The Expectations of Others[*]

Ezequiel Garcia-Lembergman[†] Ina Hajdini[‡] John Leer[§]
Mathieu Pedemonte[¶] Raphael Schoenle[||]

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Abstract

How do social networks affect inflation expectations? In a model of memory and recall, we analytically show conditions under which social networks amplify inflation expectations as well as necessary conditions for belief stability. In particular, sharing salient experiences or sharing experiences among similar individuals can intensify amplification. Using a novel dataset that integrates information on inflation expectations with social network connections, our empirical analysis reveals several key findings in line with the model predictions: Inflation expectations within one's social network are positively associated with individual inflation expectations. This 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 disseminates strongly through the network. Our estimates imply that the influence of the social network amplifies but does not destabilize inflation expectations.

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[†]Pontificia Universidad Catolica de Chile, ezequiel.garcia@uc.cl
[‡]Federal Reserve Bank of Cleveland, ina.hajdini@clev.frb.org
[§]Morning Consult jleer@morningconsult.com
[¶]Federal Reserve Bank of Cleveland, mathieu.pedemontelavis@clev.frb.org
[||]Brandeis University and CEPR, schoenle@brandeis.edu

1 Introduction

A growing body of literature is investigating how consumers form inflation expectations, and how these expectations matter for individual economic decisions and macroeconomic dynamics.[1] In this context, a central finding goes back to the behavioral work of Tversky and Kahneman (1973): Consumers may rely on availability heuristics to form expectations whereby events that are more salient or easier to recall are more likely than others.[2] However, a central insight from social psychology, pioneered by Festinger (1954), is usually not considered in the inflation expectations literature: The formation of inflation expectations takes place in a social context while we interact with others. We weave this insight back into a behavioral model of expectations formation, and empirically show that social networks indeed matter for the formation of inflation expectations.

In particular, our paper makes three contributions. First, we extend the memory and recall model of Bordalo et al. (2023) to allow for experiences that are shared through one's social network, and use the model as a laboratory to generate several testable implications for the role of social networks on individual expectations. Second, by merging inflation expectations with social network connections we create a novel dataset that is dense enough to facilitate an analysis of inflation expectations in a social network context. Third, we implement several empirical strategies to rigorously isolate the causal effect that the social network has on individual inflation expectations. Our empirical analysis provides strong evidence for the model's predictions: Inflation expectations of the social network are significantly and positively associated with individual inflation expectations. This relationship is stronger for groups that share common demographic characteristics such as gender, income, or political affiliation. Additionally, implementing an instrumental variable approach establishes causality of these results while also showing that salient information transmits strongly through the network. Finally, our estimates imply that the social network does not destabilize inflation expectations.

Our paper incorporates the role of social networks into the memory and recall model of Bordalo et al. (2023). In this framework, subjective probability assessments of events like "high inflation" – and hence, high inflation expectations – rise when such hypotheses are more similar to episodes in an individual's memory. Our extension explicitly allows

[1]See, for instance, for individual decisions Coibion et al. (2019a), Coibion et al. (2019b), and Hajdini et al. (2022b). For macro implications, see Coibion and Gorodnichenko (2015a), Gabaix (2020), Kohlhas and Walther (2021), and L'Huillier et al. (2021), among many others.

[2]See, for example, Carroll (2003). Moreover, recent work by da Silveira and Woodford (2019) and Bordalo et al. (2023) has focused on understanding the role of memory in belief formation. 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. Gas prices constitute an example of a well-known salient price that affects consumer inflation expectations, as for example recently shown in D'Acunto et al. (2021b).

an individual's memory to incorporate episodes retrievable from their social network and thus, affect their probability assessments and expectations. Moreover, similarity between a hypothesis and such shared experiences may now positively depend on common demographic characteristics among friends, embodying the possibility that experiences shared by similar friends can be perceived as more relevant to a probability assessment.

Several directly testable implications emerge in this setup. First, an individual's inflation expectations are positively influenced by those of others in her social network if the individual pays attention to shared experiences. Second, the influence of the social network on inflation expectations is stronger among individuals who share common demographics, provided that these similarities tend to provide subjectively more relevant information. Third, idiosyncratic shocks to inflation expectations that are shared through one's social network are more likely to destabilize individual inflation expectations when sharing them increases their subjective relevance for probability assessments. For instance, instability can occur if a person perceives the shared experience to be more salient for "high inflation" than if it were their own. Such a stability condition appears intuitive in our social network setup but perhaps less so in statistical models of social learning like DeGroot (1974).

Empirically, pinning down the causal effects of social networks on individual inflation expectations is challenging. First, the analysis necessitates a dataset that combines geographically dense data on individuals inflation expectations with a map of the social network. Second, when "other factors," such as aggregate or local shocks, are sufficiently common across locations, they may spuriously create co-movement in individual inflation expectations and inflation expectations of others. Examples of such "other factors" include common trade or retail networks, or homophily in social networks, both of which can make specific shocks common to groups of individuals and induce co-movement in their expectations.

Our analysis overcomes these challenges in various ways. To address the first challenge, we have constructed a novel dataset that contains inflation expectations and social networks. For consumer inflation expectations, we use data from the Indirect Consumer Inflation Expectations (ICIE) survey, which not only captures individual inflation expectations but also provides detailed geographic and demographic information about the respondents.[3] Social connections at the county level are derived from the Social Connectedness Index Database (SCI), initially introduced by Bailey et al. (2018a). The SCI measures the social connectedness between different counties of the United States as of April 2016, based on Facebook friendship connections. Analysing this data at a monthly

[3]The survey is nationally representative of the US. See Hajdini et al. (2022a) for details.

frequency and at the county level yields sufficiently thick data for our purpose, with over 1.9 million observations from March 2021 to July 2023.

Central to our empirical analysis is exploiting these data to construct a monthly measure of *inflation expectations of others* to whom we are connected via the social network: Thanks to the thickness of our data, we can compute average inflation expectations for each U.S. county. Then, we construct expectations of others relevant for an individual in a given county by taking a weighted average of these average expectations in other counties. In this calculation, the SCI weights used are proper to each county and give greater importance to other counties that are more strongly connected through the social network to an individual's own county.

Given this novel dataset, our analysis deploys three strategies to show that social networks are an important channel for the formation of individual inflation expectations. Each approach regresses individual inflation expectations on the inflation expectations of others while accounting in different ways for "other factors" and endogeneity concerns. Our first approach accounts for "other factors" directly, by including detailed fixed effects that capture any systematic unobserved county characteristics and time variation. To rule out spurious transmission of common local shocks, a variant of this approach excludes proximate counties, while other variants include controls interacted with time fixed effects, such as individual demographic characteristics and county demographic characteristics, as well as an explicit measure of price shocks transmitted through common retail networks. These variables aim to explicitly account for variation that stems, for example, from the co-movement of prices in similar consumption baskets and may induce common movements in the associated inflation expectations.

The second approach creates additional variation at the county level to remove variation in "other factors" at the county-time level that affects identification. Specifically, we construct county $\times$ demographic $\times$ time inflation expectations of others that allow us to include such county-time fixed effects. These county-time fixed effects absorb any variability that equally affects all demographic groups in a county at a given time. They alleviate concerns about, for instance, spatial spillovers, trade relationships, or demand spillovers from nearby regions, among other confounding factors. Exploiting common-demographic expectations of others additionally allows our analysis to identify the role that shared demographics have on the transmission of inflation expectations through one's network.

Finally, we apply an instrumental variables approach that addresses any remaining endogeneity concerns, including those implied by the Manski (1993) reflection problem. The idea behind the instrument is simple: Gas prices are relevant for the formation of inflation expectations (Coibion and Gorodnichenko (2015b)) and such relevance varies across cities, depending on the importance of gas usage, which is not related to the social network weights. The approach therefore exploits 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. Using these shocks as an instrument then allows one to estimate an unbiased effect of the expectations of others on individual inflation expectations.[4] Not least in their totality, these three approaches contribute to the strength of identification. At the same time, they address different aspects of the model predictions.

Across all approaches, our empirical findings consistently demonstrate the relevance of social networks in shaping individual inflation expectations, highlighting the significant impact of shared experiences within these networks: Inflation expectations of others shared through the social network bear a positive, causal relationship with individual inflation expectations. Moreover, our empirical results align with predictions related to similarity in our model, showing that the beliefs of demographically similar individuals exert a greater influence on inflation expectations than those from a more diverse network. Viewed through the lens of the model, this finding implies a higher perceived relevance of shared experiences within common-demographic networks. In terms of stability, our analysis reveals that while the influence of others' inflation expectations does not destabilize individual expectations overall, the salience of shared experiences through social networks can have a marginally destabilizing effect. This finding suggests that policymakers should focus on identifying and managing salient events that propagate strongly through social networks to mitigate potential instabilities in inflation expectations.

Literature. The findings from our analysis are related to several strands of the literature. On one hand, there is extensive work aiming to understand how individuals form social networks and learn from them, as for example in Banerjee (1992), Acemoglu et al. (2011), and Golub and Sadler (2016).[5] Another 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)). Our paper connects both strands of the literature, by considering a memory-

[4]Because the instrument embodies idiosyncratic local gas price experiences, any resulting relevance of inflation expectations of others does not derive from simply speeding up learning about common shocks, but truly from idiosyncratic experiences becoming available over the network.

[5]Other notable papers in the social learning literature in a network context include Ellison and Fudenberg (1993), Mobius and Rosenblat (2014), Chandrasekhar et al. (2020), Board and Meyer-ter Vehn (2021), and Elliott and Golub (2022). Other papers, such as Arifovic et al. (2013) and Grimaud et al. (2023), among others, consider social learning in a New Keynesian framework, where agents either do not interact with one another or their forecasts are assumed to converge towards the best-performing ones.

based theoretical framework and showing that a key macroeconomic variable – inflation expectations – is influenced by social interactions. Extending the network literature to the context of inflation expectations paves the way for future research on questions central to policymakers and modelers alike that for example relate to the existence of multiple equilibria, the role of super-nodes in communication, and the transmission of shocks from different regions and of different sizes (as in Gabaix (2011)).

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 empirical literature that 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 behavioral 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. Finally, Section 5 concludes.

2 Theoretical Framework

This section outlines a model for the formation of inflation expectations in the presence of social networks. The framework we propose extends the memory and recall model of Bordalo et al. (2022) and Bordalo et al. (2023) by incorporating the feature of social interaction. We start off by describing a baseline setting in which individuals in the economy do not socially interact (similar to Bordalo et al. (2022) and Bordalo et al. (2023)). We then allow for individuals to socially interact and exchange experiences, deriving a number of testable implications. The exposition of the framework concludes by delineating belief stability conditions that embody an interaction of the social network and the salience of the experiences shared through the network, enriching more statistical social learning models as DeGroot (1974).

2.1 Baseline: No Social Interaction

Consider an individual j, who has stored a set of *personal* experiences in her memory database E_i of size $|E_i|$. For simplicity, we split the set of experiences of j into three mutually exclusive subsets containing high-inflation experiences, E_i^H, low inflation experiences, E_i^L, and experiences that are irrelevant to high or low inflation experiences, E_i^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 $u_i \in E_i$ and $v_i \in E_i$, that is, $S_i(u_i, v_i) : E_i \times E_i \to \begin{bmatrix} 0 & \bar{S}_i \end{bmatrix}$, that quantifies the similarity between individual i's experience u_i and v_i. The similarity between any two experiences u_i and v_i increases in the number of shared features between the two experiences, and the highest value of similarity, $\bar{S}_i$, is achieved when $u_i = v_i$. We purposely abstract from providing a particular functional form for S_i to warrant generality of our results.[6]

Based on this setup, we define recall probabilities of experiences and link them to expectations as follows. First, assume that similarity between an experience e_i and a subset of experiences, $A \subset E_i$, is given by $S_i(e_i, A) = \sum_{u_i \in A} \frac{S_i(e_i, u_i)}{|A|}$. Further, assume that the probability $r(e_i, k)$ that individual i recalls experience e_i, when presented with hypothesis k, is given by the similarity between e_i and event k as a share of the total similarity between all the experiences in the memory database and hypothesis k, that is, $r(e_i, k) = \frac{S_i(e_i, k)}{\sum_{e \in E_i} S(e, k)}$.

Then, the probability that individual i 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

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

of the total similarity between all the experiences in the memory database and hypothesis k, that is,

$$r_i(k) = \frac{\sum_{e \in E_i^k} S_i(e,k)}{\sum_{e \in E_i^H} S_i(e,k) + \sum_{e \in E_i^L} S_i(e,k) + \sum_{e \in E_i^O} S_i(e,k)} \tag{1}$$

Notably, an enlargement of experiences related to k leads to a higher recall probability of hypothesis k, but experiences E_i^O unrelated to k imply interference for $r_i(k)$.

We now link recall probabilities with the focal object of the current paper: inflation expectations. Consistent with our two hypotheses of interest and without loss of generality, inflation can be characterized as a process with two states: a high regime (H) with inflation equal to $\bar{\pi}^H$ and a low regime (L) with inflation equal to $\bar{\pi}^L$. Assume that the presence of the two regimes and the inflation levels associated with each regime are common knowledge.

Further, given probabilities of recall, assume that individual i draws T_i experiences with replacement from her memory database, E_i. Let $R_i(k)$ denote the number of times that i successfully recalls events aligned with hypothesis $k \in \{H, L\}$; that is, $R_i(k)$ is binomially distributed as $R_i(k) \sim Bin(T_i, r_i(k))$. Then, individual i's *perceived* probability that regime k will realize is $p_i(k) = \frac{R_i(k)}{R_i(H)+R_i(L)}$ for any $k \in \{H, L\}$. Her expected inflation is given by

$$\pi_i^e = p_i(H)\bar{\pi}^H + (1 - p_i(H))\bar{\pi}^L = p_i(H)(\bar{\pi}^H - \bar{\pi}^L) + \bar{\pi}^L \tag{2}$$

where $p_i(H)$ is the source of heterogeneous expectations in this simple setting.

In this setup, an increase in $r_i(H)$ increases, on average, the odds of successful recalls of experiences aligned with hypothesis H, that is, $R_i(H)$. An increase in the latter raises the probability that individual i assigns to the high-inflation regime, thus putting upward pressure on her inflation expectations as shown in equation (2). Proposition 1 formalizes this positive relationship between inflation and the recall probability of events linked to the hypothesis of high inflation.

Proposition 1. *Individual inflation expectations π_i^e are increasing in the recall probability of the high-inflation regime.*

Proof. See Appendix A.1. □

2.2 Social Interaction

Now suppose that individual i socially interacts with other individuals $j \in \{1, 2, ..., i-1, i+1, ..., N_i + 1\}$, such that every individual j shares experiences with i. N_i denotes the total number of individuals who i interact with. We denote the set of experiences that individual j shares with individual i by $E_{i \to j}$ (without putting any restrictions on the flow of information in the reverse direction). Experiences shared by individual j are categorized into three mutually exclusive subsets: high inflation experiences, $E^H_{i\to j}$, low inflation experiences, $E^L_{i\to j}$, and experiences irrelevant to high or low inflation, $E^O_{i\to j}$.

We assume that, when interacting with others, individual i's assessment of similarity between k-related experiences shared by any individual j and any hypothesis k is conditional on the share of common demographic characteristics between i and j, δ_{ij}. Therefore, the similarity between any experience $e \in E^k_{i\to j}$ and hypothesis k is given by $S_i(e,k \mid \delta_{ij})$. This assumption allows for a heterogeneous function to judge the similarity between a given hypothesis and experiences shared by others that explicitly depends on characteristics of other individuals in the network.[7]

When computing recall probabilities, we assume that individual i assigns weight γ_i to her own experiences and weight $(1-\gamma_i)$ to everyone else's experiences. We further assume that she assigns weight $\omega_{ij} \in [0,1]$ to experiences shared by individual j that depends on the share of common demographic factors between individual i and j, and that is such that $\sum_i \omega_{ij} = 1$. Let $\hat{r}_i(k)$ denote individual i's probability of recalling experiences linked to hypothesis $k \in \{H, L\}$ when she socially interacts with others, described by:

$$\hat{r}_i(k) = \frac{\gamma_i \sum_{e\in E^k_i} S_i(e,k) + (1-\gamma_i)\sum_i \omega_{ij} \sum_{e\in E^k_{i\to j}} S_i(e,k \mid \delta_{ij})}{\gamma_i \sum_{e\in E_i} S_i(e,k) + (1-\gamma_i)\sum_i \omega_{ij} \sum_{e\in E_{i\to j}} S_i(e,k \mid \delta_{ij})} \tag{3}$$

where $\sum_{e\in E_i} S_i(e,k) = \sum_{e\in E^H_i} S_i(e,k) + \sum_{e\in E^L_i} S_i(e,k) + \sum_{e\in E^O_i} S_i(e,k)$ denotes total own-experience similarity and $\sum_{e\in E_{i\to j}} S_i(e,k \mid \delta_{ij}) = \sum_{e\in E^H_{i\to j}} S_i(e,k \mid \delta_{ij}) + \sum_{e\in E^L_{i\to j}} S_i(e,k \mid \delta_{ij}) + \sum_{e\in E^O_{i\to j}} S_i(e,k \mid \delta_{ij})$ denotes total shared-experience similarity. In the subsequent analysis, we assume without loss of generality that individual i always pays some attention to her own personal experiences, that is, $\gamma_i \in (0,1]$ and that the personal as well as the network memory databases contain both k-relevant and k-irrelevant experiences, so that $\sum_{e\in E^H_i} S_i(e,k) > 0$ for any $k \in \{H, L\}$.

To understand the effects that experiences shared on social networks have for individual inflation expectations, we decompose the recall probability into a personal and

[7] Using common demographic characteristics is a natural way to do so, given the growing empirical evidence 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). Golub and Jackson (2012) discuss the role that homophily plays for the convergence of beliefs to a consensus. More generally, sociologists, anthropologists and many others, such as McPherson et al. (2001) have established the role of homophily in the network formation process which likely naturally carries over to similarity functions in the social network.

network component as follows:

$$\hat{r}_i(k) = \underbrace{\frac{\gamma_i \mathbf{S}_i^k}{\gamma_i \mathbf{S}_i + (1-\gamma_i)(\mathbf{S}_{\delta_{i.}}^k + \mathbf{S}_{\delta_{i.}}^{K\setminus k})}}_{\text{personal}} + \underbrace{\frac{(1-\gamma_i)\mathbf{S}_{\delta_{i.}}^k}{\gamma_i \mathbf{S}_i + (1-\gamma_i)(\mathbf{S}_{\delta_{i.}}^k + \mathbf{S}_{\delta_{i.}}^{K\setminus k})}}_{\text{network}} \tag{4}$$

where $\mathbf{S}_i^k = \sum_{e \in E_i^k} S_i(e,k)$ denotes the total similarity of relevant own experiences; $\mathbf{S}_i^{K\setminus k} = \sum_{e \in E_i^{K\setminus k}} S_i(e,k)$ denotes the total similarity of irrelevant own experiences; $\mathbf{S}_{\delta_{i.}}^k = \sum_i \omega_{ij} \sum_{e \in E_{i\to j}^k} S_i(e,k \mid \delta_{ij})$ denotes the total similarity of shared relevant experiences; and $\mathbf{S}_{\delta_{i.}}^{K\setminus k} = \sum_i \omega_{ij} \sum_{e \in E_{i\to j}^{K\setminus k}} S_i(e,k \mid \delta_{ij})$ denotes the total similarity of shared irrelevant experiences. It is clear that the network will have an effect on the recall probability of individual i if and only if she pays attention to experiences shared on the network, that is, if and only if $\gamma_i < 1$. Conditional on $\gamma_i < 1$, two opposing forces arise when the network shares k-relevant experiences, that is, when $\mathbf{S}_{\delta_{i.}}^k$ increases. On the one hand, the personal component declines since it becomes more difficult to retrieve personal k-relevant experiences. On the other hand, the network component increases since it becomes easier to retrieve k-relevant experiences that are shared from the network. On net, it is straightforward to show that the latter effect always prevails since $\frac{\partial \hat{r}_i(k)}{\partial \mathbf{S}_{\delta_{i.}}^k} > 0$. By contrast, network k-irrelevant experiences increase $\mathbf{S}_{\delta_{i.}}^{K\setminus k}$ and thus interfere with both the personal and network components of the recall probability of hypothesis k, that is, $\frac{\partial \hat{r}_i(k)}{\partial \mathbf{S}_{\delta_{i.}}^{K\setminus k}} < 0$. Put differently, such experiences make it more difficult for k-relevant experiences to be retrieved from the memory database. Proposition 2 formalizes this analysis.

Proposition 2. *Consider individual i's recall probability of hypothesis k in equation (4). Then, the following statements are true:*

1. *The social network has an effect on the recall probability of individual i if and only if individual i allocates attention to experiences shared by others, that is, if and only if $\gamma_i \in (0,1)$.*
2. *Suppose that i assigns some weight to the experiences shared by others, that is, $\gamma_i \in (0,1)$. Then,*

$$\frac{\partial \hat{r}_i(k)}{\partial \mathbf{S}_{\delta_{i.}}^k} > 0 \text{ and } \frac{\partial \hat{r}_i(k)}{\partial \mathbf{S}_{\delta_{i.}}^{K\setminus k}} < 0 \tag{5}$$

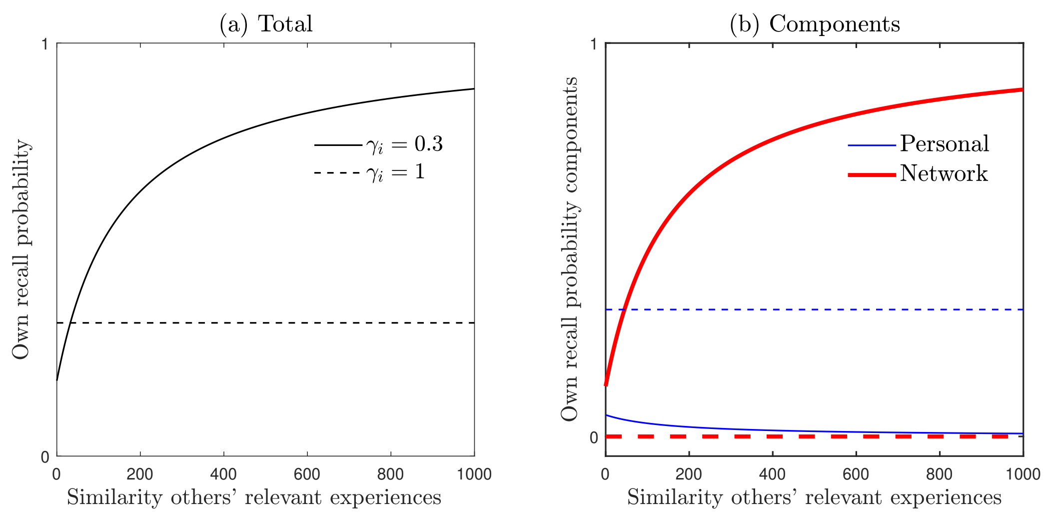
that is, additional k-relevant experiences increase the recall probability $\hat{r}_i(k)$, whereas additional k-irrelevant experiences decrease recall probability $\hat{r}_i(k)$.

Proof. See Appendix A.2. □

Figure 1 illustrates the results of Proposition 2 when there is variation in $\mathbf{S}^k_{\delta_{i.}}$ induced by individual j in the network of i, while all the other experiences remain fixed. We implicitly assume that $\omega_{ij} \neq 0$. Panel (a) shows that the response of $\hat{r}_i(k)$ is strictly increasing in the relevance added by individual j, $\mathbf{S}^k_{\delta_{ij}}$, when $\gamma_i \in (0,1)$. Eventually, as j adds substantial amounts of relevance relative to the relevance granted by the personal and the rest of the network databases, the recall probability converges to 1. When $\gamma_i = 1$ (only own experiences receive attention), the recall probability is invariant to any changes in the relevance added by individual j.

Zooming into the two components of the recall probability in panel (b), when $\gamma_i \in (0,1)$, the personal component is strictly decreasing in the relevance added by individual j and it converges to 0, implying that it is nearly impossible to retrieve any k-relevant personal experiences when j adds substantial relevance. By contrast, the network component is strictly increasing in the relevance added by individual j and individual i will almost always retrieve k-relevant experiences shared by the network when j adds substantial relevance. Obviously, when $\gamma_i = 1$, the personal component is fixed and the network component is turned off.

Figure 1: Illustration of Proposition 2



Note: The solid and dashed lines exhibit the responses of $\hat{r}_i(k)$ and its components for $\gamma_i = 0.3$ and $\gamma_i = 1$, respectively. We implicitly assume that $\omega_{ij} \neq 0$. The model is parameterized as follows: $\mathbf{S}^k_i = 20$, $\mathbf{S}^k_{\delta_{ij}} = [0,1000]$, $\mathbf{S}^k_{\delta_{i,-j}} = 20$, $\mathbf{S}^{K\setminus k}_i = 40$, $\mathbf{S}^{K\setminus k}_{\delta_{i.}} = 90$, $\mathbf{S}^k_j = [0,1000]$, $\mathbf{S}^k_{\delta_{j.}} = 40$, $\mathbf{S}^{K\setminus k}_j = 50$, $\mathbf{S}^{K\setminus k}_{\delta_{i.}} = 80$, $\gamma_j = 0.9$, $T_i = T_j = 10000$.

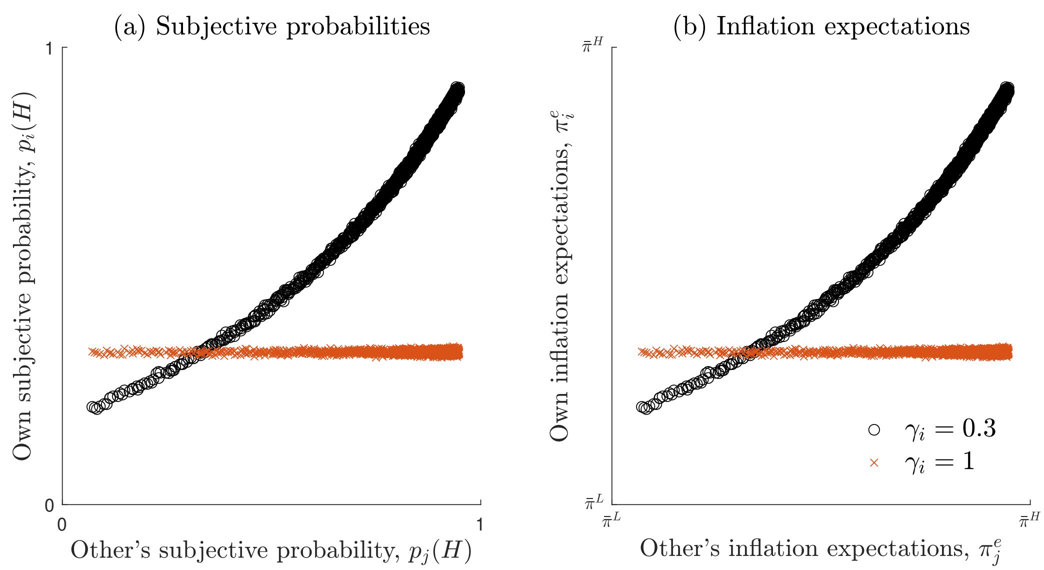
Our ultimate goal is to understand how the network affects inflation expectations. Consider two individuals i and j that are connected via the network. Suppose that individual j adds a new personal experience that is relevant for the high-inflation regime into her memory database and she shares the experience with individual i. From Proposition 1, the inflation expectations of individual j increase due to an increase in her subjective probability assigned to the high inflation regime, $p_j(H)$. Then, as long as $\gamma_i < 1$ and $\omega_{ij} \neq 0$, this exogenous increase in the expectations of i's network should lead to an increase in the individual inflation expectations of individual i.

Corollary 1 formalizes this result. Its important that, conditional on the individual paying attention to the network, increases in the inflation expectations of others should increase individual inflation expectations.

Corollary 1. *Suppose that individual i pays attention to her network and to the experiences that j shares, that is, $\gamma_i < 1$ and $\omega_{ij} \neq 0$. Suppose further that the inflation expectations of j increase because she observes an additional H-relevant* personal *experience. Then, this increase in the inflation expectations of individual j will lead to an increase in the inflation expectations of i.*

Proof. Follows directly from Propositions 1 and 2. □

Figure 2: Illustration of Corollary 1



Note: Panel (a) scatter plots the subjective probability $p_i(H)$ as a function of $p_j(H)$ when $\gamma_i = 0.3$ (black) and $\gamma_i = 1$ (orange). Panel (b) scatter plots the inflation expectations of individual i, π_i^e, as a function of π_j^e when $\gamma_i = 0.3$ (black) and $\gamma_i = 1$ (orange). Parameterization is as in Figure 1.

Figure 2 visualizes the result of Corollary 1. We consider a similar setting to the one in Figure 1, that is, all else but $\mathbf{S}^H_{\delta_{ij}}$, the total similarity of shared, high-inflation-relevant experiences, is fixed. For each simulated value of $\mathbf{S}^H_{\delta_{ij}}$, we compute $\hat{r}_i(k)$ and $\hat{r}_i(k)$ for $k = \{H, L\}$. Then, for each value of $\hat{r}_i(k)$ we draw $R_i(k) \sim Bin(T_i, \hat{r}_i(k)$ for $k = \{H, L\}$. Next, we compute $p_i(H)$ and π^e_i, as shown in the previous section. Finally, we repeat the same computation for individual j. Panel (a) plots the probability that i assigns to the high inflation regime $p_i(H)$ as a function of $p_j(H)$, whereas panel (b) plots the inflation expectations of i as a function of the expectations of others. Figure 2 shows that, as long as individual i pays attention to the experiences shared by j who is the source of variation in the expectations of the network, then her inflation expectations are positively affected by changes in the inflation expectations of j. When the network gets no weight ($\gamma_i = 1$), then there is no effect.

Finally, we are interested in understanding the effects that social networks of specific demographic groups have for the individual recall probability.

$$\hat{r}_i(k) = \underbrace{\frac{\gamma_i \mathbf{S}^k_i}{\gamma_i \mathbf{S}_i + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}}}_{\text{personal}} + \underbrace{\frac{(1-\gamma_i)\mathbf{S}^k_{\delta_{i.}=1}}{\gamma_i \mathbf{S}_i + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}}}_{\text{common-demographics network}} + \underbrace{\frac{(1-\gamma_i)\mathbf{S}^k_{\delta_{i.}=0}}{\gamma_i \mathbf{S}_i + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}}}_{\text{other-demographics network}} \tag{6}$$

where $\mathbf{S}_{\delta_{i.}} = \mathbf{S}^k_{\delta_{i.}} + \mathbf{S}^{K\setminus k}_{\delta_{i.}}$. Suppose there is a k-relevant "experience" shock due to additional k-relevant experiences that increases $\mathbf{S}^k_{\delta_{i.}}$. We compare the effect of such as shock on the recall probability $\hat{r}_i(k)$ in two cases: i) all the k-relevant experiences have been shared exclusively by the common-demographics network; ii) part of the k-relevant experiences have been shared by the common-demographics network and the rest by the other-demographics network. In i), the shock will interfere with the personal and other-demographics network components of the recall probability, but it will amplify the common-demographics network component. In ii), the shock will interfere only with the personal component, but it will amplify both the common and other-demographics network components. Proposition 3 shows that for the effect of the shock on the recall probability $\hat{r}_i(k)$ to be higher in i) than in ii), it has to be that the marginal relevance of the common-demographics network (change in the similarity between k and k-relevant experiences in the common-demographics network) is higher than the marginal relevance of the other-demographics network (change in the similarity between k and k-relevant experiences in the complete network).

Proposition 3. *Suppose that the network of individual i is shocked by a k-relevant "experience" shock that increases* $\mathbf{S}^k_{\delta_{i.}}$. *The effect of the shock on* $\hat{r}_i(k)$ *is higher when the shock hits only the common-demographics network than when it occurs to the complete network if, following the shock, the common-demographics network adds more relevance then the other-demographics net-*

work, that is, if

$$\frac{\partial S^{k}_{\delta_{i.}=1}}{\partial e} > \frac{\partial S^{k'}_{\delta_{i.}=0}}{\partial e} \tag{7}$$

where $\frac{\partial S^{k'}_{\delta_{i.}}}{\partial e}$ *denotes the change in* $\mathbf{S}^{k}_{\delta_{i.}}$*, for any* $\delta_{i.} \in \{1,2\}$*, in response to an additional k-relevant experience e.*

Proof. See Appendix A.3. □

Importantly, Proposition 3 implies that networks of common-demographics raise expectations more than complete networks, if, in response to an inflationary shock in the network, the common-demographics network adds more relevance than the other-demographics network.

2.3 Implications for Stability

Social networks can play an important role for the stability of inflation expectations, as we show next. While this result aligns with models of social learning (e.g. DeGroot (1974)), we highlight how the salience of shared experience can interact with the network structure in affecting stability conditions.

To assess the role of social networks for the stability of recall probability of hypothesis k, consider an idiosyncratic shock to the recall probability of a member in the network. Again, focus on a social network of two individuals, and assume, for simplicity, that the two individuals share all personal experiences with one another and that they pay the same degree of attention to their personal experiences, $\gamma \in (0,1)$. The recall probability of i for any $i \in \{1,2\}$ can be written as

$$\hat{r}_i(k) = \frac{\gamma \mathbf{S}^k_i + (1-\gamma)\mathbf{S}^k_{\delta_{ij}}}{\gamma \mathbf{S}^k_i + (1-\gamma)\mathbf{S}^k_{\delta_{ij}} + \gamma \mathbf{S}^{K\setminus k}_i + (1-\gamma)\mathbf{S}^{K\setminus k}_{\delta_{ij}}} \tag{8}$$

where $\mathbf{S}^k_i$ denotes individual i's total similarity of her own, k-relevant experiences and $\mathbf{S}^{K\setminus k}_i$ denotes individual i's total similarity of her own k-irrelevant experiences with hypothesis k, respectively; $\mathbf{S}^k_{\delta_{ij}}$ and $\mathbf{S}^{K\setminus k}_{\delta_{ij}}$ denote individual i's similarity between the network k-relevant experiences and k-irrelevant experiences with hypothesis k, respectively. Importantly, the two individuals do not have to assign the same similarity to experiences relative to hypothesis k, that is, $\mathbf{S}^k_{\delta_{ij}} \neq \mathbf{S}^k_i$ in general. To fix ideas, we set $\mathbf{S}^k_{\delta_{ij}} = \epsilon \mathbf{S}^k_i$, where $\epsilon > 0$ captures this potential difference between individual i's and individual j's interpretation of the same k-relevant experiences. When $\epsilon = 1$, the two individuals interpret experiences in exactly the same way, that is, they share the same similarity functions. When

$\epsilon > 1$, i perceives more salience than j in the experiences that j shares. By contrast, when $0 < \epsilon < 1$, i sees less salience than j in the experiences that j shares. More broadly, we think of ϵ as capturing the degree of additional salience of experiences obtained when experiences are shared, and as the perceived heightened similarity induced by such salience.

To illustrate this notion of salience, consider the following example. A person who commutes often by car observes an increase in the gas price at the local gas station and shares this personal experience with friends on a social platform. Then, relative to the person sharing this experience, friends can interpret it as more salient, as salient, or less salient for inflation and effectively more, equally or less relevant. We come back to this example when discussing the importance of ϵ for instability.

To further simplify the analysis without missing key insights, we assume that $\gamma \mathbf{S}_1^{K\backslash k} + (1-\gamma)\mathbf{S}_{\delta_{12}}^{K\backslash k} = \gamma \mathbf{S}_2^{K\backslash k} + (1-\gamma)\mathbf{S}_{\delta_{21}}^{K\backslash k} = \mathbf{S}^{K\backslash k}$. That is, the total own- and shared-experience similarity of irrelevant experiences, appropriately weighted in the network, is the same across individuals. The recall probabilities of hypothesis k for individuals 1 and 2, respectively, can be then re-written as

$$\hat{r}_1(k) = \frac{\gamma \mathbf{S}_1^k + \epsilon(1-\gamma)\mathbf{S}_2^k}{\gamma \mathbf{S}_1^k + \epsilon(1-\gamma)\mathbf{S}_2^k + \mathbf{S}^{K\backslash k}} \quad \text{and} \quad \hat{r}_2(k) = \frac{\gamma \mathbf{S}_2^k + \epsilon(1-\gamma)\mathbf{S}_1^k}{\gamma \mathbf{S}_2^k + \epsilon(1-\gamma)\mathbf{S}_1^k + \mathbf{S}^{K\backslash k}} \tag{9}$$

Fixing all k-irrelevant experiences, individual 2 has an effect on the recall probability of individual 1 through $\mathbf{S}_2^k$ and individual 1 has an effect on the recall probability of individual 2 through $\mathbf{S}_1^k$. Therefore, for given $\mathbf{S}_2^k$, $\mathbf{S}^{K\backslash k}$, and ϵ, we have $\hat{r}_2(k) = f\left(\hat{r}_1(k) \mid \mathbf{S}_2^k, \mathbf{S}^{K\backslash k}, \epsilon\right)$. Similarly, for given $\mathbf{S}_1^k$, $\mathbf{S}^{K\backslash k}$, and ϵ, we have $\hat{r}_1(k) = g\left(\hat{r}_2(k) \mid \mathbf{S}_1^k, \mathbf{S}^{K\backslash k}, \epsilon\right)$. From here, it is straightforward 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) $\hat{r}_1^{***}(k) = \hat{r}_2^{***}(k) = 1$.[8] However, two equilibria occur under special circumstances: for $\hat{r}_1^*(k) = \hat{r}_2^*(k) = 0$ it must be that $\mathbf{S}_1^k = \mathbf{S}_2^k = 0$, and for $\hat{r}_1^{***}(k) = \hat{r}_2^{***}(k) = 1$ it must be that $\mathbf{S}_1^{K\backslash k} = \mathbf{S}_2^{K\backslash k} = 0$. For this reason, focus on the more likely equilibrium with $0 < \hat{r}_1^{**}(k), \hat{r}_2^{**}(k) < 1$.

Proposition 4. *Consider the setting above where* $\hat{r}_2(k) = f\left(\hat{r}_1(k) \mid S_2^k, S^{K\backslash k}, \epsilon\right)$ *and* $\hat{r}_1(k) = g\left(\hat{r}_2(k) \mid S_1^k, S^{K\backslash k}, \epsilon\right)$ *where both* $f(.)$ *and* $g(.)$ *are increasing functions. We assume that* $\mathbf{S}_i^k, \mathbf{S}_i^{K\backslash k} > 0$*, for any* $j \in \{1, 2\}$*. implying that there is a unique equilibrium with* $0 < \hat{r}_1^{**}(k), \hat{r}_2^{**}(k) < 1$*. This equilibrium is stable if and only if*

$$\frac{\partial f(\hat{r}_1(k))}{\partial \hat{r}_1(k)} \times \frac{\partial g(\hat{r}_2(k))}{\partial \hat{r}_2(k)} < 1 \tag{10}$$

[8] As shown Figure 3, in the case of $\gamma/(1-\gamma) > \epsilon$, 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 $\gamma/(1-\gamma) < \epsilon$ all three are equilibria.

for recall probabilities close to equilibrium $(\hat{r}_1^{**}(k), \hat{r}_2^{**}(k))$.

Proof. See Appendix A.4. □

Proposition 4 provides the general condition under which the equilibrium of interest $(\hat{r}_1^{**}(k), \hat{r}_2^{**}(k))$ is stable. Specifically, stability is granted if the product of the marginal responses of recall probabilities is less than unity. Corollary 2 contextualizes Proposition 4 and shows that the equilibrium with $0 < \hat{r}_1^{**}(k), \hat{r}_2^{**}(k) < 1$ is stable only if the degree of perceived salience for experiences shared on the network ϵ is lower than attention to personal experiences relative to attention paid to shared experiences, $\gamma/(1-\gamma)$.

Corollary 2. *Consider the setting as in Proposition 4. Perturbating $\hat{r}_1(k)$ or $\hat{r}_2(k)$ away from the equilibrium $(\hat{r}_1^{**}(k), \hat{r}_2^{**}(k))$ yields two outcomes in terms of equilibrium stability:*

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

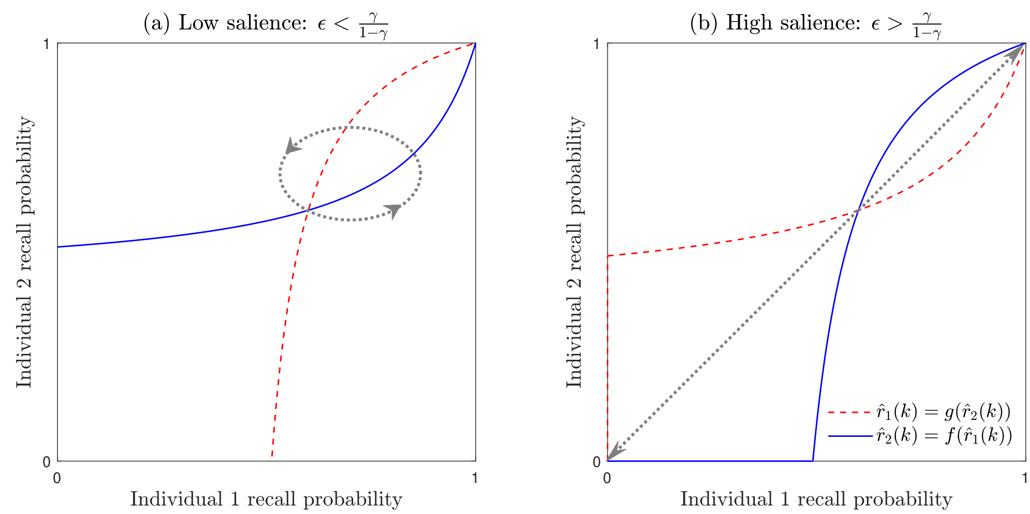
Proof. See Appendix A.5. □

Corollary 2 shows that if the additional degree of salience for shared experiences exceeds attention to own experiences relative to shared experiences ($\epsilon > \frac{\gamma}{1-\gamma}$), then an incremental positive shock to the recall probability of one person will push $\hat{r}_1(k)$ and $\hat{r}_2(k)$ toward 1, whereas a small negative shock will lead to convergence of $\hat{r}_1(k)$ and $\hat{r}_2(k)$ towards 0. On the contrary, if the aggregate attention to own experiences surpasses the additional degree of perceived salience for shared experiences, then a shock to an individual recall probability cannot pull recall probabilities away from their equilibrium. There is, therefore, an interaction between attention to shared experiences and salience of shared experiences. Figure 3 visualizes the stability properties of this equilibrium for both cases.

Because Corollary 2 contains an interaction between salience and the network structure, it nests several nests several interesting extreme cases. First, if individuals pay almost no attention to shared experiences, that is, $\gamma \to 1$, salience – captured by ϵ – has to be extremely high (approaching ∞) for instability to occur. Second, by the same token, if $\gamma \to 0$, one would need very little salience to induce instability in expectations. Last, when $\epsilon = 1$ it is simply the total attention to own experiences (2γ) that defines the stability condition. That is, if total attention to own experiences exceeds total attention to shared experiences, there is stability ($\gamma > 1/2$).

This implication of our model would also arise in the model of DeGroot (1974) with some slight modifications. In particular, for $\epsilon = 1$, our model's stability conditions coincide with the DeGroot (1974) model. What is novel in our setting is that the stability properties of inflation expectations are more generally dependent on ϵ – they depend on how salient shared experiences are perceived to be. As shared experiences become relatively more salient, these experiences are more easily retrievable and contribute more to inflation expectations, affecting the stability condition.

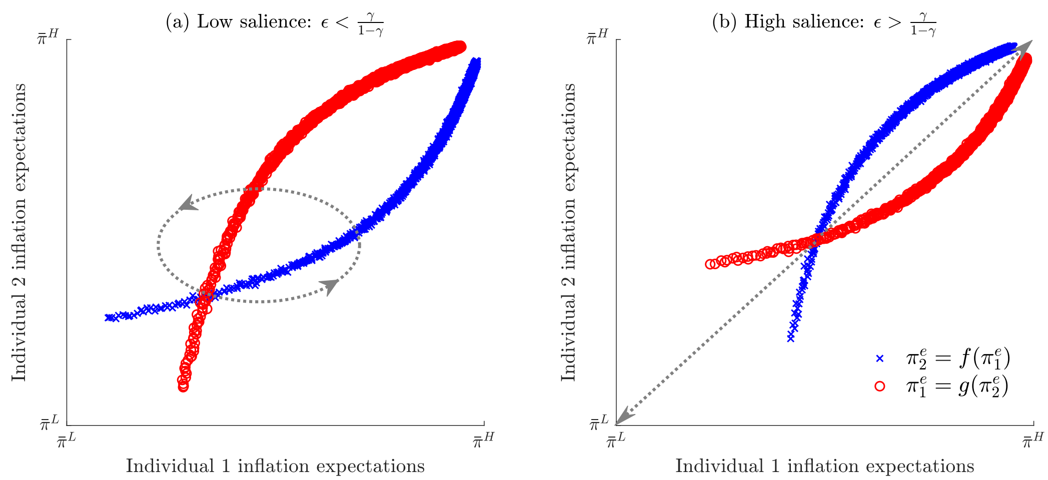
Figure 3: Illustration of Proposition 4



Note: The figure plots the recall probability of individual 2 (dashed red curve) as a function of the recall probability of individual 1 (solid blue curve) as well as the recall probability of individual 1 as a function of the recall probability of individual 2. In panel (a) we set $\epsilon = 0.3$, whereas in panel (b) we set $\epsilon = 2.8$. Moreover, $\gamma = 0.5$, $\bar{\pi}^L = 2$, $\bar{\pi}^H = 10$, $T_1 = T_2 = 10000$, $\mathbf{S}_1^k = [0,1000]$, $\mathbf{S}_2^k = 10$, and $\mathbf{S}^{K\setminus k} = 15$.

Finally, Figure 4 illustrates that there is a one-to-one mapping between the stability condition for the recall probability and the stability condition for inflation expectations. The figure scatter-plots the response of the inflation expectations of individual 2 as a function of the inflation expectations of individual 1 (blue) as well as the response of the inflation expectations of individual 1 as a function of the inflation expectations of individual 2 (red). The left panel shows that when $\epsilon < \gamma/(1-\gamma)$, inflation expectations remain stable, however, as shown in the right panel, they become unstable when $\epsilon > \gamma/(1-\gamma)$.

Figure 4: Stability for Inflation Expectations



Note: The figure scatter plots the inflation expectations of individual 2 as a function of the inflation expectations of individual 1 (blue crosses) as well as the inflation expectations of individual 1 as a function of the inflation expectations of individual 2 (red circles). Parameterization is as in Figure 3.

To gain further intuition, revisit the example of a local gas price increase. Recall that individual i shared the personal experience of a local gas price increase. If this event is perceived as having a sufficiently high salience, then every friend this experience is shared with interprets it as more salient than if it were their own. This chain of reactions will eventually destabilize inflation expectations. By contrast, if ϵ is sufficiently low, every person the experience is shared with downplays the importance this experience has for inflation, thus inducing stability.

2.4 Testable Implications for Inflation Expectations

The model has several directly testable implications, most eminently predicting an impact of the social network for the inflation expectations formation process but also for belief stability. Here, we briefly sketch out how predictions of the model may map into a fairly general empirical environment.

Following Proposition 2, if a researcher has access to data on the inflation expectations of an individual or region i, π_i^e, who is potentially socially connected to individual or region $j \in \{1, 2, ..., i-1, i+1, ..., N, N+1\}$, respectively, combined with data on the intensity of the network connections ω_{ij}, then it is possible to estimate the following specification to test for the importance of expectations of others:

$$\pi_i^e = \alpha + \beta \times \sum_{j=1}^{N} \omega_{ij} \pi_j^e + \varepsilon_i \tag{11}$$

Here, if one finds $\beta > 0$, then the social network matters. In addition, one can use the estimates of Equation 11 to test the stability of the network based on Proposition 4, which holds whenever $\beta < 1$. Finally, if the source of variation in the expectations of others is coming from movement of salient prices, such as gas prices, denoting the corresponding estimate of β by β^S, one would expect $\beta^S > \beta$ according to the proposition.

Additionally, if a researcher has access to demographic characteristics d, it is possible to split the network's expectations into common-demographics and other-demographics components, testing Proposition 3. That is, for each individual i with inflation expectations $\pi_{i,d}^e$ one then can construct common-demographics and other-demographics network expectations as $\sum_{j=i}^{N} \omega_{ij} \pi_{j,d}^e$ and $\sum_{j=i}^{N} \omega_{ij} \pi_{j,-d}^e$, respectively, in analogy to the respective elements in Proposition 3. The following specification provides a mapping from these propositions to the data:

$$\pi_{i,d}^e = \alpha + \beta_1 \times \sum_{j=i}^{N} \omega_{ij} \pi_{j,d}^e + \beta_2 \times \sum_{j=i}^{N} \omega_{ij} \pi_{i,-d}^e + \varepsilon_i \tag{12}$$

In summary, these specifications allow one to test the four main implications of our model:

Testable Implications

(T.1) $\beta > 0$: Social interaction has a positive effect on inflation expectations if people pay attention to experiences shared by others (see Proposition 2).

(T.2) $\beta_1 > \beta$: Networks of common demographics raise expectations more than complete networks, if, in response to a shock in the network, the common-demographics network adds more relevance than the complete network (See Proposition 3).

(T.3) $\beta < 1$: Social networks do not induce instability to inflation expectations (See Proposition 4).

(T.4) $\beta^S > \beta$: Idiosyncratic inflationary shocks that are *perceived* to be more salient are more likely to destabilize inflation expectations (See Corollary 2)

3 Data

To test these predictions of the model, analysis requires a dataset that combines dense survey data on inflation expectations of consumers with a map of their social network.

We construct a novel dataset that contains these two essential features.

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. This survey is nationally representative of the US and Hajdini et al. (2022c,a) describe its properties in detail. Of note, the survey elicits expectations of changes in individually relevant prices instead of aggregate prices; hence any measured effect of the social network will not be in relation to aggregate inflation, but rather individually relevant expectations. The main variables of interest pertinent to our analysis that the survey records – in addition to inflation expectations – 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). To remove outliers, our analysis drops the top and bottom 5 percent of responses at each point in time, resulting in 1.9 million monthly observations for the period from March 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 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 so weights add up to unity:

$$\omega_{c,k} = \frac{SCI_{c,k}}{\sum\limits_{k} SCI_{c,k}}$$

Using these weights, we then construct the central variable in our analysis, the expectations of others:

$$\pi^{e,others}_{c,t} = \sum_{k \neq c} \omega_{c,k} \pi^{e}_{k,t} \tag{13}$$

where $\pi^e_{k,t}$ captures 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. Because our SCI weights were sampled in 2016, our measure of inflation expectations of others is unlikely to be influenced by weights that are endogenous to the post-pandemic rise of inflation and inflation expectations. Our analysis at the same time assumes that social networks in 2021 are correlated with social networks in 2016.

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,[9] but instead in common patterns of social connections. The SCI is a proxy for such a deeper social relationship between individuals spatially separated.

While Bailey et al. (2018a) establish in detail the social connectednesss properties of the measure, we provide examples of the connectedness weights as applicable to our analysis. In Appendix B.1, we show heat maps depicting the weights ($\omega_{c,k}$) for different cities. We observe three distinct patterns. First, as expected, geography plays a significant role, with Cleveland, OH (Cuyahoga county) showing stronger connections to nearby counties. Second, interestingly, we also observe robust social links with more distant counties. Third, there is substantial heterogeneity in social connectedness, so even neighboring counties show varying degrees of influence on cities. Our empirical strategy and robutness exercises will take into considerations those geographic patterns, as we discuss in the subsequent sections.

4 Empirical Analysis

This section shows that the social network affects individual inflation expectations in line with the predictions of the model.

4.1 Empirical Challenges and Identification Strategy

The main challenge to identifying the effect of the social network lies in ruling out that the empirical measures of beliefs of others reflect "other factors" common across counties in

[9]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.

the social network. Whenever such other factors are sufficiently common across counties, they may create spurious co-movement in individual inflation expectations and inflation expectations of others.

Several factors are likely to constitute such a challenge to identification. First, common shocks may create co-movement in individual beliefs and beliefs in the network. These common shocks may occur at the aggregate level, or at more disaggregated but influential local levels. Second, other networks may transmit shocks and thereby create spurious co-movement in inflation expectations. Such networks may be (local) trade networks that connect counties or they may include common retail networks that generate price co-movement in consumption baskets across counties. Such common price co-movement may then lead people in the social network to form similar inflation expectations. Third, homophily in social networks – we are friends with similar people – may induce common price movements because friends who are similar share similar consumption baskets, and hence, shared information about similar baskets may lead to co-movement in inflation expectations.

While many more factors may create co-movement in inflation expectations, the subsequent analysis builds on three different approaches to provide identification. Not least in their totality, the three approaches contribute to the strength of identification. At the same time, they address different aspects of the model predictions.

Our first approach accounts for "other factors" directly, as much as is possible. It consists of enriching the data structure of the network and creating additional variation at the county level that can then be used to filter out variation associated with "other factors." Our third approach is to construct exogenous, idiosyncratic local shocks to inflation expectations which can be used to gauge the causal impact of social interaction on inflation expectations, irrespective of the concerns outlined above. All three approaches provide an estimate for the importance of social networks on the formation of inflation expectations as well as network stability (Propositions 2 and 4). The second approach additionally gauges the importance of common demographics in the social network whose relevance is posited in Proposition 3, while the third approach considers the role of salience for the stability of inflation beliefs in the social network (Corollary 2). The third approach also addresses endogeneity concerns such the Manski (1993) reflection problem.[10]

[10]Notably, 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 A.1 we prove this result. 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

Specifically, to overcome the identification challenges, the first approach filters out common aggregate shocks and time-county-specific variation by including time fixed effects as well as the average expectations of others in that county. These latter, time-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 also filter out any systematic county characteristics through county fixed effects. Then, to identify whether information is transmitted through social networks or other local networks that may be spuriously correlated with social networks, we explicitly exclude proximate counties and only keep counties beyond a certain distance; hence, we ignore data from counties that are more likely to share spatial shocks. As a further step to take into account the role of other networks that might spuriously correlate with the social network, we include detailed time-varying controls. These controls include individual demographic characteristics and demographic-time fixed effects as well as an explicit measure of price shocks transmitted through common retail networks. These controls aim to explicitly remove variation that stems for example from the co-movement of prices in similar consumption baskets which homophily embodied in social networks might generate.

The second, complementary approach creates additional variation at the county level to gain identification. Specifically, we construct county $\times$ demographic $\times$ time networks that allow us to include county-time fixed effects. These county-time fixed effects absorb any variability that affects all demographic groups in a county in a given period of time equally. They alleviate concerns about spatial spillovers, trade relationships, or demand spillovers from nearby regions, among other confounding but unobserved factors.

Finally, the third approach applies an instrumental variables approach that addresses any remaining endogeneity concerns, including those implied by the Manski (1993) reflection problem. Specifically, the approach exploits the interaction of commuting shares by car across counties[11] and the national gas price to obtain county-time specific exogenous shocks to gas prices after filtering out any common time variation. We project inflation expectations on this exogenous local variable and use it to construct a measure of exogenous variation in the inflation expectations of others. This instrument then allows one to estimate an unbiased effect of the expectations of others on individual inflation expectations.[12] Since we know that higher gas prices lead to higher inflation beliefs, the instrumented regression also provides a glimpse into the type of information that flows

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.

[11] As Appendix B.2 shows, these shares are not correlated with the social network shares.

[12] Because the instrument embodies idiosyncratic local gas price experiences, any resulting relevance of inflation expectations of others does not derive from simply speeding up learning about common shocks, but truly from idiosyncratic experiences becoming available over the network.

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, as we show next, we find strong evidence in favor of the hypothesis that social networks are important in determining individual inflation expectations.

4.2 Individual Inflation Expectations and the Inflation Expectations of Others

Social interaction has a positive association with the inflation expectations of others as we show in this section, even if we take into account a plethora of potentially confounding "other factors."

To establish the evidence in support of this first model prediction (T.1), we estimate several specifications. These specifications use individual-level data which allows us to take into account detailed fixed effecsts. Specifically, we estimate a set of specifications based on the following one:

$$\pi^e_{i,c,t} = \alpha_0 + \alpha_1 \pi^e_{-i,c,t} + \beta \sum_{k \neq c} \omega_{c,k} \pi^e_{k,t} + \varepsilon_{i,c,t}, \tag{14}$$

where $\pi^e_{i,c,t}$ denotes the inflation expectations of individual i, located in county c at time t. $\pi^e_{-i,c,t}$ denotes the expectations of others in county c which exclude the expectations of individual i from the county average. In addition, to take into account "other factors" as discussed above, we include into the set of specifications county fixed effects, time fixed effects, demographic characteristics, interactions of demographics and time fixed effects, as well as an interaction of county demographic characteristics such as the county-level share of Hispanics and time fixed effects. We also estimate specifications where we exclude nearby counties, or take into account the presence of common retail networks. All observations are weighted by the number of respondents in a county in a given period of time.

Across specifications, strong evidence emerges for the first testable implication of the model: the inflation expectations of others are statistically highly significantly associated with individual inflation expectations. Table 1 reports the estimation results from a first set of specifications. The first row displays the coefficient estimates associated with the network-weighted inflation expectations of other counties, and the second row displays the estimates for county "leave-out" inflation expectations. The OLS estimates in Column 1 indicate an elasticity of inflation expectations of 0.19 for an individual with respect to inflation expectations in other counties. The inclusion of time fixed effects that absorb

Table 1: Individual Inflation Expectations and the Inflation Expectations of Others

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expectations of Others	0.194***	0.176***	0.252***	0.115**	0.051***	0.068***	0.058***	0.059***
	(0.043)	(0.050)	(0.074)	(0.047)	(0.017)	(0.019)	(0.020)	(0.020)
County Expectations	0.755***	0.732***	0.603***		0.557***	0.542***	0.469***	0.454***
	(0.048)	(0.042)	(0.058)		(0.049)	(0.051)	(0.019)	(0.016)
Time FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
County FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Demographic FE	No	No	No	No	No	Yes	Yes	Yes
Demographic-Time FE	No	No	No	No	No	No	Yes	Yes
Combined Dem-Time FE	No	No	No	No	No	No	No	Yes
Observations	1,926,282	1,926,282	1,926,282	1,926,282	1,926,282	1,925,393	1,925,393	1,925,393
R-squared	0.017	0.017	0.017	0.014	0.017	0.033	0.036	0.049

Note. The table shows the results of regression (14), where the dependent $\pi^e_{i,c,t}$ is the inflation expectations of individual i who answers from county c at time t. Observations are weighted by the number of responses in a county in each period. Demographics fixed effects are the income, age, politics and gender definitions used in the paper and are at the individual level. Combined Dem-Time FE is a time fixed effect interacted by the combination of demographic characteristics that an individual has (for example, male-<35 yo, <100k, independent fixed effect interacted by a time fixed effect. Standard errors are clustered at the county level.

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 the systematic, time-invariant effect of county characteristics preserves this result at a similar magnitude, with a coefficient of 0.25 (Column 3). Absorbing jointly most of this variation by including both county and time fixed effects again implies a statistically significant coefficient (Columns 4 and 5), whether or not county-level expectations of others are taken into account.[13] Now, an increase of 1 percentage point in the inflation expectations of others is associated with an increase of 0.05 to 0.12 percentage points in an individual's inflation expectations.[14]

An important finding is that this relationship between individual inflation expectations and the inflation expectations of others notably remains robust when we take into account demographic fixed effects (Column 6), an interaction of demographic characteristics one at a time with time fixed effects (Column 7) and an interaction of multiple demographic characteristics with time fixed effects (Column 8). These demographic fixed effects include indicator variables for brackets of income, age, political affinity and gender. An example for the cells captured by this third interaction is given by an indicator variable for men under 35 years of age and with income less than 100k. As discussed, these demographic variables and their interactions may correlate with the network weights – we are friends with similar people – and similar time trends we experience along with

[13] In line with other surveys of households expectations, even in controlled environments, as in Coibion et al. (2022), our analysis accounts for little of the variation in terms of R^2. This result is due to high heterogeneity at the individual level. At the county level when this heterogeneity is average out, we find similar results, but crucially, also an R^2 greater than 40%.

[14] In Appendix A.2 we show that the inclusion of a time fixed effect when the network has common distribution across counties can generate a negative bias. Therefore, these results present a lower bound for the true OLS coefficient. We address this issue in the next sections.

our friends. As a consequence, they might lead to an exposure to similar prices across counties and hence, correlated inflation expectations. But, because we explicitly filter out variation associated with these common demographic factors and their trends, our results indicate that inflation expectations of others transmitted through social connections – *beyond* what is due to similarity in social connections – are indeed driving individual inflation expectations. That is, the density of our network data provides sufficient heterogeneity in social connections to allow us to detect transmission of inflation expectations through the social network.[15]

The first model prediction (T.1) is also robust to taking into account common, local spatial shocks. To establish this finding, our analysis uses expectations of others computed only from counties outsides a certain radius of a given respondent's county. When we then re-estimate the main specifications above, we find across specifications that the inflation expectations from far-away counties affect a respondent's own inflation expectations when respondents are connected through social networks to those counties. Table 6 in Appendix D shows the results for this exercise. These results align with the findings in Bailey et al. (2018b, 2019) that the experiences in the housing market of far-away friends affect an individual's local housing decisions, such as the choice of renting or buying.

While common retail networks and their common prices across counties might also imply a spurious transmission of inflation expectations through the social network, this channel is likely not the explanation for our findings either. Consider, for instance, the scenario where retailers implement uniform pricing strategies across locations, as is the case for the US (DellaVigna and Gentzkow, 2019). In such cases, counties that share common retail chains may experience synchronized price adjustments (Garcia-Lembergman (2020)), likely synchronizing inflation expectations. In order to control for the propagation of shocks through the retail-chain networks, we construct exposure to common retail chains using weights that characterize the connectedness of each pair of counties in the retail chain dimension, as measured by Garcia-Lembergman (2020). These weights place higher weight on counties k that are important in terms of sales for the dominant retail chains in county c. Based on these weights, we calculate the exposure to inflation expectations in counties with shared retail chains and incorporate this measure of exposure as a control variable in our regression analysis. Including such controls for inflation expecta-

[15] Additionally, in Table 7 in Appendix D, we take into account further demographic characteristics measurable at the county level, again interacted with a time fixed effect to control for similar trends of similar counties. Such characteristics include the share of foreign born individuals at the county level, income per capita, the share of African American, the share of the Hispanic population, the share of white non-Hispanic population, the poverty rate and the share of votes that Joseph Biden got in the county in the 2020 presidential election. Similarly, we find that our key coefficient of interest, on the expectations of others, remains positive and significant.

tions in counties with shared retail chains does not change our key findings, as Table 8 in Appendix D shows. Therefore, our findings likely come from the social network and not a common price shock given a similar consumption basket and common retail networks.[16]

In the next section we also provide another set of results that show that it is unlikely that the main findings come from other common factors, and not 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 Individual Inflation Expectations and the Inflation Expectations of *Similar* Others

Strong evidence for the role of expectations of others affecting individual inflation expectations (Proposition 2) also emerges when we apply our second identification approach. The evidence from applying this approach moreover aligns with predictions specific to our memory model (Proposition 3) rather than with those of a basic statistical model of learning: The beliefs of *similar* others influence inflation expectations if experiences shared in networks of similar others are perceived as more relevant rather than irrelevant.

To generate these findings, our analysis constructs exposure to inflation expectations of *similar* others 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+).

Our analysis then estimates the following specification:

$$\pi^e_{i,d,c,t} = \alpha_0 + \alpha_1 \pi^e_{-i,d,c,t} + \beta_1 \sum_{k \neq c} \omega_{c,k} \pi^e_{d,k,t} + \theta_{ct} + \varepsilon_{i,c,t}. \tag{15}$$

which represents a not only a direct test of model predictions (T.2), but also (T.3) by using expectations of *similar* others. Why? $\pi^e_{i,d,c,t}$ 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

[16] Garcia-Lembergman (2020) finds that such networks influence local prices, so our result imply that the influence on inflation expectations seems to originate from the social network and not from price shocks transmitted through shared retail networks.

average inflation expectations of all the other individuals in that same county c that share the same demographic characteristics d with individual i; and $\sum_{k \neq c} \omega_{c,k} \pi^e_{k,t}$ captures the inflation expectations of similar others in distant counties. If the similarity between individuals matters for the transmission of inflation expectations, then we expect to find a positive estimate of $\beta_1 > \beta$, that is larger than when using expectations of all others in distant counties regardless of demographics $\sum_{k \neq c} \omega_{c,k} \pi^e_{k,t}$.

This specification also implements our second identification approach, in addition to testing our model predictions: Because by construction there are multiple expectations of others at each point in time for a given county – one for each demographic category – we can exploit this additional variation in beliefs of others by including *county-time* fixed effects. This inclusion of county-time fixed effects addresses one main concern for identification, which is that counties connected by social ties are exposed to common regional shocks which may create spurious co-movement of expectations. 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 spuriously co-move. The county-time fixed effects take into account any such common regional shocks in California and even shocks in the county itself. The identifying variation needed on top of the common 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 results show that demographic similarity along several dimensions – gender, political affiliation, income, and age – always plays an important role in the process of belief formation. For example, in the case of gender,[17] the effect of one's social network turns out to be statistically significant and economically 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. Table 2 shows these results. Qualitatively, the same findings hold for the other demographic characteristics we consider, as Tables 9, 10, and 11 in Appendix D show. When including the belief of similar others across all demographic dimensions jointly, they all have a highly significantly relationship with individual beliefs, as the last two columns of Table 12 in

[17] Gender is a particularly appealing similarity feature to illustrate the role of similarity because it does not depend on people's choices, as much as, for example, in the case of political affiliation.

Appendix D illustrates.

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 (15), 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. Observations 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 Proposition 3. To do so, we estimate specification (15), but include the network-weighted expectations of the respectively omitted other demographic group, $\sum_{k \neq c} \omega_{c,k} \pi^e_{-d,k,t}$. This term captures dissimilarity. Two results emerge: First, such *dissimilarity* of others – denoted by “Dissimilarity-Network” – generally has an economically negligible relationship with individual inflation expectations. It is always smaller than the similarity effect itself, which continues to be highly significant, always positive and higher than the point estimates in the baseline with only similarity terms present. Second, there is a positive, statistically significant difference between the similarity and dissimilarity effects across specifications. Table 13 in Appendix D illustrates these findings in multiple specifications for gender, and Table 14 in Appendix D for all other demographic characteristics in the analysis.

Viewed through the lens of the model, these dissimilarity results suggest that the beliefs of "other others" embody experiences that are perceived to be less relevant than the experiences shared by "similar others." As a result, the inflation expectations of the “other others" affect individual inflation expectations to a much lesser extent relative to the inflation expectations of "similar others." Results in the next section further align with these findings.

4.4 Transmission of Exogenous Shocks through the Network

Applying our third, instrumental-variable approach to identification confirms our preceding, main findings but also provides further insights: First, inflation expectations of others shared through the social network bear a positive, causal relationship with individual inflation expectations, with a somewhat stronger relationship than implied by a corresponding OLS specification. Second, while this estimate and those in the previous sections may also be read in light of general stability conditions in models of social learning (e.g. DeGroot (1974)), the results in this section point beyond a statistical interpretation: Salience embodied in the experiences shared through the social network may play an additional, marginally destabilizing role for inflation expectations, in line with Corollary 2. Yet, as we show, on net, expectations of others do not induce instability in individual inflation expectations (Proposition 4).

The instrumental variable approach taken in this section follows Hajdini et al. (2022a) and utilizes a shift-share approach, combining cross-county variation in the proportion of individuals who use cars in their commute to work with 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. Estimating the following specification, as a first stage, shows that the instrument indeed affects local inflation expectations:

$$\pi^e_{i,d,c,t} = \alpha_{c(i)} + \theta_t + \beta_d P_{gas,t} \times Comm_{c(i)} + \varepsilon_{i,d,c,t}, \tag{16}$$

where, as in the previous section, $\pi^e_{i,d,c,t}$ denotes the inflation expectations of individual i in county c with gender d, at time t. $P_{gas,t}$ denotes the average national price of regular gas according to the US Energy Information Administration;[18] $Comm_{c(i)}$ denotes the share of people who use their own car to commute according to the ACS[19]; $\alpha_{c(i)}$ denotes a county fixed effect and θ_t a time fixed effect. Allowing for differences in the sensitivity to gas

[18] Our analysis uses 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.

[19] This measure is not correlated with the weights. Figure 12 in Appendix B.2 shows results for regression at each county level, results show that for most counties the coefficient is very small and non statistically different from zero. In addition, a regression that adds all the counties has a very small and non statistically different from zero coefficient.

price exposure, β_d, 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. That is, gasoline prices are more salient to men. We estimate this regression specification for the period of February 2021 through July 2023.

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 $d \in (male, female)$. Observations are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

In line with the well-established impact of gas prices on inflation expectations, estimates across specifications indeed show a positive, highly statistically significant effect of the instrument on inflation expectations. As Table 3 shows, a one-dollar increase in the price of gas raises individual-level inflation expectations between 3.171 and 3.414 percentage points in a county where everybody uses their car to commute, relative to a counterfactual county where nobody uses a car to commute.

In particular, our analysis also exploits demographic differences in the way consumers' perceive these specific price shocks, providing evidence for model prediction (T.3) about the salience of experiences in the network amplifying the transmission of information. How do such differences matter? As D'Acunto et al. (2021a) show at the *individual* level, men exhibit a significantly higher sensitivity to local gas prices than women, and men also rely more strongly on gas prices to form inflation expectations. The results in Columns 5 and 6 align with these findings: male respondents react more strongly to gas shocks than women, in places where gas is used more intensively to commute. The estimated coefficient for men is 3.958 while it is 0.834 for women. Aggregating these salient shocks to the *network* level shows that these results also hold at this level, with a coefficient of 1.980 for men and 0.571 for women, as Columns (1) and (2) of Table 4 show. This difference is statistically significantly different from zero as a test in Appendix Table 16 formally shows. Through the lens of our model assumptions, these findings suggest an $\epsilon > 1$.

As a second stage, our analysis uses this exogenous, local variation to implement our third, instrumental-variable approach that delivers an unbiased estimate for the effect of inflation expectations of others on individual inflation expectations. To arrive at this unbiased estimate that addresses any remaining endogeneity issues including the reflection problem, we construct the variable $Gas\_effect_{d,c,t} = \widehat{\beta_d} P_{gas,t} \times Comm_{c(i)}$, based on the above equation (16), which contains county-time variation. Then, combining these exogenous, local shocks and the social network weights to form an instrument, $\sum_{k \neq c} \omega_{c,k} Gas\_effect_{d,k,t}$, we estimate variants of the following specification as our main, instrumental-variable regression:

$$\pi^e_{i,d,c,t} = \alpha_{c(i)} + \theta_t + \rho_1 \pi^e_{-i,d,c,t} + \rho_2 \sum_{k \neq c} \omega_{c,k} \pi^e_{d,k,t} + \varepsilon_{i,d,c,t}, \tag{17}$$

where inflation expectations of others have been instrumented accordingly. While time fixed effects have already been filtered out from the instrument $Gas\_effect_{d,c,t}$, we nonetheless include a time fixed effect θ_t in some specifications in this instrumented regression. As in the previous exercises that took into account "other factors", this analysis also takes into account average county-gender inflation expectations, $\pi^e_{-i,d,c,t}$, which excludes the respondent's own expectations.[20] Overall, all these specifications show whether or not variation in the inflation expectations of others in distant counties due to local gas price shocks in *other* counties *causally* affects individual expectations in a given county.

[20] Alternatively, we run regressions where we control for the own-county/demographic gas effect $Gas\_effect_{d,c,t}$. Appendix D, Table 15 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)
$\sum_{k\neq c}\omega_{c,k}Gas\_effect_{c,d,t}$	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)
$\pi^e_{-i,d,c,t}$	0.532***	0.365***	0.593***	0.561***
	(0.023)	(0.012)	(0.029)	(0.040)
Sample	Men	Female	All	All
Time FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Regression	OLS	OLS	OLS	IV
F-Test	-	-	-	1459
Observations	882,338	1,028,341	1,910,679	1,910,679
R-squared	0.020	0.018	0.026	0.012

Note: This table shows results from estimating two specifications. Columns (1) and (2) for $\pi^e_{i,d,c,t} = \alpha_c + \theta_t + \alpha_1\pi^e_{-i,d,c,t} + \beta_s\sum_{k\neq c}\omega_{c,k}Gas\_effect_{d,k,t} + \varepsilon_{i,d,c,t}$,. Column (3) 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 (4) runs the same specification as for Column (3), 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; $\pi^e_{-i,d,c,t}$ 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. Observations are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Here, our main finding – but now with a causal underpinning – is confirmed: When we apply the instrumental variables approach, the coefficient estimate on the inflation expectations of others is positive, statistically significantly different from zero, and increases compared to the coefficient estimate from a corresponding OLS regression. As shown in the previous sections, an OLS baseline estimate of the network effect that takes into account fixed effects is 0.359 (replicated in Column (3)). The corresponding IV coefficient is 0.491, more than a third higher (Column (4)). 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 that affects inflation expectations, and social networks tap such salient experiences from the memory database.

Finally, the unbiased estimates from the instrumental variable approach have two implications for stability: First, on net, expectations of others do not induce instability in individual inflation expectations. As summarized by model prediction (T.3) and in line with general stability conditions of social learning models like DeGroot (1974), a one-time county-specific shock to inflation expectations can destabilize inflation expectations in all the other counties only if the effect of shocks is bigger than unity, $\mid \beta \mid \geq 1$. However, according to our estimates, even if we add together in the calculation of the stability coefficient β both own-county effects and the effects from other counties, that is, $\beta = \rho_1 \omega_{ii} + \rho_2(1 - \omega_{ii})$ with own-county weights of $\omega_{ii} = 0.39$, such a calculation yields only an effective $\beta = 0.519 < 1$: Social networks have no destabilizing effect on individual inflation expectations.

Second, on the margin, the results may suggest a destabilizing effect of salient experiences. Why? As discussed above, the instrument captures variation due to salient, local exogenous gas price shocks; instrumentation results in a higher estimate relative to an OLS specification. While such an increase can simple originate from an elimination of bias rather than salience captured by the instrument, it can also suggest that a potentially additional, marginally destabilizing role for inflation expectations in line with Corollary 2 and summarized by model prediction (T.4). In this latter case, an important policy implication emerges: As suggested in Coibion et al. (2020c), effective communication from policymakers that emphasizes inflation as a broad rather than as a salient, good-specific or salient, local phenomenon can help reduce the feedback effects of social networks.

5 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 testable implications. These explicitly allow for a role of demographic similarity and include stability conditions for the propagation of shocks to inflation expectations in social networks. In particular, unlike in simpler models of network stability such as DeGroot (1974), our model allows for a role of salience in the stability conditions.

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. Our results indicate that social networks matter for inflation expectations, in particular when individuals share similar demographic characteristics. These findings emerge under three different approaches to identification, all of which also imply overall stability in the transmission of shocks to inflation expectations over the social network. However, salience amplifies their transmission and marginally implies decreased stability.

These findings open up new avenues for exploring the formation of inflation expectations in the context of social networks. For example, future work remains in the context of stability and multiple equilibria, regarding the role of network super-nodes, or the transmission of shocks from different regions and of different sizes. Such future work may benefit policymakers who aim to keep inflation expectations anchored, but currently do not assign a role to social networks.

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Appendix

A Proofs

A.1 Proof of Proposition 1

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

$$\mathbb{E}\left(p_i(H)\right) = \mathbb{E}\left(\frac{R_i(H)}{R_i(H) + R_i(L)}\right)$$

By the central limit theorem, we have that

$$z_i^H = \frac{R_i(H) - T_i r_i(H)}{\sqrt{T_i}} \sim N(0, r_i(H)(1 - r_i(H))$$

Therefore,

$$\frac{R_i(H)}{R_i(H) + R_i(L)} = \frac{z_i^H / \sqrt{T_i} + r_i(H)}{z_i^H / \sqrt{T_i} + r_i(H) + z_i^L / \sqrt{T_i} + r_i(L)}$$

and

$$\lim_{T_i \to \infty} \frac{R_i(H)}{R_i(H) + R_i(L)} = \lim_{T_i \to \infty} p_i(H) = \frac{r_i(H)}{r_i(H) + r_i(L)}$$

If the recall probability of the high-inflation regime increases, then the perceived probability of regime H increases leading to an increase inflation expectations.

A.2 Proof of Proposition 2

Consider individual j's recall probability of hypothesis k

$$\hat{r}_i(k) = \frac{\gamma_i \mathbf{S}_i^k + (1 - \gamma_i)\mathbf{S}_{\delta_{i.}}^k}{\gamma_i \mathbf{S}_i + (1 - \gamma_i)\mathbf{S}_{\delta_{i.}}} \tag{A.1}$$

Then, the response of $\hat{r}_i(k)$ to a change in $\mathbf{S}_{\delta_{i.}}^k$ is given by

$$\frac{\partial \hat{r}_i(k)}{\partial \mathbf{S}_{\delta_{i.}}^k} = (1 - \gamma_i)\frac{\gamma_i \mathbf{S}_i^{K \setminus k} + (1 - \gamma_i)\mathbf{S}_{\delta_{i.}}^{K \setminus k}}{\gamma_i \mathbf{S}_i + (1 - \gamma_i)\mathbf{S}_{\delta_{i.}}} \geq 0 \tag{A.2}$$

Clearly, $\frac{\partial \hat{r}_i(k)}{\partial \mathbf{S}_{\delta_{i.}}^k} > 0$ if $\gamma_i < 1$ and $\frac{\partial \hat{r}_i(k)}{\partial \mathbf{S}_{\delta_{i.}}^k} = 0$ if $\gamma_i = 1$.

A.3 Proof of Proposition 3

Let $\hat{r}_i(k)'$ be the response of the recall probability to the "experience" shock composed of a total of M k-relevant experiences, where $M \geq 2$. Then, the effect of the shock on the recall probability when the shock hits only the common-demographics network is given by

$$\hat{r}_i(k)' = (1-\gamma_i)\frac{\gamma_i \mathbf{S}_i^{K\setminus k} + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}^{K\setminus k}}{\gamma_i \mathbf{S}_i + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}}\left(\sum_{m=1}^{M-n}\frac{\partial \mathbf{S}_{\delta_{i.}=1}^{k}}{\partial e_m}\right) > 0 \tag{A.3}$$

Moreover, the effect of the shock on the recall probability when the shock hits both the common- and other-demographics network is given by

$$\hat{r}_i(k)' = (1-\gamma_i)\frac{\gamma_i \mathbf{S}_i^{K\setminus k} + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}^{K\setminus k}}{\gamma_i \mathbf{S}_i + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}}\left(\sum_{m=1}^{M-n}\frac{\partial \mathbf{S}_{\delta_{i.}=1}^{k}}{\partial e_m} + \sum_{m=M-n+1}^{M}\frac{\partial \mathbf{S}_{\delta_{i.}=0}^{k}}{\partial e_m}\right) > 0 \tag{A.4}$$

where $\mathbf{S}_{\delta_{i.}}^{k'} = \omega \mathbf{S}_{\delta_{i.}=1}^{k'} + (1-\omega)\mathbf{S}_{\delta_{i.}=0}^{k'}$. Clearly, the effect in (A.3) is guaranteed to be higher than the one in (A.4) if $\frac{\partial \mathbf{S}_{\delta_{i.}=1}^{k}}{\partial e} > \frac{\partial \mathbf{S}_{\delta_{i.}=0}^{k}}{\partial e}$ for any k-relevant experience e.

A.4 Proof of Proposition 4

To simplify notation, let $\hat{r}_i(k) = \hat{r}_i$ for any $i \in \{1,2\}$. Suppose we perturbate $\hat{r}_1$ away from $\hat{r}_1^{**}$. Then, the chain of responses in every step τ is given by

$$\begin{aligned}
\tau = 1 &: \frac{\partial \hat{r}_2}{\partial \hat{r}_1} = f'(\hat{r}_1) \\
\tau = 2 &: \frac{\partial \hat{r}_1}{\partial \hat{r}_2} = g'(f(\hat{r}_1)) = g'(\hat{r}_2)f'(\hat{r}_1) \\
\tau = 3 &: \frac{\partial \hat{r}_2}{\partial \hat{r}_1} = f'(g(f(\hat{r}_1))) = f'(\hat{r}_1)(f'(\hat{r}_1)g'(\hat{r}_2)) \\
\tau = 4 &: \frac{\partial \hat{r}_1}{\partial \hat{r}_2} = g'(f(g(f(\hat{r}_1)))) = (f'(\hat{r}_1)g'(\hat{r}_2))^2 \\
&\ldots
\end{aligned} \tag{A.5}$$

where $\tau = 1$ indicates the response of $\hat{r}_1$ on impact. Clearly, if $f'(\hat{r}_1)(f'(\hat{r}_1)g'(\hat{r}_2)) < 1$, the chain of reaction will dissipate quickly and recall probabilities would revert back to equilibrium $(\hat{r}_1^{**}, \hat{r}_2^{**})$. By contrast, if $f'(\hat{r}_1)(f'(\hat{r}_1)g'(\hat{r}_2)) > 1$, the responses of recall probabilities increase as we progress through the chain of reaction, implying that recall probabilities would just get far away from the equilibrium $(\hat{r}_1^{**}, \hat{r}_2^{**})$.

A.5 Proof of Corollary 2

We simplify notation and re-write the recall probabilities of hypothesis k for individuals 1 and 2 as

$$\hat{r}_1 = \frac{\gamma x_1 + \epsilon(1-\gamma)x_2}{\gamma x_1 + \epsilon(1-\gamma)x_2 + y} \tag{A.6}$$

$$\hat{r}_2 = \frac{\gamma x_2 + \epsilon(1-\gamma)x_1}{\gamma x_2 + \epsilon(1-\gamma)x_1 + y} \tag{A.7}$$

where $x_j = \mathbf{S}_j^k$, $y = \mathbf{S}^{K\setminus k}$, for any $j \in \{1,2\}$ and $i \neq j$. Isolating x_1 from (A.6), we can write x_1 as $x_1 = \frac{(x_2\epsilon(1-\gamma)+y)\hat{r}_1 - \epsilon(1-\gamma)x_2}{\gamma(1-\hat{r}_1)}$. Substituting for x_1 into (A.7), we get

$$\begin{aligned}\hat{r}_2 &= \frac{\gamma x_2 + \epsilon(1-\gamma)\frac{(x_2\epsilon(1-\gamma)+y)\hat{r}_1 - \epsilon(1-\gamma)x_2}{\gamma(1-\hat{r}_1)}}{\gamma x_2 + \epsilon(1-\gamma)\frac{(x_2\epsilon(1-\gamma)+y)\hat{r}_1 - \epsilon(1-\gamma)x_2}{\gamma(1-\hat{r}_1)} + y} \\ &= \frac{(\epsilon(1-\gamma)y + (\epsilon(1-\gamma)-\gamma)(\epsilon(1-\gamma)+\gamma)x_2)\hat{r}_1 - (\epsilon(1-\gamma)-\gamma)(\epsilon(1-\gamma)+\gamma)x_2}{((\epsilon-\gamma)y + (\epsilon(1-\gamma)-\gamma)(\epsilon(1-\gamma)+\gamma)x_2 - \gamma y)\hat{r}_1 - (\epsilon(1-\gamma)-\gamma)(\epsilon(1-\gamma)+\gamma)x_2 + \gamma y}\end{aligned} \tag{A.8}$$

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

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

where $a_j = \epsilon(1-\gamma)y + (\epsilon(1-\gamma)-\gamma)(\epsilon(1-\gamma)+\gamma)x_j$, $b_j = -(\epsilon(1-\gamma)-\gamma)(\epsilon(1-\gamma)+\gamma)x_j$, $c_j = a_j - \gamma y$, and $d_j = b_j + \gamma y$ for any $j \in \{1,2\}$. Similarly, the recall probability of $\hat{r}_i$ as a function of $\hat{r}_j$

$$\hat{r}_i = \frac{a_i\hat{r}_j + b_i}{c_i\hat{r}_j + d_i} \Rightarrow \hat{r}_j = g(\hat{r}_j) = \frac{b_i - d_i\hat{r}_i}{c_i\hat{r}_i - d_i}$$

Without loss of generality, let $j = 2$. An equilibrium occurs wherever f intersects with g, that is whenever the following equation has a solution

$$h(\hat{r}_1) = \underbrace{(c_2a_1 + d_2c_1)}_{\varphi_2}\hat{r}_1^2 + \underbrace{(c_2b_1 + d_1d_2 - b_2c_1 - a_1a_2)}_{\varphi_1}\hat{r}_1 + \underbrace{(-b_2d_1 - a_2b_1)}_{\varphi_0} = 0$$

Note that $h(1) = 0$, hence $\hat{r}_1 = \hat{r}_2 = 1$ is always an equilibrium. Moreover, one can show that $\varphi_2 = -y(\epsilon(1-\gamma)-\gamma)(\epsilon(1-\gamma)+\gamma)(y + \gamma x_1 + \epsilon(1-\gamma)x_2)$; $\varphi_0 = -y(\epsilon(1-\gamma)-\gamma)(\epsilon(1-\gamma)+\gamma)(\gamma x_1 + \epsilon(1-\gamma)x_2)$; and $\varphi_1 = -(\varphi_2 + \varphi_0)$. φ_2 and φ_0 share the same sign, thus, if h is convex then $h(0) > 0$ and if h is concave, then $h(0) < 0$. It is straightforward to show that $h(\hat{r}_1) = 0$ for $\hat{r}_1 = 1$ and $\hat{r}_1 = \frac{\varphi_0}{\varphi_2} = \frac{\gamma x_1 + \epsilon(1-\gamma)x_2}{\gamma x_1 + \epsilon(1-\gamma)x_2 + y} \in (0,1)$, therefore, there is always an equilibrium $(\hat{r}_1^{**}, \hat{r}_2^{**})$, such that $0 < \hat{r}_1^{**}, \hat{r}_2^{**} < 1$.

We now analyze the features of f and g that are relevant for the stability properties of $(\hat{r}_1^{**}, \hat{r}_2^{**})$, and consider two cases: i) $0 < \epsilon < \frac{\gamma}{1-\gamma}$ and ii) $\epsilon > \frac{\gamma}{1-\gamma}$.

i) $\mathbf{0 < \epsilon < \frac{\gamma}{1-\gamma}}$. In this case, $b_1, b_2, d_1, d_2 > 0$; $c_1, c_2 < 0$; $f(\hat{r}_1) > 0$, for any $\hat{r}_1 \in [0,1]$ and $f(\hat{r}_1)$ is convex with $f(0) > 0$. On the other hand, $g(\hat{r}_1)$ is a concave function for $\hat{r}_1 > -a_1/c_1$ with $-a_1/c_1 < 1$. Moreover, g has a vertical asymptote at $\hat{r}_1 = -a_1/c_1$ and $g = 0$ for $\hat{r}_1 = b_1/d_1$. To ensure that g is continuous for any $\hat{r}_1 \in [0,1]$, we assume that the vertical asymptote occurs at $\hat{r}_1 = -a_1/c_1 < 0$, implying that $a_1 < 0$. Therefore, in this case, there are only 2 equilibria $0 < \hat{r}_1^{**}, \hat{r}_2^{**} < 1$ and $\hat{r}_1^{***} = \hat{r}_2^{***} = 1$. Because f is convex whereas g is concave at their intersection with $(\hat{r}_1^{**}, \hat{r}_2^{**})$, this equilibrium is stable.

ii) $\boldsymbol{\epsilon > \frac{\gamma}{1-\gamma}}$. In this case, $b_1, b_2 < 0$; $a_1, a_2, c_1, c_2 > 0$. Moreover, f has a vertical asymptote at $\hat{r}_1 = -d_2/c_2$ and $f = 0$ for $\hat{r}_1 = -b_2/a_2 > 0$. To ensure that f is continuous for any $\hat{r}_1 \in [0,1]$, we assume that the vertical asymptote occurs at $\hat{r}_1 = -d_2/c_2 < 0$, implying that $d_2 > 0$. Therefore, $f > 0$ for any $\hat{r}_1 \in (-b_2/a_2, 1]$, implying that

$$f(\hat{r}_1) = \max\left[0, \frac{a_2\hat{r}_1 + b_2}{c_2\hat{r}_1 + d_2}\right]$$

Furthermore, f is concave. On the other hand, g is convex and, similar to f, it can also take negative values for certain $\hat{r}_1 \in (0,1)$, implying that

$$g(\hat{r}_1) = \max\left[0, \frac{-d_1\hat{r}_1 + b_1}{c_1\hat{r}_1 - a_1}\right]$$

and that there are three equilibria in this case, $\hat{r}_1^{*}, \hat{r}_2^{*} = 0$, $0 < \hat{r}_1^{**}, \hat{r}_2^{**} < 1$ and $\hat{r}_1^{***} = \hat{r}_2^{***} = 1$. Because g is convex whereas f is concave at their intersection with $(\hat{r}_1^{**}, \hat{r}_1^{**})$, this equilibrium is unstable.

A ONLINE APPENDIX: The Reflection Problem

A.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

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

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

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

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

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.

A.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:

$$\pi_t^e = \boldsymbol{\alpha} + \gamma_t L_N + \beta\Omega\pi_t^e + \boldsymbol{\varepsilon}_t \tag{A.1}$$

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 A.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

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

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

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

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.[21]

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

[21] 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.

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

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

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

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

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 A.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.

A.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.

A.3.1 No Time Fixed Effect

We start with the basic problem

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

with

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

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

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

A.3.2 With Time Fixed Effect

We now define the matrix

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

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

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

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

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

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 $\beta^{OLS,TFE}$:

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

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

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

Then,

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

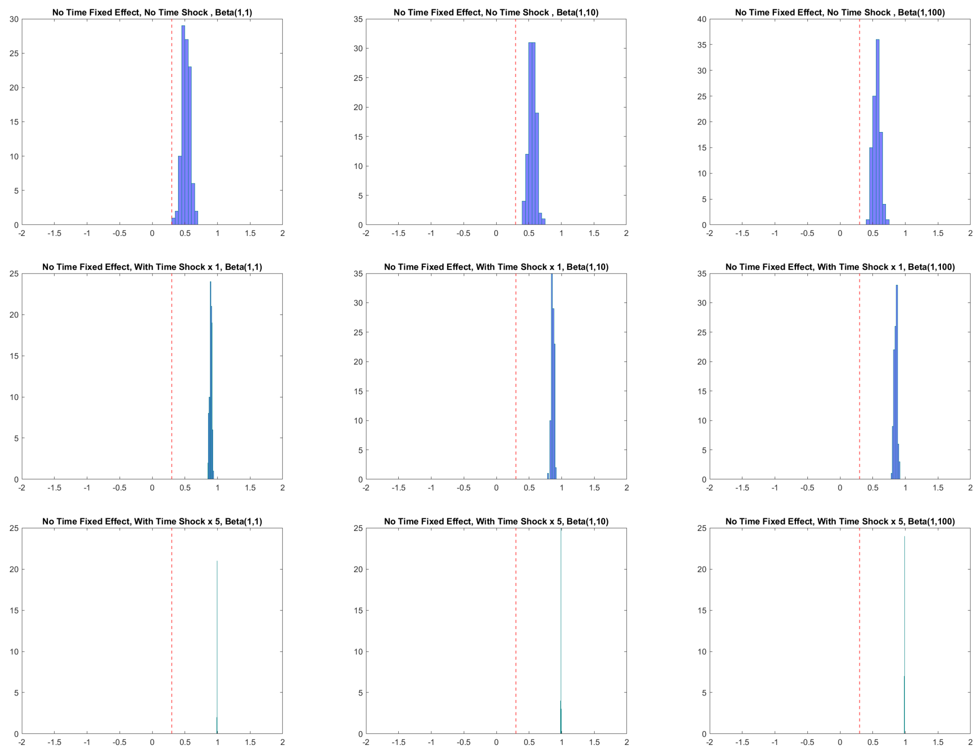
We can see that in this case, the $\beta^{OLS,TFE}$ is constant, negative and does not depend on the actual value of β.

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

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

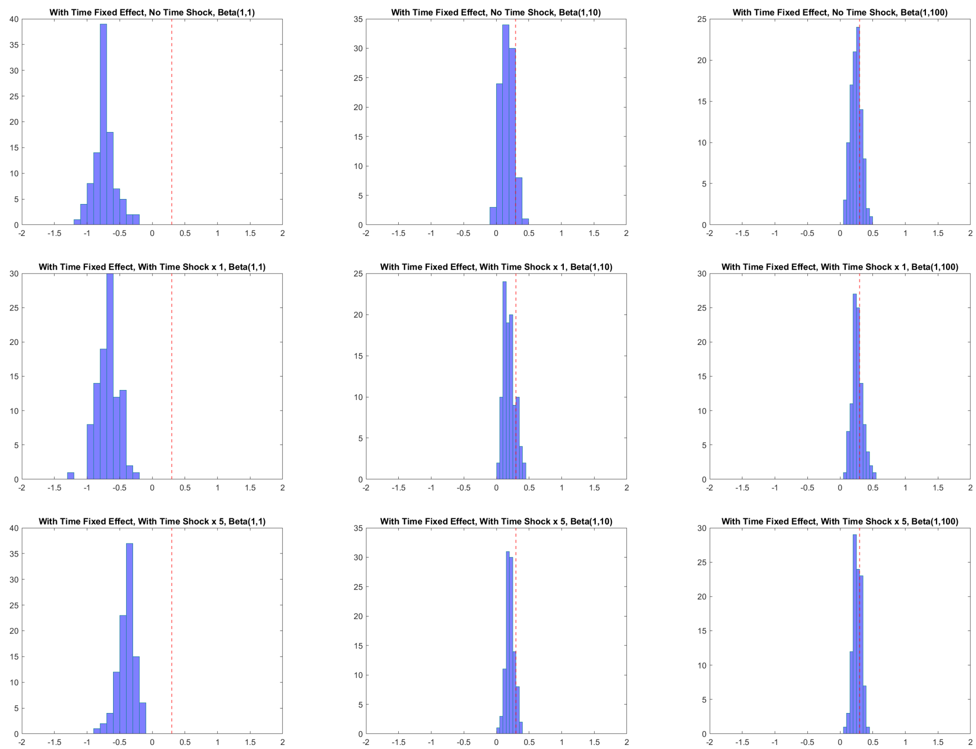
where $\boldsymbol{\varepsilon}_t = \left[\varepsilon_{1,t}, \varepsilon_{2,t}, ..., \varepsilon_{N,t}\right]'$ will have two forms, one where $\boldsymbol{\varepsilon^I}_t = \left[\varepsilon_{1t} \quad ... \quad \varepsilon_{Nt}\right]'$ denotes a set of county-specific i.i.d. shocks to inflation expectations 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 $u_t = \left[u_1, u_2, ..., u_T\right]'$, 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 5 shows the results of the simulation without time FE for each formation process of the network and Figure 6 shows the result with time FE.

Figure 5: Regression Results without Fixed Effects



Note: The figure shows the results of the regression (A.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 6: Regression Results with Fixed Effects



Note: The figure shows the results of the regression (A.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.

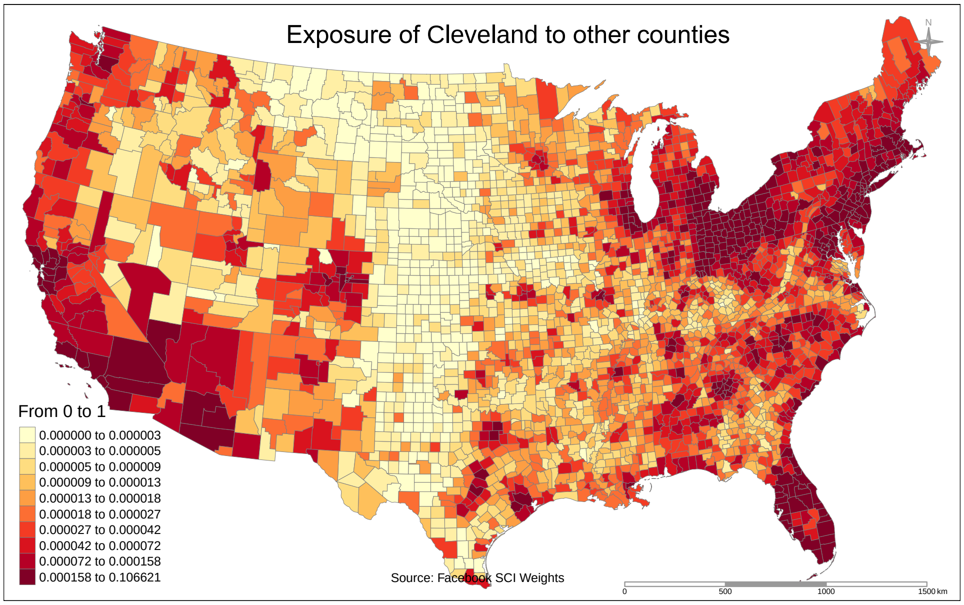
These results speak directly to the results in Tables 1 and 6. Column (5) of Table 1 is similar to Columns (2), (4) and (6) in Table 6: All regressions have time fixed effects, but in Columns (2), (4) and (6) of Table 6 we drop counties that are spatially close. By doing that, we are effectively moving 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 4.4, 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.

B Additional Figures

B.1 Social Connectedness Weights: Examples

We consider the social connectedness of Cuyahoga County, where Cleveland, Ohio is located, with other counties across the United States. Figure 7 illustrates this social connectedness through a heat map depicting the weights ($\omega_{c,k}$) for $c = Cleveland$. In Appendix B, 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.

Figure 7: 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

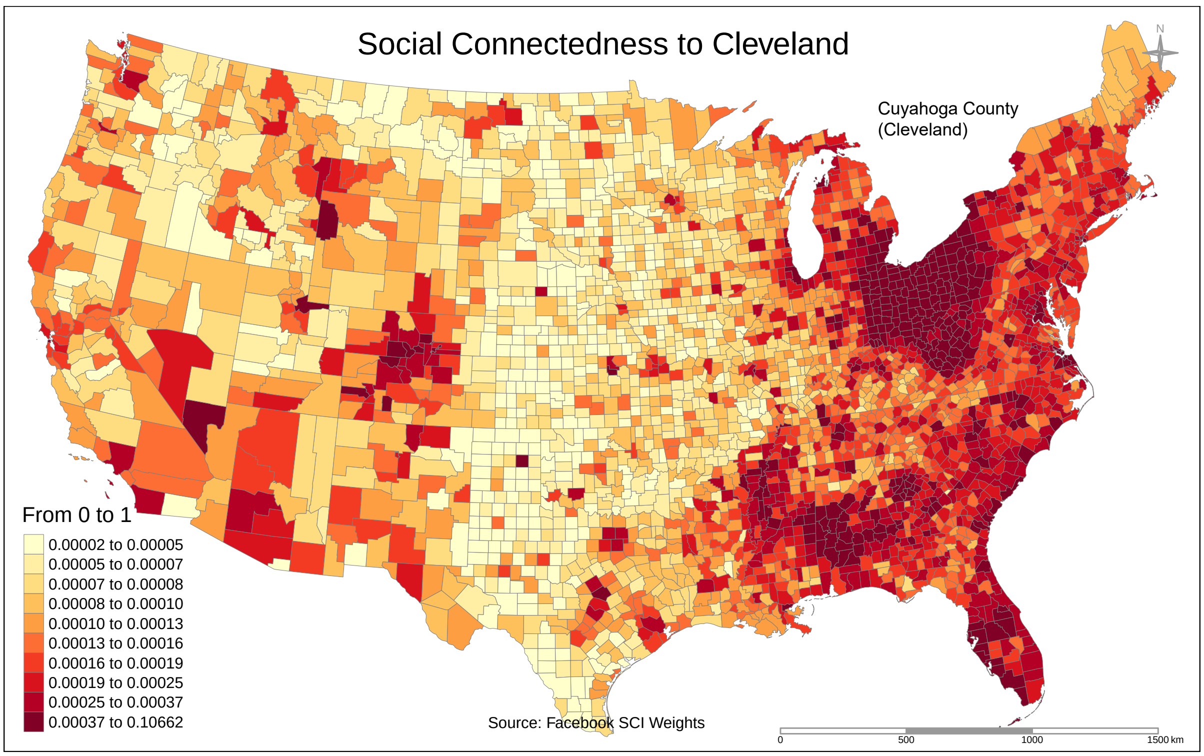
consider the social connectedness of each county in the US to Cuyahoga county (where Cleveland, OH is located). The heat map in Figure 8 shows the weights ω_{ck} for $k = Cleveland$. In Appendix B, we include similar maps for other counties. We assign colors ranging from light yellow to red, with red counties being those that are more socially important for Cleveland. Three patterns emerge. First, not surprisingly, geography plays an important role. Individuals living in counties near Cuyahoga are more likely to be connected to individuals living in Cuyahoga. Second, however, we also observe strong social links for counties that are farther away. For example, Cuyahoga county is relatively important to individuals living in Hillsborough, Florida (Tampa) and Clark County (Las Vegas), Nevada. All of this relative to the importance of Cuyahoga for others. Third, there is substantial heterogeneity in the social connectedness to a county. Cuyahoga is relatively important for some populated counties (such as Wayne, Michigan or Fulton, Georgia), but not too much for others (such as San Francisco, CA).[22]

In reverse, we also present the social connectedness of other counties to Cuyahoga

[22]This analysis is relative to the average importance of Cuyahoga to the rest. For example, Clark county might have a share of connections to Cuyahoga that is high for Cuyahoga, but small for more connected counties, such as Los Angeles, CA.

County, Ohio. The heat map in Figure 8 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. We also provide the social Connectedness to three other illustrative examples: Cambridge (Middlesex County), Miami (Miami-Dade County), and Los Angeles (Los Angeles County). We observe similar patterns.

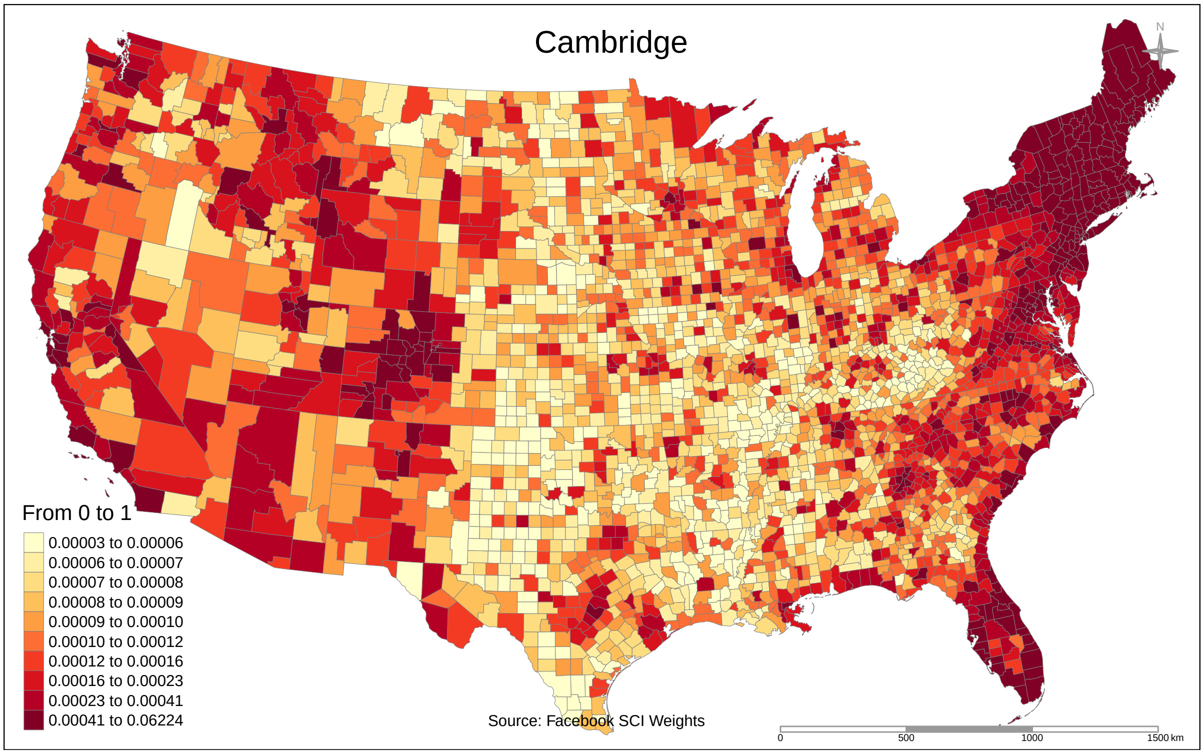
Figure 8: Social Connectedness of Each County to Cleveland ($\omega_{c,Cleveland}$)



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

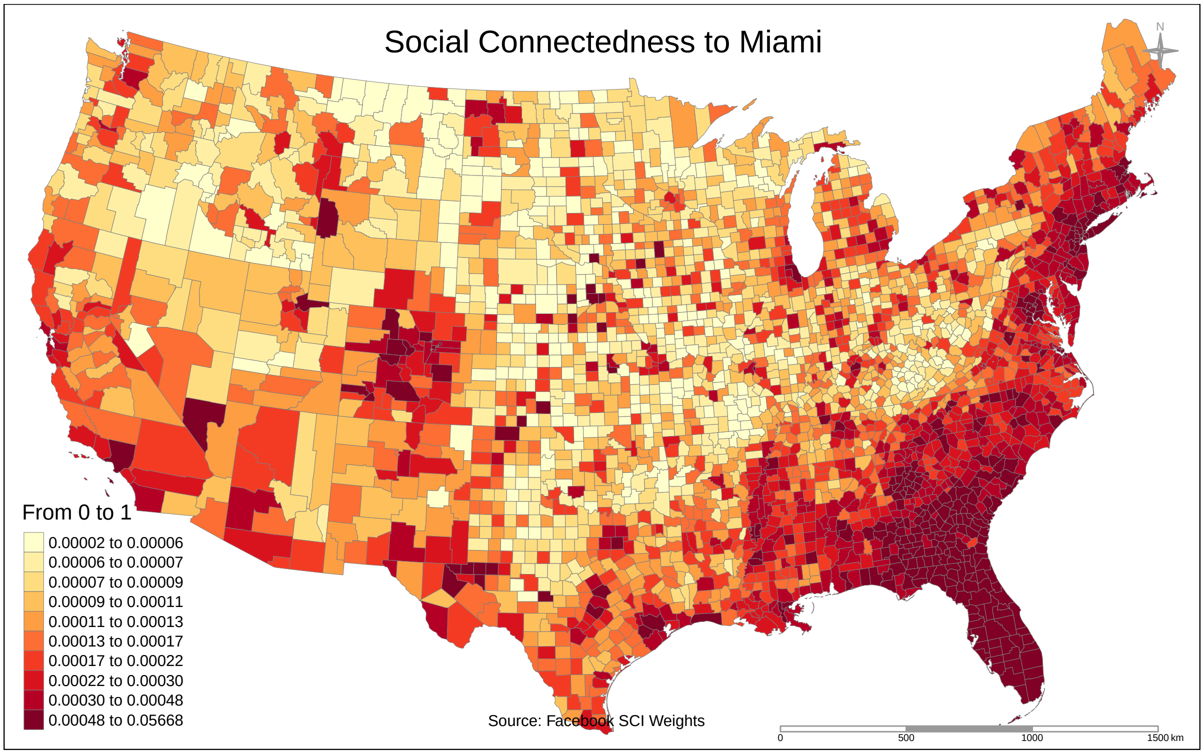
Below we show similar maps for other counties such as Cambridge, Miami, and Los Angeles.

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



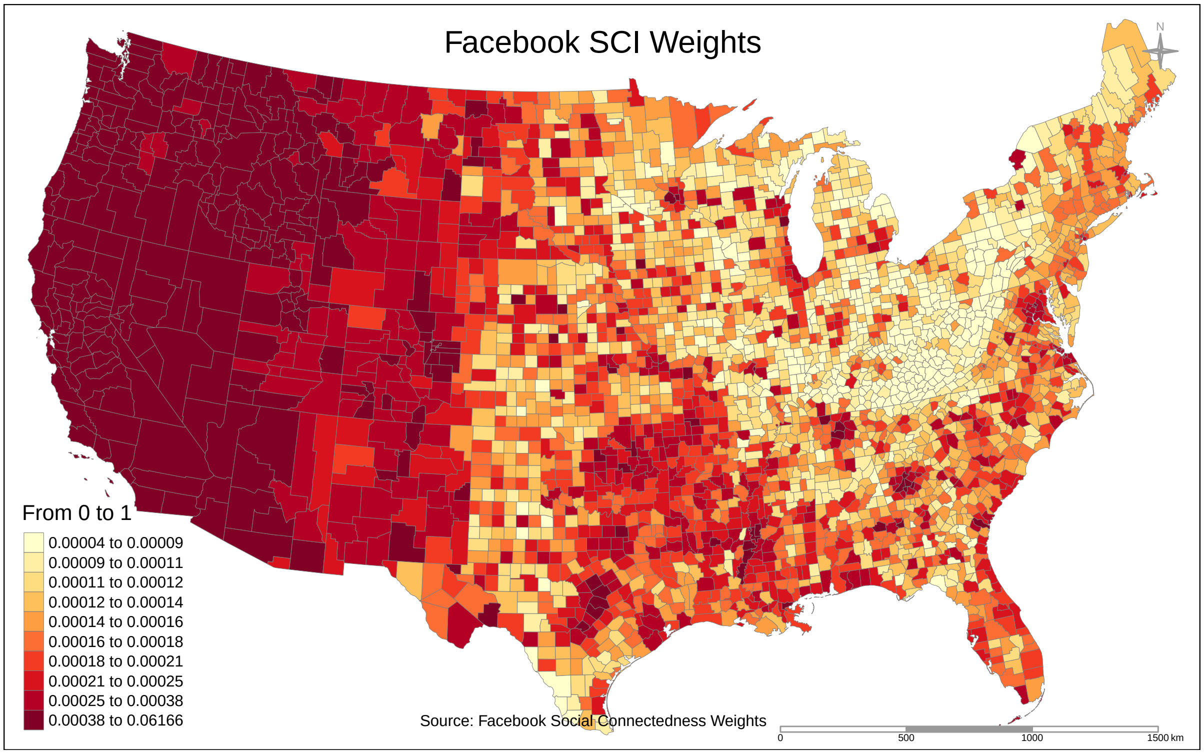
<u>Note:</u> The yellow-to-red color scale represents the degree to which counties are socially connected to Cambridge, based on $\omega_{c,Cambridge}$. Red indicates higher $\omega_{c,Cambridge}$. Source: Social Connectedness Index

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

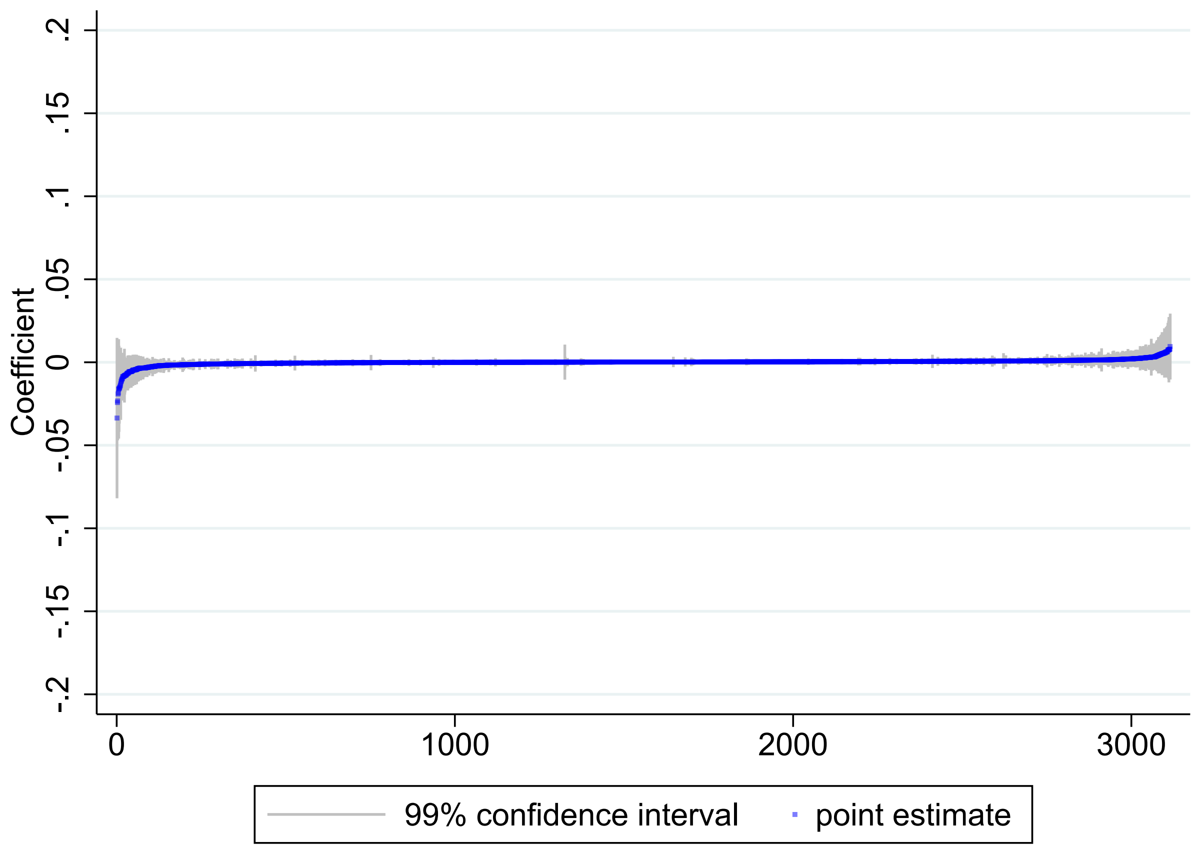
Figure 11: Social Connectedness of Each County to Los Angeles ($\omega_{c,LA}$)



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

B.2 Other Additional 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 confident intervals.

C Additional Evidence: 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 0.3 and 6.4 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 Other Additional 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 A.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.[23]

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 (14), where the dependent $\pi^e_{i,c,t}$ is the inflation expectations of individual i who answers from county c at time t. Observations 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.

[23]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 7: 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

Note: The table shows the results of a version of regression (14), where the dependent $\pi^e_{i,c,t}$ is the inflation expectations of individual i who answers from county c at time t. The regression includes time fixed effect interacted by demographic characteristics at the county level. "Sr Foreign" is the share of foreign born individuals at the county level. "PC Income" is the income per capita. "Sh Black" is the share of black population. "Sh Hisp" is the share of hispanic population. "Sh White NH" is the share of white non-hispanic population. "Pov Rate" is the poverty rate. All these variables coming from the latest census information at the county level. "Biden Sh" is the share of votes that Joseph Biden got in the county in the 2020 presidential election. Observations are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Table 8: Price Network and Social Network

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price Network	0.231***	0.046	0.351***	-0.036	-0.043	-0.094*	-0.091*
	(0.061)	(0.084)	(0.076)	(0.056)	(0.055)	(0.057)	(0.053)
Expectations of Others					0.050**	0.070***	0.063**
					(0.023)	(0.025)	(0.026)
County Expectations	0.712***	0.687***	0.546***	0.497***	0.497***	0.476***	0.434***
	(0.051)	(0.038)	(0.053)	(0.032)	(0.032)	(0.026)	(0.014)
Time FE	No	Yes	No	Yes	Yes	Yes	Yes
County FE	No	No	Yes	Yes	Yes	Yes	Yes
Demographic FE	No	No	No	No	No	Yes	Yes
Demographic-Time FE	No	No	No	No	No	No	Yes
Observations	1,277,247	1,277,247	1,277,247	1,277,247	1,277,247	1,276,612	1,276,612
R-squared	0.012	0.012	0.012	0.013	0.013	0.029	0.031

Note: The table shows the results of a version of regression (14), where the dependent $\pi^e_{i,c,t}$ is the inflation expectations of individual i who answers from county c at time t. Price network uses a network from Garcia-Lembergman (2020). Expectations of Others uses the SCI network. Demographics fixed effects are the income, age, politics and gender definitions used in the paper and are at the individual level. Observation are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Table 9: 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 (15), where the dependent variable $\pi^e_{i,d,c,t}$ is the inflation expectations of individual i, of political affiliation 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. Observations are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Table 10: 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 (15), where the dependent variable $\pi^e_{i,d,c,t}$ is the inflation expectations of individual i, of income 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. Observations 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 Age

	(1)	(2)	(3)	(4)	(5)	(6)
$Network - Age$	0.291***	0.302***	0.292***	0.306***	0.325***	0.429***
	(0.020)	(0.026)	(0.032)	(0.030)	(0.037)	(0.041)
$Inf - Age$	0.643***	0.633***	0.593***	0.585***	0.557***	0.447***
	(0.038)	(0.031)	(0.037)	(0.030)	(0.023)	(0.035)
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	0.033	0.035

Note: The table shows the results of regression (15), where the dependent variable $\pi^e_{i,d,c,t}$ is the inflation expectations of individual i, of age 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. Observations are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Table 12: 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 (15), 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. Observations are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Table 13: 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 (15), 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. Observations are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Table 14: 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 (15), 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. Observations 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 15: 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, $\pi^{e}_{i,c,t} = \alpha_c + \theta_t + \alpha_s Gas\_effect_{c,t} + \beta_s\sum_{k\neq c}\omega_{c,k}Gas\_effect_{d,k,t} + \varepsilon_{i,d,c,t}$, and second, $\pi^{e}_{i,d,c,t} = \alpha_c + \theta_t + \alpha_s Gas\_effect_{c,t} + \beta_s\sum_{k\neq c}\omega_{c,k}\pi^{e}_{d,k,t} + \varepsilon_{i,t}$, 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 $\sum_{k\neq c}\omega_{c,k}\pi^{e}_{d,k,t}$ Observations are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level

Table 16: Demographic Differences

	(1)	(2)
$P_{gas,t} \times Comm_{c(i)}$	3.958***	
	(0.475)	
$P_{gas,t} \times Comm_{c(i)} \times I(Fem=1)$	-3.124***	
	(0.572)	
$\sum_{k \neq c} \omega_{c,k} Gas\_effect_{c,d,t}$		0.532***
		(0.023)
$\left(\sum_{k \neq c} \omega_{c,k} Gas\_effect_{c,d,t}\right) \times I(Fem=1)$		-0.167***
		(0.023)
$\pi^e_{-i,d,c,t}$		1.980***
		(0.200)
$\pi^e_{-i,d,c,t} \times I(Fem=1)$		-1.398***
		(0.319)
Observations	1,239,055	1,910,679
R-squared	0.024	0.028

Note: This table replicates results of Tables 3 and Table 4, but including interactions between gender to test the different between the coefficient found. Column (1) shows results for the regressions of Columns (5) and (6) of Table 3, but in a single regression, where we interact the coefficients with a indicator variable $I(Fem=1)$ that takes a value of 1 if the respondent's gender is female and zero otherwise. Column (2) shows results for the regressions of Columns (4) and (5) of Table 4, but in a single regression, with the main coefficient interacted by the gender indicator variable. Both regression include time fixed effects, county fixed effects and the interaction of both with the gender indicator variable. We use weights by the number of respondents in a given county and standard errors are clustered at the county level.