phenomenon can help reduce the feedback effects of social networks.

6 Conclusion

Our analysis brings to the fore the idea that experiences shared through social networks can have an impact on the formation of expectations. Our theoretical analysis incorporates this idea into the framework of Bordalo et al. (2023) of memory and recall. The model shows that social networks can affect expectations, and provides a set of three main testable implications. First, social networks can affect expectations. Second, demographics can be an important factor in affecting the implications of social interactions on expectations. Third, social interaction is more likely to increase (respectively, decrease) expectations if people interact with a social network with which they share a larger number of (respectively, fewer) demographic factors. While our theoretical analysis is embedded into the context of inflation expectations, it may easily generalize the other expectational domains.

Our empirical analysis shows that these predictions, when viewed through the lens of inflation expectations, bear relevance in the empirical environment. In particular, to do so, we take advantage of a novel large dataset that merges inflation expectations of around 2 million US consumers with their local index of social connectedness. We find that social networks matter for inflation expectations. We also show that individuals that share similar demographic characteristics tend to pay more attention to each other. We finally show, using exogenous variation, that the coefficient is high, but in the range of stability suggested by the model.

These findings open up new avenues of exploring the formation of expectations in the context of social networks. Our analysis represents only a first step as questions for future work remain aplenty, for example in the context of stability and multiple equilibria, about the role of supernodes in the network, or the transmission of shocks from different regions and of different sizes. Further work may therefore lead to additional insights with important implications for policymakers that aim to keep inflation expectations anchored.

References

Bailey, Michael, Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong, "Social connectedness: Measurement, determinants, and effects," *Journal of Economic Perspectives*, 2018, *32* (3), 259–80.

_ , Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel, "The economic effects of social networks: Evidence from the housing market," *Journal of Political Economy*, 2018, *126* (6), 2224–2276.

Bordalo, Pedro, Giovanni Burro, Katie Coffman, Nicola Gennaioli, and Andrei Shleifer, "Imagining the Future: Memory, Simulation and Beliefs about Covid," Technical Report 30353, National Bureau of Economic Research 2022.

_ , John Conlon, Nicola Gennaioli, Spencer Y. Kwon, and Andrei Shleifer, "Memory and Probability," *Quarterly Journal of Economics*, 2023, *138* (1), 265–311.

_ , Nicola Gennaioli, and Andrei Shleifer, "Diagnostic expectations and credit cycles," *Journal of Finance*, 2018, *73* (1), 199–227.

_ , _ , Rafael La Porta, and Andrei Shleifer, "Diagnostic expectations and stock returns," *Journal of Finance*, 2019, *74* (6), 2839–2874.

Carroll, Christopher D., "Macroeconomic Expectations of Households and Professional Forecasters," *Quarterly Journal of Economics*, 02 2003, *118* (1), 269–298.

Coibion, Olivier and Yuriy Gorodnichenko, "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts," *American Economic Review*, August 2015, *105* (8), 2644–2678.

_ and _ , "Is the Phillips curve alive and well after all? Inflation expectations and the missing disinflation," *American Economic Journal: Macroeconomics*, 2015, *7* (1), 197–232.

_ , Dimitris Georgarakos, Yuriy Gorodnichenko, and Maarten Van Rooij, "How does consumption respond to news about inflation? Field evidence from a randomized control trial," Working paper 26106, National Bureau of Economic Research July 2019.

— , **Yuriy Gorodnichenko, and Tiziano Ropele**, "Inflation Expectations and Firm Decisions: New Causal Evidence*," *The Quarterly Journal of Economics*, 09 2019, *135* (1), 165–219.

— , — , **Saten Kumar, and Mathieu Pedemonte**, "Inflation expectations as a policy tool?," *Journal of International Economics*, 2020c, *124*, 103297.

da Silveira, Rava Azeredo and Michael Woodford, "Noisy Memory and Over-Reaction to News," *AEA Papers and Proceedings*, May 2019, *109*, 557–561.

D'Acunto, Francesco, Ulrike Malmendier, Juan Ospina, and Michael Weber, "Exposure to grocery prices and inflation expectations," *Journal of Political Economy*, 2021, *129* (5), 1615–1639.

Dow, James, "Search Decisions with Limited Memory," *Review of Economic Studies*, 1991, *58* (1), 1–14.

Festinger, Leon, "A theory of social comparison processes," *Human relations*, 1954, *7* (2), 117–140.

Gabaix, Xavier, "The Granular Origins of Aggregate Fluctuations," *Econometrica*, 2011, *79* (3), 733–772.

— , "A Behavioral New Keynesian Model," *American Economic Review*, 2020, *110* (8), 2271–2327.

Gennaioli, Nicola and Andrei Shleifer, "What Comes to Mind," *Quarterly Journal of Economics*, 2010, *125* (4), 1399–1433.

Hajdini, Ina, Edward S Knotek II, John Leer, Mathieu Pedemonte, Robert Rich, and Raphael Schoenle, "Indirect Consumer Inflation Expectations: Theory and Evidence," *Federal Reserve Bank of Cleveland Working Paper*, 2022.

— , **Edward S. Knotek II, John Leer, Mathieu Pedemonte, Robert W. Rich, and Raphael S. Schoenle**, "Low Passthrough from Inflation Expectations to Income Growth Expectations: Why People Dislike Inflation," Working Paper 22-21, Federal Reserve Bank of Cleveland June 2022.

— , **Edward S. Knotek II, Mathieu Pedemonte, Robert Rich, John Leer, and Raphael Schoenle**, "Indirect Consumer Inflation Expectations," *Economic Commentary*, 2022, (2022-03).

Kahneman, Daniel and Amos Tversky, "Subjective probability: A judgment of representativeness," *Cognitive psychology*, 1972, *3* (3), 430–454.

Kohlhas, Alexandre N. and Ansgar Walther, "Asymmetric Attention," *American Economic Review*, 2021, *111* (9), 2879–2925.

Kuchler, Theresa and Basit Zafar, "Personal Experiences and Expectations about Aggregate Outcomes," *The Journal of Finance*, 2019, *74* (5), 2491–2542.

_ , Dominic Russel, and Johannes Stroebel, "JUE Insight: The geographic spread of COVID-19 correlates with the structure of social networks as measured by Facebook," *Journal of Urban Economics*, 2022, *127*, 103314.

L'Huillier, Jean-Paul, Sanjay R Singh, and Donghoon Yoo, "Diagnostic expectations and macroeconomic volatility," 2021.

Malmendier, Ulrike and Stefan Nagel, "Learning from inflation experiences," *Quarterly Journal of Economics*, 2016, *131* (1), 53–87.

Manski, Charles F., "Identification of Endogenous Social Effects: The Reflection Problem," *The Review of Economic Studies*, 1993, *60* (3), 531–542.

Mullainathan, Sendhil, "A Memory-based Model of Rationality," *Quarterly Journal of Economics*, 2002, *117* (3), 735–774.

Pedemonte, Mathieu, Hiroshi Toma, and Esteban Vertugo, "Aggregate Implications of Heterogeneous Inflation Expectations: The Role of Individual Experience," Working paper 23-04, Federal Reserve Bank of Cleveland 2023.

Tversky, Amos and Daniel Kahneman, "Availability: A heuristic for judging frequency and probability," *Cognitive psychology*, 1973, *5* (2), 207–232.

Appendix

A Implications of the Theoretical Framework for Stability

Consider the setup described in Section 2.3, and recall that the recall probabilities of hypothesis k for individuals 1 and 2 are given by, respectively

$$\hat{r}_1(k) = \frac{\gamma_1 x_1 + (1-\gamma_1)x_2}{\gamma_1 x_1 + (1-\gamma_1)x_2 + y_1} \tag{A.1}$$

$$\hat{r}_2(k) = \frac{\gamma_2 x_2 + (1-\gamma_2)x_1}{\gamma_2 x_2 + (1-\gamma_2)x_1 + y_2} \tag{A.2}$$

Isolating x_1 from (A.1), we can write x_1 as $x_1 = \frac{(x_2(1-\gamma_1)+y_1)\hat{r}_1(k)-(1-\gamma_1)x_2}{\gamma_1(1-\hat{r}_1(k))}$. Substituting for x_1 into (A.2), we get

$$\begin{aligned}
\hat{r}_2(k) &= \frac{\gamma_2 x_2 + (1-\gamma_2)\frac{(x_2(1-\gamma_1)+y_1)\hat{r}_1(k)-(1-\gamma_1)x_2}{\gamma_1(1-\hat{r}_1(k))}}{\gamma_2 x_2 + (1-\gamma_2)\frac{(x_2(1-\gamma_1)+y_1)\hat{r}_1(k)-(1-\gamma_1)x_2}{\gamma_1(1-\hat{r}_1(k))} + y_2} \\
&= \frac{[(1-\gamma_2)y_1 + (1-\gamma_1-\gamma_2)x_2]\hat{r}_1(k) + (\gamma_1+\gamma_2-1)x_2}{[(1-\gamma_2)y_1 - \gamma_1 y_2 + (1-\gamma_1-\gamma_2)x_2]\hat{r}_1(k) + \gamma_1 y_2 + (\gamma_1+\gamma_2-1)x_2}
\end{aligned} \tag{A.3}$$

We proceed in a similar fashion to express $\hat{r}_1(k)$ as a function of $\hat{r}_2(k)$. Hence, the recall probability of individual j can be written as a function of the recall probability of individual i:

$$\hat{r}_j(k) = \frac{a_j \hat{r}_i(k) + b_j}{c_j \hat{r}_i(k) + d_j}$$

where $a_j = (1-\gamma_j)y_i + (1-\gamma_1-\gamma_2)x_j$, $b_j = (\gamma_1+\gamma_2-1)x_j$, $c_j = a_j - \gamma_i y_j$, and $d_j = b_j + \gamma_i y_j$.

In what follows, we analyze a number of properties of $\hat{r}_j$ as a function of $\hat{r}_i$, and, in the interest of simpler notation, we denote the recall probability of k for any individual j as $\hat{r}_j$. For $\hat{r}_i = 1$, $\hat{r}_j = 1$, and for $\hat{r}_i = 0$, $\hat{r}_j = b_j/d_j$. Next, $\hat{r}_j = 0$ if $\hat{r}_i = -\frac{b_j}{a_j}$; $\hat{r}_j$ has a vertical asymptote at $\hat{r}_i = -\frac{d_j}{c_j}$ and a horizontal asymptote at $\hat{r}_i = \frac{a_j}{c_j}$. Furthermore, $\hat{r}_j$ is increasing in $\hat{r}_i$, that is, $\hat{r}_j' = \frac{\gamma_i(1-\gamma_j)y_1 y_2}{(c_j\hat{r}_i(k)+d_j)^2} \geq 0$. The second-order derivative of $\hat{r}_j$ w.r.t. $\hat{r}_i$ then is given by $\hat{r}_j'' = -2\gamma_i(1-\gamma_j)y_1 y_2 \frac{c_j}{(c_j\hat{r}_i(k)+d_j)^3}$. Hence, $\hat{r}_j$ is concave if $\frac{c_j}{(c_j\hat{r}_i(k)+d_j)^3} > 0$ and convex otherwise. At this point, it is useful to study the sign of

c_j. In particular,

$$\begin{aligned} c_j &= (1-\gamma_j)y_i - \gamma_i y_j + (1-\gamma_1-\gamma_2)x_j \\ &= (1-\gamma_j)(\gamma_i z_i + (1-\gamma_i)z_j) - \gamma_i(\gamma_j z_j + (1-\gamma_j)z_i) + (1-\gamma_1-\gamma_2)x_j \\ &= (1-\gamma_1-\gamma_2)(x_j+z_j) \end{aligned} \tag{A.4}$$

where the second equality follows from equation (9) in Section 2.3. Therefore, $c_j \gtreqless 0$ iff $\gamma_1+\gamma_2 \lesseqgtr 1$. We consider two cases: i) $\gamma_1+\gamma_2<1$ and ii) $\gamma_1+\gamma_2>1$.

i) $\boldsymbol{\gamma_1+\gamma_2<1}$. In this case, $c_j>0$ and thus $a_j>c_j>0$, so the horizontal asymptote is higher than 1. Furthermore, the intersection of r_j with the x-axis occurs at $0<-b_j/a_j<1$, and the vertical asymptote $-d_j/c_j<-b_j/a_j$. For $\hat{r}_i<-d_j/c_j$, it has to be that $\hat{r}_j>1$ since the horizontal asymptote is higher than 1. To ensure that the function is continuous for any $\hat{r}_i\in[0,1]$, we assume that the vertical asymptote occurs for $\hat{r}_i<0$, implying that $d_j>0$, that is, $(1-\gamma_1-\gamma_2)x_j>\gamma_i y_j$. It is then easy to see that $\hat{r}_j$ is concave for any $\hat{r}_i\in[0,1]$. Given that $\hat{r}_j$ is negative for any $r_i\in[0,-b_j/a_j)$, the function describing $\hat{r}_j$ is given by

$$\hat{r}_j = max\left[0, \frac{a_j\hat{r}_i+b_j}{c_j\hat{r}_i+d_j}\right]$$

Equilibria. With a similar analysis, one can show that $\hat{r}_i = max\left[0, \frac{a_i\hat{r}_j+b_i}{c_i\hat{r}_j+d_i}\right]$. Eventually, $\hat{r}_i^*=\hat{r}_j^*=1$ is an equilibrium. Given the max operator, $\hat{r}_i^*=\hat{r}_j^*=0$ is also an equilibrium. For other equilibria, we have to search for the intersection between $\hat{r}_j$ and $\hat{r}_i$ when $\hat{r}_i\in[-b_j/a_j,1)$ and $\hat{r}_j\in[-b_i/a_i,1)$. Substituting for $\hat{r}_i$ into $\hat{r}_j$, we have that an equilibrium occurs whenever

$$f(\hat{r}_j) = \varphi_2\hat{r}_j^2+\varphi_1\hat{r}_j+\varphi_0 = 0$$

where $\varphi_2 = c_ja_i+d_jc_i \geq 0$, $\varphi_1 = c_jb_i+d_id_j-b_jc_i-a_ja_i \leq 0$, and $\varphi_0 = -b_jd_i-a_jb_i \geq 0$. It follows that f is a convex function, $f(0)>0$, and $f(1)=0$. Furthermore, f reaches its minimum value for $\hat{r}_j=-\varphi_1/(2\varphi_2)<1$, so $f=0$ for some $\hat{r}_j^*\in(0,-\varphi_1/(2\varphi_2))$. It is straightforward to see that $f(-b_j/a_j)>0$, implying that $\hat{r}_j^*\geq -b_j/a_j$. So, in the case when $\gamma_1+\gamma_2<1$, there exist three equilibria: $(\hat{r}_i^*,\hat{r}_j^*)=\{(0,0),(1,1),(\hat{r}_i^{**},\hat{r}_j^{**})\}$, where $\hat{r}_i^{**},\hat{r}_j^{**}\in(-b_j/a_j,-\varphi_1/(2\varphi_2))$.

ii) $\boldsymbol{\gamma_1+\gamma_2>1}$. In this case, the vertical asymptote, $-d_j/c_j$ is higher than 1. Furthermore, the intersection of $\hat{r}_j$ with the y-axis occurs at $0<b_j/d_j<1$. To ensure that the function is continuous for any $\hat{r}_i\in[0,1]$, we assume that the horizontal asymptote occurs at some $\hat{r}_j<0$, implying that

$a_j > 0$, that is, $(\gamma_1 + \gamma_2 - 1)x_j > (1 - \gamma_j)y_i$.[15] It is then easy to see that $\hat{r}_j$ is convex for any $\hat{r}_i \in [0,1]$. Given that $\hat{r}_j$ is positive for any $\hat{r}_i \in [0,1]$, the function describing $\hat{r}_j$ is given by

$$\hat{r}_j = max\left[0, \frac{a_j\hat{r}_i + b_j}{c_j\hat{r}_i + d_j}\right] = \frac{a_j\hat{r}_i + b_j}{c_j\hat{r}_i + d_j}$$

Equilibria. One can similarly show that $\hat{r}_i = \frac{a_i\hat{r}_j + b_i}{c_i\hat{r}_j + d_i}$. Differently from the case in i), $\hat{r}_i^* = \hat{r}_j^* = 0$ is *not* an equilibrium. Eventually, $\hat{r}_i^* = \hat{r}_j^* = 1$ is an equilibrium. The rest of the analysis is similar to i), with the difference that f is a concave function with $\varphi_2 =\leq 0$, $\varphi_1 = c_jb_i + d_id_j - b_jc_i - a_ja_i \geq 0$, and $\varphi_0 \leq 0$. To summarize, in the case when $\gamma_1 + \gamma_2 > 1$, there exist two equilibria: $(\hat{r}_i^*, \hat{r}_j^*) = \{(1,1), (\hat{r}_i^{**}, \hat{r}_j^{**})\}$, where $\hat{r}_i^{**}, \hat{r}_j^{**} \in (-b_j/a_j, -\varphi_1/(2\varphi_2))$.

B The Reflection Problem

Consider the following generic regression specification:

$$\pi_t^e = \boldsymbol{\alpha} + \beta\Omega\pi_t^e + \boldsymbol{\varepsilon}_t$$

where $\pi_t^e = \begin{bmatrix} \pi_{1t}^e & \pi_{2t}^e & \dots & \pi_{Nt}^e \end{bmatrix}'$ embeds inflation expectations in county 1 through county N, $\boldsymbol{\varepsilon}_t = \begin{bmatrix} \varepsilon_{1t} & \dots & \varepsilon_{Nt} \end{bmatrix}'$ denotes a set of county-specific i.i.d. shocks to inflation expectations such that $\varepsilon_{it} \sim \mathcal{N}(0, \sigma_i^2)$ for any $i \in \{1, 2, ..., N\}$, $\boldsymbol{\alpha} = \begin{bmatrix} \alpha_1 & \dots & \alpha_N \end{bmatrix}'$ denotes a vector of constants (county fixed effects), β denotes a scalar, and Ω is a $N \times N$ matrix with 0-diagonal and with row elements summing to 1. We re-write the equation above as

$$\underbrace{\pi_t^e - \bar{\pi}}_{y_t} = \beta \underbrace{[\Omega(\pi_t^e - \bar{\pi})]}_{\Omega y_t} + \boldsymbol{\varepsilon}_t$$

where $\bar{\pi} = \begin{bmatrix} \bar{\pi}_1^e & \bar{\pi}_2^e & \dots & \bar{\pi}_N^e \end{bmatrix}'$. Note that $y_t = (I - \beta\Omega)^{-1}\boldsymbol{\varepsilon}_t = M\boldsymbol{\varepsilon}_t$. Let $\hat{\beta}$ be the OLS estimate of β. Then,

$$\hat{\beta} = \beta + \left[(y_t'\Omega'\Omega y_t)^{-1}(y_t'\Omega\boldsymbol{\varepsilon}_t)\right] = \beta + \left[(\boldsymbol{\varepsilon}_t'M'\Omega'\Omega M\boldsymbol{\varepsilon}_t)^{-1}(\boldsymbol{\varepsilon}_t'M'\Omega\boldsymbol{\varepsilon}_t)\right]$$

[15] Note that both assumptions we impose to guarantee well-behaved functions simply put upper bounds on the similarity between hypothesis k and experiences that do *not* belong to the subset of experiences related k.

where

$$(\boldsymbol{\varepsilon}_t' M' \Omega \boldsymbol{\varepsilon}_t) = \begin{bmatrix} \varepsilon_{1t} & \varepsilon_{2t} & ... & \varepsilon_{Nt} \end{bmatrix} \begin{bmatrix} m_{11} & m_{21} & ... & m_{N1} \\ m_{12} & 0 & ... & m_{N2} \\ ... & ... & ... & ... \\ m_{1N} & m_{2N} & ... & m_{NN} \end{bmatrix} \begin{bmatrix} 0 & \omega_{12} & ... & \omega_{1N} \\ \omega_{21} & 0 & ... & \omega_{2N} \\ ... & ... & ... & ... \\ \omega_{N1} & \omega_{N2} & ... & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ ... \\ \varepsilon_{Nt} \end{bmatrix}$$

$$= \begin{bmatrix} \sum_i m_{1i}\varepsilon_{it} & \sum_i m_{2i}\varepsilon_{it} & ... & \sum_i m_{Ni}\varepsilon_{it} \end{bmatrix} \begin{bmatrix} \sum_{i\neq 1} \omega_{1i}\varepsilon_{it} \\ \sum_{i\neq 2} \omega_{2i}\varepsilon_{it} \\ ... \\ \sum_{i\neq N} \omega_{Ni}\varepsilon_{it} \end{bmatrix} = \sum_{j=1}^{N} \left(\sum_{i\neq 1} \omega_{ji} m_{ji} \sigma_i^2 \right) \neq 0$$

If $\beta = 0$, then $y_t = \boldsymbol{\varepsilon}_t$ and $\hat{\beta} = \left[(\boldsymbol{\varepsilon}_t' \Omega' \Omega \boldsymbol{\varepsilon}_t)^{-1} (\boldsymbol{\varepsilon}_t' \Omega \boldsymbol{\varepsilon}_t) \right]$, where

$$(\boldsymbol{\varepsilon}_t' \Omega \boldsymbol{\varepsilon}_t) = \begin{bmatrix} \varepsilon_{1t} & \varepsilon_{2t} & ... & \varepsilon_{Nt} \end{bmatrix} \begin{bmatrix} 0 & \omega_{12} & ... & \omega_{1N} \\ \omega_{21} & 0 & ... & \omega_{2N} \\ ... & ... & ... & ... \\ \omega_{N1} & \omega_{N2} & ... & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ ... \\ \varepsilon_{Nt} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1t} & \varepsilon_{2t} & ... & \varepsilon_{Nt} \end{bmatrix} \begin{bmatrix} \sum_{i\neq 1} \omega_{1i}\varepsilon_{it} \\ \sum_{i\neq 2} \omega_{2i}\varepsilon_{it} \\ ... \\ \sum_{i\neq N} \omega_{Ni}\varepsilon_{it} \end{bmatrix} = 0$$

with the final equality following from the fact that the error terms are uncorrelated across counties. Therefore, if $\beta = 0$, the OLS estimate of it should also be equal to 0.

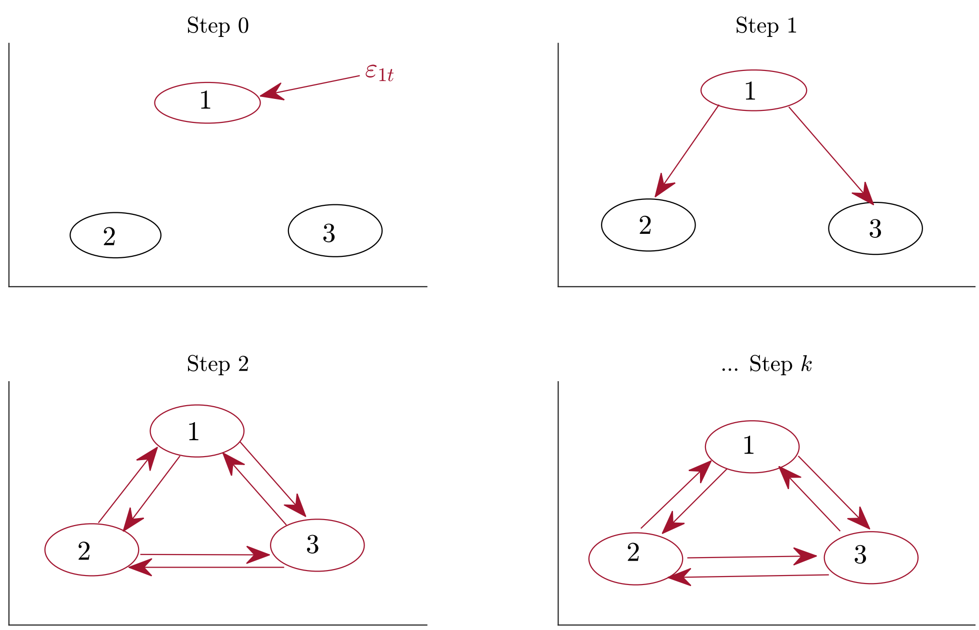
C Empirical Implications for Stability

Given a one-time shock to the expectations in county n *only*, inflation expectations in county n are given by $\pi_{nt}^e = \boldsymbol{\alpha}_n + \boldsymbol{\varepsilon}_{nt}$. However, due to social ties, expectations in the other counties get affected as well, which will in turn feed back to expectations, and so on. We describe the within-network, within-period feedback process, initiated by a one-time $\varepsilon_{nt} \neq 0$, as follows:

$$\begin{aligned} \pi_t^e(0) &= \boldsymbol{\alpha} + \boldsymbol{\varepsilon}_t \\ \pi_t^e(1) &= \boldsymbol{\alpha} + \beta\Omega\pi_t^e(0) = (I + \beta\Omega)\boldsymbol{\alpha} + \beta\Omega\boldsymbol{\varepsilon}_t \\ ... &= ... \\ \pi_t^e(k) &= \sum_{\kappa=0}^{k} (\beta\Omega)^{\kappa}\boldsymbol{\alpha} + (\beta\Omega)^{k}\boldsymbol{\varepsilon}_t \end{aligned} \tag{C.1}$$

and so on, where $\pi_t^e(k)$ denotes inflation expectations at the k^{th} step of the feedback loop. We visualize the steps of the feedback loop in the case of $N = 3$ and $n = 1$ in Figure 4.

Figure 4: Feedback Loop



Note: The subplots visualize the feedback loop in the case of three counties, when there is a one-time shock to the inflation expectations of county 1 only. Red ellipses denote counties that have been affected by ε_{1t}, whereas black ellipses are counties that have not been affected by ε_{1t}. Red arrows indicate the flow of effects through the social network.

Therefore, county-level expectations will converge to

$$\pi_t^e = \lim_{k\to\infty} \pi_t^e(k) = \begin{cases} (I - \beta\Omega)^{-1}\boldsymbol{\alpha} & \text{if } \rho(\beta\Omega) < 1 \\ \pm\infty & \text{otherwise} \end{cases} \tag{C.2}$$

where $\rho(\beta\Omega)$ denotes the largest eigenvalue of $\beta\Omega$ in absolute value. From the Gershgorin circle theorem, all the eigenvalues of Ω should lie within the unit circle, thus all eigenvalues of $\beta\Omega$ lie within $[-\beta, \beta]$.[16] Furthermore, one can show that 1 is always an eigenvalue of Ω, implying

[16]The Gershgorin circle theorem states that every eigenvalue of a matrix lies within at least a disc centered at a diagonal element with radius equal to the sum of the off-diagonal elements (in absolute value) in the row of the diagonal element. In our case, every diagonal element of Ω is equal to 0, and the sum of the off-diagonal elements in each row is equal to 1.

that $\rho(\beta\Omega) = \mid \beta \mid$.[17] As a result, a one-time county-specific shock to inflation expectations cannot de-stabilize inflation expectations in all the other counties if $\mid \beta \mid < 1$. By contrast, if $\mid \beta \mid \geq 1$, then inflation expectations grow exponentially with every step of the feedback loop, converging to $\pm\infty$.

D Proofs

D.1 Proof of Proposition 1

We need to find conditions for which the difference $\hat{r}_j(k) - r_j(k) > 0$. To simplify notation, let $\sum_i \omega_{ji} \sum_{e\in E^h_{i\to j}} S_j(e,k \mid \theta_{ji}) = \hat{a}^h_j$ for any $h \in \{k, K\backslash k, O\}$ and $\sum_i \omega_{ji} \sum_{e\in E_{i\to j}} S_j(e,k \mid \theta_{ji}) = \hat{a}_j = \hat{a}^k_j + \hat{a}^{K\backslash k}_j + \hat{a}^O_j$. Similarly, let $\sum_{e\in E^h_j} S_j(e,k) = a^h_j$ for any $h \in \{k, K\backslash k, O\}$ and $\sum_{e\in E_j} S_j(e,k) = a_j = a^k_j + a^{K\backslash k}_j + a^O_j$.

$$\begin{aligned}
\hat{r}_j(k) - r_j(k) &= \frac{\gamma_j \sum_{e\in E^k_j} S_j(e,k) + (1-\gamma_j)\sum_i \omega_{ji} \sum_{e\in E^k_{i\to j}} S_j(e,k \mid \theta_{ji})}{\gamma_j \sum_{u\in E_j} S_j(u,k) + (1-\gamma_j)\sum_i \omega_{ji} \sum_{u\in E_{i\to j}} S_j(u,k \mid \theta_{ji})} - \frac{\sum_{e\in E^k_j} S_j(e,k)}{\sum_{u\in E_j} S_j(u,k)} \\
&= \frac{(1-\gamma_j)\left[\hat{a}^k_j(a^k_j + a^{K\backslash k}_j + a^O_j) - a^k_j(\hat{a}^k_j + \hat{a}^{K\backslash k}_j + \hat{a}^O_j)\right]}{a_j(\gamma_j a_j + (1-\gamma_j)\hat{a}_j)} \\
&= \frac{(1-\gamma_j)\left[\hat{a}^k_j(a^{K\backslash k}_j + a^O_j) - a^k_j(\hat{a}^{K\backslash k}_j + \hat{a}^O_j)\right]}{a_j(\gamma_j a_j + (1-\gamma_j)\hat{a}_j)}
\end{aligned} \tag{D.1}$$

Hence, $\hat{r}_j(k) - r_j(k) > 0$ if the numerator is positive, that is, if

$$\hat{a}^k_j(a^{K\backslash k}_j + a^O_j) - a^k_j(\hat{a}^{K\backslash k}_j + \hat{a}^O_j) > 0 \iff \frac{\hat{a}^k_j}{a^k_j} > \frac{\hat{a}^{K\backslash k}_j + \hat{a}^O_j}{a^{K\backslash k}_j + a^O_j} \tag{D.2}$$

After replacing terms, the right-hand side inequality is identical to the one in (6).

D.2 Proof of Corollary 1

- If the social network only shares experiences that are similar with hypothesis k, then $\sum_i \omega_{ji} \sum_{e\in E^{K\backslash k}_{i\to j}} S_j(e,k \mid \theta_{ji}) = \sum_i \omega_{ji} \sum_{e\in E^O_{i\to j}} S_j(e,k \mid \theta_{ji}) = 0$, whereas $\sum_i \omega_{ji} \sum_{e\in E^k_{i\to j}} S_j(e,k \mid \theta_{ji}) \neq 0$. As a consequence, the condition in (6) always applies.
- If the social network only shares experiences that are not similar with hypothesis k, then

[17] To do so, all one has to show is that the determinant of $(\Omega - I)$ is 0. Note that

$$det(\Omega - I) = det\left(\begin{bmatrix} -1 & \omega_{12} & \dots & \omega_{1N} \\ \omega_{21} & -1 & \dots & \omega_{2N} \\ \dots & \dots & \dots & \dots \\ \omega_{N1} & \omega_{N2} & \dots & -1 \end{bmatrix}\right) = det\left(\begin{bmatrix} 0 & \omega_{12} & \dots & \omega_{1N} \\ 0 & 1 & \dots & \omega_{2N} \\ \dots & \dots & \dots & \dots \\ 0 & \omega_{N2} & \dots & 1 \end{bmatrix}\right) = 0$$

where the second equality follows from adding to the first column all the others.

$\sum_i \omega_{ji} \sum_{e \in E^k_{i \to j}} S_j(e,k \mid \theta_{ji}) = 0$, whereas $\sum_i \omega_{ji} \sum_{e \in E^{K\setminus k}_{i \to j}} S_j(e,k \mid \theta_{ji})$ and $\sum_i \omega_{ji} \sum_{e \in E^O_{i \to j}} S_j(e,k \mid \theta_{ji}) \neq 0$. As a consequence, the condition in (6) is always violated.

D.3 Proof of Proposition 2

To find out the effect of γ_j on the recall probability, we compute the first-order derivative of $\hat{r}_j(k)$ with respect to γ_j, while preserving the same notation as in the proof of Proposition D.1.

$$\begin{aligned}
\frac{\partial \hat{r}_j(k)}{\partial \gamma_j} &= \frac{(a^k_j - \hat{a}^k_j)(\gamma_j a_j + (1-\gamma_j)\hat{a}_j) - (a_j - \hat{a}_j)(\gamma_j a_j + (1-\gamma_j)\hat{a}_j)}{(\gamma_j a_j + (1-\gamma_j)\hat{a}_j)^2} \\
&= -\frac{\hat{a}^k_j(a^{K\setminus k}_j + a^O_j) - a^k_j(\hat{a}^{K\setminus k}_j + \hat{a}^O_j)}{(\gamma_j a_j + (1-\gamma_j)\hat{a}_j)^2} \\
&= \begin{cases} (+) & \text{if relative relevance} < \text{relative irrelevance} \\ \\ (-) & \text{if relative relevance} > \text{relative irrelevance} \end{cases}
\end{aligned} \tag{D.3}$$

As the attention that individual j allocates to the experiences shared by her social network increases, that is, as γ_j declines, the recall probability of events related to hypothesis k is amplified if it is already higher than the recall probability of events related to hypothesis k under no social interaction.

D.4 Proof of Proposition 3

To see the effect that a change in one of the weights, we re-write the condition in (6) as a difference, that is, $\Delta_j(k) =$ relative relevance $-$ relative irrelevance. We assume that weight assigned to experiences shared by individual l, ω_{lj}, changes, and given that $\sum_{i \neq j} \omega_{ji} = 1$, at least one other weight has to change in the opposite direction for the constraint to hold. For simplicity and without loss of generality, we assume that the weight assigned to experiences shared by individual q, ω_{qj}, changes.[18]

We then take the first-order derivative of $\Delta_j(k)$ with respect to ω_{lj}:

$$\frac{\partial \Delta_j(k)}{\partial \omega_{ji}} = \frac{\sum_{e \in E^k_{l \to j}} S_j(e,k \mid \theta_{ji}) - \sum_{e \in E^k_{q \to j}} S_j(e,k \mid \theta_{ji})}{\sum_{e \in E^k_j} S_j(e,k)} - \frac{\sum_{e \in E^{K\setminus k}_{l \to j}} S_j(e,k \mid \theta_{ji}) + \sum_{e \in E^O_{l \to j}} S_j(e,k \mid \theta_{ji}) - \sum_{e \in E^{K\setminus k}_{q \to j}} - \sum_{e \in E^O_{q \to j}} S_j(e,k \mid \theta_{ji})}{\sum_{e \in E^{K\setminus k}_j} S_j(e,k) + \sum_{e \in E^O_j} S_j(e,k)} \tag{D.4}$$

[18] The main takeaway of Proposition 3 would not change if we assumed that other weights changed as well in response to the change in ω_{lj}.

Then, $\frac{\partial \Delta_j(k)}{\partial \omega_{ji}} > 0$ if

$$\frac{\sum_{e \in E^k_{l \to j}} S_j(e,k \mid \theta_{ji}) - \sum_{e \in E^k_{q \to j}} S_j(e,k \mid \theta_{ji})}{\sum_{e \in E^k_j} S_j(e,k)} > \frac{\sum_{e \in E^{K \setminus k}_{l \to j}} S_j(e,k \mid \theta_{ji}) + \sum_{e \in E^O_{l \to j}} S_j(e,k \mid \theta_{ji}) - \sum_{e \in E^{K \setminus k}_{q \to j}} - \sum_{e \in E^O_{q \to j}} S_j(e,k \mid \theta_{ji})}{\sum_{e \in E^{K \setminus k}_j} S_j(e,k) + \sum_{e \in E^O_j} S_j(e,k)}$$

D.5 Proof of Proposition 4

Recall that $\hat{r}_2(k) = f(\hat{r}_1(k)) = \max\left[0, \frac{a_2 \hat{r}_1(k) + b_2}{c_2 \hat{r}_1(k) + d_2}\right]$ and $\hat{r}_1(k) = \max\left[\frac{a_1 \hat{r}_2(k) + b_1}{c_1 \hat{r}_2(k) + d_1}\right]$. From the latter, we can isolate $\hat{r}_2(k)$ and write it as a function of $\hat{r}_1(k)$, that is, $\hat{r}_2(k) = g(\hat{r}_1(k)) = \frac{-d_1 \hat{r}_1(k) + b_1}{c_1 \hat{r}_1(k) - a_1}$. The goal is then to figure out whether $f(\hat{r}_1(k))$ is higher/lower than $g(\hat{r}_1(k))$ for $\hat{r}_1(k) > \hat{r}_1(k)^{**}, \hat{r}_2(k) > \hat{r}_2(k)^{**}$ and $\hat{r}_1(k) < \hat{r}_1(k)^{**}, \hat{r}_2(k) < \hat{r}_2(k)^{**}$. We consider the two cases: i) $\gamma_1 + \gamma_2 < 1$ and ii) $\gamma_1 + \gamma_2 < 1$.

i) $\boldsymbol{\gamma_1 + \gamma_2 < 1}$. Given the assumption in Appendix A, one can show that $g(\hat{r}_1(k))$ is a convex function, intersecting the y-axis at $-b_1/a_1 > 0$. As shown in Appendix A, $f(\hat{r}_1(k))$ is a concave function intersecting the x-axis at $-b_2/a_2 > 0$, and $f(.)$ and $g(.)$ meet each other at $\hat{r}_1(k) = \hat{r}_2(k) = 1$ and $(\hat{r}_1(k), \hat{r}_2(k)) = (\hat{r}_1(k)^{**}, \hat{r}_2(k)^{**})$, where $-b_2/a_2 < \hat{r}_1(k)^{**} < 1$ and $-b_1/a_1 < \hat{r}_2(k)^{**} < 1$. As a result, it must be that $f \gtreqless g$ for any $\hat{r}_1(k) \gtreqless \hat{r}_1(k)^{**}$, $\hat{r}_2 \gtreqless \hat{r}_2(k)^{**}$. This implies that any perturbation to $\hat{r}_1(k)^{**}$, however small, will trigger larger and larger deviations of recall probabilities from the equilibrium (see Figure 2, panel (b) for visualization).

ii) $\boldsymbol{\gamma_1 + \gamma_2 > 1}$. Given the assumptions in Appendix A, one can show that $g(\hat{r}_1(k))$ is a concave function, intersecting the x-axis at $b_1/d_1 > 0$. As shown in Appendix A, $f(\hat{r}_1(k))$ is convex intersecting the y-axis at $b_2/d_2 > 0$, and $f(.)$ and $g(.)$ meet each other at $\hat{r}_1(k) = \hat{r}_2(k) = 1$ and $(\hat{r}_1(k), \hat{r}_2(k)) = (\hat{r}_1^{**}, \hat{r}_2^{**})$, where $b_1/d_1 < \hat{r}_1^{**} < 1$ and $b_2/d_2 < \hat{r}_2^{**}(k) < 1$. As a result, it must be that $g \gtreqless f$ for any $\hat{r}_1(k) \gtreqless \hat{r}_1(k)^{**}$, $\hat{r}_2 \gtreqless \hat{r}_2(k)^{**}$. This implies that any perturbation to $\hat{r}_1(k)^{**}$ will force recall probabilities back to the equilibrium (see Figure 2, panel (a) for visualization).

D.6 Proof of Proposition 5

The mean of the perceived probability of high inflation is given by

$$\mathbb{E}\left(p_j(H)\right) = \mathbb{E}\left(\frac{R_j(H)}{R_j(H) + R_j(L)}\right)$$

By the Central Limit Theorem, we have that

$$z_j^H = \frac{R_j(H) - T_j r_j(H)}{\sqrt{T_j}} \sim N(0, r_j(H)(1 - r_j(H))$$

Therefore,

$$\frac{R_j(H)}{R_j(H)+R_j(L)} = \frac{z_j^H/\sqrt{T_j}+r_j(H)}{z_j^H/\sqrt{T_j}+r_j(H)+z_j^L/\sqrt{T_j}+r_j(L)}$$

and

$$\lim_{T_j\to\infty}\frac{R_j(H)}{R_j(H)+R_j(L)} = \lim_{T_j\to\infty} p_j(H) = \frac{r_j(H)}{r_j(H)+r_j(L)}$$

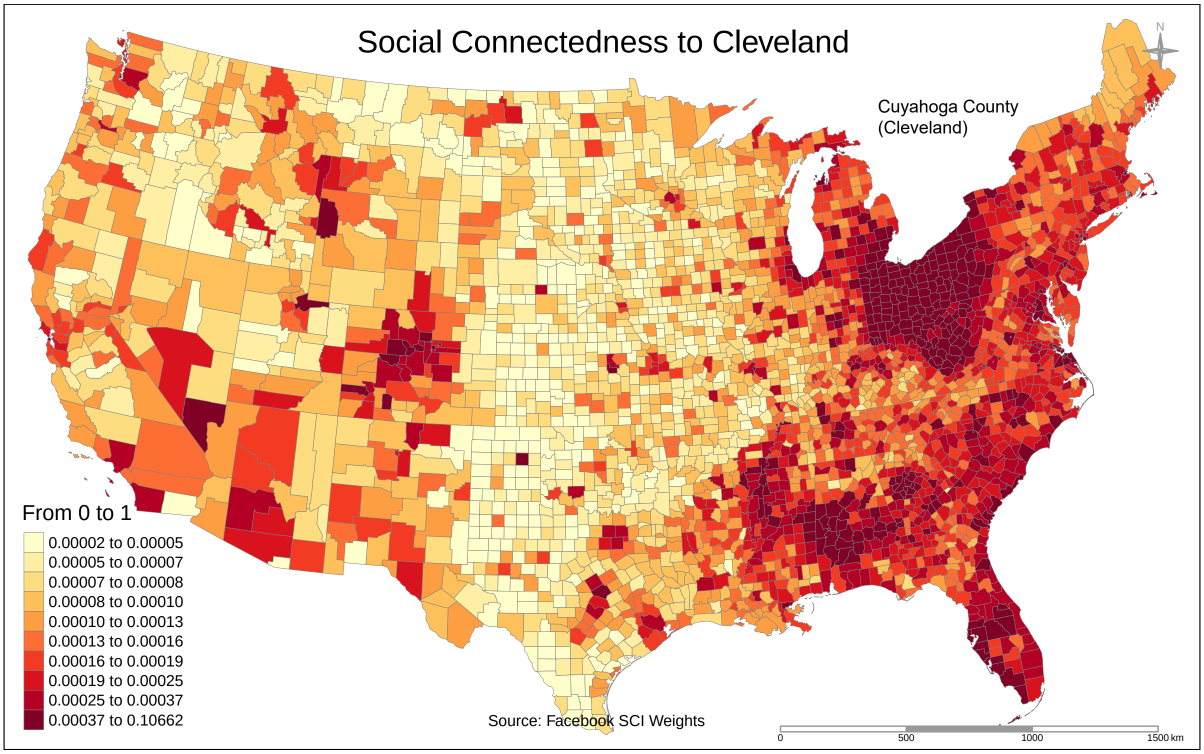
Similarly, when there is social interaction, the probability of hypothesis H converges to $\frac{\hat{r}_j(H)}{\hat{r}_j(H)+\hat{r}_j(L)}$. Therefore, if social interaction amplifies the recall probability of the high inflation regime, that is, if $\hat{r}_j(H) > r_j(H)$, then social connectedness will increase the perceived probability that regime H will realize.

E Additional Figures

E.1 Social Connectedness: other examples

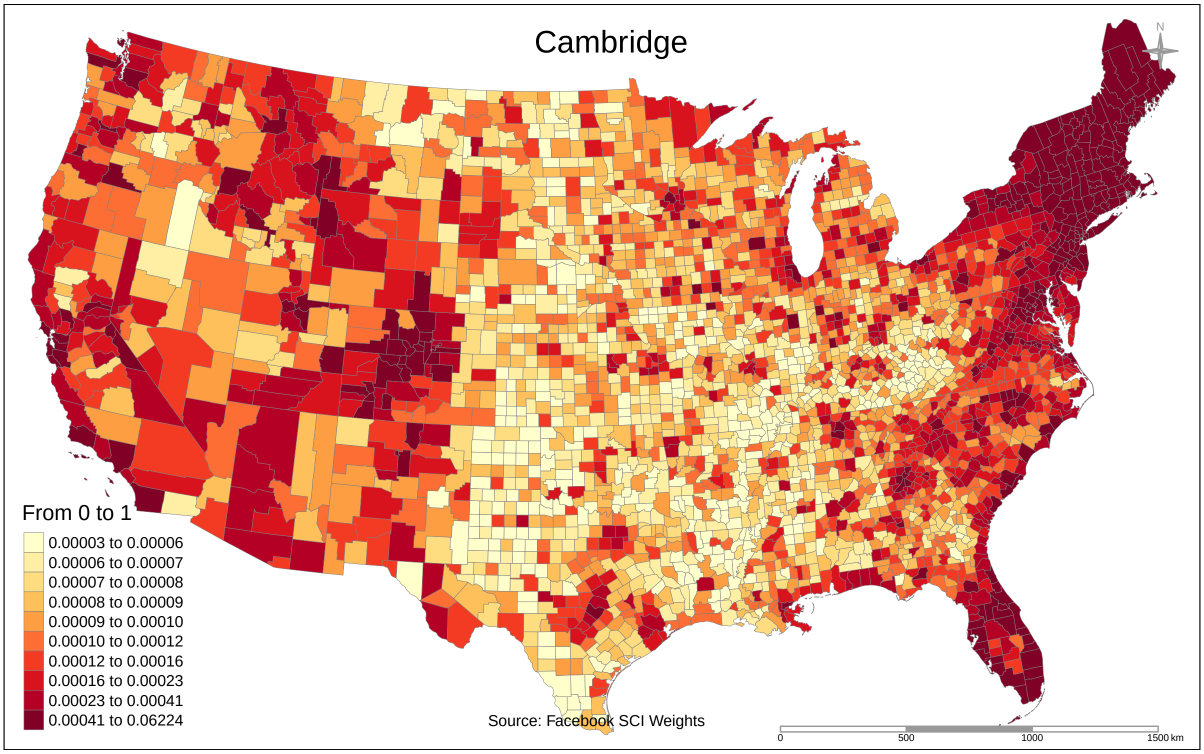
In the body of the text, we presented the connections of counties to Cleveland. Here, we provide the social Connectedness to Cleveland and three other illustrative examples: Cambridge, Miami, and Los Angeles. We observe similar patterns.

Figure 5: Social connectedness of each county to Cleveland ($\omega_{c,Cleveland}$)



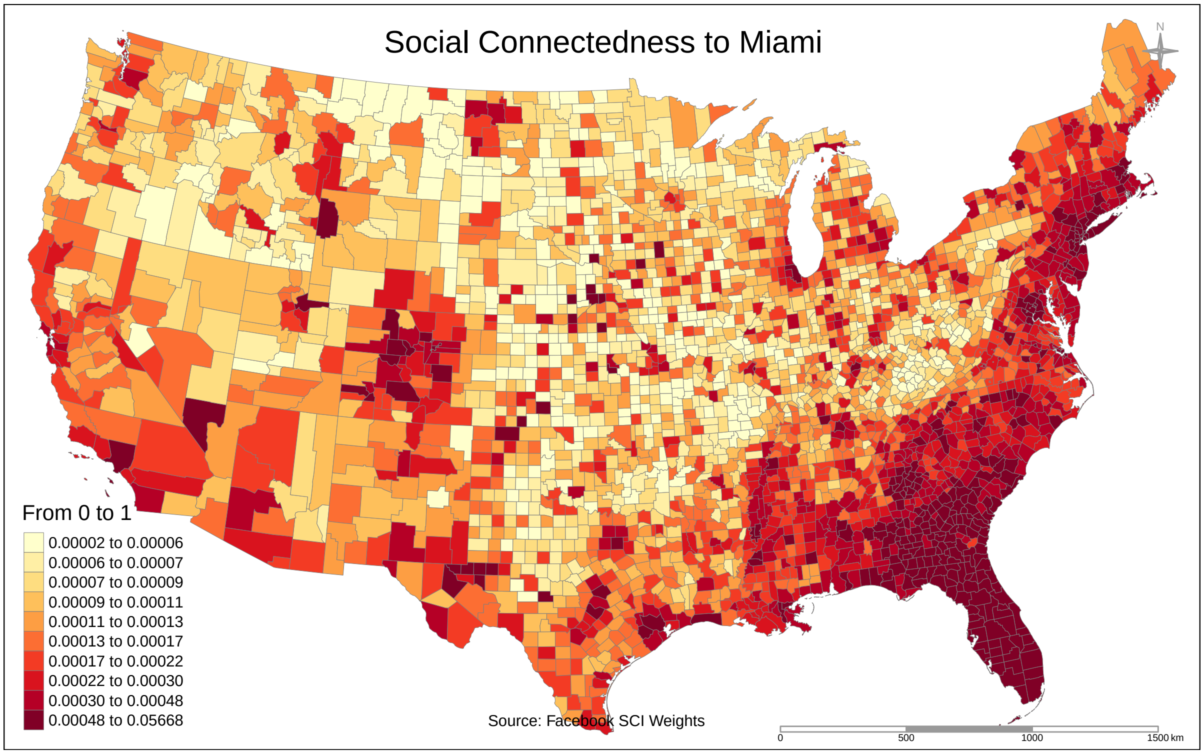
Note: The yellow-to-red color scale represents the degree to which counties are socially connected to Cleveland, based on $\omega_{c,Cleveland}$. Red indicates higher $\omega_{c,Cleveland}$. Source: Social Connectedness Index

Figure 6: Social connectedness of each county to Cambridge ($\omega_{c,Cambridge}$)



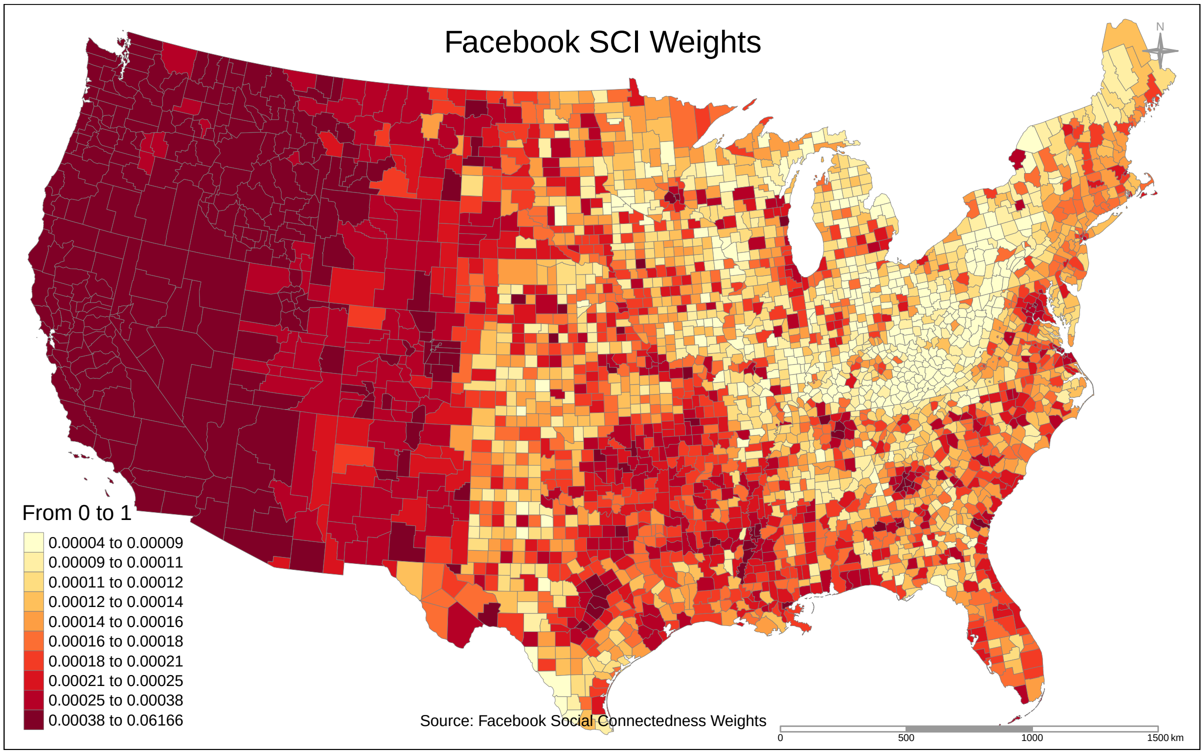
Note: The yellow-to-red color scale represents the degree to which counties are socially connected to Cambridge, based on $\omega_{c,Cambridge}$. Red indicates higher $\omega_{c,Cambridge}$. Source: Social Connectedness Index

Figure 7: Social connectedness of each county to Miami ($\omega_{c,Miami}$)



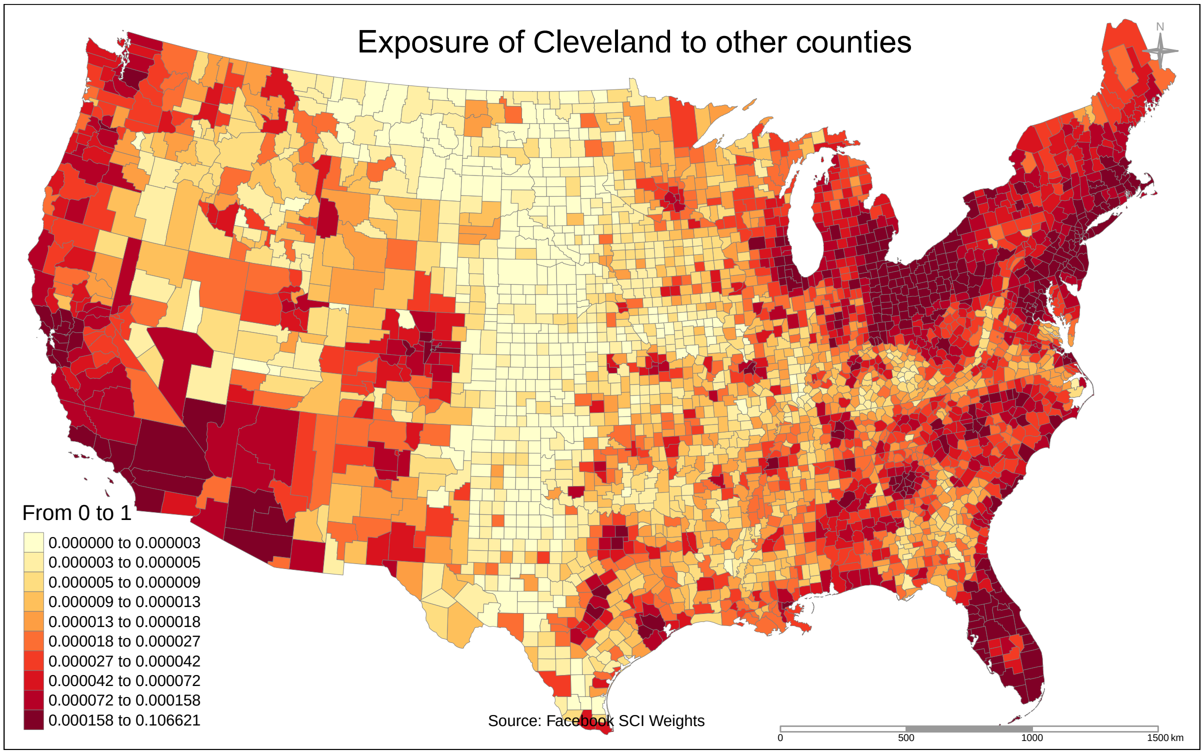
Note: The yellow-to-red color scale represents the degree to which counties are socially connected to Miami, based on $\omega_{c,Miami}$. Red indicates higher $\omega_{c,Miami}$. Source: Social Connectedness Index

Figure 8: Social connectedness of each county to Los Angeles ($\omega_{c,LA}$)



Note: The yellow-to-red color scale represents the degree to which counties are socially connected to Los Angeles, based on $\omega_{c,LA}$. Red indicates higher $\omega_{c,LA}$. Source: Social Connectedness Index

Figure 9: Social connectedness Cleveland to each of each county ($\omega_{Cleveland,k}$)



Note: The yellow-to-red color scale represents the degree to which Cleveland is socially connected to other counties, based on $\omega_{Cleveland,k}$. Red indicates higher $\omega_{Cleveland,k}$. Source: Social Connectedness Index

F Other Tables

	(1)	(2)	(3)	(4)	(5)	(6)
$Network - Politics$	0.284***	0.215***	0.277***	0.163***	0.168***	0.258***
	(0.019)	(0.040)	(0.038)	(0.033)	(0.035)	(0.053)
$Inf - County$	0.635***	0.622***	0.569***	0.552***	0.512***	0.340***
	(0.028)	(0.033)	(0.030)	(0.031)	(0.025)	(0.042)
County FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes	Yes
State-Time FE	No	No	No	No	Yes	No
County-Time FE	No	No	No	No	No	Yes
Observations	1,600,553	1,600,553	1,600,553	1,600,553	1,600,553	1,600,553
R-squared	0.022	0.022	0.023	0.023	0.023	0.025

	(1)	(2)	(3)	(4)	(5)	(6)
$Network - Income$	0.216***	0.165***	0.213***	0.146***	0.159***	0.244***
	(0.034)	(0.031)	(0.051)	(0.037)	(0.040)	(0.071)
$Inf - Income$	0.671***	0.656***	0.615***	0.595***	0.557***	0.393***
	(0.032)	(0.034)	(0.036)	(0.034)	(0.028)	(0.054)
County FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes	Yes
State-Time FE	No	No	No	No	Yes	No
County-Time FE	No	No	No	No	No	Yes
Observations	1,603,436	1,603,436	1,603,436	1,603,436	1,603,436	1,603,436
R-squared	0.024	0.024	0.024	0.025	0.025	0.027

	(1)	(2)	(3)	(4)	(5)	(6)
$Network - age$	0.297***	0.290***	0.301***	0.299***	0.419***	0.299***
	(0.019)	(0.029)	(0.032)	(0.031)	(0.044)	(0.031)
$Inf - age$	0.632***	0.624***	0.583***	0.576***	0.442***	0.576***
	(0.035)	(0.035)	(0.039)	(0.036)	(0.044)	(0.036)
County FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes	Yes
State-Time FE	No	No	No	No	Yes	No
County-Time FE	No	No	No	No	No	Yes
Observations	1,589,828	1,589,828	1,589,828	1,589,828	1,589,828	1,589,828
R-squared	0.030	0.030	0.031	0.031	0.033	0.031