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 variable approach further establishes causality of these results while also showing that salient information transmits strongly through the network. Our estimates imply that the influence of the social network overall amplifies but does not destabilize inflation expectations.

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1 Introduction

Inflation expectations have been 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]

However, while these modeling frameworks of *individual* belief formation have been inspired by insights from psychology, they largely remain silent about a central insight from *social* psychology that goes back to the original work of Festinger (1954): The formation of beliefs takes place in a social context, when we interact with others. This paper aims to contribute to the current literature by showing – through the lens of inflation expectations – that social networks can play a complementary, important role in the process of belief formation. 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. He also 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.

We then 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 consumers across counties in the US with information on a county's social network connections with other counties (see, e.g., Bailey et al. (2018a)). Exploit-

[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 also been studied in Dow (1991), Mullainathan (2002), and Gennaioli and Shleifer (2010), among others.

ing cross-sectional and time variation while taking into account 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 that we can interpret this finding to be causal as well as immune to the endogeneity concerns embodied by the reflection problem (Manski (1993)). Moreover, using data on demographic characteristics, we find that 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 hypotheses matter 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 framework. 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. The 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. Individuals further divide attention allocated to the network among the experiences shared by the various members in the network. Finally, we allow for an individual's similarity function between hypothesis k and experiences shared by a member of her social network to depend on the number of their common demographic characteristics.

[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.

The model analysis yields three predictions for the formation of inflation expectations in the 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. 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 the merger of a uniquely dense survey of inflation expectations for nearly 2 million consumers across counties in the US with data on the social networks across counties based on Facebook friendships between counties. Bailey et al. (2018a, 2019) in work on house prices describe in detail the properties of the Facebook data, demonstrating its ability to capture the impact of social networks on economic decision-making in the housing market and the link to housing market beliefs. In the domain of inflation expectations, making a connection between beliefs and social networks has so far not been possible because conventional datasets of inflation expectations are not dense enough for such an analysis. The merger of the Facebook data with our inflation expectations data overcomes this challenge, allowing 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, and the inflation expectations of individuals in other counties. Moreover, we have inflation expectations at a monthly frequency, allowing us to measure the influence of others at a high frequency.

We use these data to, first, 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 by Bailey et al. (2020). Given these weights, we compute network-weighted inflation expectations of expectations based on all respondents in the other counties, as well as for sets of individuals with similar demographics only (based on gender, age, 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 the experiences of individuals in geographically distant, but socially connected counties, matter for the formation of inflation expectations. First, we find a positive and statistically significant effect of the county-specific weighted average inflation expectations of the connected counties. This effect remains constant after controlling for the inflation expectations of others in the county, a time fixed effect and after excluding the closest values. While the coefficient found might be biased, we show that these results are evidence that the social interaction matters for the expectation formation process. We then work to get an unbiased coefficient.

Second, we explore the role of similar experiences. We split the network by common demographic characteristics and find that consumers are more influenced by people that share the same characteristics, such as gender, age, income, or political affiliation. This exercise allows us to control for county-time fixed effects, controlling for any common county-specific shock coming from inside or from other non-social networks.

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 the reflection problem (Manski (1993)), which, as we prove, remains present even after accounting for time fixed effects.[5] Therefore, we develop an instrumental variable approach to obtain an unbiased estimate. 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. In addition, we explore difference by gender. We confirm D'Acunto et al. (2021a) results, which find that males' inflation expectations are more influenced

[5]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 the relevance of social networks for inflation expectations. Our reduced-form OLS results show the 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.

by gas prices, conditional on the use of gas. Then, by showing that a network-weighted measure of these exogenous, county-demographic-specific time-varying 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 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?[6] 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 that show that our empirical findings still indicate stability. Importantly, this conclusion holds for the results based on the instrumental variables approach, which yields an even higher coefficient estimate. Variation coming from salient prices, which individuals discuss more, can exacerbate inflation expectations significantly. These findings indicate that policymakers might want to identify those informational shocks that transmit strongly through the network to control unstable movements in inflation expectations.

At the same time, these results – by virtue of the variation contained in the instrument – provide an insight into the nature of experiences communicated through the social network in the context of inflation expectations. The fact that price experiences in other counties for a salient good, gasoline, when transmitted through the social network generate an amplifying effect on inflation expectations suggests that, as in Bordalo et al. (2023), the social memory database that is activated must comprise experiences that are overall salient and relevant to inflation expectations. This interpretation aligns with the positive coefficients from the OLS estimation and the higher coefficient from the instrumental variables estimations. Ideally, one would like to analyze the precise experiences communicated through the social network, for example, by looking at the

[6] 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.

messages exchanged. However, this task is beyond the scope of this paper and its data.

The findings from our analysis are related to several literatures in economics. One strand of the literature comprises recent work in macroeconomics focused on the transmission of shocks through networks, such as input-output linkages (see, for example, Baqaee and Farhi (2018), Rubbo (2020), Pasten et al. (2020)). In line with the main question of this macroeconomic literature, our findings imply that micro-economic shocks can transmit through the *social* network, via inflation expectations, and have aggregate implications. Extending the network literature to the context of inflation expectations raises many important and interesting questions related to, for example, the existence of multiple equilibria, the role of super-nodes, and the transmission of shocks from different regions and of different sizes (Gabaix (2011)). Further work may lead to additional insights with relevant implications for policymakers that aim to keep inflation expectations anchored.

Our analysis is also related to a large behavioral literature in which many studies have shown how *individual* characteristics and experiences affect the process of expectations formation (for example, Malmendier and Nagel (2016), D'Acunto et al. (2021b), Kuchler and Zafar (2019), Hajdini et al. (2022a)). The findings in these papers are related to a theoretical literature that argues that individuals use 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), and L'Huillier et al. (2021)), as well as through the idea of memory in the expectations formation process (da Silveira and Woodford (2019), Bordalo et al. (2023)). Relative to this literature, our paper emphasizes theoretically and empirically the role of *social* interaction for further disciplining the formation of expectations.

Our analysis is also related to a growing literature that empirically studies the effects of social interactions on economic decision-making. For example, in the context of housing, Bailey et al. (2018b) find that individuals whose geographically distant friends experienced larger house price increases are more likely to transition from renting to owning. Using a survey for individuals in Los Angeles, Bailey et al. (2019) also show that the social network can affect house price expectations. Likewise emphasizing the role of social networks, Burnside et al. (2016) use "social dynamics" to explain how there can be booms and busts in the housing market. Housing is an important but also atypical, durable good that is purchased at most a few times during one's lifetime, and by contrast, our analysis focuses on the entire consumption basket in the economy. Its broader scope makes expectations about the future price of consumption a central macroeconomic variable not least in the monetary policy context, especially in times of high inflation. The formal framework of inflation expectations formation in the context of social networks that we provide and validate may moreover help policymakers in understanding and exploiting these mechanisms for the benefit of macroeconomic stabilization goals and the optimal design of central bank communication.

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. Section 4 presents the main empirical results. Section 5 applies an instrumental variable strategy to the empirical analysis and discusses the stability of inflation beliefs in the context of social networks. Finally, Section 6 concludes.

2 Theoretical Framework

This section extends the memory and recall model of Bordalo et al. (2022) and Bordalo et al. (2023) to incorporate the feature of social interaction. It starts 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 assess 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, $S_j(u_j, v_j) : E_j \times E_j \to \begin{bmatrix} 0 & \bar{S}_j \end{bmatrix}$, 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.[7]

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 presented 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 E_j^O 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 who j interact with. We denote the set of experiences that individual i shares with individual j by $E_{i \to j}$ (without putting any restrictions on the flow of information in the reverse direction). Experiences shared by individual i are categorized into three mutually exclusive subsets: high inflation experiences, $E_{i \to j}^H$, low inflation experiences, $E_{i \to j}^L$, and experiences irrelevant to high or low inflation, $E_{i \to j}^O$.

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

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

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 the 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. (2021b), 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 $\omega(\theta_{ji}) \in [0,1]$ to experiences shared by individual i that is increasing on the share of common demographic factors between individual j and i, and that is such that $\sum_i \omega(\theta_{ji}) = 1$.

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:

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

where $\sum_{e\in E_j} S_j(e,k) = \sum_{e\in E_j^H} S_j(e,k) + \sum_{e\in E_j^L} S_j(e,k) + \sum_{e\in E_j^O} S_j(e,k)$ and $\sum_{e\in E_{i\to j}} S_j(e,k \mid \theta_{ji}) = \sum_{e\in E_{i\to j}^H} S_j(e,k \mid \theta_{ji}) + \sum_{e\in E_{i\to j}^L} S_j(e,k \mid \theta_{ji}) + \sum_{e\in E_{i\to j}^O} S_j(e,k \mid \theta_{ji})$.

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,

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

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 effect 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:*

$$\underbrace{\frac{\sum_i \omega(\theta_{ji}) \sum_{e \in E^k_{i \to j}} S_j(e,k \mid \theta_{ji})}{\sum_{e \in E^k_j} S_j(e,k)}}_{\textit{relative relevance}} > \underbrace{\frac{\sum_i \omega(\theta_{ji}) \left(\sum_{u \in E^{K \setminus k}_{i \to j}} S_j(u,k \mid \theta_{ji}) + \sum_{u \in E^O_{i \to j}} S_j(u,k \mid \theta_{ji}) \right)}{\sum_{u \in E^{K \setminus k}_j} S_j(u,k) + \sum_{u \in E^k_j} S_j(u,k)}}_{\textit{relative irrelevance}} \tag{6}$$

Proof. See Appendix E.1. □

We call the term on the left-hand side of inequality (6) *relative relevance* and the term on 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 related to hypothesis k; and second, when any individual i shares with individual j only experiences not related 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 only related to hypothesis k. Then, social interaction amplifies individual j's recall probability of k.*

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

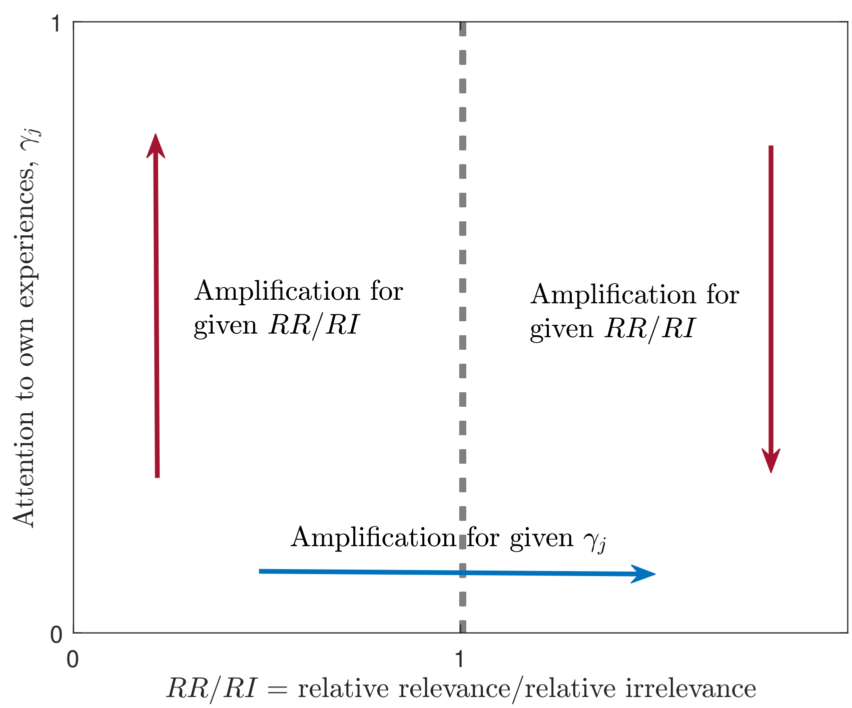
Proof. See Appendix E.2. □

Proposition 2 shows the implications that a change in attention to shared experiences has for 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 E.3. □

Figure 1: Visual Summary of the Main Theoretical Results



Note: Summary of the direction of amplification for the recall probability related to hypothesis k, for any $\gamma_j \in [0,1)$ and RR/RI. 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. Dashed gray line: relative relevance = relative irrelevance.

Figure 1 visually summarizes the main theoretical results of Propositions 1 and 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.

Next, we are interested to understand the effects that similar and likewise demographic social networks have for individual inflation expectations. Without loss of generality, we set $\theta_{ji} \in \{0,1\}$ and decompose the recall probability into three components as follows.

$$\hat{r}_j(k) = \underbrace{\frac{\mathbf{S}_j^k}{\mathbf{S}_j + \mathbf{S}_{\theta_{j.}=1} + \mathbf{S}_{\theta_{j.}=0}}}_{\text{individual}} + \underbrace{\frac{\mathbf{S}_{\theta_{j.}=1}^k}{\mathbf{S}_j + \mathbf{S}_{\theta_{j.}=1} + \mathbf{S}_{\theta_{j.}=0}}}_{\text{similar demographics network}} + \underbrace{\frac{\mathbf{S}_{\theta_{j.}=0}^k}{\mathbf{S}_j + \mathbf{S}_{\theta_{j.}=1} + \mathbf{S}_{\theta_{j.}=0}}}_{\text{dissimilar demographics network}} \tag{7}$$

where $\mathbf{S}_j^k = \gamma_j \sum_{e \in E_j^k} S_j(e,k)$; $\mathbf{S}_j = \gamma_j \sum_{e \in E_j} S_j(e,k)$; $\mathbf{S}_{\theta_{j.}}^k = (1-\gamma_j) \sum_i \omega(\theta_{ji}) \sum_{e \in E_{i \to j}^k} S_j(e,k \mid \theta_{ji})$; and $\mathbf{S}_{\theta_{j.}} = (1-\gamma_j) \sum_i \omega(\theta_{ji}) \sum_{e \in E_{i \to j}} S_j(e,k \mid \theta_{ji})$.

Suppose that an additional member i with $\theta_{ji} = 0$ enters the network of j and contributes with experiences belonging to $E_{i \to j}^k$, $E_{i \to j}^{Kk}$,and $E_{i \to j}^O$. If j pays no attention at all to experiences shared by individuals with dissimilar demographics, then individual i has no marginal effect on $\hat{r}_j(k)$. On the other hand, if $\omega(\theta_{ji}) > 0$, it is straightforward from (7) that this network extension interferes with the individual and similar demographics network memory databases through an increase in $\mathbf{S}_{\theta_{j.}=0}$. However, its effect on the dissimilar demographics network memory is ambiguous. On net, an additional network member can increase the recall probability of hypothesis k if it contributes with sufficiently more similarity than interference with hypothesis k.

Proposition 3 formalizes these results.

Proposition 3. *Without loss of generality, let $\theta_{ji} \in \{0,1\}$. Then, given that ω is a strictly increasing function in θ_{ji}, the following two results apply:*

1. *If $\omega_{\theta_{ji}=0} = 0$, then the effect of dissimilar demographic groups (social networks that satisfy $\theta_{ji} = 0$) on the recall probability of j is 0.*

2. *If $\omega_{\theta_{ji}} > 0$ for any θ_{ji}, then the effect of specific demographic groups on the recall probability is positive (negative, respectively) if they add sufficiently more similarity than interference with hypothesis k.*

Proof. See Appendix A.1. □

Importantly, Proposition 3 opens up the possibility of opposite sign effects of social networks with common versus dissimilar demographics on the recall probability due to behavioral interpretation of ... [8]

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 in 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_j^k with hypothesis k, for any $j \in \{1,2\}$:

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

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 $E_j^{K\setminus k}$ and E_j^O 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

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

[8] In Appendix , we

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

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

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 a 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 a 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 equilibrium 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 toward either $\hat{r}_1(k) = \hat{r}_2(k) = 0$ or $\hat{r}_1(k) = \hat{r}_2(k) = 1$.*

Proof. See Appendix E.5. □

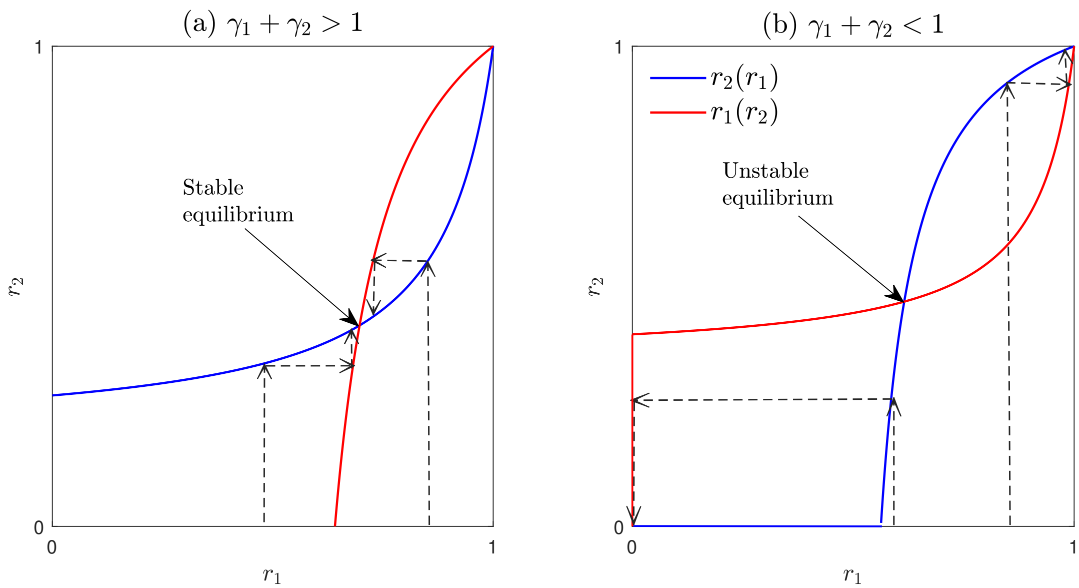
Proposition 4 shows that if the aggregate attention paid to the social network exceeds the aggregate attention to own experiences, then an incremental positive shock to the recall probability

[10] See Appendix A.3 for details.

[11] As shown in Appendix A.3 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.

of one person will push $\hat{r}_1(k)$ and $\hat{r}_2(k)$ toward 1, whereas a small negative shock to an individual recall probability will converge $\hat{r}_1(k)$ and $\hat{r}_2(k)$ toward 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 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 2 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 2. *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 the inflation levels associated with each regime are common knowledge. However, distinct experiences and, as a result, distinct probabilities of recall lead to heterogeneous 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

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

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 E.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 $\hat{r}_1(H)$ toward 0 or 1, with expectations converging toward $\mathbb{E}_1\pi = \mathbb{E}_2\pi \in \{\bar{\pi}^L, \bar{\pi}^H\}$. 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 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 $r_j^{**}(H)$.

To see this, consider the simple network of only two individuals we analyzed in Section 2.3. First, let's positively perturbate the recall probability of hypothesis H for individual j *only* around the stable equilibrium, where $\frac{\partial \hat{r}_i(H)}{\partial \hat{r}_j(H)} < 1$, in the case when $\gamma_1 + \gamma_2 > 1$, as shown in panel (a) of Figure 2. The perceived probability $p_j(H)$ will also increase, putting upward pressure on the expected inflation of individual j. Since the two individuals are connected through the network, the increase in $\hat{r}_j(H)$ will induce an increase in $\hat{r}_i(H)$, which in turn increases the perceived probability of individual i for regime H. The response of inflation expectations of individual i given the change in the expectations of individual j is given by[12]

[12]The derivation is described here:

$$\frac{\partial \mathbb{E}_2\pi}{\partial \mathbb{E}_1\pi} = \frac{\partial \mathbb{E}_2\pi}{\partial p_1(H)} \frac{\partial p_2(H)}{\partial \hat{r}_2(H)} \frac{\partial \hat{r}_2(H)}{\partial \hat{r}_1(H)} \frac{\partial \hat{r}_1(H)}{\partial \mathbb{E}_1\pi}$$

$$\frac{\partial \mathbb{E}_i \pi}{\partial \mathbb{E}_j \pi} = \widetilde{\beta}_i = \frac{\partial p_i(H)}{\partial p_j(H)} \in (0,1) \tag{13}$$

where $\frac{\partial p_i(H)}{\partial p_j(H)} \in (0,1)$ follows from the fact that $\frac{\partial \hat{r}_i(H)}{\partial \hat{r}_j(H)} \in (0,1)$. Clearly, in this case, a small perturbation to the inflation expectations of individual j cannot destabilize inflation expectations away from the equilibrium because the response to the expectations of others is always less than 1.

Now, consider the case when $\gamma_1 + \gamma_2 < 1$ as shown in panel (b) of Figure 2. Let's positively perturbate the recall probability of hypothesis H for individual j *only*, around the unstable equilibrium, where $\frac{\partial \hat{r}_i(H)}{\partial \hat{r}_j(H)} > 1$. The perceived probability $p_j(H)$ will increase, leading to upward pressure on the expected inflation of individual j. The increase in $\hat{r}_j(H)$ will induce a higher increase in $\hat{r}_i(H)$, which in turn increases the perceived probability of individual i for regime H. Then, the response of inflation expectations of individual i is given by

$$\frac{\partial \mathbb{E}_i \pi}{\partial \mathbb{E}_j \pi} = \widetilde{\beta}_i = \frac{\partial p_i(H)}{\partial p_j(H)} > 1 \tag{14}$$

where $\frac{\partial p_i(H)}{\partial p_j(H)} > 1$ stems from the fact that $\frac{\partial \hat{r}_i(H)}{\partial \hat{r}_j(H)} > 1$. Contrary to the case with $\gamma_1 + \gamma_2 > 1$, now a small perturbation to the inflation expectations of individual j destabilizes inflation expectations away from the equilibrium because the response to the expectations of others is always higher than 1. We return to this discussion at the end of the empirical analysis in Section 5.1.

Finally, we summarize our 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 the similarity between shared experiences and the event of high inflation.
3. Idiosyncratic shocks can destabilize inflation expectations if aggregate attention to the experiences of the social network exceeds aggregate attention to personal experiences.

Our theoretical framework provides additional implications: First, social interaction increases

where $\frac{\partial \mathbb{E}_2 \pi}{\partial p_1(H)} = (\bar{\pi}^H - \bar{\pi}^L)$ and $\frac{\partial \mathbb{E}_1 \pi}{\partial \hat{r}_1(H)} = \frac{\partial \mathbb{E}_1 \pi}{\partial p_1(H)} \frac{\partial p_1(H)}{\partial \hat{r}_1(H)} = (\bar{\pi}^H - \bar{\pi}^L) \frac{\partial p_1(H)}{\partial \hat{r}_1(H)}$. Substituting for these two expressions, we have that $\frac{\partial \mathbb{E}_2 \pi}{\partial \mathbb{E}_1 \pi} = \frac{\partial p_i(H)}{\partial p_j(H)}$.

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

At the heart of the empirical analysis of the relationship between inflation expectations and the social network lies a novel dataset. This dataset combines dense survey data on inflation expectations of US consumers with a map of their social network, based on Facebook connections.

Data on consumer inflation expectations come from the Indirect Consumer Inflation Expectations (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 and precise information on the geographic location and demographic characteristics of each consumer. Of note, the ICIE survey uses an approach to measuring inflation expectations that differs from the conventional approach (see Hajdini et al. (2022c) and Hajdini et al. (2022a)). Instead of asking directly for aggregate inflation expectations, it takes an indirect utility approach and elicits the change in expected 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 good properties in terms of how it measures consumers' expectations and how it relates to other common measures. The measure elicits expectations of changes in individual prices instead of aggregate prices; so the social network would not influence an aggregate variable, but rather on the price changes that individuals expect to experience.

The granularity of our analysis requires a large enough sample size of respondents at the county level – our geographical unit of analysis – to obtain statistical significance. Without loss of generality, this requirement leads us to use a monthly frequency as the time unit. The main variables of interest that 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 the expectations of some of these groups behave in the time series. To remove outliers, we drop the top and bottom 5 percent of responses at each point in time. We use data from February 2021 to July 2023.

Data on social connections at the county level come from the Social Connectedness Index Database (SCI). The 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, based on Facebook friendship connections. Specifically, the SCI measures the relative probability that two representative individuals across two US counties are friends with each other on Facebook. That is,

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

where FB $\text{Connections}_{i,j}$ 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 location j. Intuitively, if $SCI_{i,j}$ is twice as large as $SCI_{i,l}$, a given Facebook user in location i is about twice as likely to be connected with a given Facebook user in location j than with a given Facebook user in location l.

In our analysis, we normalize the SCI by county and use it to weigh up the expectations of others in connected counties using bilateral social connectedness weights between any two counties c and k,

$$\omega_{c,k} = \frac{SCI_{c,k}}{\sum_k SCI_{c,k}}$$

We then construct the expectations of others:

$$\pi^{e,others}_{c,t} = \sum_{k \neq c} \omega_{c,k} \pi^{e}_{k,t} \tag{15}$$

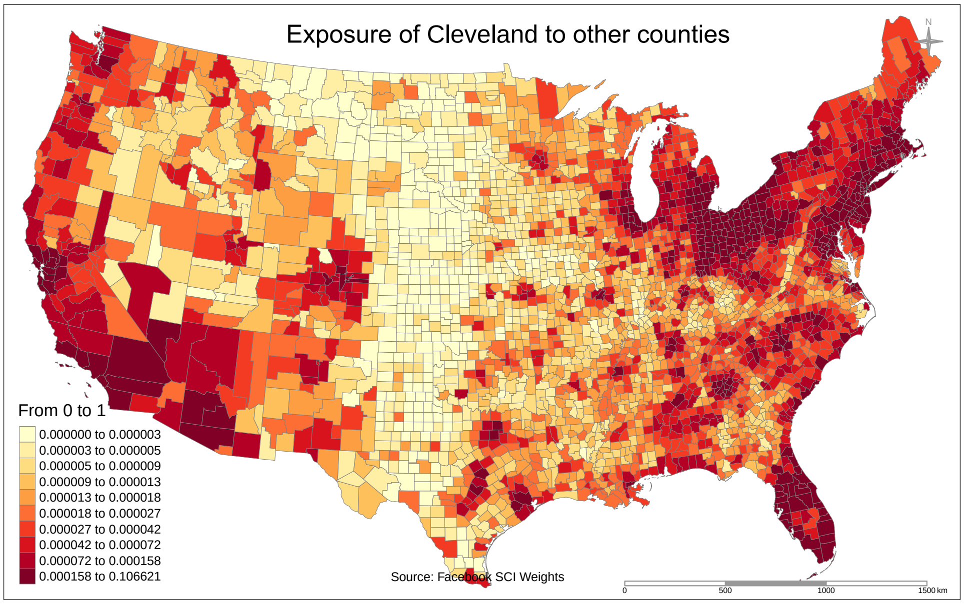
where $\pi^e_{k,t}$ denotes the average inflation expectations of individuals in county k at time t. In particular, this measure implies that a county c will be more exposed to information in county k if many users of county k have Facebook friendship connections with users in county c.

The analysis uses the SCI for 2016 and holds those weights constant across the sample. Several properties of the data are convenient for the analysis at hand. 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 ones after 2020.

It is important to highlight that we do not analyze individual-level social connectedness. The SCI is a proxy of how connected an *average* individual of a given county is to individuals in another county. This measure has advantages and disadvantages. Its usefulness for our analysis stems from the common factors that explain connections between regions, such as past migration patterns (see Bailey et al. (2018a), Bailey et al. (2022)). In line with this feature of the data, we are not necessarily interested in the information shared exclusively on Facebook,[13] but instead in common patterns of social connections. The SCI is a proxy for such a deeper social relationship between individuals spatially separated.

[13]Our instrumental variables strategy below, which exploits salient local gas prices as the instrument, does suggest that salient information such as information on local gas prices flows through the network – information that is highly relevant for the formation of inflation expectations.

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

To provide a concrete example, consider the social connectedness of Cuyahoga County, where Cleveland, Ohio is located, with other counties across the United States. Figure 3 illustrates this social connectedness through a heat map depicting the weights ($\omega_{c,k}$) for $c = Cleveland$. In Appendix F, 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. First, as expected, geography plays a significant role, with Cleveland showing stronger connections to nearby counties. Second, 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. Third, 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.

In reverse, we also present the social connectedness of other counties to Cuyahoga County, Ohio. The heat map in Figure 8 in Appendix F shows the weights $\omega_{c,k}$ for $k = Cleveland$. 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 that the analysis will subsequently exploit as a source of variation.

4 Empirical Analysis

4.1 Overview of Empirical Challenges and Strategy

This section shows that consumers incorporate information from their social networks when forming expectations. To do so, our main analysis employs county averages of social connectedness to gauge the impact of interconnected counties on inflation expectations.

Understanding the role of social networks for shaping inflation expectations comes with several challenges. First, social networks might be spuriously correlated with other types of 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* when the network matters for expectations in the first place. By contrast, if the social networks are, in reality, irrelevant for individual expectations, then the Manski (1993) reflection problem disappears. In Appendix B.1 we prove this result.[14]

Our analysis utilizes different approaches to overcome such challenges. As a first step, we establish that the network matters *per se*. We do so by showing that inflation expectations of the network bear a significant coefficient, even after taking into account common aggregate factors (a time fixed effect) and time-varying county-specific variation (expectations of others in the own county). The time-varying county-level controls capture the role of common trends, close-by connections due to proximity in space, and county-specific shocks, such as local price shocks. We interpret the finding of this first step as indicating that there is a correlation in the inflation expec-

[14]We prove this result in Appendix B.1. 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. 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 the relevance of social networks for inflation expectations.

tations of counties that are connected through social networks.[15] As a second step, once we have established that the network matters, we employ several empirical strategies to identify whether information is transmitted through social networks or other networks that may be spuriously correlated with social networks. Our first strategy is to exclude proximate counties and to only keep counties beyond a certain distance; hence, we are ignoring data from counties that are more likely to share spatial shocks. Our second main strategy is to construct county $\times$ demographic $\times$ time networks that allow us to include county-time fixed effects. These fixed effects absorb any variability that affects all demographic groups in a county in a given period of time equally, alleviating concerns about spatial spillovers, trade relationships, or demand spillovers from nearby regions, among other confounding factors.

As a third strategy to address the challenges of analyzing expectations in social networks, we apply an instrumental variables approach that addresses any remaining endogeneity concerns, including those implied 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. This strategy allows us to find an unbiased estimate of the relevance of the social network, exploiting the variation of specific exogenous shocks, in this case coming from gas prices. Since we know that higher gas prices lead to higher inflation beliefs, this step also provides a glimpse into the type of information that flows through the social network: On average, people must be talking about salient inflation-relevant experiences, such as prices at the pump.

Across all of these strategies, we find strong evidence in favor of 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 descriptive evidence 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. This result holds at the individual level and also at the county level (see Appendix C for the county-level results).

[15] Note that concerns about 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.

4.2.1 Individual-Level Evidence

To establish this result in support of the first model prediction, we estimate several specifications. These specifications use individual-level data that allow us to take into account county and time fixed effects. Formally, we estimate:

$$\pi^e_{i,c,t} = \beta_0 + \beta_1 \pi^e_{-i,c,t} + \beta_2 \sum_{k \neq c} \omega_{c,k} \pi^e_{k,t} + \varepsilon_{i,c,t}, \tag{16}$$

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

Across specifications, we find strong evidence for the first prediction of the model: the expectations of others are associated with individual inflation expectations. Table 1 reports the estimation results. The first row displays the coefficient associated with the network-weighted inflation expectations of other counties, and the second row displays 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 0.19. The inclusion of time fixed effects that absorb time variation in inflation common to all counties leaves this result almost unchanged, with a coefficient of 0.18 (Column 2). Likewise, the inclusion of county fixed effects that capture characteristics of the county that are correlated with the network and invariant over time also leaves this result with a similar magnitude, with a coefficient of 0.25 (Column 3). Absorbing most of the variation by including both county and time fixed effects again implies a statistically significant coefficient (Columns 4 and 5). Now, an increase of 1 percentage point in the inflation expectations of others leads to an increase of 0.05 to 0.12 percentage points in an individual's inflation expectations.

Table 1: Effect of Expectations of Others on Own Inflation Expectations

	(1)	(2)	(3)	(4)	(5)
Expectations of Others	0.194***	0.176***	0.252***	0.115**	0.051***
	(0.043)	(0.050)	(0.074)	(0.047)	(0.017)
County Expectations	0.755***	0.732***	0.603***		0.557***
	(0.048)	(0.042)	(0.058)		(0.049)
Time FE	No	Yes	No	Yes	Yes
County FE	No	No	Yes	Yes	Yes
Observations	1,926,282	1,926,282	1,926,282	1,926,282	1,926,282
R-squared	0.017	0.017	0.017	0.014	0.017

Note: The table shows the results of regression (16), where the dependent variable $\pi^e_{i,c,t}$ denotes the inflation expectation of individual i in county c at time t. Regressions are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Finally, these results are robust to different specifications. For example, we show that potentially similar shocks experienced in nearby counties do not explain the results. To do so, we construct the network-weighted expectations by explicitly excluding counties located within a certain radius of the respondent's county. We then repeat the above set of exercises. In Table 6 in Appendix G we report the results for this exercise. Across several specifications, we find that the inflation expectations from long-distant counties connected by social networks affect an individual's own inflation expectations. Additionally we control for several demographic characteristics, include those characteristics interacted with time fixed effects, are the results are mostly unchanged.

While the main takeaway from this section lies in the robust statistically significant relationship between beliefs in the social network and individual inflation expectations, the precise results likely remain biased. For example, as we prove in Appendix B.2, taking into account time fixed effects does not mean that the estimate of β_2 does not suffer from biases due to the reflection problem.[16] We also show in Appendix B.3 that the inclusion of the time fixed effect might bias downward the coefficient when the network is common, which can explain the changes in the coefficient. In Section 5, we therefore use an instrumental variable approach to obtain an unbiased estimate that would address those issues. Nonetheless, the set of estimates presented in this section consistently provides strong evidence of a stylized fact that is in line with the first prediction of the theoretical model: When forming expectations, consumers are generally attentive to

[16] We refer the reader to Lee and Yu (2010) for an insightful discussion of the biases that spatial models generally suffer from, even when one appropriately accounts for time and individual fixed effects.

experiences shared through their social networks.

Another potential problem that this regression could have is that the weights are correlated with some other characteristics that can explain the results. One such variable is the exposure to similar pricing structures. This exposure might stem from the demographic characteristics of the respondents, which influence their propensity to purchase specific types of goods, or it could arise from groups of people encountering comparable stores that are subject to similar cost shocks. To address this issue, we have incorporated demographic-time fixed effects into our model. The results, as presented in Table 7 in Appendix G, affirm the robustness of our findings against the inclusion of these demographic controls, even when they are interacted with time fixed effects. Notably, the point estimates remain significant and exhibit a slight increase in magnitude.

An additional challenge is to separate the transmission of inflation expectations through social networks from the transmission through other networks that affect prices and are correlated with the social network. Consider, for instance, the scenario where retailers implement uniform pricing strategies across various locations. In such cases, counties sharing common retail chains often experience synchronized price adjustments (Garcia-Lembergman (2020)), potentially impacting inflation expectations. In order to control for propagation of shocks through the retail chains networks, we construct exposure to the retail chains networks using weights that characterize the connectedness of each pair of counties in the retail chain dimension, as measured by Garcia-Lembergman (2020). The weights place higher weight to counties k that are important in terms of sales for the dominant retail chains in county c. Subsequently, we calculate the exposure to inflation expectations in counties with shared retail chains and incorporate this as a control variable in our regression analysis. As demonstrated in Table 9 in Appendix G, including controls for inflation expectations in counties with shared retail chains does not alter our main findings.

In the next section we also provide another set of results that show that it is unlikely that the main findings come from other characteristics different than the social network. By splitting the network at the county level, we can add county-time fixed effects, controlling for common variation at the county level, including price shocks.

4.3 Similarity in the Social Network

In line with the second and third predictions of the model, this subsection shows that demographic similarity increases the effect of beliefs in the social network on individual inflation expectations while dissimilarity tends to reduce it. This finding concurs 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. It also concurs with our theoretical results on the amplification of beliefs based on relevant and irrelevant experiences. Finally, incorporating the demographic dimension into the analysis allows us to improve the identification strategy.

In order to examine the influence of demographic similarity and dissimilarity on inflation expectations through the network, we construct exposure to inflation expectations of similar groups in distant counties. In particular, we define such exposure as:

$$\sum_{k \neq c} \omega_{c,k} \pi^{e}_{d,k,t}$$

where $\pi^{e}_{d,k,t}$ denotes the average inflation expectations across individuals with demographic characteristic d located in county k in period t. The demographic characteristics we consider include gender (male, female), political affiliation (Democrats, Republicans, Independents), income (less than 50k, between 50k and 100k, over 100k), and age (18-34, 35-44, 45-64, 65+).

We then estimate the following specification:

$$\pi^{e}_{i,d,c,t} = \beta_0 + \beta_1 \pi^{e}_{-i,d,c,t} + \beta_2 \sum_{k \neq c} \omega_{c,k} \pi^{e}_{d,k,t} + \gamma_{ct} + \varepsilon_{i,c,t}. \tag{17}$$

Equation (17) represents a direct test of the model predictions 2 and 3. $\pi^{e}_{i,d,c,t}$ denotes the inflation expectations of individual i, with demographic characteristic d, in county c at time t; $\pi^{e}_{-i,d,c,t}$ represents the average inflation expectations of all the other individuals in that same county c that share the same demographic characteristics d with individual i. If the similarity between individuals matters for the transmission of inflation expectations, then we expect a positive estimate of 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 that 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 cities. Hence, even if San Francisco and Los Angeles were not connected by the social network, 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 the inflation expectations of individuals who live in the same county and are connected to the same other counties, but who have absorbed different experiences of others because they belong to different demographic groups.

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's choices, as, for example, in the case of political affiliation. In the case of gender, variation stems from a given demographic characteristic rather than a possibly endogenous choice.

Results are reported in Table 2. They show that gender similarity plays an important amplifying role for social interaction in the process of belief formation: The effect of one's social network turns out to be significant and relevant. A 1 percentage point increase in the inflation expectations of the gender-specific network increases own-inflation expectations between 0.28 and 0.78 percentage points. Notably, after we additionally filter out granular time, state-time, county, and county-time fixed effects, the coefficient is always statistically significant and the fixed effects increase its magnitude. In Appendix G, Tables 10, 11, and 12 present results for similarity of political affiliation, income, and age, respectively. Qualitatively, the same findings hold.

Table 2: Similarity Effect by Gender

	(1)	(2)	(3)	(4)	(5)	(6)
$Similarity - Network$	0.282***	0.334***	0.306***	0.359***	0.413***	0.777***
	(0.038)	(0.028)	(0.057)	(0.047)	(0.052)	(0.092)
$Similarity - County$	0.684***	0.667***	0.610***	0.593***	0.535***	0.204***
	(0.040)	(0.029)	(0.043)	(0.029)	(0.015)	(0.056)
County FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes	Yes
State-Time FE	No	No	No	No	Yes	Yes
County-Time FE	No	No	No	No	No	Yes
Observations	1,910,679	1,910,679	1,910,679	1,910,679	1,910,679	1,910,679
R-squared	0.026	0.026	0.026	0.026	0.027	0.030

Note: The table shows the results of estimating specification (17), where the dependent variable $\pi^e_{i,d,c,t}$ denotes the inflation expectations of individual i of gender d in county c at time t. $Similarity - Network$ is the average of inflation expectations of individuals of the same gender in other counties. $Similarity - County$ is the average of inflation expectations of respondents of the same gender within her/his own county. Regressions are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Further evidence of the importance of demographic similarity within demographic groups emerges when the analysis explicitly includes a measure of *dissimilarity*, or interference, as in Corollary 3. To do so, we estimate specification (17), but include as a variable that captures dissimilarity the network-weighted expectations of the respectively other, omitted demographic group, $\sum_{k \neq c} \omega_{c,k} \pi^e_{-d,k,t}$. Two results emerge: First, such *dissimilarity* of others – denoted by "Dissimilarity-Network" in Table 14 in Appendix G – generally has a zero effect on the formation of inflation expectations and it is always smaller than the similarity effect, which continues to be highly significant, always positive and higher than the point estimates in Table 1.

Viewed through the lens of the model, these results suggest that the beliefs of "other others" embody *relatively* irrelevant experiences that can affect expectations on a lower extent, probably not affecting individuals expectations at all. At the same time, beliefs in a similar group tend to embody relatively relevant experiences that raise inflation expectations. Analysis of similarity and dissimilarity defined across a range of demographic characteristics – age, income, and political choice – affirms these findings: Beliefs in the social network have a strong impact on the process of belief formation, and the impact is higher in more similar groups. Table 13 and Table 15 in Appendix G show these results.

5 Transmission of Exogenous Shocks through the Network

In order to address any remaining concerns in terms of identification, this section applies an instrumental variable strategy. The approach follows Hajdini et al. (2022a) and utilizes a shift-share approach that combines cross-county variations in the proportion of individuals who use cars in their commute 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, as a first stage we show that the shift-share instrument affects local inflation expectations. We estimate

$$\pi^e_{i,c,t} = \alpha_{c(i)} + \gamma_t + \beta P_{gas,t} \times Comm_{c(i)} + \varepsilon_{i,c,t}, \tag{18}$$

where $\pi^e_{i,c,t}$ denotes the inflation expectations of individual i in county c at time t; $P_{gas,t}$ denotes the average national price of regular gas according to the US Energy Information Administration;[17] $Comm_{c(i)}$ denotes the share of people who use their own car to commute according to the ACS[18]; $\alpha_{c(i)}$ denotes a county fixed effect and γ_t a time fixed effect. We estimate this regression specification for the period of February 2021 through July 2023. Table 3 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 individual-level inflation expectations between 3.171 and 3.958 percentage points in a county where everybody uses their car to commute, compared to a counterfactual county where nobody uses a car to commute.

[17] 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, since gas is very tradeable, its price is correlated across regions following aggregate gas price shocks.

[18] This measure is not correlated to the weights. Figure fig:corr$_{g}asinAppendix$F.2$showsresultsforregressionateachcountylevel,resultssho$

Table 3: Cross-Sectional Effect of Gas Price on Expectations

	(1)	(2)	(3)	(4)	(5)	(6)
$P_{gas,t}$	-0.874**	-1.060				
	(0.375)	(0.211)				
$Comm_{c(i)}$	-7.457***		-8.383***			
	(1.347)		(1.130)			
$P_{gas,t} \times Comm_{c(i)}$	3.171***	3.318***	3.310***	3.414***	3.958***	0.834**
	(0.513)	(0.386)	(0.444)	(0.407)	(0.475)	(0.379)
County FE	No	Yes	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes
Sample	All	All	All	All	Men	Female
Observations	1,239,680	1,239,680	1,239,680	1,239,680	606,305	632,750
R-squared	0.008	0.012	0.011	0.015	0.014	0.015

Note: Columns (1)-(4) show results from estimating the first-stage specification $\pi^e_{i,c,t} = \alpha_{c(i)} + \gamma_t + \beta P_{gas,t} \times Comm_{c(i)} + \varepsilon_{i,c,t}$, where $\pi^e_{i,c,t}$ 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 who use their own car to commute according to the ACS; and $\alpha_{c(i)}$ and γ_t are county and time fixed effects included as appropriate in the first 4 columns. Columns (5) and (6) show the results from estimating $\pi^e_{i,d,c,t} = \alpha_{c(i)} + \gamma_t + \beta_d P_{gas,t} \times Comm_{c(i)} + \varepsilon_{i,d,c,t}$, where $d \in (male, female)$. Regressions are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level

As a refinement to the first stage, we allow for differences in sensitivity to the shift-share measure by gender. That is, we estimate the following specification:

$$\pi^e_{i,d,c,t} = \alpha_{c(i)} + \gamma_t + \beta_d P_{gas,t} \times Comm_{c(i)} + \varepsilon_{i,d,c,t}, \tag{19}$$

where, as before, $\pi^e_{i,d,c,t}$ denotes the inflation expectations of individual i in county c with demographic characteristic d at time t. This approach is motivated by the results in D'Acunto et al. (2021a), who find that gender differences in inflation expectations can be explained by gender roles associated with shopping experiences. In particular, D'Acunto et al. (2021a) show that men tend to refer more to gasoline prices when they form expectations. Column (5) shows the estimated sensitivity to the shift-share measure for male respondents only, and Column (6) for female respondents only. Results show that men have a higher, statistically significant coefficient than women.

We exploit the exogenous variation embodied in the above specification to show two results: On the one hand, the exogenous local variation in 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 $Gas\_effect_{d,c,t} = \widehat{\beta_d} P_{gas,t} \times Comm_{c(i)}$, based on the above equation (19), which contains county-time variation. Then, using the network linkages, we estimate regression specifications of the type:

$$\pi^e_{i,d,c,t} = \alpha_c + \gamma_t + \beta_1 \pi^e_{-i,d,c,t} + \beta_2 \sum_{k \neq c} \omega_{c,k} Gas\_effect_{d,k,t} + \varepsilon_{i,d,c,t}, \tag{20}$$

While time fixed effects have already been filtered out from the measure $Gas\_effect_{d,c,t}$, we nonetheless include a time fixed effect γ_t in some specifications. As in the previous exercises, we take into account average county-gender inflation expectations, $\pi^e_{-i,d,c,t}$, which exclude the respondent's own expectations.[19] Overall, these specifications 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 expectations with the weighted $Gas\_effect_{d,c,t}$. That is, we estimate the following specification:

$$\pi^e_{i,d,c,t} = \alpha_{c(i)} + \gamma_t + \rho_1 \pi^e_{-i,d,c,t} + \rho_2 \sum_{k \neq c} \omega_{c,k} \pi^e_{d,k,t} + \varepsilon_{i,d,c,t}, \tag{21}$$

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

[19] Alternatively, we run regressions where we control for the own-county/demographic gas effect $Gas\_effect_{d,c,t}$. Appendix G, Table 16 presents the findings, which are very similar.

Table 4: Effect of Gas Price Variation in the Social Network on Inflation Expectations

	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{k\neq c} \omega_{c,k} Gas\_effect_{c,t}$	0.190***	1.925***				
	(0.054)	(0.222)				
$\sum_{k\neq c} \omega_{c,k} Gas\_effect_{c,d,t}$			1.980***	0.571***		
			(0.200)	(0.190)		
$\sum_{k\neq c} \omega_{c,k} \pi^e_{d,k,t}$					0.359***	0.491***
					(0.047)	(0.088)
$\pi^e_{-i,c,t}$	0.652***	0.519***				
	(0.043)	(0.030)				
$\pi^e_{-i,d,c,t}$			0.532***	0.365***	0.593***	0.561***
			(0.023)	(0.012)	(0.029)	(0.040)
Sample	All	All	Men	Female	All	All
Time FE	No	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Regression	OLS	OLS	OLS	OLS	OLS	IV
F-Test	-	-	-	-	-	1459
Observations	1,926,282	1,926,282	882,338	1,028,341	1,910,679	1,910,679
R-squared	0.017	0.018	0.020	0.018	0.026	0.012

Note: This table shows results from estimating three specifications. Columns (1) and (2) show results for $\pi^e_{i,c,t} = \alpha_c + \gamma_t + \beta_1 \pi^e_{-i,c,t} + \beta_2 \sum_{k\neq c} \omega_{c,k} Gas\_effect_{k,t} + \varepsilon_{i,c,t}$. Columns (3) and (4) for $\pi^e_{i,d,c,t} = \alpha_c + \gamma_t + \beta_1 \pi^e_{-i,d,c,t} + \beta_2 \sum_{k\neq c} \omega_{c,k} Gas\_effect_{d,k,t} + \varepsilon_{i,d,c,t}$,. Column (5) shows the results for $\pi^e_{i,d,c,t} = \alpha_c + \rho_1 \pi^e_{-i,c,t} + \rho_2 \sum_{k\neq c} \omega_{c,k} \pi^e_{d,k,t} + \varepsilon_{i,d,c,t}$. Column (6) runs the same specification as for Column 5, but instruments $\sum_{k\neq c} \omega_{c,k} \pi^e_{d,k,t}$ with $\sum_{k\neq c} \omega_{c,k} Gas\_effect_{d,k,t}$. $\pi^e_{i,d,c,t}$ denotes the inflation expectations of individual i of gender d in county c at time t; $\pi^e_{-i,c,t}$ inflation expectations of county c at time t excluding individual i; $\pi^e_{-i,d,c,t}$ inflation expectations of respondents of demographic d in county c at time t excluding individual i; and $\pi^e_{d,k,t}$ gender d inflation expectations in county k at time t; $Gas\_effect_{d,k,t}$ denotes the gas effect variable constructed as described in the text; and α_c and γ_t are county and time fixed effects. Regressions are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

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 4 shows this result in its first 4 columns. Columns (1) and (2) use a common gas effect for both genders, whereas Columns (3) and (4) use a gender-county-specific gas effect, splitting the sample by gender, with results for men reported in Column (3) and for women in Column (4). 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. As shown before, the network effect is 0.359, considering time fixed effects (Column (5)). The IV coefficient is 0.491, more than a third higher (Column (6)). These results indicate that when inflation expectations are affected by certain salient prices, such as gasoline prices, the transmission through the network is stronger. Our finding aligns with the result in Coibion and Gorodnichenko (2015b) that consumers pay more attention to gas prices than to the prices of other goods.

Besides establishing causality, instrumentation – by virtue of the nature of the instrument – also provides a glimpse into the content of the information that flows through the social network and the memories recalled (Bordalo et al. (2023)): Gas prices are a salient object, and social networks tap salient experiences from the memory database, perhaps not surprisingly. At the same time, gas prices are inflation-relevant rather than irrelevant. In line with our model predictions, this finding suggests that communication through social networks on average must transmit inflation-relevant, salient price experiences.

5.1 Implications for Stability

A further natural question arises in the same context of communication through social networks: Are social networks a stabilizing force for the formation of inflation expectations? We answer this question by building on and generalizing the simple framework that analyzes the inflation expectations feedback loop in Section 2.4.

Our empirical findings suggest that social networks are not associated with unstable propagation of shared experiences. To see this, consider our generic regression specification:

$$\pi_t^e = \boldsymbol{\alpha} + \beta \Omega \pi_t^e + \boldsymbol{\varepsilon}_t, \tag{22}$$

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 an $N \times N$ matrix with 0-diagonal and with row elements summing to 1. Importantly, equation (22) represents a generalized version of the relationship between the inflation expectations of two individuals analyzed in Section 2.4, where β captures the average of $\widetilde{\beta}_1$ and $\widetilde{\beta}_2$,[20] defined in equation (13) in the case of stability and in equation (14) in the case of instability. As shown, when total attention to experiences shared by others in the network

[20]Because our main empirical specifications reside at the individual level with county controls and fixed effects, our empirical estimates extract the average marginal effect over individuals in a given county. For simplicity of exposition, the subsequent derivations reside at the county level but with no loss of generality interpreting the index n.

exceeds (respectively, falls behind) total attention to own experiences, then $\widetilde{\beta}_1, \widetilde{\beta}_2 \geq 1$ (respectively, $0 < \widetilde{\beta}_1, \widetilde{\beta}_2 < 1$) and the social network is destabilizing (stabilizing). Consistently, as we show in what follows, if $\beta > 1$ social networks are destabilizing but stabilizing if $0 < \beta < 1$.

To see this, consider 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 $\pi^e_{nt} = \alpha_n + \varepsilon_{nt}$. Second, π^e_{nt} will affect the expectations in the other counties by propagation through the network. Appendix D 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,[21]

$$\pi^e_t = \begin{cases} (I - \beta\Omega)^{-1}\boldsymbol{\alpha} & \text{if } \mid \beta \mid < 1 \\ \pm\infty & \text{otherwise} \end{cases} \tag{23}$$

A one-time county-specific shock to inflation expectations can destabilize inflation expectations in all the other counties only if $\mid \beta \mid \geq 1$. In our specification, we have separated the own county effect from the rest of the counties. We obtain own county shares, ω_{ii}, from the data: On average, we have that $\omega_{ii} = 0.39$. With this, the relevant β at the individual level will use the estimates in (21) as $\beta = \rho_1\omega_{ii} + \rho_2(1 - \omega_{ii})$.

Empirically, which scenario are we in? Focusing on the IV empirical results in Column (6) of Table 4, our estimate of β is given by $\hat{\beta} = 0.519 < 1$, implying that social networks have not had a destabilizing effect on expectations. However, we note that even though $\hat{\beta} < 1$,it is higher compared to the OLS result (0.451), 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 larger spillover effects on expectations through social networks. As suggested in Coibion et al. (2020c), effective communication from policymakers that emphasizes inflation as a broad rather than as a goods-specific or local phenomenon can help reduce the feedback effects of social networks.

[21] We highlight that throughout our empirical analysis, we find the estimate of β to always be positive, but in this analytical analysis, we do not limit the sign of β in order to be as general as possible.

6 Conclusion

Our analysis brings to the fore the idea that experiences shared through social networks can have an impact on the formation of inflation 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 in the context of inflation expectations, it may easily be generalized to 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 the 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 who share similar demographic characteristics tend to pay more attention to each other. We finally show, using exogenous variation, that the coefficient of interest is high, but in the range of stability suggested by the model.

These findings open up new avenues for exploring the formation of inflation 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 super-nodes 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 who aim to keep inflation expectations anchored.

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Appendix

A Other Theoretical Results

A.1

We present an example for the similarity function that would yield opposite sign effcets... Let

$$S_j(e,k \mid \theta_{ji}) = \frac{e^{-(e-k)^2/2(2-\theta_{ji})^2}}{2-\theta_{ji}}$$

A.2 Effects of Weights on Recall Probabilities

What about paying more attention to a specific individual? The effects that weights $\omega(\theta_{ji})$ have on the implications of social interaction for recall probabilities are not trivial to analyze. Proposition 6 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 6. *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:*

$$\underbrace{\frac{\sum_{e\in E^k_{l\to j}} S_j(e,k \mid \theta_{jl}) - \sum_{e\in E^k_{q\to j}} S_j(e,k \mid \theta_{jq})}{\sum_{e\in E^k_j} S_j(e,k)}}_{\text{marginal relative relevance}} > \underbrace{\frac{\sum_{e\in E^{k^-}_{l\to j}} S_j(e,k \mid \theta_{jl}) - \sum_{e\in E^{k^-}_{q\to j}} S_j(e,k \mid \theta_{jq})}{\sum_{e\in E^{K\setminus k}_j} S_j(e,k) + \sum_{e\in E^O_j} S_j(e,k)}}_{\text{marginal relative irrelevance}} \tag{A.1}$$

where $k^- = \{K\backslash k, O\}$, 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 E.4. □

We refer to the term on the left-hand side of condition (A.1) as marginal relative relevance and to the term on the right-hand side as marginal relative irrelevance. Proposition 6 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 it is more probable that social interaction will 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 3. 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 3. *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 6. □

To illustrate Corollary 3, 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 3 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 (A.1), Corollary 3 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.

A.3 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

$$\hat{r}_1(k) = \frac{\gamma_1 x_1 + (1-\gamma_1)x_2}{\gamma_1 x_1 + (1-\gamma_1)x_2 + y_1} \tag{A.2}$$

$$\hat{r}_2(k) = \frac{\gamma_2 x_2 + (1-\gamma_2)x_1}{\gamma_2 x_2 + (1-\gamma_2)x_1 + y_2} \tag{A.3}$$

Isolating x_1 from (A.2), 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.3), we get

$$\begin{aligned}\hat{r}_2(k) &= \frac{\gamma_2 x_2 + (1-\gamma_2)\frac{(x_2(1-\gamma_1)+y_1)\hat{r}_1(k)-(1-\gamma_1)x_2}{\gamma_1(1-\hat{r}_1(k))}}{\gamma_2 x_2 + (1-\gamma_2)\frac{(x_2(1-\gamma_1)+y_1)\hat{r}_1(k)-(1-\gamma_1)x_2}{\gamma_1(1-\hat{r}_1(k))} + y_2} \\ &= \frac{[(1-\gamma_2)y_1 + (1-\gamma_1-\gamma_2)x_2]\,\hat{r}_1(k) + (\gamma_1+\gamma_2-1)x_2}{[(1-\gamma_2)y_1 - \gamma_1 y_2 + (1-\gamma_1-\gamma_2)x_2]\,\hat{r}_1(k) + \gamma_1 y_2 + (\gamma_1+\gamma_2-1)x_2}\end{aligned} \tag{A.4}$$

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,

$$\begin{aligned} c_j &= (1-\gamma_j)y_i - \gamma_i y_j + (1-\gamma_1-\gamma_2)x_j \\ &= (1-\gamma_j)(\gamma_i z_i + (1-\gamma_i)z_j) - \gamma_i(\gamma_j z_j + (1-\gamma_j)z_i) + (1-\gamma_1-\gamma_2)x_j \\ &= (1-\gamma_1-\gamma_2)(x_j + z_j)\end{aligned} \tag{A.5}$$

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, $(\gamma_1 + \gamma_2 - 1)x_j > (1 - \gamma_j)y_i$.[22] 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 $\hat{r}_i^{**}, \hat{r}_j^{**} \in (-b_j/a_j, -\varphi_1/(2\varphi_2))$.

[22]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 to k.

B The Reflection Problem

B.1 Baseline

Consider the following generic regression specification:

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

where $\pi_t^e = \begin{bmatrix} \pi_{1t}^e & \pi_{2t}^e & ... & \pi_{Nt}^e \end{bmatrix}'$ embeds inflation expectations in county 1 through county N, $\boldsymbol{\varepsilon}_t = \begin{bmatrix} \varepsilon_{1t} & ... & \varepsilon_{Nt} \end{bmatrix}'$ 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 $i \in \{1, 2, ..., N\}$, $\boldsymbol{\alpha} = \begin{bmatrix} \alpha_1 & ... & \alpha_N \end{bmatrix}'$ denotes a vector of constants (county fixed effects), β denotes a scalar, and Ω is an $N \times N$ 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 $\bar{\pi} = \begin{bmatrix} \bar{\pi}_1^e & \bar{\pi}_2^e & ... & \bar{\pi}_N^e \end{bmatrix}'$. 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,

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

where

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

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

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

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

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.

B.2 Time Fixed Effects

Now suppose the true data generating process is given by the more general regression specification with time and county fixed effects:

$$\pi_t^e = \alpha + \gamma_t L_N + \beta\Omega\pi_t^e + \varepsilon_t \tag{B.1}$$

where $L_N = \mathbf{1}_{N\times 1}$ is a vector of 1s of length N, γ_t is the time fixed effect, and all the other variables are as defined in Appendix B.1. Let $\bar{\pi}_{N.} = \frac{1}{T}\left[\sum_{t=1}^{T}\pi_{1t}^e \quad \sum_{t=1}^{T}\pi_{2t}^e \quad \dots \quad \sum_{t=1}^{T}\pi_{Nt}^e\right]'$, $\bar{\pi}_{.t} = \left(\frac{1}{N}\sum_{n=1}^{N}\pi_{nt}^e\right)L_N$, and $\bar{\pi}_{..} = \left(\frac{1}{NT}\sum_{n=1}^{N}\sum_{t=1}^{T}\pi_{nt}^e\right)L_N$. Then, following a strategy similar to Wallace and Hussain (1969), we re-write the equation above as

$$\underbrace{\pi_t^e - \bar{\pi}_{.t} - \bar{\pi}_{N.} + \bar{\pi}_{..}}_{y_t} = \beta\underbrace{\left[\Omega(\pi_t^e - \bar{\pi}_{.t} - \bar{\pi}_{N.} + \bar{\pi}_{..})\right]}_{\Omega y_t} + \varepsilon_t$$

Note that $y_t = (I - \beta\Omega)^{-1}\varepsilon_t = M\varepsilon_t$. Let $\hat{\beta}$ be the OLS estimate of β, and as shown in Appendix B.1,

$$\hat{\beta} = \beta + \left[(y_t'\Omega'\Omega y_t)^{-1}(y_t'\Omega\varepsilon_t)\right] = \beta + \underbrace{\left[(\varepsilon_t'M'\Omega'\Omega M\varepsilon_t)^{-1}(\varepsilon_t'M'\Omega\varepsilon_t)\right]}_{bias}$$

What is important to note from the equation above is that even if the econometrician appropriately accounts for the time and county fixed effects (as in the true data generating process), the estimate of β will suffer from a bias.[23]

In an alternative exercise, suppose that the true data generating process is given by the equa-

[23]See Lee and Yu (2010) as well for a detailed discussion on the biases that arise in spatial models with time and individual fixed effects.

tion in (B.2), but the econometrician does not account for time fixed effects, that is, one runs the following regression instead:

$$\underbrace{\pi_t^e - \bar{\pi}_{N.}}_{\hat{y}_t} = \beta \underbrace{[\Omega(\pi_t^e - \bar{\pi}_{N.})]}_{\Omega\hat{y}_t} + \boldsymbol{u}_t \tag{B.2}$$

where $\boldsymbol{u}_t = \boldsymbol{\varepsilon}_t + (I - \beta\Omega)(\bar{\pi}_{.t} - \bar{\pi}_{..}) = \boldsymbol{\varepsilon}_t + M^{-1}(\bar{\pi}_{.t} - \bar{\pi}_{..}) = \boldsymbol{\varepsilon}_t + M^{-1}x_t$. Then, the OLS estimate of β is given by

$$\begin{aligned}
\hat{\beta} &= \beta + \underbrace{\left[(\boldsymbol{u}_t' M'\Omega'\Omega M \boldsymbol{u}_t)^{-1}(\boldsymbol{u}_t' M'\Omega \boldsymbol{u}_t)\right]}_{bias} \\
&= \beta + \underbrace{\left[\left((\boldsymbol{\varepsilon}_t + M^{-1}x_t)' M'\Omega'\Omega M(\boldsymbol{\varepsilon}_t + M^{-1}x_t)\right)^{-1}\left((\boldsymbol{\varepsilon}_t + M^{-1}x_t)' M'\Omega(\boldsymbol{\varepsilon}_t + M^{-1}x_t)\right)\right]}_{bias} \\
&= \beta + \underbrace{\left[\left(\boldsymbol{\varepsilon}_t' M'\Omega'\Omega M \boldsymbol{\varepsilon}_t + x_t'\Omega'\Omega x_t\right)^{-1}\left(\boldsymbol{\varepsilon}_t' M'\Omega \boldsymbol{\varepsilon}_t + x_t'\Omega M^{-1} x_t\right)\right]}_{bias}
\end{aligned}$$

where the third equality follows from the fact that x_t must be uncorrelated with $\boldsymbol{\varepsilon}_t$. Now the bias is similar to what we identified in Appendix B.1, with the additional terms coming from the fact that we are not accounting for time fixed effects. What this Appendix highlights is that, even if one appropriately accounts for all fixed effects (time and county), the reflection problem still arises.

B.3 Time Fixed Effect with Constant Weights and Bias

Here, we explicitly show the OLS estimate of the network effect under different assumptions for the weights matrix and demonstrate how the inclusion of the time fixed effect affects the results.

B.3.1 No Time Fixed Effect

We start with the basic problem

$$\pi_t^e = \beta\Omega\pi_t^e + \boldsymbol{\varepsilon}_t \tag{B.3}$$

with

$$\Omega = \begin{bmatrix} 0 & \omega_{12} & ... & \omega_{1N} \\ \omega_{21} & 0 & ... & \omega_{2N} \\ ... & ... & ... & ... \\ \omega_{N1} & \omega_{N2} & ... & 0 \end{bmatrix}$$

This setup captures the main estimated specification in the text.

Then, we have that

$$\pi_t^e = (I - \beta\Omega)^{-1} \boldsymbol{\varepsilon}_t$$

and

$$\beta^{OLS} = \left[(\Omega\pi_t^e)' (\Omega\pi_t^e) \right]^{-1} (\Omega\pi_t^e)' \pi_t^e$$

or

$$\beta^{OLS} = \left[\left(\Omega (I - \beta\Omega)^{-1} \boldsymbol{\varepsilon}_t \right)' \left(\Omega (I - \beta\Omega)^{-1} \boldsymbol{\varepsilon}_t \right) \right]^{-1} \left(\Omega (I - \beta\Omega)^{-1} \boldsymbol{\varepsilon}_t \right)' \pi_t^e$$

B.3.2 With Time Fixed Effect

We now define the matrix

$$P = \begin{bmatrix} \frac{1}{N} & \frac{1}{N} & ... & \frac{1}{N} \\ \frac{1}{N} & \frac{1}{N} & ... & \frac{1}{N} \\ ... & ... & ... & ... \\ \frac{1}{N} & \frac{1}{N} & ... & \frac{1}{N} \end{bmatrix}$$

So the average expectation at each period of time is:

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

So a regression with time fixed effects is equivalent to running a regression over this equation:

$$(I - P)\, \pi_t^e = \beta (I - P)\, \Omega \pi_t^e + (I - P)\, \boldsymbol{\varepsilon}_t$$

or

$$\pi_t^{e,TFE} = \beta (\Omega - P\Omega)\, \pi_t^e + \boldsymbol{\varepsilon}_t^{e,TFE} \tag{B.4}$$

Then,

$$\beta^{OLS,TFE} = \left[\left(\left(\Omega - P\Omega \right) \pi_t^e \right)' \left(\left(\Omega - P\Omega \right) \pi_t^e \right) \right]^{-1} \left(\left(\Omega - P\Omega \right) \pi_t^e \right)' \pi_t^{e,TFE}$$

or

$$\beta^{OLS,TFE} = \left[\left(\left(\Omega - P\Omega \right) \pi_t^e \right)' \left(\left(\Omega - P\Omega \right) \pi_t^e \right) \right]^{-1} \left(\pi_t^{e\prime} \left(\Omega - P\Omega \right)' \left(I - P \right) \pi_t^e \right.$$

Then,

$$\beta^{OLS,TFE} = \left[\pi_t^{e\prime} \left(\Omega - P\Omega \right)' \left(\Omega - P\Omega \right) \pi_t^e \right]^{-1} \pi_t^{e\prime} \left(\Omega - P\Omega \right)' \left(I - P \right) \pi_t^e$$

Special Case:

To build intuition and derive a closed-form expression for β, let's assume an extreme case where the network is constant and equal for everybody, where the weights are $\frac{1}{N-1}$, so

$$\Omega = \begin{bmatrix} 0 & \frac{1}{N-1} & \dots & \frac{1}{N-1} \\ \frac{1}{N-1} & 0 & \dots & \frac{1}{N-1} \\ \dots & \dots & \dots & \dots \\ \frac{1}{N-1} & \frac{1}{N-1} & \dots & 0 \end{bmatrix}$$

It is direct to show that $P\Omega = \frac{1}{N} * P$, then $(\Omega - P\Omega) = (\Omega - P)$. Further, it is direct to show that $(I - P) = (1 - N) * (\Omega - P)$ or $(I - P) = (1 - N) * (\Omega - P\Omega)$. We replace this value in the definition if $\beta^{OLS,TFE}$:

$$\beta^{OLS,TFE} = \left[\pi_t^{e\prime} \left(\Omega - P\Omega \right)' \left(\Omega - P\Omega \right) \pi_t^e \right]^{-1} \pi_t^{e\prime} \left(\Omega - P\Omega \right)' \left(I - P \right) \pi_t^e$$

$$\beta^{OLS,TFE} = \left[\pi_t^{e\prime} \left(\Omega - P\Omega \right)' \left(\Omega - P\Omega \right) \pi_t^e \right]^{-1} \pi_t^{e\prime} \left(\Omega - P\Omega \right)' \left(1 - N \right) * (\Omega - P\Omega) \pi_t^e$$

$$\beta^{OLS,TFE} = (1 - N) * \left[\pi_t^{e\prime} \left(\Omega - P\Omega \right)' \left(\Omega - P\Omega \right) \pi_t^e \right]^{-1} \pi_t^{e\prime} \left(\Omega - P\Omega \right)' (\Omega - P\Omega) \pi_t^e$$

Then,

$$\beta^{OLS,TFE} = -(N - 1)$$

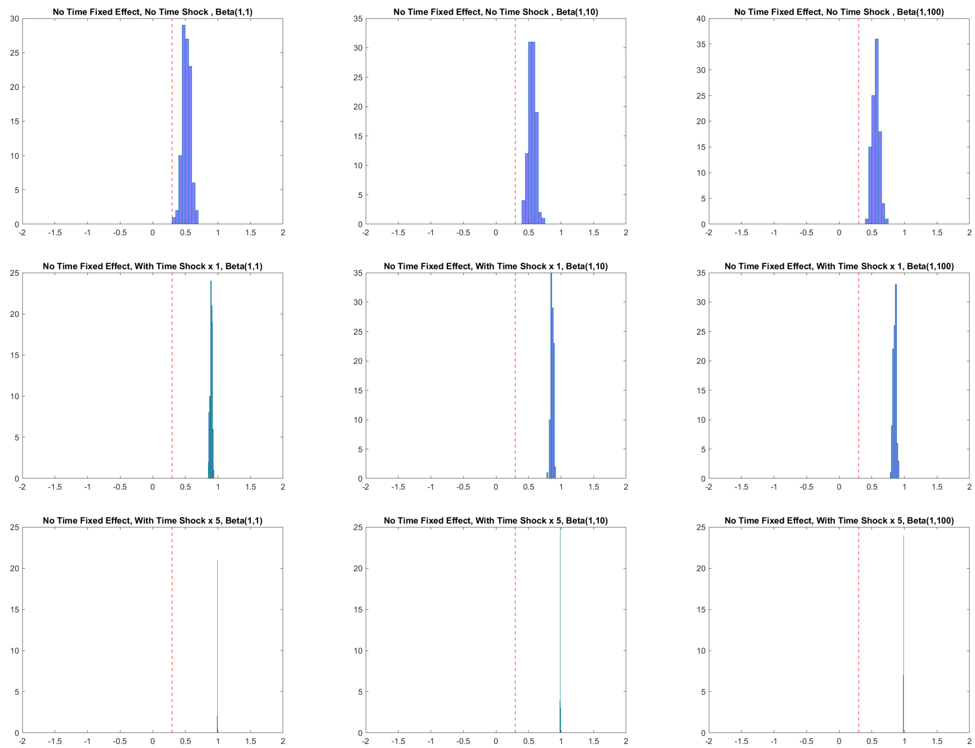
We can see that in this case, the $\beta^{OLS,TFE}$ is constant, negative and does not depend on the actual value of β.

The network structure in our case is not constant, so that case just works as a benchmark. To explore the potential biases from the potential inclusion of the time fixed effect, we simulate data and a network structure. The network structure will come from a Beta distribution with difference parameters. In one case, the network will be built from drawing from a Beta(1,1) or a uniform distribution, second from a Beta(1,10) and third from a Beta(1,20), in which case the distribution will be moving more to an extreme value distribution, with less common nodes. The data generating process comes from the structure

$$\pi_t^e = (I - \beta\Omega)^{-1}\boldsymbol{\varepsilon}_t$$

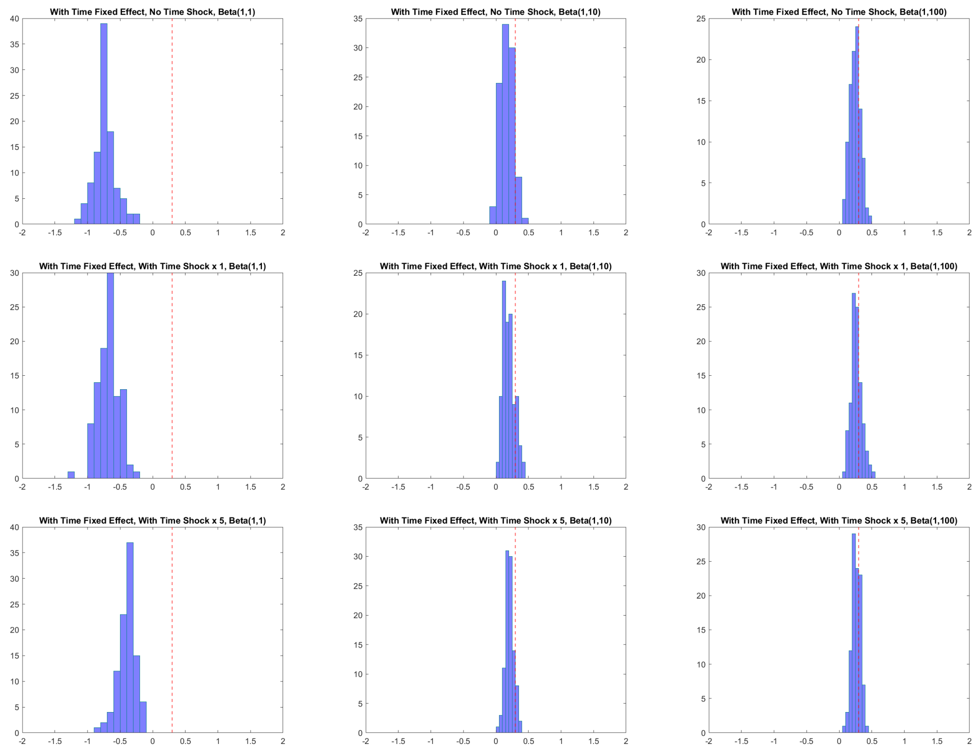
where $\boldsymbol{\varepsilon}_t = \begin{bmatrix} \varepsilon_{1,t}, \varepsilon_{2,t}, ..., \varepsilon_{N,t} \end{bmatrix}'$ will have two forms, one where $\boldsymbol{\varepsilon^I}_t = \begin{bmatrix} \varepsilon_{1t} & ... & \varepsilon_{Nt} \end{bmatrix}'$ denotes a set of county-specific i.i.d. shocks to inflation expectations such that $\varepsilon_{it} \sim \mathcal{N}(0, \sigma_{\varepsilon^2})$. In the other case, we also have a case where there is a common time shock, so $\boldsymbol{\varepsilon^T}_t = \boldsymbol{\varepsilon^I}_t + u_t \bigotimes \mathbb{1}_{N,1}$, with $u_t = \begin{bmatrix} u_1, u_2, ..., u_T \end{bmatrix}'$, a $Tx1$ matrix that contains time shocks with $u_t \sim \mathcal{N}(0, \sigma_u^2)$. We use $\sigma_\varepsilon = 1$ and $\sigma_u = 0.1$, so $\frac{\sigma_\varepsilon}{\sigma_u}$ is similar to what the variation in time fixed effects in the data look like compared to the residuals on the data from that regression. We use $\beta = 0.3$, $N = 300$ and $T = 100$ and simulate 100 times, keeping the network constant. Figure 4 shows the results of the simulation without time FE for each formation process of the network and Figure 5 shows the result with time FE.

Figure 4: Regression Results without Fixed Effects



Note: The figure shows the results of the regression (B.3) of the data simulated as described in the text. The first row shows results of simulations without a common time shock. The second row shows results of a simulation with a common time shock that is 0.1 the size of the individual shock and the last row shows results of a simulation with a common time shock that is 0.5 the size of the individual shock. All regression do not include a time fixed effect.

Figure 5: Regression Results with Fixed Effects



Note: The figure shows the results of the regression (B.4) of the data simulated as described in the text. The first row shows results of simulations without a common time shock. The second row simulation with a common time shock that is 0.1 the size of the individual shock and the last row shows results of a simulation with a common time shock that is 0.5 the size of the individual shock. All regression include a time fixed effect.

We can see that, from the extreme case of complete homogeneity in the network, to the uniform distribution case, there are some similarities. When there is no time shock (top left panel in both figures), the OLS without a fixed effect is positively biased, but not by much. In the case of the time FE, there is a strong negative bias that leads the coefficient to negative values. This effect is present in the uniform distribution case, regardless of whether there is a time common shock or not. This effect is smaller when the distribution of the network changes. We can see that in the case of the Beta(1,100) distribution, the bias is still negative, but very close to the true value. With a time shock, the regression without a time fixed effect is biased and goes to 1.

These results speak directly to the results in Table 1. There is an important difference in the estimates of Column (4) and Column (5). Both regressions have time fixed effects, but in Column (5) we drop counties that are spatially close. By doing that, we are effectively moving the distribution of shares closer to an extreme value of one, as we are inputting a zero share to a group of counties in the common network. In those cases, the regression with the time fixed effect results in a less biased estimate, even when there is no aggregate time shock. Something similar happens in Section 4.3, when we split the sample by demographics. Because of these issues, we use the first OLS results to show the importance of the network, but the results in Section 5, where we use an instrumental variable approach, using county and gender variation, will be the coefficient that would help us to obtain the unbiased estimate.

C 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:

$$\pi^e_{c,t} = \alpha_c + \gamma_t + \beta \sum_{k \neq c} \omega_{c,k} \pi^e_{k,t} + \varepsilon_{c,t} \tag{C.1}$$

where $\pi^e_{c,t}$ denotes the average inflation expectations in county c in month t. Weights $\omega_{c,k}$ capture the linkages in the social network between county c and county k. α_c denotes a county fixed effect, γ_t denotes a 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, $\sum_{k \neq c} \omega_{c,k} \pi^e_{k,t}$. All estimated specifications of equation C.1 cluster standard errors at the county level.

Various combinations of the fixed effects, restricting the sample to counties with more than 10 observations, and weighting by the number of responses per period make up our specifications. Table 5 lists the different specifications and associated estimates of β across its columns. Column 1 presents a baseline without county and time fixed effects. Column 5 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 between 0.62 and 0.03 percentage points in a county's inflation expectations. The ample range of the point estimate is explained by the fixed effects used and the amount of variation that take out, when the network contains common nodes. These results show that the expectations of others matter when individuals form expectations.

Table 5: Network Effect at the County Level

	(1)	(2)	(3)	(4)	(5)	(6)
Expectations of Others	0.644***	0.268***	0.619***	0.274***	0.046**	0.032*
	(0.019)	(0.017)	(0.019)	(0.016)	(0.018)	(0.017)
Sample	N>10	All	N>10	All	N>10	All
Weights	Yes	No	Yes	No	Yes	No
County FE	No	No	No	Yes	Yes	Yes
Time FE	No	No	No	No	Yes	Yes
Observations	29,465	74,534	29,268	74,488	29,268	74,488
R-squared	0.125	0.007	0.384	0.173	0.433	0.188

Note: The table shows the results of regression (C.1), where the dependent $\pi^e_{c,t}$ is the average inflation expectations of a county *c* at time t. Columns (1), (3), and (5) uses only counties at times where they have at least 10 observations ($N > 10$) and weights the regression by the number of responses in each period (*Weights = Yes*). Standard errors are clustered at the county level.

Estimating all other specifications confirms this finding. Across specifications, beliefs in the network turn out to matter when individuals form expectations.

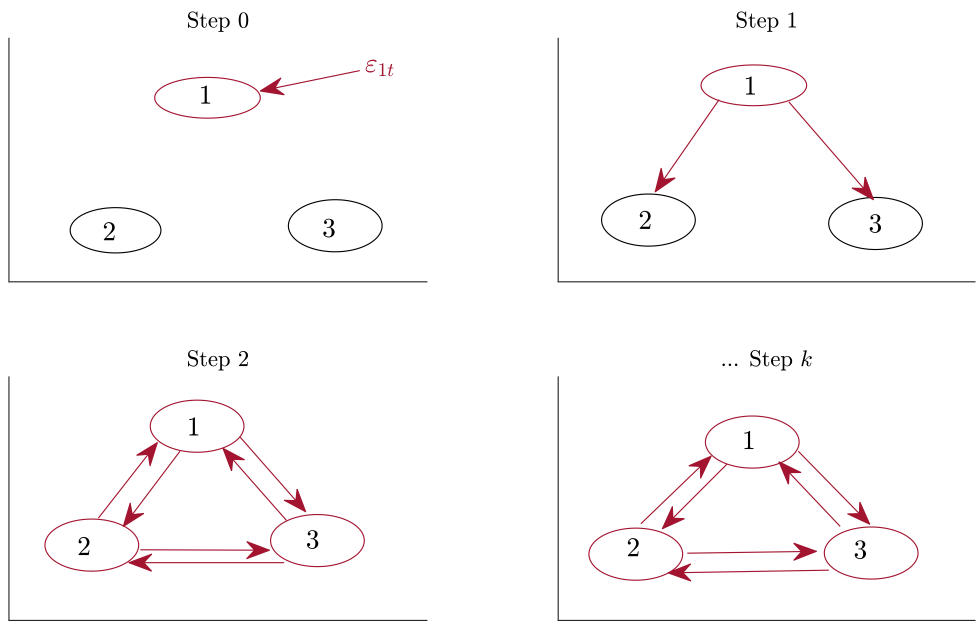
D Empirical Implications for Stability

Given a one-time shock to the expectations in county n *only*, inflation expectations in county n are given by $\pi^e_{nt} = \boldsymbol{\alpha}_n + \boldsymbol{\varepsilon}_{nt}$. However, due to social ties, expectations in the other counties are 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:

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

and so on, where $\pi^e_t(k)$ 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 6.

Figure 6: 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

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

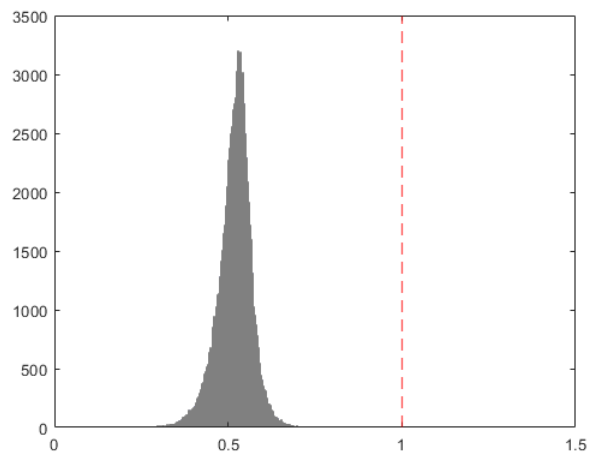
where $\rho(\beta\Omega)$ denotes the largest eigenvalue of $\beta\Omega$ in absolute value. From the Gershgorin circle theorem, all the eigenvalues of Ω should lie within the unit circle; thus all eigenvalues of $\beta\Omega$ lie within $[-\beta, \beta]$.[24] Furthermore, one can show that 1 is always an eigenvalue of Ω, implying that

[24] 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.

$\rho(\beta\Omega) = |\beta|$.[25] As a result, a one-time county-specific shock to inflation expectations cannot destabilize inflation expectations in all the other counties if $|\beta| < 1$. By contrast, if $|\beta| \geq 1$, then inflation expectations grow exponentially with every step of the feedback loop, converging to $\pm\infty$.

Finally, we perform a simple exercise to account for the uncertainty in the estimates of ρ_1 and ρ_2 reported in Column (6) of Table 4. Specifically, we simulate 100,000 draws of $\begin{pmatrix} \rho_1 \\ \rho_2 \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \hat{\rho}_1 \\ \hat{\rho}_2 \end{pmatrix}, \begin{pmatrix} \sigma_{\hat{\rho}_1} & \sigma_{\hat{\rho}_1,\hat{\rho}_2} \\ \sigma_{\hat{\rho}_2,\hat{\rho}_1} & \sigma_{\hat{\rho}_2} \end{pmatrix}\right)$, and $\omega_{ii} \sim \mathcal{N}(\hat{\omega}_{ii}, \sigma_{\hat{\omega}_{ii}})$ and construct the distribution of $\beta = \omega_{ii}\rho_1 + (1-\omega_{ii})\rho_2$ shown in Figure 7. We find no case of instability.

Figure 7: Distribution of β



Note: Histogram of $\beta = \omega_{ii}\rho_1 + (1-\omega_{ii})\rho_2$, constructed from 100,000 draws of $\begin{pmatrix} \rho_1 \\ \rho_2 \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \hat{\rho}_1 \\ \hat{\rho}_2 \end{pmatrix}, \begin{pmatrix} \sigma_{\hat{\rho}_1} & \sigma_{\hat{\rho}_1,\hat{\rho}_2} \\ \sigma_{\hat{\rho}_2,\hat{\rho}_1} & \sigma_{\hat{\rho}_2} \end{pmatrix}\right)$, and $\omega_{ii} \sim \mathcal{N}(\hat{\omega}_{ii}, \sigma_{\hat{\omega}_{ii}})$, using point estimates and standard errors reported in Column (6) of Table 4. The dashed red line at $\beta = 1$ denotes the threshold for instability.

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

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

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

E Proofs

E.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 $\sum_i \omega(\theta_{ji}) \sum_{e \in E^h_{i \to j}} S_j(e,k \mid \theta_{ji}) = \hat{a}^h_j$ for any $h \in \{k, K\backslash k, O\}$ and $\sum_i \omega(\theta_{ji}) \sum_{e \in E_{i \to j}} S_j(e,k \mid \theta_{ji}) = \hat{a}_j = \hat{a}^k_j + \hat{a}^{K\backslash k}_j + \hat{a}^O_j$. 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 $\sum_{e \in E_j} S_j(e,k) = a_j = a^k_j + a^{K\backslash k}_j + a^O_j$.

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

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

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

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

E.2 Proof of Corollary 1

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

E.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 E.1.

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

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.

E.4 Proof of Proposition 6

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 the weight assigned to experiences shared by individual l, ω_{lj}, changes, and given that $\sum_{i \neq j} \omega(\theta_{ji}) = 1$, 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.[26]

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

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

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

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

[26]The main takeaway of Proposition 6 would not change if we assumed that other weights changed as well in response to the change in ω_{lj}.

E.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.3, 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.3, $f(\hat{r}_1(k))$ 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.3, 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.3, $f(\hat{r}_1(k))$ 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).

E.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

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

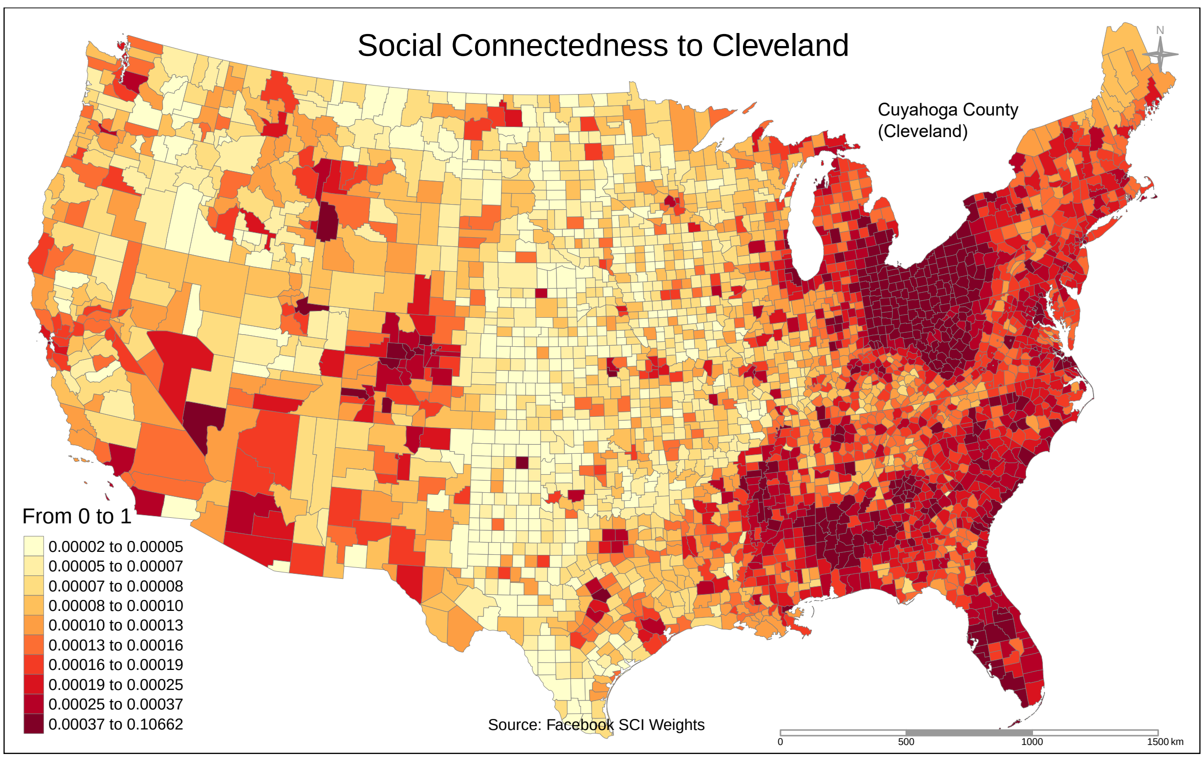
Similarly, when there is social interaction, the probability of hypothesis H converges to $\frac{\hat{r}_j(H)}{\hat{r}_j(H)+\hat{r}_j(L)}$. Therefore, if social interaction amplifies the recall probability of the high inflation regime, that is, if $\hat{r}_j(H) > r_j(H)$, then social connectedness will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

F Additional Figures

F.1 Social Connectedness: Other Examples

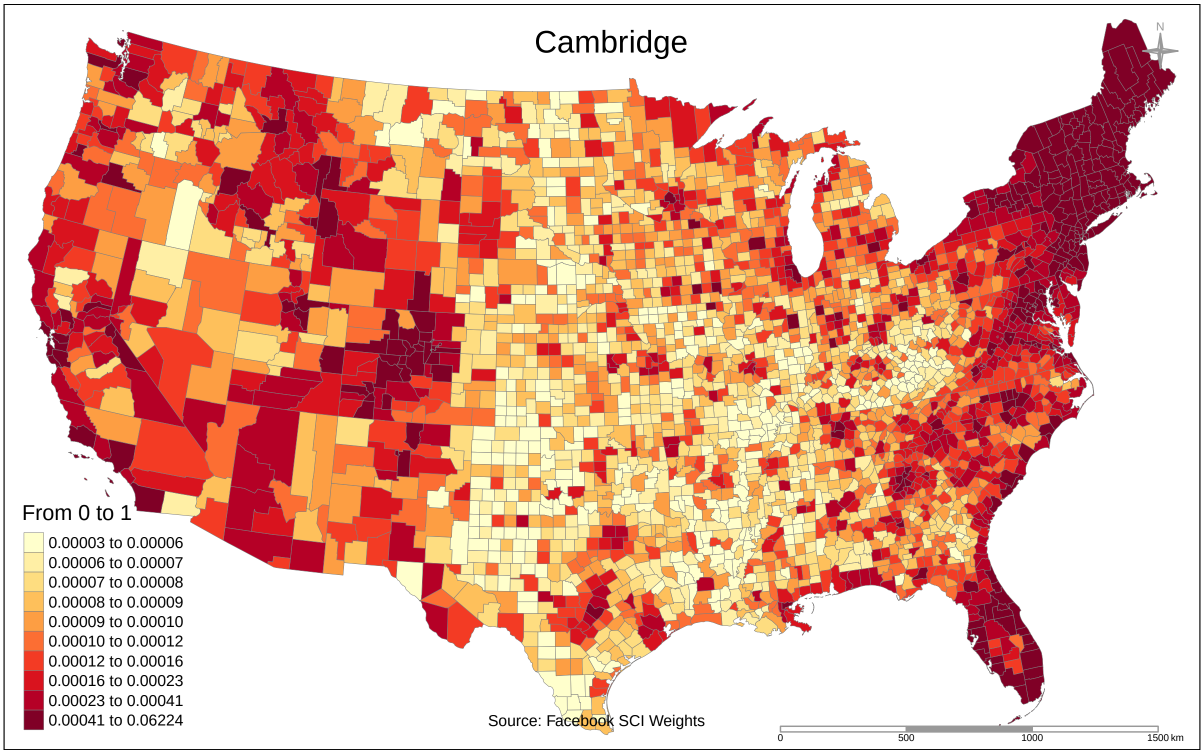
In the body of the text, we presented the connections of counties to Cleveland. Here, we provide the social Connectedness to Cleveland and three other illustrative examples: Cambridge, Miami, and Los Angeles. We observe similar patterns.

Figure 8: Social Connectedness of Each County to Cleveland ($\omega_{c,Cleveland}$)



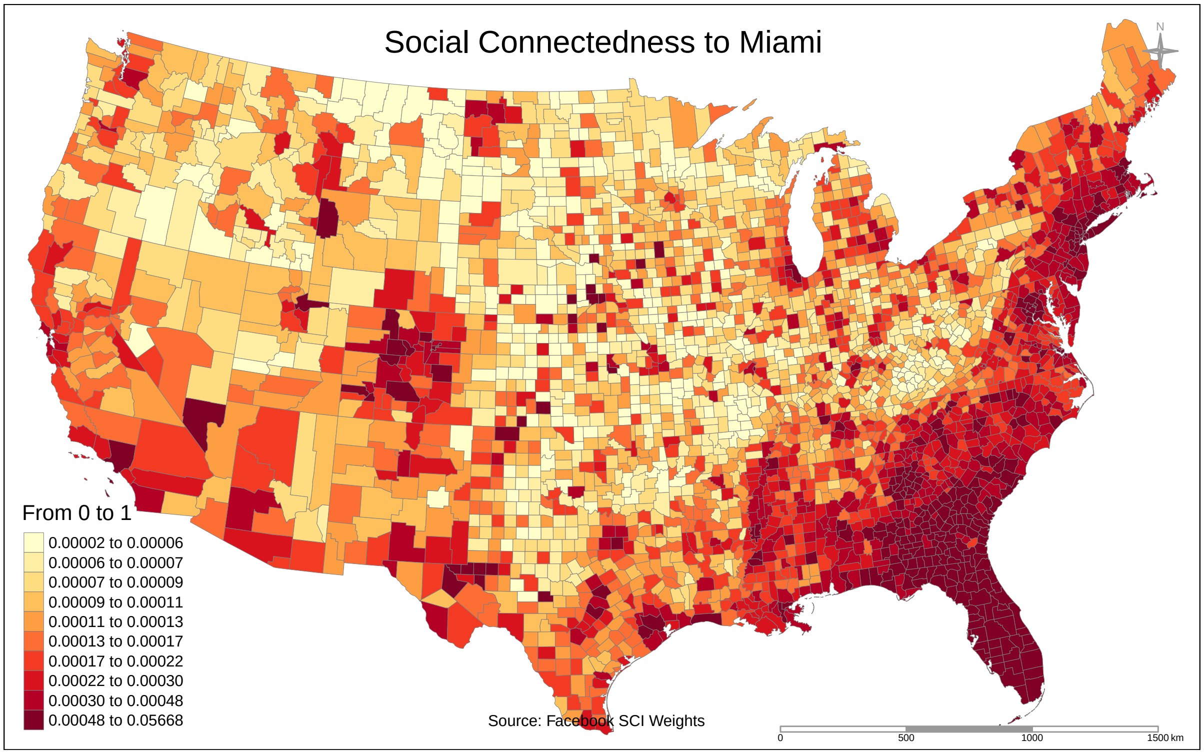
Note: The yellow-to-red color scale represents the degree to which counties are socially connected to Cleveland, based on $\omega_{c,Cleveland}$. Red indicates higher $\omega_{c,Cleveland}$. Source: Social Connectedness Index

Figure 9: Social Connectedness of Each County to Cambridge ($\omega_{c,Cambridge}$)



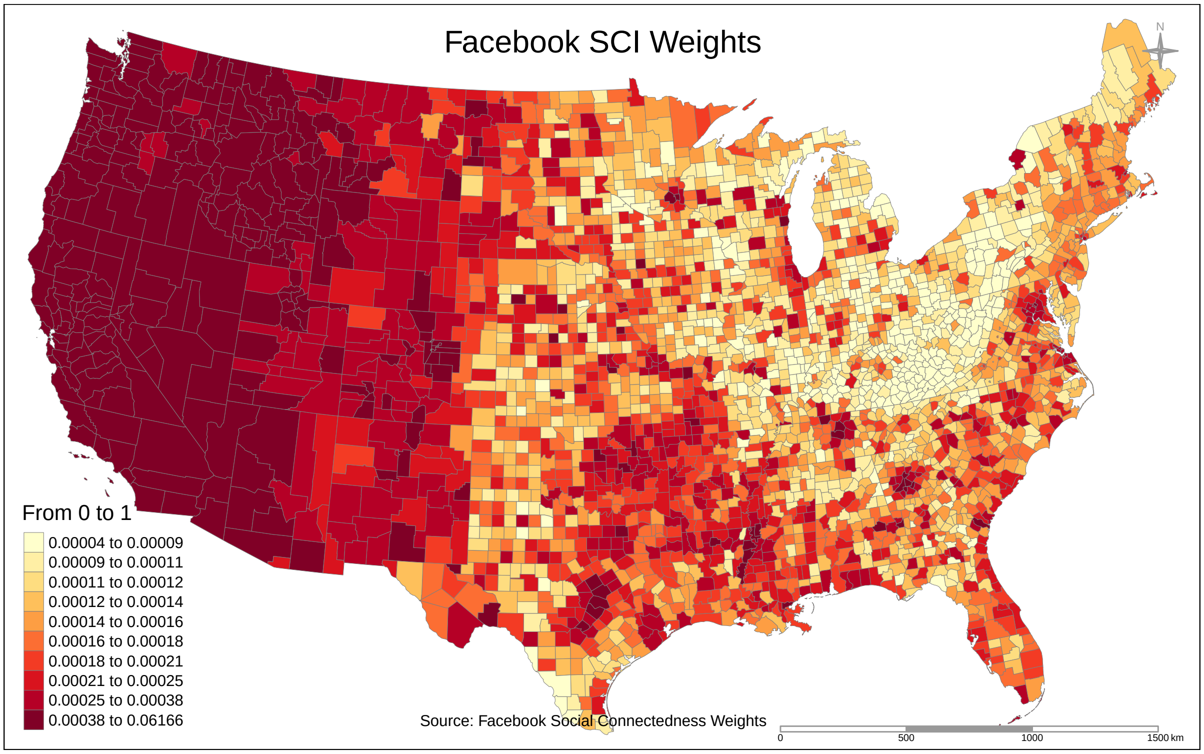
Note: The yellow-to-red color scale represents the degree to which counties are socially connected to Cambridge, based on $\omega_{c,Cambridge}$. Red indicates higher $\omega_{c,Cambridge}$. Source: Social Connectedness Index

Figure 10: 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

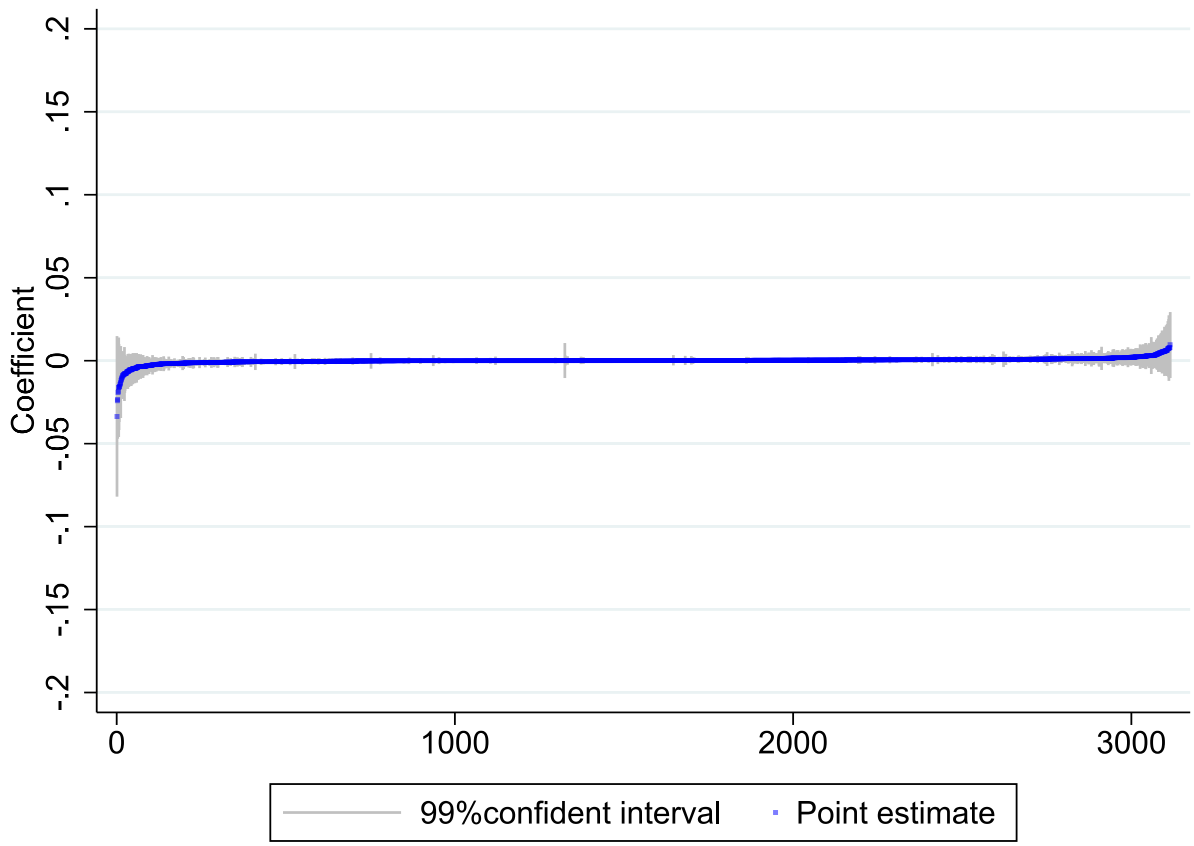
Figure 11: Social Connectedness of Each County to Los Angeles ($\omega_{c,LA}$)



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

F.2 Other Figures

Figure 12: Correlation between SCI and Own Car Commuting Shares



Note: The figure shows results of regressions where the dependant variables are the weights in a given county and the independent variable is the share of households that use their own car to commute. The blue dots are the point estimates and the grey lines represent 99 percent condifent intervals.

G Other Tables

First, we explore whether our main results are explained by proximity in space. In Table 6 we repeat our main analysis excluding nearby counties from the network. We find that even inflation expectations from distant locations are an important determinant of an individual's inflation expectations. In particular, the main coefficient increases compared to the benchmark estimate. In Appendix B.3 we show that incorporating time fixed effects can introduce a bias that attenuates the coefficient, particularly in scenarios characterized by a homogeneous network structure.

Hence, the increase in the main coefficient is consistent with the fact that when we exclude inflation expectations in nearby counties, we induce greater heterogeneity in the network, which reduces this attenuation bias.[27]

Table 6: Effect of Removing Close Counties on Inflation Expectations

	(1)	(2)	(3)	(4)	(5)	(6)
Expectations of Others	0.282***	0.352**	0.280***	0.281**	0.281***	0.291**
	(0.089)	(0.149)	(0.090)	(0.130)	(0.089)	(0.130)
County Expectations	0.590***	0.554***	0.591***	0.556***	0.591***	0.556***
	(0.065)	(0.047)	(0.066)	(0.048)	(0.065)	(0.048)
Distance	>200m	>200m	>250m	>250m	>300m	>300m
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Observations	1,926,635	1,926,635	1,926,635	1,926,635	1,926,635	1,926,635
R-squared	0.017	0.017	0.017	0.017	0.017	0.017

Note: The table shows the results of regression (16), where the dependent $\pi^e_{i,c,t}$ is the inflation expectations of individual i who answers from county c at time t. Regressions are weighted by the number of responses in a county in each period. We build a network excluding counties that are less than a certain amount of miles from the individual's county. Standard errors are clustered at the county level.

Table 7: Effect with Demographic Controls

	(1)	(2)	(3)	(4)	(5)
Expectations of Others	0.252***	0.266***	0.051***	0.068***	0.058***
	(0.074)	(0.076)	(0.017)	(0.019)	(0.020)
County Expectations	0.603***	0.575***	0.557***	0.542***	0.469***
	(0.058)	(0.053)	(0.049)	(0.051)	(0.019)
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
Demografics FE	No	Yes	No	Yes	Yes
Dem-Time FE	No	No	No	No	Yes
Observations	1,926,282	1,925,393	1,926,282	1,925,393	1,925,393
R-squared	0.017	0.033	0.017	0.033	0.036

[27] The result is tied to the following intuition: Inclusion of a time fixed effect is equivalent to filtering out average inflation expectations of respondents, which is similar to estimating a network coefficient, only with different weights. By removing nearby counties from the data underlying the estimation of the second coefficient, we are making the two fixed effects dissimilar. It then turns out that this change can reduce the attenuation bias in the coefficient on expectations in the social network.

Table 8: County Demographic Controls

	Sh Foreign	PC Income	Sh Black	Sh Hisp	Sh White NH	Pov Rate	Biden Sh
Exp of Others	0.337***	0.326***	0.234***	0.288***	0.097***	0.243***	0.331***
	(0.032)	(0.062)	(0.055)	(0.064)	(0.024)	(0.032)	(0.427)
County Exp	0.555***	0.551***	0.583***	0.564***	0.565***	0.564***	0.555***
	(0.036)	(0.022)	(0.048)	(0.048)	(0.054)	(0.038)	(0.285)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Dem FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,926,282	1,926,282	1,926,282	1,926,282	1,926,282	1,926,276	1,920,803
R-squared	0.017	0.017	0.017	0.017	0.017	0.017	0.017

Table 9: Placebo

	(1)	(2)	(3)	(4)	(5)
Placebo	0.231***	0.046	0.351***	-0.036	-0.043
	(0.061)	(0.084)	(0.076)	(0.056)	(0.055)
Expectations of Others					0.050**
					(0.023)
County Expectations	0.712***	0.687***	0.546***	0.497***	0.497***
	(0.051)	(0.038)	(0.053)	(0.032)	(0.032)
Time FE	No	Yes	No	Yes	Yes
County FE	No	No	Yes	Yes	Yes
Observations	1,277,247	1,277,247	1,277,247	1,277,247	1,277,247
R-squared	0.012	0.012	0.012	0.013	0.013

Table 10: Network Effect by Political Affiliation

	(1)	(2)	(3)	(4)	(5)	(6)
$Network - Politics$	0.273***	0.225***	0.259***	0.166***	0.169***	0.264***
	(0.022)	(0.041)	(0.040)	(0.031)	(0.034)	(0.051)
$Inf - County$	0.646***	0.631***	0.575***	0.558***	0.514***	0.333***
	(0.032)	(0.033)	(0.031)	(0.030)	(0.023)	(0.037)
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	1,896,092	1,896,092	1,896,092	1,896,092	1,896,092	1,896,092
R-squared	0.022	0.023	0.023	0.023	0.024	0.025

Note: The table shows the results of regression (17), where the dependent variable $\pi^e_{i,d,c,t}$ is the inflation expectations of individual i, with gender d, who answers from county c at time t.. The network is defined as all the answers that are for individuals from the same political affiliation in other counties. $Inf - County$ is the average of responses from respondents with the same political affiliation in her/his own county. Respondents choose between Democrat, Republican, or Independent. Regressions are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Table 11: Network Effect by Income

	(1)	(2)	(3)	(4)	(5)	(6)
$Network - Income$	0.214***	0.173***	0.205***	0.147***	0.164***	0.258***
	(0.035)	(0.030)	(0.052)	(0.036)	(0.038)	(0.069)
$Inf - Income$	0.676***	0.662***	0.613***	0.596***	0.553***	0.375***
	(0.035)	(0.034)	(0.036)	(0.032)	(0.026)	(0.049)
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	1,899,700	1,899,700	1,899,700	1,899,700	1,899,700	1,899,700
R-squared	0.024	0.024	0.025	0.025	0.025	0.027

Note: The table shows the results of regression (17), where the dependent variable $\pi^e_{i,d,c,t}$ is the inflation expectations of individual i, with gender d, who answers from county c at time t.. The network is defined as all the answers that are for individuals from the same income bracket in other counties. $Inf - Income$ is the average of responses from respondents in the same income bracket in her/his own county. Respondents choose between less than 50k, 50-100k, and more than 100k annual income. Regressions are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Table 12: Network Effect by Age

	(1)	(2)	(3)	(4)	(5)	(6)
$Network - Age$	0.291***	0.302***	0.292***	0.306***	0.429***	0.306***
	(0.020)	(0.026)	(0.032)	(0.030)	(0.041)	(0.030)
$Inf - Age$	0.643***	0.633***	0.593***	0.585***	0.447***	0.585***
	(0.038)	(0.031)	(0.037)	(0.030)	(0.035)	(0.030)
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	1,883,123	1,883,123	1,883,123	1,883,123	1,883,123	1,883,123
R-squared	0.032	0.032	0.032	0.032	0.035	0.032

Note: The table shows the results of regression (17), where the dependent variable $\pi^e_{i,d,c,t}$ is the inflation expectations of individual i, with gender d, who answers from county c at time t.. The network is defined as all the answers that are for individuals from the same age group in other counties. $Inf - Age$ is the average of responses from respondents with the same age group in her/his own county. Respondents choose between 18-34, 35-44, 45-64, and more than 65 years old. Regressions are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Table 13: Similarity Effects by Other Demographic Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Network-Age	0.316***				0.363***	0.465***
	(0.035)				(0.031)	(0.039)
County-Age	0.585***				0.514***	0.413***
	(0.032)				(0.026)	(0.032)
Network-Income		0.149***			0.138**	0.242***
		(0.035)			(0.054)	(0.075)
County-Income		0.608***			0.506***	0.325***
		(0.020)			(0.018)	(0.029)
Network-Politics			0.179***		0.141***	0.235***
			(0.036)		(0.035)	(0.045)
County-Politics			0.551***		0.451***	0.281***
			(0.014)		(0.015)	(0.020)
Network-Gender				0.377***	0.366***	0.739***
				(0.041)	(0.052)	(0.091)
County-Gender				0.610***	0.497***	(0.151)
				(0.019)	(0.018)	(0.036)
Network	-0.158***	-0.077**	-0.079***	-0.250***	-0.702***	
	(0.020)	(0.038)	(0.024)	(0.038)	(0.041)	
County	-0.009	-0.036	-0.021	-0.043	-1.377***	
	(0.036)	(0.039)	(0.039)	(0.036)	(0.030)	
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Time FE	No	No	No	No	no	Yes
Observations	1,883,123	1,899,700	1,896,092	1,910,679	1,850,340	1,848,409
R-squared	0.031	0.025	0.023	0.027	0.050	0.045

Note: The table shows the results of regression (17), where the dependent variable $\pi^e_{i,d,c,t}$ denotes the inflation expectations of individual i of gender d in county c at time t. *Network* is defined as the average of inflation expectations of individuals from the same demographic group in other counties. *County* denotes the average in the own county. Network and county combinations of demographic categories denote the averages conditional on other individuals belonging to the same demographic categories. Regressions are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Table 14: Similarity and Dissimilarity Effect by Gender

	(1)	(2)	(3)	(4)	(5)	(6)
Similarity-Network	0.303***	0.285***	0.325***	0.211***	0.512***	0.460***
	(0.036)	(0.021)	(0.054)	(0.022)	(0.108)	(0.088)
Dissimilarity-Network	-0.086***	-0.106**	-0.004	-0.153***	0.052	-0.002
	(0.026)	(0.040)	(0.031)	(0.031)	(0.154)	(0.136)
Similarity-County	0.675***	0.662***	0.602***	0.578***	0.558***	0.560***
	(0.035)	(0.030)	(0.040)	(0.033)	(0.033)	(0.035)
Dissimilarity-County	0.037***	0.029**	-0.032***	-0.051***	-0.038***	-0.036***
	(0.012)	(0.013)	(0.011)	(0.008)	(0.006)	(0.006)
County FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes	Yes
Counties	All	All	All	All	>200m	>250m
Observations	1,858,010	1,858,010	1,858,010	1,858,010	1,858,010	1,858,010
R-squared	0.026	0.026	0.026	0.026	0.027	0.027

Note: The table shows the results of regression (17), where the dependent variable $\pi^e_{i,d,c,t}$ denotes the inflation expectations of individual i of gender d in county c at time t. $Similarity - Network$ denotes the average of inflation expectations of individuals of the same gender in other counties. $Dissimilarity - Network$ denotes the average of inflation expectations of individuals of the opposite gender in other counties. $Similarity - County$ denotes the average of inflation expectations of respondents of the same gender within her/his own county. $Dissimilarity - County$ denotes the average of inflation expectations of respondents of the opposite gender within her/his own county. Column (5) shows regression where the network is built removing counties that are closer than 200 miles and Column (6) removing counties closer than 250 miles. Regressions are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Table 15: Similarity Effects by Other Demographic Characteristics

	Age	Income	Politics	Gender
	(1)	(2)	(3)	(4)
Network-Dem	0.006	0.025**	0.031*	0.030**
	(0.011)	(0.013)	(0.017)	(0.014)
Own County Dem	0.574***	0.559***	0.566***	0.549***
	(0.018)	(0.021)	(0.025)	(0.025)
County FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Dem-Time FE	Yes	Yes	Yes	Yes
Observations	1,883,123	1,899,700	1,330,360	1,910,679
R-squared	0.039	0.027	0.024	0.029

Note: The table shows the results of regression (17), where the dependent variable $\pi^e_{i,d,c,t}$ denotes the inflation expectations of individual i of gender d in county c at time t. *Network* is defined as the average of inflation expectations of individuals from the same demographic group in other counties. *County* denotes the average in the own county. Network and county combinations of demographic categories denote the averages conditional on other individuals belonging to the same demographic categories. Regressions are weighted by the minimum number of responses by gender in a county in each period. Standard errors are clustered at the county level.

Table 16: Exogenous Variation and Network Effect

	(1)	(2)	(3)	(4)	(5)
$\sum_{k\neq c}\omega_{c,k}Gas\_effect_{c,t}$	1.771***				
	(1.248)				
$\sum_{k\neq c}\omega_{c,k}Gas\_effect_{c,d,t}$		2.196*	0.727		
		(1.126)	(0.948)		
$\sum_{k\neq c}\omega_{c,k}\pi^e_{d,k,t}$				0.972***	1.173***
				(0.126)	(0.122)
$Gas\_effect_{c,t}$	2.091*	2.107*	0.220	3.192***	3.145***
	(1.187)	(1.203)	(1.106)	(0.396)	(0.387)
Sample	All	Men	Female	All	All
Time FE	No	Yes	Yes	Yes	Yes
County FE	Yes	No	Yes	Yes	Yes
Regression	OLS	OLS	OLS	OLS	IV
F-Test	-	-	-	-	179.8
Observations	1,239,680	606,305	632,750	1,239,055	1,239,055
R-squared	0.014	0.014	0.014	0.020	0.006

Note: This table shows results from estimating two specifications. First, $\pi^e_{i,c,t} = \alpha_c + \gamma_t + \beta_1 Gas\_effect_{c,t} + \beta_2 \sum_{k\neq c}\omega_{c,k}Gas\_effect_{d,k,t} + \varepsilon_{i,d,c,t}$, and second, $\pi^e_{i,d,c,t} = \alpha_c + \gamma_t + \beta_1 Gas\_effect_{c,t} + \beta_2 \sum_{k\neq c}\omega_{c,k}\pi^e_{d,k,t} + \varepsilon_{i,t}$, where $\pi^e_{i,d,c,t}$ denotes the inflation expectations of individual i, of gender d, in county c, at time t; $Gas\_effect_{c,t}$ denotes the gas effect variable constructed as described in the text of county c at time t; $\pi^e_{d,k,t}$ gender d inflation expectations in county k at time t; $Gas\_effect_{d,k,t}$ denotes the gas effect variable constructed as described in the text; and α_c and γ_t are county and time fixed effects. Column (6) use as instrument $\sum_{k\neq c}\omega_{c,k}Gas\_effect_{d,k,t}$ for $\sum_{k\neq c}\omega_{c,k}\pi^e_{d,k,t}$ Regressions are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level