The Expectations of Others*

Ezequiel Garcia-Lembergman Ina Hajdini John Leer
Mathieu Pedemonte Raphael Schoenle

October 18, 2024

Abstract

Using a novel dataset that integrates inflation expectations with social network connections, we show that inflation expectations within one's social network have a positive, causal relationship with individual inflation expectations. This relationship is stronger for groups that share common demographic characteristics such as gender, income, or political affiliation and when salient information is shared. In a monetary-union New-Keynesian model, socially determined inflation expectations induce imperfect risk-sharing, and can affect the inflation and real output propagation of local and aggregate shocks. To reduce welfare losses, monetary policy should optimally put more weight on the inflation rate of socially more connected regions.

JEL classifications: E31, E71, C83

Keywords: Inflation expectations, Social network, Monetary union

*We thank Philippe Andrade, Martin Baraja, Saki Bigio, Job Boerma, Markus Brunnermeier, Ricardo Caballero, Chris Campos, Olivier Coibion, Nicola Gennaioli, Jonathon Hazell, Oleg Itskhoki, Baris Kaymak, Ed Knotek, Theresa Kuchler, Jean-Paul L'Huillier, Benjamin Moll, Damjan Pfajfar, Michael Weber, Ivan Werning, Alexander Wolitzky, Sonya Zhu and seminar participants at the CEBRA Annual Meeting, Cleveland Fed, Boston Fed, LMU Munich, UT Austin Macro/International Conference, EABCN Conference, Challenges for Monetary Policy in Times of High Inflation workshop, LAEF, Brandeis, Fed's System Macro, LSE, Bank of England, MIT, NBB Workshop, and Banco Central de Chile for useful comments and suggestions. IRB protocol #23166R-E at Brandeis University. The views expressed here are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Cleveland or the Federal Reserve System. Garcia-Lembergman: Pontificia Universidad Catolica de Chile, ezequiel.garcia@uc.cl, Hajdini: Federal Reserve Bank of Cleveland, ina.hajdini@clev.frb.org. Leer: Morning Consult jleer@morningconsult.com. Pedemonte: Inter-American Development Bank, mathieu.pedemonte@gmail.com. Schoenle: 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, individual experiences and the use of availability heuristics (Tversky and Kahneman (1973)) have been found to play an important role in the formation of expectations. However, a central insight from social psychology, pioneered by Festinger (1954), is usually not emphasized in the inflation expectations literature: the formation of inflation expectations takes place in a social context of interaction with others. Our analysis shows, both theoretically and empirically, that inflation expectations in the social network matter for the formation of individual inflation expectations, and can affect macroeconomic dynamics and policymaking.

In doing so, our paper makes three contributions. First, 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. Second, we implement several empirical strategies to rigorously establish a positive, causal effect of the social network on individual inflation expectations. This relationship is stronger for groups that share common demographic characteristics such as gender, income, or political affiliation and when salient information transmits strongly through the network. Third, our analysis uses a monetary-union New-Keynesian model to highlight the theoretical implications of our empirical findings, showing that socially determined inflation expectations can affect the inflation and real output propagation of local and aggregate shocks. A novel policy implication also arises: to reduce welfare losses due to socially determined expectations, monetary policy should optimally put more weight on the inflation rate of socially more connected regions.

Empirically, pinning down the causal effects of social networks on individual inflation expectations is challenging. First, that analysis necessitates a dataset that combines geographically dense data on individual inflation expectations with a

[1] See, for instance, for individual decisions Coibion et al. (2023), and Hajdini et al. (2022b). For macro implications, see Gabaix (2020), Kohlhas and Walther (2021), and L'Huillier et al. (2021), among many others; and specifically, for recent work on the formation of inflation expectations, Gennaioli et al. (2024).

map of the social network. Second, when "other factors" 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" may not only trivially coincide with common regional or aggregate shocks. They may also 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 construct a detailed, novel dataset that contains both inflation expectations and information on 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.[2] Social connections 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. Analyzing this data at a monthly 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 in-

[2]The survey is nationally representative of the US and aligns with the aggregate trends in the NY Fed's Survey of Consumer Expectations and the University of Michigan's Survey of Consumers. See Hajdini et al. (2022a) for details.

flation 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 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.

A second approach creates additional variation at the county level to remove variation in "other factors" at the county-time level that may affect identification. Specifically, we construct county $\times$ demographic $\times$ time inflation expectations of others that allow us to include 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.

Finally, we apply an instrumental-variable 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 (2015)) and that relevance varies across locations, depending on the importance of gas usage, which we show is not related to the social network weights. The approach captures this variation with a variable that interacts commuting share and the national gas price. A regression of inflation expectations on this variable allows us to then construct local shocks to inflation expectations from the predicted value, after carefully filtering out any common time variation and county-specific effects. Then, the analysis aggregates up these shocks across the network, for each county. Using this measure as an instrumented value in a final step for inflation expectations in the social network allows one to gain an unbiased causal estimate for the effect of inflation expectations in the network on individual inflation expectations. Not least in their totality, these three approaches contribute to the strength of identification while consistently demonstrating the relevance of social networks in shaping individual inflation expectations.

Beyond establishing this empirical importance of social networks for the formation of inflation expectations, our analysis also shows an example of the theoretical relevance of socially determined inflation expectations in a monetary policy context. We do so by means of a simple two-region monetary-union New Keynesian model à la Nakamura and Steinsson (2014), where we allow for regions to place more weight on the expectations of the other region than implied by the trade shares in the consumption aggregator. The regions are otherwise homogeneous but can differ in their economic size and exposure to regional supply and demand shocks. We analytically derive in this general equilibrium setting how socially determined inflation expectations can distort the dependence of both regional and aggregate variables on the terms of trade relative to a full information rational expectations (FIRE) benchmark.

Several theoretical results arise, all tracing back to the fact that in the presence of home bias, households under-weight the inflation rate of locally-produced goods, but over-weight the inflation rate of goods produced in the other region. As a consequence of this full-information rational-expectations (FIRE) deviation in relative expectations and hence, prices, perfect risk-sharing breaks down. Likewise, with regards to the dynamics of key variables, FIRE dynamics of regional inflation and output are distorted following local shocks, but not common aggregate shocks. With regards to aggregate effects, dynamics of inflation and output are also distorted by the presence of socially determined inflation expectations—but only if consumers in one region are disproportionally attentive to the other region's inflation rate compared to the two regions' relative economic sizes.

Finally, our analysis presents a novel policy implication: to reduce welfare losses due to socially determined inflation expectations, monetary policy should optimally put more weight on the inflation rate of socially more connected regions. This optimal response is isomorphic in our model to policy responding to the terms of trade between the two regions in addition to aggregate inflation. It also mimics the spirit of results in the open-economy literature such as Aoki (2001).

Quantitatively, socially determined inflation expectations can be important as a simple calibration of our model shows. First, we find that as a result of socially determined expectations an economically significant impact effect arises in the case of local supply shocks, while it remains small for local demand shocks. The impact of a one-time home supply shock on output and inflation is about 3.7% and 6.2% lower compared to a full-information rational-expectations benchmark, respectively. Second, in terms of the weight on the regional inflation rates, policy should assign as 26% higher weight to the inflation rate of the home region.

Literature. The findings from our analysis are related to several strands of the literature, in addition to the papers already referenced above. At a fundamental level, our analysis is most related to a large literature that studies the formation of inflation expectations and has shown how *individual* characteristics and experiences affect the process of expectations formation (for example, among many, Malmendier and Nagel (2016), D'Acunto et al. (2021b), Kuchler and Zafar (2019), Hajdini et al. (2022a) or Gennaioli et al. (2024)). A behavioral theoretical literature in parallel argues 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 expectations model (Bordalo et al. (2018), Bordalo et al. (2019), and operationalized in the New Keynesian modeling and policy framework by L'Huillier et al. (2021) and Bianchi et al. (2023). Relative to these papers, our analysis emphasizes theoretically and empirically the notion of *socially* determined inflation expectations and their potential impact on the dynamics of regional and aggregate inflation and output.

Our analysis, moreover segues with a growing empirical literature that has emphasized the role of social interactions on economic decision-making. Most related is the seminal work by Bailey et al. (2018b) in the context of housing, which shows 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. Our relative empirical contribution lies in focusing on inflation expectations of the entire consumption basket, heightening the relevance of socially determined inflation expectations in light of a monetary policy context. On the theory side, we demonstrate the potential importance of socially determined inflation expectations in a simple monetary-union New Keynesian model, a framework which can in principle also be extended to evaluate some of the earlier empirical findings (Bailey et al. (2018b, 2019)).

Extensive work also aims to understand how individuals form social networks, as in Banerjee (1992), Acemoglu et al. (2011), and Golub and Sadler (2016).[3] Another strand of the literature on networks comprises work in macroeconomics focused on the transmission of shocks through production networks as, for example, in Baqaee and Farhi (2018), Rubbo (2020), Pasten et al. (2020). Our paper relates to both strands by showing that a key macroeconomic variable—inflation expectations—is influenced by social interactions. Unlike the first set of papers, as well as Arifovic et al. (2013) and Grimaud et al. (2023) who consider specific forms of social learning in a New-Keynesian framework, our analysis abstracts from learning. Instead, our theoretical analysis highlights the implications of socially determined inflation expectations in a monetary-union New Keynesian model, such as the implication for risk-sharing or optimal regional inflation weights.

2 Empirical Analysis

To gauge the effect of the social network on individuals' inflation expectations, our analysis subsequently estimates variants of the following specification:

$$\pi_i^e = \alpha + \beta \sum_{j=1}^{N} \omega_{ij} \pi_j^e + \epsilon_i, \tag{1}$$

relating inflation expectations π_i^e of some individual/region to inflation expectations π_j^e of individuals/regions j whose importance for i's beliefs are captured by social network weights ω_{ij}. Specifications of this type are common in the social

[3]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).

learning literature, and we show in Online Appendix B how they can be micro-founded in a model of memory and recall, a framework particularly relevant in the inflation expectations literature.[4] The coefficient of interest for our analysis is contained in β, which is positive if social interaction positively affects inflation expectations.

Estimating this equation is challenging for reasons of data availability and due to empirical challenges proper to the social network context. The next sections show how we address them, first describing a novel dataset that contains inflation expectations and social network weights required to estimate this equation. An ensuing section describes the particular empirical challenges in the estimation of this type of equation and the strategies we apply to overcome them. Our results, finally, show that social interaction has a causal, positive relation with the inflation expectations of others.

2.1 Data

To establish a network effect on individual inflation expectations, any 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. Hajdini et al. (2022a) describe its properties in detail, showing in particular its high correlation with inflation expectations from established surveys. Of note, the survey elicits expectations of changes in individually relevant prices instead of aggregate prices, which will be directly relevant for consumers' decisions in the model we introduce in Section 4. Respondents are sampled in repeated cross-sections; 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

[4]See, for example, the recent work by Gennaioli et al. (2024) that shows the ability of such models to explain de-anchoring of inflation expectations through selective recall.

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 $\text{Connections}_{i,j}$ denotes the total number of Facebook friendship connections between individuals in counties i and j and FB Users_i, FB Users_j denote the number of users in location j. Intuitively, if $SCI_{i,j}$ is twice as large as $SCI_{i,l}$, a given Facebook user in location i is about twice as likely to be connected with a given Facebook user in location j than with a given Facebook user in location l.

In our analysis, we normalize the SCI by county so weights add up to unity, that is, $\omega_{c,k} = \frac{SCI_{c,k}}{\sum_k SCI_{c,k}}$. Using these weights, we then construct the central variable in our analysis, the expectations of others:

$$\pi^{e,others}_{c,t} = \sum_{k \neq c} \omega_{c,k} \pi^{e}_{k,t}, \tag{2}$$

where $\pi^{e}_{k,t}$ captures the average inflation expectations of individuals in county k at time t. In particular, this measure implies that 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,[5] 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 (see Online Appendix D.1). We observe three distinct patterns. First, as expected, geography plays a significant role, with stronger connections to nearby counties appearing. 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 consideration those geographic patterns, as we discuss in the subsequent sections.

2.2 Challenges and Identification Strategy

The main challenge to identifying an effect of the social network on inflation expectations lies in ruling out that the empirical measures of beliefs of others reflect "other factors" common across counties in the social network. Whenever such other factors are sufficiently common across counties, they may create spurious comovement 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

[5] 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.

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 (i.e., we are friends with similar people) may induce common price movements because similar friends 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, these three approaches contribute to the strength of identification.

Our first approach accounts for "other factors" directly, as much as possible. Our second approach 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. The second approach additionally gauges the importance of common demographics in the social network. The third approach additionally considers the role of salience for the stability of inflation beliefs in the social network. The third approach also addresses endogeneity concerns such as the Manski (1993) reflection problem.[6]

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

[6] If the social networks are, in reality, irrelevant for individual expectations, then the Manski (1993) reflection problem disappears. In Online Appendix C.1 we prove this result.

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 remove variation that stems for example from the co-movement of prices in similar consumption baskets which homophily embodied in social networks might generate. Thus, after taking into account all the observational characteristics of the individuals, our identifying variation comes from the residual inflation expectations of others in the social network, above and beyond the expectations that can be accounted for by observables.

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 implements an instrumental variables strategy that addresses any remaining endogeneity concerns. Specifically, the approach follows Hajdini et al. (2022a), that measure whether a national change in gas prices will disproportionately impact inflation expectations in areas with higher car usage intensity. The approach takes two steps: First, one regresses inflation expectations on the interaction of commuting shares by car and the national gas price while filtering out any common time variation or county-specific fixed effects. One then uses the regression results to generate local, county-specific shocks in inflation expectations as the component of inflation expectations predicted by the county-specific exposure. The first step concludes by aggregating these local inflation expectations shocks across counties, county by county, using the social network weights of each county. Second, this resulting measure then serves in a second regression as an instrumented value for inflation expectations in the social network, allowing us to isolate an unbiased, causal effect of inflation expectations in the social network on inflation expectations.

This third approach rests on two assumptions in particular: First, it assumes that shares of commuters and social network weights are not related, which rules out spurious correlation in inflation expectations in the network because gas price movements are translated more strongly if two counties both have high gas use shares. We test this assumption and find no correlation.[7] Second, it assumes that local county-level shocks in the cross section do not influence US demand for gas significantly, nor do any other local policies that can jointly influence expectations and local gas price.

Since it is well known from the inflation expectations literature that higher gas prices lead to higher inflation expectations (Coibion and Gorodnichenko, 2015), this third instrumental-variable approach may also provide a glimpse into the type of information that flows through the social network: on average, if a positive relationship emerges from the estimation, people must be talking about salient inflation-relevant experiences, such as prices at the pump.

3 Results

Across all approaches, our analysis finds strong evidence that social networks constitute an important determinant of individual inflation expectations.

3.1 Relation with Inflation Expectations of Others

This subsection presents the part of this conclusion that is due to our first approach: Individual inflation expectations have a positive association with inflation expectations in the social network, even after we take into account a plethora of "other factors" that might spuriously imply a correlation of inflation expectations. Because subsequent sections reach the same conclusion, while based on the other

[7]Figure 9 in the Online Appendix D.2 confirms this assumption by displaying results from a regression of network weights and gas use shares across all county pairs. The coefficient is very small and not statistically different from zero for most counties. A joint regression adding all counties and including individual and time fixed-effects fixed effects has a small coefficient that is not statistically different from zero.

approaches, this first section can thus be read as delineating the common, key message of our analysis.

We implement our first approach by estimating several specifications. These specifications all use individual-level data, which allows us to take into account detailed fixed effects. Specifically, we estimate specifications of the following type:

$$\pi^e_{i,c,t} = \alpha_0 + \alpha_1 \pi^e_{-i,c,t} + \beta \sum_{k \neq c} \omega_{c,k} \pi^e_{k,t} + \varepsilon_{i,c,t}, \tag{3}$$

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, respondents' demographic characteristics fixed effects, interactions of demographics and time fixed effects, and the combination of all demographic characteristics together interacted with a time fixed effect. We also provide robustness exercises including county characteristics interacted with a time fixed effect and 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. Standard errors are clustered at the county level.[8]

Across specifications, strong evidence emerges that individual inflation expectations are highly significantly associated with the inflation expectations of others. Table 5 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 time variation in inflation common to all counties leaves this result almost

[8] The results remain robust when using unweighted specifications (see Online Appendix Table 7) or weighting by county population (Online Appendix Table 8) and are consistent under alternative clustering methods, such as clustering standard errors at the state level (see Online Appendix Table 9).

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 (3), 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.

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.[9] 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.[10]

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

[9] 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%.

[10] In Online Appendix C.2 we show that when the network linkages is more homogeneous, the inclusion of a time fixed effect 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.

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 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.[11]

The findings of this section are also robust to taking into account common, local spatial shocks. For that, our analysis uses expectations of others computed only from counties outside 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 10 in Online Appendix F 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

[11] Additionally, in Table 11 in Online Appendix F, we take into account further demographic characteristics measurable at the county level, interacted with a time fixed effect. We find that our key coefficient of interest, on the expectations of others, remains positive and significant.

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 a 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 expectations in counties with shared retail chains does not change our key findings, as Table 12 in Online Appendix F 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.[12]

3.2 Relation with Inflation Expectations of *Similar* Others

Strong evidence for the role of expectations of others affecting individual inflation expectations also emerges when we apply our second identification approach. The results from this second approach systematically alleviate concerns arising from confounding but potentially unobserved common factors, such as demand spillovers from nearby regions or trade linkages. They also show that demographic similarity in the social network plays an important role in the transmission of inflation expectations.

To generate these findings, our analysis constructs exposure to inflation expectations of *similar* others in distant counties. 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:

$$\pi^e_{i,d,c,t} = \alpha_0 + \alpha_1 \pi^e_{-i,d,c,t} + \beta_1 \sum_{k \neq c} \omega_{c,k} \pi^e_{d,k,t} + \theta_{ct} + \varepsilon_{i,c,t}. \tag{4}$$

[12] 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.

$\pi^e_{i,d,c,t}$ denotes the inflation expectations of individual i, with demographic characteristic d, in county c at time t; $\pi^e_{-i,d,c,t}$ represents the average inflation expectations of all the other individuals in that same county c that share the same demographic characteristics d with individual i; and $\sum_{k\neq c}\omega_{c,k}\pi^e_{k,t}$ captures the inflation expectations of similar others in distant counties.

Because by construction there are now multiple expectations of others at each point in time for a given county—one for each demographic category—this treatment of the data allows us to implement our second identification approach: "Splitting" the network allows us to exploit additional variation in beliefs of others and include *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 comovement of expectations, but may be unobserved. Such concerns may in particular include common shocks due to spatial spillovers, trade relationships, or demand spillovers from nearby regions, among many others.[13] 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. Additionally, "splitting" the data as proposed by construction also allows our analysis to gauge the importance of demographic similarity in the transmission of inflation expectations through the network.

Strong evidence emerges from implementing this second approach: The inflation expectations of others are positively related to individual inflation expectations. Moreover, our results also show that demographic similarity along several dimensions—gender, political affiliation, income, and age—always plays an important role in the transmission of inflation expectations. For example, in the case of gender,[14] the effect of one's social network turns out to be statistically

[13]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.

[14]Gender is a particularly appealing similarity feature because it does not depend on people's

and economically significant. A 1 pp. increase in the inflation expectations of the gender-specific network increases own-inflation expectations between 0.28 and 0.78 pps. 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 13, 14, and 15 in Online Appendix F 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 16 illustrates, extending support to our main finding of socially determined inflation expectations.

Table 2: Similarity Effect by Gender

	(1)	(2)	(3)	(4)	(5)	(6)
$Sim - Network$	0.282***	0.334***	0.306***	0.359***	0.413***	0.777***
	(0.038)	(0.028)	(0.057)	(0.047)	(0.052)	(0.092)
$Sim - County$	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 (4), 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. $Sim - Network$ is the average of inflation expectations of individuals of the same gender in other counties. $Sim - County$ 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*. To do so, we estimate specification (4), 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

choices, as much as, for example, in the case of political affiliation.

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 17 in Online Appendix F illustrates these findings in multiple specifications for gender, and Table 18 for all other demographic characteristics.

3.3 Transmission of Exogenous Shocks through the Network

Further strong evidence for the role of the social network in shaping individual inflation expectations emerges when we implement our third, instrumental-variable approach. Applying this approach gives the results in this section a causal, bias-free interpretation which makes them our preferred estimate. Relative to the preceding sections, this section also establishes that salient information must travel through the network, an effect that at the network level mimics the individual-level findings in the empirical expectations literature such as D'Acunto et al. (2021b).

As laid out in the methodology section, the approach follows the approach of Hajdini et al. (2022a), exploiting cross-county variation in the share of individuals commuting by car combined with monthly fluctuations in national gas prices. The results that we present below align with the two steps of the approach, which can be summarized as follows:

1. Step 1: project $\pi^e_{d,c,t}$ on $Comm_{c(i)} \times P_{gas,t}$, including time fixed effects θ_t to filter out any common variation across counties:

$$\pi^e_{i,d,c,t} = \alpha_{c(i)} + \theta_t + \beta_d P_{gas,t} \times Comm_{c(i)} + \varepsilon_{i,d,c,t}, \tag{5}$$

   Then, obtain predicted $GasEffect_{d,c,t} = \hat{\beta}_d P_{gas,t} \times Comm_{c(i)}$.

2. Step 2: instrument $\sum_{k \neq c} \omega_{ck} \pi^e_{d,k,t}$ with predicted $\sum_{k \neq c} \omega_{ck} GasEffect_{d,k,t}$ in the following regression:

$$\pi^e_{i,d,c,t} = \alpha_{c(i)} + \theta_t + \rho_1 \pi^e_{-i,d,c,t} + \rho_2 \sum_{k \neq c} \omega_{c,k} \pi^e_{d,k,t} + \varepsilon_{i,d,c,t}, \tag{6}$$

where $\pi^e_{d,c,t}$ denotes inflation expectations of demographic group d in county c in period t, $\alpha_{c(i)}$ denotes county fixed effects, $P_{gas,t}$ denotes the average national price of regular gas according to the US Energy Information Administration, $Comm_{c(i)}$ denotes the share of people who use their own car to commute according to the ACS and $\pi^e_{-i,d,c,t}$ denotes average county-demographic inflation expectations that exclude the respondent's own expectations. Notably, the results below focus on demographic differences along the gender dimension although we also present results irrespective of such differences. Allowing for gender differences in the sensitivity to gas 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. Gasoline prices, as they show, are analogously more salient to men.

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.

The regression results from the first step of the approach show a positive, highly statistically significant effect of the network weighted measure on inflation expectations. This finding holds across specifications and is in line with the well-established impact of gas prices 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 does.

The findings from the first step also show that salience of experiences in the network can amplify the transmission of information. According to Columns 5 and 6, 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 the aggregate 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 (see Table 20 in Online Appendix for a formal test). As Table 19 in Online Appendix F shows, additionally taking into account own-county demographic gas effects $Gas\_effect_{d,c,t}$ also does not change these findings.

Our main finding in the paper—but now with a causal underpinning—is confirmed by the results from the second step: When we apply the instrumental variables approach, the coefficient estimate on the inflation expectations in the social network 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)). Results are economically meaningful. The estimated coefficient of 0.491 implies that an individual exposed to the 75th percentile of inflation expectations in their social network holds inflation expectations that are 1.15 percentage points higher than those of a comparable individual exposed to the 25th percentile of expectations in their social network. Given the causal, bias-free estimate interpretation from this second step, we consider the estimated coefficient of 0.491 to be our preferred estimate of the social network effect. Accordingly, the calibrations in the subsequent model analysis will be based on it.

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. We weight by the observations in a county in each period. Standard errors clustered at the county level.

4 Macroeconomic Implications

The above results establish a positive, causal relationship between the inflation expectations of others and consumers' own inflation expectations, a result that aligns with the social determination of beliefs also found in other contexts (e.g. Bailey et al. (2018b, 2020)). This section tractably incorporates such a determination of beliefs into a New-Keynesian dynamic general-equilibrium model of a monetary union, showing its macroeconomic importance relative to a full-information rational expectations framework (FIRE).

Two main sets of results emerge: first, socially determined beliefs can significantly distort the propagation of supply and demand shocks, while also optimally requiring the central bank to shift policy weights across regions, mimicking the spirit of results in the open-economy literature such as Aoki (2001). Second, risk-sharing is incomplete, similar to the results in Itskhoki and Mukhin (2021). Underlying these macroeconomic implications is a simple over-weighting of inflation expectations for goods in other regions, aggravated by regional asymmetries, which amplifies distortions of relative prices and their dynamics.

4.1 Model Setup

The model economy comprises a monetary union where consumers live in two regions, *home (h)* and *foreign (f)*, that trade with each other, but workers are immobile across regions, as in Nakamura and Steinsson (2014) and Herreno and Pedemonte (2022). We assume that the size of the home region is $n \in (0,1)$ whereas the size of the foreign region is $1-n$. In what follows, we describe the economy of the home region (H); the economy of the foreign region is symmetric to the home region (F).

Households. Households maximize their utility with respect to consumption, labor hours, and bond holdings, subject to their budget constraint:

$$\max_{C_{Ht},L_{Ht},B_{Ht}/P_{Ht}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \zeta_{Ht} \left[\frac{C_{Ht}^{1-\gamma}}{1-\gamma} - \psi \frac{L_{Ht}^{1+\alpha}}{1+\alpha} \right] \tag{7}$$

$$B_{H,t+1} + P_{Ht}C_{Ht} = W_{Ht}L_{Ht} + B_{Ht}R_t + D_{Ht} \tag{8}$$

where B_{Ht} denotes risk-less nominal bond holdings of consumers in the home region at time t, paying gross nominal interest R_t; C_{Ht} is real consumption; P_{Ht} is the price level in the home region in period t; L_{Ht} denotes labor hours at nominal wage rate W_{Ht} for consumers in the home region at time t; and D_{Ht} are the nominal profits of firms in the home region paid to consumers in that region; ζ_{Ht} is a regional preference shock. Similar to Nakamura and Steinsson (2014), we assume that labor is immobile across regions.

Households have CES preferences over varieties produced across all regions with elasticity of substitution ν and preferences for the local good ϕ_H. Specifically,

$$C_{Ht} = \left[\phi_H^{\frac{1}{\nu}} C_{H,H,t}^{\frac{\nu-1}{\nu}} + (1-\phi_H)^{\frac{1}{\nu}} C_{H,F,t}^{\frac{\nu-1}{\nu}} \right]^{\frac{\nu}{\nu-1}} \tag{9}$$

where $C_{j,i,t}$ is consumption of goods produced in region i by consumers located in region j. We assume that preferences for local goods are proportional to the sizes of the regional economies, so that, $(1-n)(1-\phi_F) = n(1-\phi_H)$. The price index of the home region is defined by the CES preferences,

$$P_{Ht} = \left(\phi_H p_{Ht}^{1-\nu} + (1-\phi_H) p_{Ft}^{1-\nu}\right)^{\frac{1}{1-\nu}} \tag{10}$$

where p_{Ht} denotes the price of the good produced in the home region and p_{Ft} is the price of the good produced in the foreign region, which is a CES aggregate of a continuum of varieties z with an elasticity of substitution η_t,

$$C_{i,j,t} = \left(\int_0^1 c_{i,j,t}(z)^{\frac{\eta_t - 1}{\eta_t}} dz\right)^{\frac{\eta_t}{\eta_t - 1}} \tag{11}$$

Firms. There is a continuum of firms in the home region that produce tradable varieties and face demand coming from all regions. We denote the demand for the home region products by Y_{Ht}, and it is equal to

$$Y_{Ht} = nC_{H,H,t} + (1-n)C_{F,H,t} \tag{12}$$

Firms produce using a production function linear in local labor, $Y_{Ht}(z) = L_{Ht}(z)$. Real marginal costs, expressed in terms of domestic prices, are common across firms within the region, and equal to the real wage $mc_{Ht} = \frac{W_{Ht}}{P_{Ht}}$.

Firms' price-setting problem is subject to Calvo (1983) price rigidity, where in each period firms cannot re-adjust their price with probability θ.

$$\max_{p_{Ht}(z)} \mathbb{E}_t \sum_{j=0}^{\infty} (\theta\beta)^{t+j} Q_{t,t+j} \left[p_{Ht}(z) y_{H,t+j}(z) - mc_{H,t+j} L_{t+j}(z)\right] \tag{13}$$

where $Y_{H,t+j}(z) = \left(\frac{p_{Ht}(z)}{p_{H,t+j}}\right)^{-\eta} Y_{H,t+j}$ and $Q_{t,t+j}$ is a stochastic discount factor.

Monetary policy. The central bank sets the interest rate R_t according to a standard Taylor rule,

$$\frac{R_t}{\bar{R}} = \left(\frac{\pi_{Ht}^{n}\pi_{Ft}^{1-n}}{\bar{\pi}}\right)^{r_\pi} \tag{14}$$

where $\bar{R}$ is the steady-state value of the nominal interest rate and $\bar{\pi}$ is the inflation target.

4.2 Socially Determined Expectations

Our empirical analysis above showed that consumers form expectations based on the expectations of others. We incorporate this finding into the consumer's inflation expectations formation process by making two assumptions:[15] First, expectations within each region are formed rationally using FIRE expectations for the prices of local and imported goods, as well as region weights ϕ_i from the appropriate consumption aggregator. That is, based on the linearized model, local inflation equals

$$\hat{\Pi}_{i,t} = \phi_i \hat{\pi}_{i,t} + (1-\phi_i)\hat{\pi}_{j,t}$$

and local inflation expectations equal

$$\mathbb{E}_t \hat{\Pi}_{i,t+1} = \phi_i \mathbb{E}_t \hat{\pi}_{i,t+1} + (1-\phi_i)\mathbb{E}_t \hat{\pi}_{j,t+1}.$$[16]

Second, there is a also a cross-region, behavioral element in the expectations formation process which we implement similarly to L'Huillier et al. (2021) and Bianchi et al. (2023): As our empirical results show, consumers attach weights Γ_i and $1-\Gamma_i$ to their own local inflation expectations, and respectively to those of other regions. That is,

$$\widetilde{\mathbb{E}}_{it}\hat{\Pi}_{i,t+1} = \Gamma_i \mathbb{E}_t \hat{\Pi}_{i,t+1} + (1-\Gamma_i)\mathbb{E}_t \hat{\Pi}_{j,t+1}$$

Note that learning about an individual's consumption basket does not feature in this setup. The motivation for this modeling choice derives from our empirical findings: the instrumental-variable results show that exogenous local shocks in

[15] Online Appendix G generalizes this process to firms as well, leading to very similar conclusions.

[16] Our approach can easily be cast in more detailed terms of expectations formation processes, such as signal extraction problems.

other counties which are fundamentally exogenous to an individual's local consumption prices affect beliefs of individuals about these own consumption prices. There is nothing to learn about fundamentals, yet these shocks matter for beliefs. The empirical results that take into account "other factors" further suggest validity of the modeling choice. Additionally, in Online Appendix B we present a model to micro-found the expression for the formation process of expectations, based on Bordalo et al. (2023). These assumptions taken together imply that

$$\widetilde{\mathbb{E}}_{it}\hat{\Pi}_{i,t+1} = \Theta_i^{own}\mathbb{E}_t\hat{\pi}_{i,t+1} + \Theta_i^{other}\mathbb{E}_t\hat{\pi}_{j,t+1} \tag{15}$$

where $\Theta_i^{own} = (1 - \phi_i - \Gamma_i + 2\phi_i\Gamma_i)$ and $\Theta_i^{other} = 1 - \Theta_i^{own}$. These weights on inflation expectations differ from trade weights ϕ_i and $1 - \phi_i$ in a systematic way as the following proposition shows, and make up the basis for all subsequent deviations from FIRE results:

Proposition 1 (Under-weighing local goods but over-weighing foreign goods)**.** *Relative to FIRE, if there is home bias ($\phi_i > 0.5$), then social determination of inflation expectations will under-weight the inflation expectations of local goods, but will over-weight the inflation expectations of goods in the other region:*

$$\Theta_i^{own} < \phi_i \quad \textit{and} \quad \Theta_i^{other} > 1 - \phi_i$$

Proof. Follows from equation (15). □

The intuition for this result is as follows: In a FIRE case ($\Gamma_i = 1$), consumers will place weights on the inflation expectations of local goods that are identical to trade weights ϕ_i. However, a deviation from FIRE ($\Gamma_i > 1$) leads to under-weighting, that is, $\Theta_i^{own} < \phi_i$, only if there is home bias. The reason is that otherwise, absent any other asymmetries such as home bias, any additional weight placed by consumers on the inflation expectations of goods in other regions will symmetrically also be placed by consumers in other regions on their respectively other regions, which on net cancels out.

A direct corollary of the resulting distortion of the weights due to the social determination of inflation expectations lies in the distortion of the risk-sharing condition between the two regions. In particular, as shown below, there will generally be incomplete risk-sharing:

Corollary 1 (Incomplete Risk-Sharing)**.** *Let $\hat{x}_t = \hat{P}_{Ht} - \hat{P}_{Ft}$ be the real terms of trade between the two regions. Under a social determination of inflation expectations, the risk-sharing condition is given by*

$$-\gamma \hat{c}_{Ht} + \gamma \hat{c}_{Ft} = \hat{x}_t - \underbrace{(2 - \Gamma_H - \Gamma_F)\hat{x}_t}_{\text{social network effect}} \tag{16}$$

An increase in the weight on the beliefs of others, $(1 - \Gamma_i)$ for any $i \in \{H, F\}$, decreases risk-sharing.

Proof. See Section A.1. □

The effect of the behavioral deviation in the formation of inflation expectations is akin to an uncovered interest parity shock in Itskhoki and Mukhin (2021); Candian and De Leo (2023) that similarly leads to a modified risk-sharing condition. In fact, the above results could be read as an alternative micro foundation to, for example, noise traders when modeling uncovered interest parity shocks. The intuition is rooted in Proposition 1: relative weights are distorted from their FIRE benchmark, which coincides with perfect risk-sharing.

Socially determined inflation expectations can significantly affect the impact effect of regional and aggregate demand and supply shocks, as well their propagation, as we show next. The propagation of these shocks is characterized by the following six equations that encapsulate the log-linearized, reduced model:

Consumption block:

$$\hat{c}_{Ht} = \mathbb{E}_t \hat{c}_{H,t+1} - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t \hat{\Pi}_{H,t+1}) + \frac{1}{\gamma}\hat{e}_{Ht} - \underbrace{\frac{1-\Gamma_H}{\gamma}\mathbb{E}_t(\hat{x}_{t+1} - \hat{x}_t)}_{\text{social network distortion}} \tag{17}$$

$$\hat{c}_{Ft} = \hat{c}_{Ht} + \frac{1}{\gamma}\hat{x}_t - \frac{1}{\gamma}(\hat{e}_{Ht} - \hat{e}_{Ft}) + \underbrace{\frac{(\Gamma_H + \Gamma_F - 2)}{\gamma}\hat{x}_t}_{\text{social network distortion}} \tag{18}$$

Inflation block:

$$\hat{\Pi}_{Ht} = \kappa(\alpha+\gamma)\hat{c}_{Ht} + \beta\mathbb{E}_t\hat{\Pi}_{H,t+1} + \kappa(1-\phi_H)\chi\hat{x}_t + \hat{u}_{Ht} - \frac{\kappa\alpha(1-\phi_H)}{\gamma}(\hat{e}_{Ht}-\hat{e}_{Ft})$$
$$+ \underbrace{\kappa(1-\phi_H)\widetilde{\chi}\hat{x}_t}_{\text{social network distortion}} \tag{19}$$

$$\hat{\Pi}_{Ft} = \kappa(\alpha+\gamma)\hat{c}_{Ft} + \beta\mathbb{E}_t\hat{\Pi}_{F,t+1} - \kappa(1-\phi_F)\chi\hat{x}_t + \hat{u}_{Ft} + \frac{\kappa\alpha(1-\phi_F)}{\gamma}(\hat{e}_{Ht}-\hat{e}_{Ft})$$
$$- \underbrace{\kappa(1-\phi_F)\widetilde{\chi}\hat{x}_t}_{\text{social network distortion}} \tag{20}$$

Terms of trade and policy rule block:

$$\hat{x}_t = \hat{x}_{t-1} + \hat{\Pi}_{Ht} - \hat{\Pi}_{Ft} \tag{21}$$

$$\hat{R}_t = r_\pi(n\hat{\Pi}_{Ht} + (1-n)\hat{\Pi}_{Ft}) \tag{22}$$

where $\hat{e}_{it} \sim \mathcal{N}(0,\sigma_e^2)$ and $\hat{u}_{it} \sim \mathcal{N}(0,\sigma_u^2)$ denote iid regional demand and supply shocks, respectively; $\chi = \frac{\alpha\nu(\phi_H+\phi_F)+1}{\phi_H+\phi_F-1} + \frac{\alpha}{\gamma}$ and $\widetilde{\chi} = \frac{\alpha(\Gamma_H+\Gamma_F-2)}{\gamma}$.

Socially determined inflation expectations, relative to FIRE, show up clearly in several of these equations: while Corollary 1 above already points to the reduction in risk-sharing, socially determined inflation expectations also distort regional consumption and inflation. Notably, socially determined inflation expectations alter the sensitivity of regional dynamics to the terms of trade $\hat{x}_t$.

The precise effect on the propagation of aggregate and local shocks, at the different levels, depends on how the real terms of trade is affected as we show in the subsequent propositions:

Proposition 2 (Regional Dynamics: Aggregate vs. local shocks)**.** *Relative to FIRE, regional dynamics are distorted by the expectations of others in response to local shocks but not in response to aggregate shocks.*

Proof. As equations (17)-(22) show, distortions due to socially determined expectations affect local dynamics as a function of the real terms of trade, x_t. The real terms of trade, however, trivially do not change when there is a common aggregate shock, only for local shocks. See Appendix A.2 for details. □

What about the aggregate effect of shocks? The aggregate dynamics of inflation and consumption are described by the following set of equilibrium equations:

$$\hat{\Pi}_t = \kappa(\alpha + \gamma)\hat{c}_t + \beta \mathbb{E}_t \hat{\Pi}_{t+1} + \hat{u}_t \tag{23}$$

$$\hat{c}_t = \mathbb{E}_t \hat{c}_{t+1} - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t \hat{\Pi}_{t+1}) - \underbrace{\frac{n(1-\Gamma_H) - (1-n)(1-\Gamma_F)}{\gamma} \mathbb{E}_t(\hat{x}_{t+1} - \hat{x}_t)}_{\text{social network distortion}} + \frac{1}{\gamma}\hat{e}_t \tag{24}$$

where $\hat{u}_t = n\hat{u}_{Ht} + (1-n)\hat{u}_{Ft}$ and $\hat{e}_t = n\hat{e}_{Ht} + (1-n)\hat{e}_{Ft}$. The distortion due to socially determined demand again depends on the real terms of trade. Unlike in the case of regional dynamics in Proposition 2, local shocks have an aggregate impact only when some asymmetries are present. The next proposition presents such an asymmetry condition:

Proposition 3 (Aggregate dynamics)**.** *Relative to FIRE, the expectations of others distort the aggregate dynamics for a regional shock if and only if there is effective belief asymmetry, that is,* $\Delta = n(1-\Gamma_H) - (1-n)(1-\Gamma_F) \neq 0$*. Aggregate shocks do not lead to a distortion relative to FIRE.*

Proof. Follows directly from equation (24). □

This proposition is again intuitive: Aggregate shocks do not affect the real terms of trade and hence do not lead to a distortion. Local shocks do affect the real terms of trade. However, some degree of regional heterogeneity is additionally necessary for socially determined inflation expectations to lead to a distortion in aggregate dynamics. For example, socially determined inflation expectations will distort aggregate inflation and output when regions have heterogeneous economic size, n, or pay heterogeneous relative attention to the expectations of the other region, captured by Γ_i.

How large is the effect of allowing for socially determined inflation expectations, relative to a FIRE benchmark? A simple calibration exercise shows that

Table 5: Model calibration

Parameter		Value
Discount factor	β	0.99
Intertemporal elasticity of substitution	γ	1
Frisch elasticity of labor supply	α	1
Varieties elasticity of substitution	ν	2
Calvo parameter	θ	0.75
Size of home region	n	0.1
Local good preference in home region	ϕ_H	0.69
Local good preference in foreign region	ϕ_F	0.9656
Feedback to inflation	r_π	1.5
Standard deviation of shocks	$\sigma_e = \sigma_u = \sigma$	1

allowing for socially determined inflation expectations matters mainly when demand shocks hit the economy. This finding follows from a standard parameterization as in Nakamura and Steinsson (2014) as reported in Table 4.2. We set the intertemporal elasticity of substitution, γ, as well the Frisch elasticity of labor supply, α, equal to 1. The discount factor is set equal to $\beta = 0.99$ and the elasticity of substitution across varieties equal to $\nu = 2$.[17] The Calvo parameter, θ, is set equal to 0.75, implying that firms adjust their prices once a year. We set the size of the home region to $n = 0.1$. The local good preference parameter for the home region is set equal to $\phi_H = 0.69$. The implied local good preference in the foreign region is $\phi_F = 1 - n(1 - \phi_H)/(1 - n) = 0.9656$. The interest rate response to aggregate inflation is set equal to $r_\pi = 1.5$. Finally, all shocks are drawn from a standard normal distribution, that is, $\sigma_e = \sigma_u = 1$.

Given this calibration, an economically significant impact effect arises in the case of local supply shocks, while it is small for local demand shocks. Setting $\Gamma_H = \Gamma_F$ to our empirical estimate of $1 - 0.491 = 0.509$ reported in column (4) of Table 4, we find that the impact of a one-time home demand shock on output and inflation is 0.11% and 0.18% lower compared to FIRE, respectively. The impact of a one-time foreign demand shock on output is 0.11% and 0.18% higher compared to FIRE, respectively. On the other hand, the impact of a one-time home supply

[17] Differently from Nakamura and Steinsson (2014), we assume that the production function is linear in labor hours.

shock on output and inflation is about 3.7% and 6.2% lower compared to FIRE, respectively. By contrast, the impact of a one-time foreign supply shock on output and inflation is about 3.7% and 6.2% higher compared to FIRE, respectively.

More generally, Figures 1 and 2 plot the heat maps of the difference between the impact of various regional shocks on aggregate output and inflation for different parameterizations of the socially determined inflation expectations parameters, Γ_H and Γ_F. The effect of socially determined inflation expectations is negligible in the case of demand shocks, but much more substantial in the case of local supply shocks. Why? The reason is that supply shocks affect the terms of trade much more than demand shocks when the regional Phillips curve slopes are sufficiently low ($\kappa = 0.0858$ for the calibration in Table 4.2).[18] Moreover, the effects of the expectations of others are largest as $\Gamma_H, \Gamma_F \to 0$, that is, when consumers focus all their attention on the other region's inflation when forming expectations.

4.3 Welfare Implications

Socially determined inflation expectations unsurprisingly not only affect the dynamics of output and inflation, but also the optimal weight in a Taylor rule that monetary policymakers place on regional inflation rates when aiming to minimize distortions from the FIRE benchmark. This section shows that monetary policy should optimally put more weight on the inflation rate of socially more connected regions, a result reminiscent of open-economy findings such as Aoki (2001).

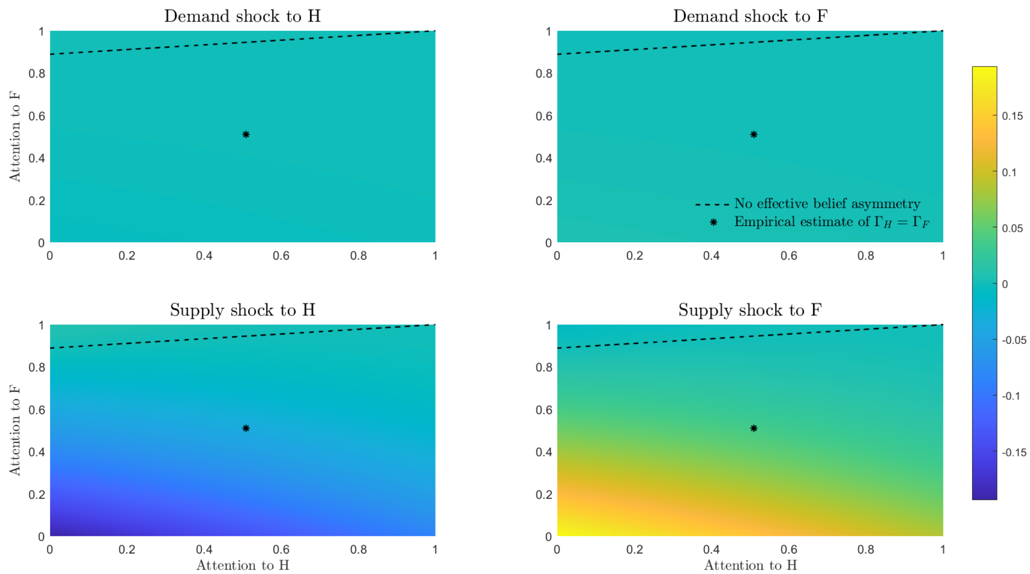
To derive this result, we assume that monetary policy is governed by the following generally parameterized Taylor rule:

$$\begin{aligned}\hat{R}_t &= r_\pi(n\psi\hat{\Pi}_{Ht} + (1-\psi n)\hat{\Pi}_{Ft}) \\ &= r_\pi\hat{\pi}_t + nr_\pi(1-\psi)(\hat{x}_t - \hat{x}_{t-1})\end{aligned} \tag{25}$$

where the key parameter of interest is ψ, with $\psi \geq 0$. When $\psi = 1$, policymakers target aggregate inflation defined as $n\hat{\Pi}_{Ht} + (1-n)\hat{\Pi}_{Ft}$; whereas when $\psi \neq 1$ policymakers target a slightly different measure of inflation where the weight as-

[18] We refer the reader to Lemma 1 for the minimum state variable solution for the terms of trade. We also note that supply shocks have been normalized similarly to Smets and Wouters (2007) and much of the related literature.

Figure 1: Impact of Socially Determined Inflation Expectations on Output Relative to FIRE



Note: Visualization of the effect of socially determined inflation expectations compared to FIRE for aggregate output, when the model is calibrated as in Table 4.2. Star in black indicates the impact relative to FIRE when $\Gamma_H = \Gamma_F = 1 - 0.491 = 0.509$, consistently with the empirical evidence reported in column (4) of Table 4. The dashed black line indicates the relationship between Γ_F and Γ_F for which there is no belief asymmetry ($\Delta = 0$).

signed to regional inflation rates are distorted by ψ. The above equation shows that then, in the case of $\psi \neq 1$, monetary policy systematically responds not only to the inflation rate, but also the evolution of the terms of trade.

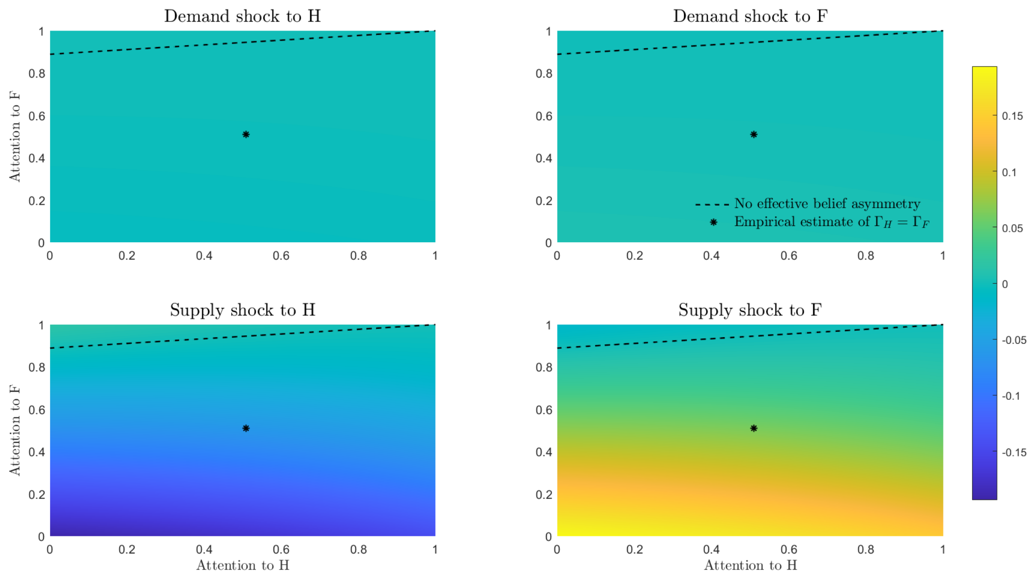
Should policymakers optimally set $\psi \neq 1$ when inflation expectations are socially determined? The optimal ψ^* can be derived by considering welfare losses that emerge from the socially distorted inflation expectations relative to FIRE. Specifically,

$$\psi^* = argmax_{\psi \geq 0} \mathbb{W} = -\frac{1}{2}\left[(\mathbb{E}(\hat{y}_t - \hat{y}_t^{FIRE})^2 + (\mathbb{E}(\hat{\pi}_t - \hat{\pi}_t^{FIRE})^2\right]$$

An analytical expression for ψ^* can be derived as the subsequent proposition shows in the case when the Phillips curve slope κ for both regions is very close to 0:

Proposition 4. *Suppose that the Phillips curve slope κ for both regions is very close to 0.*

Figure 2: Impact of Socially Determined Inflation Expectations on Inflation Relative to FIRE



Note: Visualization of the effect of socially determined inflation expectations compared to FIRE for aggregate inflation, when the model is calibrated as in Table 4.2. Star in black indicates the impact relative to FIRE when $\Gamma_H = \Gamma_F = 1 - 0.491 = 0.509$, consistently with the empirical evidence reported in column (4) of Table 4. The dashed black line indicates the relationship between Γ_F and Γ_F for which there is no belief asymmetry ($\Delta = 0$).

Then, the optimal weight to the inflation rate of region H depends on the effective belief asymmetry, in addition to its size n, and it is approximately given by

$$n(\psi^* - 1) \approx max\left(-n, -\frac{\Delta a}{r_\pi}\right) \tag{26}$$

where a is the dependence of the current terms of trade on its past realization, $\Delta = n(1 - \Gamma_H) - (1-n)(1-\Gamma_F) \neq 0$ *and* r_π *the systematic response of monetary policy to inflation.*

Proof. See Appendix A.3. □

Proposition 4 shows that monetary policy should optimally respond to the terms of trade as long as there is effective belief asymmetry ($\Delta \neq 0$). As a result, the inflation rate that monetary policy should target is slightly different from the aggregate one, $n\hat{\Pi}_{Ht} + (1-n)\hat{\Pi}_{Ft}$, that only accounts for regional economic sizes.

Importantly, more weight should be placed on the inflation rate of region H when its weight in the social network $\Gamma_H = (1 - \Gamma_F)$, is sufficiently high, relative to the weight of region F. Analogously, region F should receive more weight as its weight in the social network becomes relatively high.

How large are the distortions associated with socially determined inflation expectations quantitatively? Calibrating the model as suggested by Table 4.2 and setting $\Gamma_H = \Gamma_F = 0.509$, we find that welfare losses equal 0.0297 if policy sets $\psi = 1$. Monetary policy can minimize these losses by responding to the inflation rate of the home region by more than what is granted by its size of $n = 0.1$ and to the inflation rate of the foreign region by less than what is granted by its size of $1 - n = 0.9$. More specifically, we find that the optimal value of ψ is 1.26. This implies that the weight policy should assign to the inflation rate of the home region is 0.126 instead of 0.1, whereas the weight it should assign to the inflation rate of the foreign region is 0.874 instead of 0.9. Such optimal re-weighing also translates into different optimal aggregation weights for inflation rates of the goods produced in the two regions. In particular, monetary policy should assign a weight equal to 0.117 (instead of 0.1) to the inflation rate of goods produced in the home region and a weight 0.883 (instead of 0.9) to the inflation rate of goods produced in the foreign region.

5 Conclusion

Our analysis brings to the fore the idea that social networks can have an effect on the formation of inflation expectations. While other work has established the importance of social networks in important contexts such as housing market decisions, in this paper we focus on the expectations of a centrally important macroeconomic variable for monetary policy—inflation expectations—and the associated macroeconomic implications. Our analysis shows empirically that consumers form inflation expectations using information from their social network. In an extension of the workhorse New Keynesian model, our analysis also shows that this finding has quantitatively important implications for the dynamics of aggregate output and inflation and the conduct of monetary policy.

Our findings open up new avenues for exploring the formation of inflation expectations in the context of social networks. For example, future work might consider the context of stability and multiple equilibria, or the role of network super-nodes. Such future work may benefit policymakers who aim to keep inflation expectations anchored or provide forward guidance, but currently do not assign a role to social networks in doing so.

References

Acemoglu, Daron, Munther A Dahleh, Ilan Lobel, and Asuman Ozdaglar, "Bayesian learning in social networks," *The Review of Economic Studies*, 2011, *78* (4), 1201–1236.

Aoki, Kosuke, "Optimal monetary policy responses to relative-price changes," *Journal of Monetary Economics*, 2001, *48* (1), 55–80.

Arifovic, Jasmina, James Bullard, and Olena Kostyshyna, "Social Learning and Monetary Policy Rules*," *The Economic Journal*, 2013, *123* (567), 38–76.

Bailey, Michael, Drew M Johnston, Martin Koenen, Theresa Kuchler, Dominic Russel, and Johannes Stroebel, "Social networks shape beliefs and behavior: Evidence from social distancing during the Covid-19 pandemic," Technical Report, National Bureau of Economic Research 2020.

_ , _ , _ , _ , _ , and _ , "The social integration of international migrants: Evidence from the networks of Syrians in Germany," Technical Report, National Bureau of Economic Research 2022.

_ , Eduardo Dávila, Theresa Kuchler, and Johannes Stroebel, "House price beliefs and mortgage leverage choice," *The Review of Economic Studies*, 2019, *86* (6), 2403–2452.

_ , Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong, "Social Connectedness: Measurement, Determinants, and Effects," *Journal of Economic Perspectives*, August 2018, *32* (3), 259–80.

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

Banerjee, Abhijit V, "A simple model of herd behavior," *The Quarterly Journal of Economics*, 1992, *107* (3), 797–817.

Baqaee, David Rezza and Emmanuel Farhi, "Macroeconomics with heterogeneous agents and input-output networks," Technical Report, National Bureau of Economic Research 2018.

Bianchi, Francesco, Cosmin Ilut, and Hikaru Saijo, "Diagnostic Business Cycles," *The Review of Economic Studies*, 02 2023, *91* (1), 129–162.

Board, Simon and Moritz Meyer ter Vehn, "Learning Dynamics in Social Networks," *Econometrica*, 2021, *89* (6), 2601–2635.

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

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

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

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

Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo, "Understanding Booms and Busts in Housing Markets," *Journal of Political Economy*, 2016, *124* (4), 1088–1147.

Calvo, Guillermo A., "Staggered Prices in a Utility Maximizing Framework," *Journal of Monetary Economics*, 1983, *12*, 383–398.

Candian, Giacomo and Pierre De Leo, "Imperfect exchange rate expectations," *Review of Economics and Statistics*, 2023, pp. 1–46.

Chandrasekhar, Arun G., Horacio Larreguy, and Juan Pablo Xandri, "Testing Models of Social Learning on Networks: Evidence From Two Experiments," *Econometrica*, 2020, *88* (1), 1–32.

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

_ , Dimitris Georgarakos, Yuriy Gorodnichenko, and Maarten Van Rooij, "How does consumption respond to news about inflation? Field evidence from a randomized control trial," *American Economic Journal: Macroeconomics*, 2023, *15* (3), 109–152.

_ , Yuriy Gorodnichenko, and Michael Weber, "Monetary policy communications and their effects on household inflation expectations," *Journal of Political Economy*, 2022, *130* (6).

D'Acunto, Francesco, Ulrike Malmendier, and Michael Weber, "Gender roles produce divergent economic expectations," *Proceedings of the National Academy of Sciences*, 2021, *118* (21), e2008534118.

_ , _ , Juan Ospina, and Michael Weber, "Exposure to grocery prices and inflation expectations," *Journal of Political Economy*, 2021, *129* (5), 1615–1639.

DellaVigna, Stefano and Matthew Gentzkow, "Uniform pricing in us retail chains," *The Quarterly Journal of Economics*, 2019, *134* (4), 2011–2084.

Elliott, Matthew and Benjamin Golub, "Networks and Economic Fragility," *Annual Review of Economics*, 2022, *14* (Volume 14, 2022), 665–696.

Ellison, Glenn and Drew Fudenberg, "Rules of Thumb for Social Learning," *Journal of Political Economy*, 1993, *101* (4), 612–643.

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

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

Garcia-Lembergman, Ezequiel, "Multi-establishment firms, pricing and the propagation of local shocks: Evidence from us retail," *Available at SSRN 3813654*, 2020.

Gennaioli, Nicola, Marta Leva, Raphael Schoenle, and Andrei Shleifer, "How Inflation Expectations De-Anchor: The Role of Selective Memory Cues," Working Paper 32633, National Bureau of Economic Research June 2024.

Golub, Benjamin and Evan Sadler, "Learning in social networks," *The Oxford Handbook of the Economics of Networks*, 2016.

_ **and Matthew O. Jackson**, "How Homophily Affects the Speed of Learning and Best-Response Dynamics," *The Quarterly Journal of Economics*, 07 2012, *127* (3), 1287–1338.

Grimaud, Alex, Isabelle Salle, and Gauthier Vermandel, "Social learning expectations: microfoundations and a Dynare toolbox," WorkingPaper 339, WU Vienna University of Economics and Business July 2023.

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

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

Herreno, Juan and Mathieu Pedemonte, "The geographic effects of monetary policy shocks," *Manuscript, University of California San Diego*, 2022.

Itskhoki, Oleg and Dmitry Mukhin, "Exchange rate disconnect in general equilibrium," *Journal of Political Economy*, 2021, *129* (8), 2183–2232.

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

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

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

Lee, Lung-Fei and Jihai Yu, "Estimation of spatial autoregressive panel data models with fixed effects," *Journal of Econometrics*, 2010, *154*, 165–185.

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

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

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

McPherson, Miller, Lynn Smith-Lovin, and James M Cook, "Birds of a Feather: Homophily in Social Networks," *Annual Review of Sociology*, 2001, *27* (Volume 27, 2001), 415–444.

Mobius, Markus and Tanya Rosenblat, "Social Learning in Economics," *Annual Review of Economics*, 2014, *6* (Volume 6, 2014), 827–847.

Nakamura, Emi and Jón Steinsson, "Fiscal stimulus in a monetary union: Evidence from US regions," *American Economic Review*, 2014, *104* (3), 753–792.

Pasten, Ernesto, Raphael Schoenle, and Michael Weber, "The propagation of monetary policy shocks in a heterogeneous production economy," *Journal of Monetary Economics*, 2020, *116*, 1–22.

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

Rubbo, Elisa, "Networks, Phillips curves, and monetary policy," *manuscript, Harvard University*, 2020.

Smets, Frank and Rafael Wouters, "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach," *American Economic Review*, June 2007, *97* (3), 586â€“606.

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

Wallace, T. D. and Ashiq Hussain, "The Use of Error Components Models in Combining Cross Section with Time Series Data," *Econometrica*, January 1969, *37* (1), 55–72.

A Appendix: Proofs

A.1 Backus-Smith condition derivation

We have that

$$
\begin{aligned}
\hat{\lambda}_{F,t} - \hat{\lambda}_{H,t} &= E_{F,t}\left(\hat{\lambda}_{F,t+1} + i_t\right) - E_{H,t}\left(\hat{\lambda}_{H,t+1} + i_t\right) \\
\hat{\lambda}_{F,t} - \hat{\lambda}_{H,t} &= \sum_{k=0}^{\infty} E_{F,t}\left(i_{t+k}\right) - \sum_{k=0}^{\infty} E_{H,t}\left(i_{t+k}\right) \\
\hat{\lambda}_{F,t} - \hat{\lambda}_{H,t} &= \sum_{k=0}^{\infty} E_{F,t}\left(r_{t+i} + \Pi_{F,t+1+k}\right) - \sum_{k=0}^{\infty} E_{H,t}\left(r_{t+i} + \Pi_{H,t+1+k}\right) \\
\hat{\lambda}_{F,t} - \hat{\lambda}_{H,t} &= \sum_{k=0}^{\infty} \left(E_{F,t} r_{t+k} + E_{F,t}^{EoO} \Pi_{F,t+1+k}\right) - \sum_{k=0}^{\infty} \left(E_{H,t} r_{t+k} + E_{H,t}^{EoO} \Pi_{H,t+1+k}\right) \\
\hat{\lambda}_{F,t} - \hat{\lambda}_{H,t} &= \sum_{k=0}^{\infty} \left(E_{F,t} r_{t+k} + \mathbb{E}_t \Gamma_F \Pi_{F,t+1+k} + \mathbb{E}_t (1-\Gamma_F) \Pi_{H,t+1+k}\right) - \\
&\quad \sum_{k=0}^{\infty} \left(E_{H,t} r_{t+k} + \mathbb{E}_t \Gamma_H \Pi_{H,t+1+k} + \mathbb{E}_t (1-\Gamma_H) \Pi_{F,t+1+k}\right) \\
\hat{\lambda}_{F,t} - \hat{\lambda}_{H,t} &= \left(\Gamma_F + \Gamma_H - 2\right) \sum_{k=0}^{\infty} \mathbb{E}_t \left(\Pi_{F,t+1+k} - \Pi_{H,t+1+k}\right) + \\
&\quad \sum_{k=0}^{\infty} \left(E_{F,t} r_{t+i} + \mathbb{E}_t \Pi_{F,t+1+k}\right) - \sum_{k=0}^{\infty} \left(E_{H,t} r_{t+k} + \mathbb{E}_t \Pi_{H,t+1+k}\right)
\end{aligned}
$$

Assuming of equal initial wealth as Nakamura and Steinsson (2014), then $\sum_{k=0}^{\infty} (E_t r_{t+i} + \mathbb{E}_t \Pi_{F,t+1}$

$\sum_{k=0}^{\infty}\left(E_t r_{t+k}+\mathbb{E}_t \Pi_{H,t+1+k}\right)=0$, this version of the model assumes expectations of interest rate similar for both agents, then

$$\hat{\lambda}_{F,t}-\hat{\lambda}_{H,t}=(\Gamma_F+\Gamma_H-2)\sum_{k=0}^{\infty}\mathbb{E}_t\left(P_{F,t+1+k}-P_{F,t+k}-(P_{H,t+1+k}-P_{H,t+k})\right)$$

Assuming that after a period N log-linearized inflation is zero:

$$\mathbb{E}_t\left[\left(P_{j,t+1}-P_{j,t}\right)+\left(P_{j,t+2}-P_{j,t+1}\right)+\left(P_{j,t+3}-P_{j,t+2}\right)+...\right]=\mathbb{E}_t\left[P_{j,t+N}-P_{j,t}\right]$$

Then,

$$\hat{\lambda}_{j,t}-\hat{\lambda}_{i,t}=(\Gamma_F+\Gamma_H-2)\mathbb{E}_t\left(P_{j,t+N}-P_{j,t}-P_{i,tN}-P_{i,t}\right)$$

Using the law of one price in steady state $P_{j,t+N}-P_{i,t+N}=0$

$$\hat{\lambda}_{F,t}-\hat{\lambda}_{H,t}=(\Gamma_F+\Gamma_H-2)\left(P_{i,t}-P_{j,t}\right)$$

back to the original BS condition, and using $\hat{x}_t=P_{H,t}-P_{F,t}$ we have that

$$-\gamma\hat{c}_{i,t}+\gamma\hat{c}_{j,t}=\hat{x}_t-(2-\Gamma_F-\Gamma_H)\hat{x}_t$$

A.2 Proof of Proposition 2

Note that the distortions from the socially determined inflation expectations affect regional and aggregate dynamics through the terms of trade. Moreover, the first difference in the terms of trade is pinned down by the difference in the regional inflation rates, namely

$$
\begin{aligned}
\hat{x}_t - \hat{x}_{t-1} &= \hat{\Pi}_{Ht} - \hat{\Pi}_{Ft} \\
&= \kappa(\alpha+\gamma)(\hat{c}_{Ht} - \hat{c}_{Ft}) + \beta\mathbb{E}_t(\hat{\Pi}_{H,t+1} - \hat{\Pi}_{F,t+1}) + \kappa(2-\phi_H-\phi_F)(\chi+\widetilde{\chi})\hat{x}_t \\
&- \frac{\kappa\alpha(2-\phi_h-\phi_f)}{\gamma}(\hat{e}_{Ht} - \hat{e}_{Ft}) + (\hat{u}_{Ht} - \hat{u}_{Ft}) \\
&= \frac{\kappa(\alpha+\gamma)(1-\Gamma_H-\Gamma_F)}{\gamma}x_t + \beta\mathbb{E}_t(\hat{x}_{t+1} - \hat{x}_t) + \kappa(2-\phi_H-\phi_F)(\chi+\widetilde{\chi})\hat{x}_t \\
&+ \frac{\kappa(\alpha(1-\phi_h-\phi_f)+\gamma)}{\gamma}(\hat{e}_{Ht} - \hat{e}_{Ft}) + (\hat{u}_{Ht} - \hat{u}_{Ft})
\end{aligned} \tag{A.1}
$$

As a result, the MSV solution for the terms of trade is such that

$$\hat{x}_t = a\hat{x}_{t-1} + B\hat{s}_t$$

where $\hat{s}_t = \begin{bmatrix}\hat{e}_{Ft} & \hat{e}_{Ht} & \hat{u}_{Ht} & \hat{u}_{Ft}\end{bmatrix}' \sim \mathcal{MN}(0_{4\times 1}, \Sigma)$ with $\Sigma = diag\left(\begin{bmatrix}\sigma_e^2 & \sigma_e^2 & \sigma_u^2 & \sigma_u^2\end{bmatrix}\right)$. If both regions are shocked by the same innovations, that is, if $\hat{e}_{Ht} = \hat{e}_{Ft}$ and $\hat{u}_{Ht} = \hat{u}_{Ft}$, then the terms of trade remains in steady state. As a result, the socially determined inflation expectations do not have any effect on regional dynamics. By contrast, if $\hat{e}_{Ht} \neq \hat{e}_{Ft}$ and/or $\hat{u}_{Ht} \neq \hat{u}_{Ft}$, the terms of trade is affected by the local shocks, implying that the socially determined inflation expectations will impact regional dynamics.

A.3 Proof of Proposition 4

Before proving Proposition 4, we provide the minimum state variable solution of the model in Lemma 1 below.

Lemma 1 (MSV solution of the model)**.** *The equilibrium dynamics under EoO for output, inflation, and the terms of trade are described by the following equations:*

$$
\begin{aligned}
\hat{y}_t &= a_y\hat{x}_{t-1} + B_y\hat{s}_t \\
\hat{\pi}_t &= a_\pi\hat{x}_{t-1} + B_\pi\hat{s}_t \\
\hat{x}_t &= a\hat{x}_{t-1} + B\hat{s}_t
\end{aligned} \tag{A.2}
$$

where $a_y, a_\pi \in \mathbb{R}$; $a \in (0,1)$; $B_y, B_\pi, B \in \mathbb{R}^4$; and $\hat{s}_t = \begin{bmatrix} \hat{e}_{Ht} & \hat{e}_{Ft} & \hat{u}_{Ht} & \hat{u}_{Ft} \end{bmatrix}' \sim MN(\mathbf{0}, \Sigma)$ with $\Sigma = diag\left(\begin{bmatrix} \sigma_e^2 & \sigma_e^2 & \sigma_u^2 & \sigma_u^2 \end{bmatrix}\right)$. The MSV solution under FIRE is given by

$$\begin{aligned} \hat{y}_t &= \bar{B}_y \hat{s}_t; \quad \hat{\pi}_t = \bar{B}_\pi \hat{s}_t \\ \hat{x}_t &= \bar{a}\hat{x}_{t-1} + \bar{B}\hat{s}_t \end{aligned} \tag{A.3}$$

Proof. We start off by solving for a and B in the equation describing the terms of trade,

$$\hat{x}_t = a\hat{x}_{t-1} + B\hat{s}_t$$

Using this expression in equation (A.1), and re-organizing terms, a is the solution to the following quadratic equation

$$\beta a^2 - \underbrace{\left[1 + \beta - \kappa\left((2 - \phi_H - \phi_F)(\chi + \widetilde{\chi}) + \frac{(\alpha + \gamma)}{\gamma}(1 - \Gamma_H - \Gamma_F)\right)\right]}_{d} a + 1 = 0$$

Hence,

$$a = \frac{d \pm \sqrt{d^2 - 4\beta}}{2\beta}$$

We assume that the process for the terms of trade is stationary, so that $|a| < 1$. Furthermore, we assume that the Phillips curve slope is sufficiently small so that $d > \beta$. As a result, the unique acceptable solution for a is given by

$$a = \frac{d - \sqrt{d^2 - 4\beta}}{2\beta} \tag{A.4}$$

We now turn to the solution for B:

$$(d - \beta a)B = \underbrace{\begin{bmatrix} \frac{\kappa(\alpha(1-\phi_h-\phi_f)+\gamma)}{\gamma} \\ -\frac{\kappa(\alpha(1-\phi_h-\phi_f)+\gamma)}{\gamma} \\ 1 \\ -1 \end{bmatrix}'}_{M}$$

Therefore,

$$B = \frac{2M}{d + \sqrt{d^2 - 4\beta}} \tag{A.5}$$

Then, the solution for inflation and output, respectively, is given by

$$\begin{aligned} \hat{\pi}_t &= a_\pi \hat{x}_{t-1} + B_\pi \hat{s}_t \\ \hat{y}_t &= a_y \hat{x}_{t-1} + B_y \hat{s}_t \end{aligned} \tag{A.6}$$

We now consider the more general policy rule, $\hat{R}_t = r_\pi(n\psi\hat{\pi}_{Ht} + (1-n\psi)\hat{\pi}_{Ft}$. Applying the MSV solution above to the aggregate Euler equation and Phillips curve, we have the following two expressions for output and inflation:

$$\begin{aligned} \hat{y}_t = {} & \left(a_y + \frac{a_\pi + \Delta(1-a)}{\gamma}\right) x_t - \frac{r_\pi a_\pi}{\gamma}\hat{x}_{t-1} + \frac{nr_\pi(1-\psi)}{\gamma}(\hat{x}_t - \hat{x}_{t-1}) \\ & + \left(-\frac{r_\pi}{\gamma} B_\pi + \frac{1}{\gamma}\underbrace{\begin{bmatrix} n & 1-n & 0 & 0 \end{bmatrix}}_{B_e}\right)\hat{s}_t \\ \hat{\pi}_t = {} & \kappa(\alpha+\gamma)a_y\hat{y}_t + \beta a_\pi(a\hat{x}_{t-1} + b\hat{s}_t) + \underbrace{\begin{bmatrix} 0 & 0 & n & 1-n \end{bmatrix}}_{B_u}\hat{s}_t \end{aligned} \tag{A.7}$$

Then, the MSV solution coefficients are pinned down by the following system of linear equations:

$$\begin{aligned} a_y &= \frac{(1-a)(1-\beta a)(a\Delta - nr_\pi(1-\psi))}{\gamma(1-a)(1-\beta a) + \kappa(\alpha+\gamma)(r_\pi - a)} \\ a_\pi &= \frac{\kappa(\alpha+\gamma)}{1-\beta a} a_y \\ B_\pi &= \left(\kappa(\alpha+\gamma)B_y + \beta a_\pi B + B_u\right) \\ B_y &= \frac{1}{\gamma}\left[-r_\pi B_\pi + \left(nr_\pi(1-\psi) + \gamma a_y + a_\pi + \Delta(1-a)\right)B + B_e\right] \end{aligned} \tag{A.8}$$

We can combine the expressions for B_y and B_π as follows:

$$\begin{bmatrix} B_y \\ B_\pi \end{bmatrix}' = \begin{bmatrix} B_y \\ B_\pi \end{bmatrix}' \underbrace{\begin{bmatrix} 0_{4\times 4} & \kappa(\alpha+\gamma)I \\ -\frac{r_\pi}{\gamma}I & 0_{4\times 4} \end{bmatrix}}_{\widetilde{\Omega}} + \underbrace{\begin{bmatrix} ((nr_\pi(1-\psi)+\gamma a_y + a_\pi + \Delta(1-a))B + B_e) \\ \beta a_\pi B + B_u \end{bmatrix}'}_{D}$$

Therefore, in equilibrium,

$$\begin{bmatrix} B_y \\ B_\pi \end{bmatrix}' = D(I-\widetilde{\Omega})^{-1} \tag{A.9}$$

We denote the solution coefficients under FIRE with a bar on top. Setting $\Delta = 0$ and $\psi = 1$, we have that

$$\begin{aligned} \bar{a}_y &= \bar{a}_\pi = 0 \\ \begin{bmatrix} \bar{B}_y \\ \bar{B}_\pi \end{bmatrix}' &= \begin{bmatrix} B_e \\ B_u \end{bmatrix}' (I-\widetilde{\Omega})^{-1} \end{aligned} \tag{A.10}$$

□

Let $\delta = \frac{\kappa(\alpha+\gamma)}{1-\beta a}$. One can show that

$$B_y - \bar{B}_y = \frac{nr_\pi(1-\psi) + (\gamma+\delta-\beta\delta r_\pi)a_y + \Delta(1-a)}{\gamma + r_\pi\kappa(\alpha+\gamma)}B = mB$$

$$B_\pi - \bar{B}_\pi = (\kappa(\alpha+\gamma)m + \beta\delta a_y)B$$

Therefore,

$$\begin{aligned} \mathbb{E}(\hat{y}_t - \hat{y}_t^{FIRE})^2 &= a_y^2\mathbb{E}(x_t^2) + m^2 B\Sigma B' = \left[\frac{a_y^2}{1-a^2} + m^2\right] B\Sigma B' \\ \mathbb{E}(\hat{\pi}_t - \hat{\pi}_t^{FIRE})^2 &= a_\pi^2\mathbb{E}(x_t^2) + (\kappa(\alpha+\gamma)m + \beta\delta a_y)^2 B\Sigma B' \\ &= \left[\frac{a_\pi^2}{1-a^2} + (\kappa(\alpha+\gamma)m + \beta\delta a_y)^2\right] B\Sigma B' \end{aligned} \tag{A.11}$$

Welfare gains are then given by

$$\mathbb{W} = \left(-\frac{1}{2}(1+\delta^2)a_y^2 - \frac{(1-a^2)}{2}\left[m^2 + (\kappa(\alpha+\gamma)m + \beta\delta a_y)^2\right]\right) B\Sigma B'$$

Hence,

$$\frac{\partial \mathbb{W}}{\partial \psi} = -\left((1+\delta^2)a_y' a_y + (1-a^2)\left[mm' + (\kappa(\alpha+\gamma)m + \beta\delta a_y)(\kappa(\alpha+\gamma)m' + \beta\delta a_y')\right]\right) B\Sigma B'$$

where $a_y = \frac{(1-a)(\Delta a - nr_\pi(1-\psi))}{\gamma(1-a)+\delta(r_\pi - a)}$ and $a_y' = \frac{nr_\pi(1-a)}{\gamma(1-a)+\delta(r_\pi-a)}$.

As $\kappa \to 0$, we have that $\delta \to 0$ and

$$a_y = \frac{\Delta a - nr_\pi(1-\psi)}{\gamma}$$
$$a_y' = \frac{nr_\pi}{\gamma}$$
$$m' = \frac{-nr_\pi + \gamma a_y')}{\gamma} = 0$$

Hence, as $\kappa \approx 0$, $\psi^* - 1\left(-1, -\frac{\Delta a}{nr_\pi}\right)$.

Online Appendix

B Theoretical Framework for the Expectations of Others

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. This model aims to provide a micro-foundation of inflation expectations formation that can discipline the empirical strategy and the subsequent macroeconomic model choice of the expectation formation process. We start 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 individuals to socially interact and exchange experiences, deriving a close form to estimate the influence of social networks in the expectation formation process.

B.1 Baseline: No Social Interaction

Consider an individual i, 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 i 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 i 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 functional form for S_i to warrant generality of our results.[19]

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, $r(e_i,k) = \frac{S_i(e_i,k)}{\sum_{e \in E_i} S(e,k)}$.

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

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

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

[19]The functional form of similarity can also be unique to individual i.

$k \in \{H, L\}$. Her expected inflation is given by

$$\pi_i^e = p_i(H)\bar{\pi}^H + (1 - p_i(H))\bar{\pi}^L = p_i(H)(\bar{\pi}^H - \bar{\pi}^L) + \bar{\pi}^L \quad \text{(B.2)}$$

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 (B.2). Proposition 5 formalizes this positive relationship between inflation and the recall probability of events linked to the hypothesis of high inflation.

Proposition 5. *Individual inflation expectations π_i^e are increasing in the recall probability of the high-inflation regime.*

Proof. See Online Appendix B.4.1. □

B.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 $E_{j\to i}$ (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, $E^H_{j\to i}$, low inflation experiences, $E^L_{j\to i}$, and experiences irrelevant to high or low inflation, $E^O_{j\to i}$.

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 $e \in E^k_{j\to i}$ 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.[20]

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:

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

where $\sum_{e \in E_i} S_i(e,k) = \sum_{e \in E_i^H} S_i(e,k) + \sum_{e \in E_i^L} S_i(e,k) + \sum_{e \in E_i^O} S_i(e,k)$ denotes total own-experience similarity and $\sum_{e \in E_{j \to i}} S_i(e,k \mid \delta_{ij}) = \sum_{e \in E_{j \to i}^H} S_i(e,k \mid \delta_{ij}) + \sum_{e \in E_{j \to i}^L} S_i(e,k \mid \delta_{ij}) + \sum_{e \in E_{j \to i}^O} S_i(e,k \mid \delta_{ij})$ 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 $\sum_{e \in E_i^H} S_i(e,k) > 0$ 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 per-

[20]Using common demographic characteristics is supported by the 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, others, such as McPherson et al. (2001) have established the role of homophily in the network formation process.

sonal and network component as follows:

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

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; $\mathbf{S}_{\delta_{i.}}^k = \sum_i \omega_{ij} \sum_{e \in E_{j\to i}^k} S_i(e,k \mid \delta_{ij})$ denotes the total similarity of shared relevant experiences; and $\mathbf{S}_{\delta_{i.}}^{K\setminus k} = \sum_i \omega_{ij} \sum_{e \in E_{j\to i}^{K\setminus k}} S_i(e,k \mid \delta_{ij})$ 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 6 formalizes this analysis.

Proposition 6. *Consider individual i's recall probability of hypothesis k in equation (B.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,*

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

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 Online Appendix B.4.2. □

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 to the high-inflation regime into her memory database and she shares the experience with individual i. From Proposition 5, 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 2 formalizes this result. It is important that, conditional on the individual paying attention to the network, increases in the inflation expectations of others should increase individual inflation expectations.

Corollary 2. *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 5 and 6. □

B.3 Testable Implications for Inflation Expectations

How predictions of the model map into a fairly generally defined empirical environment? Following Proposition 6, 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 $j \in \{1,2,...,i-1,i+1,...,N,N+1\}$, combined with data on the intensity of the network connections ω_{ij}, then one can estimate the following specification to test for the importance of expectations of others:

$$\pi_i^e = \alpha + \beta \times \sum_{j=1}^{N} \omega_{ij} \pi_j^e + \varepsilon_i \tag{B.6}$$

This specification leads to the following **Testable Implication**: $\beta > 0$: social interaction has a positive effect on inflation expectations if people pay attention to experiences shared by others (see Proposition 6).

B.4 Proofs

B.4.1 Proof of Proposition 5

Recall that $R_i(H) \sim Bin(T_i, r_i(H))$ and that $p_i(H) = \frac{R_i(H)}{R_i(H)+R_i(L)}$. By the central limit theorem, we have that $z_i^H = \frac{R_i(H)-T_i r_i(H)}{\sqrt{T_i}} \sim \mathcal{N}(0, r_i(H)(1-r_i(H))$. Therefore, $\lim_{T_i \to \infty} p_i(H) = \lim_{T_i \to \infty} \frac{\frac{z_i^H}{\sqrt{T_i}}+r_i(H)}{\frac{z_i^H}{\sqrt{T_i}}+r_i(H)+\frac{z_i^L}{\sqrt{T_i}}+r_i(L)} = \frac{r_i(H)}{r_i(H)+r_i(L)}$. If the recall probability of the high-inflation regime increases, then the perceived probability of regime H increases leading to an increase inflation expectations.

B.4.2 Proof of Proposition 6

Consider individual j's recall probability of hypothesis k

$$\hat{r}_i(k) = \frac{\gamma_i \mathbf{S}_i^k + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}^k}{\gamma_i \mathbf{S}_i + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}} \tag{B.7}$$

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

$$\frac{\partial \hat{r}_i(k)}{\partial \mathbf{S}^k_{\delta_{i.}}} = (1-\gamma_i)\frac{\gamma_i \mathbf{S}_i^{K\backslash k} + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}^{K\backslash k}}{\gamma_i \mathbf{S}_i + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}} \geq 0 \tag{B.8}$$

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

C The Reflection Problem

C.1 Baseline

Consider the following generic regression specification:

$$\pi^e_t = \boldsymbol{\alpha} + \beta\Omega\pi^e_t + \boldsymbol{\varepsilon}_t$$

where $\pi^e_t = \begin{bmatrix}\pi^e_{1t} & \pi^e_{2t} & ... & \pi^e_{Nt}\end{bmatrix}'$ 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 $\varepsilon_{it} \sim \mathcal{N}(0,\sigma^2_i)$ 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

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

where $\bar{\pi} = \begin{bmatrix}\bar{\pi}^e_1 & \bar{\pi}^e_2 & ... & \bar{\pi}^e_N\end{bmatrix}'$. 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

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

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

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.

C.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:

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

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 Online Appendix C.1. Let $\bar{\pi}_{N.} = \frac{1}{T} \left[\sum_{t=1}^{T} \pi_{1t}^e \quad \sum_{t=1}^{T} \pi_{2t}^e \quad \dots \quad \sum \right.$ $\bar{\pi}_{.t} = \left(\frac{1}{N} \sum_{n=1}^{N} \pi_{nt}^e \right) L_N$, 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 Online Appendix C.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 the equation in (C.2), but the econometrician does not account for time fixed effects, that is, one runs the following regression instead:

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

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

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

[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.

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

C.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.

C.3.1 No Time Fixed Effect

We start with the basic problem

$$\pi_t^e = \beta \Omega \pi_t^e + \varepsilon_t \tag{C.3}$$

with

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

This setup captures the main estimated specification in the text.

Then, we have that

$$\pi_t^e = (I - \beta\Omega)^{-1} \varepsilon_t$$

and

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

or

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

C.3.2 With Time Fixed Effect

We now define the matrix

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

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 a regression on:

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

or

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

Then,

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

or

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

Then,

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

Special Case:

To derive a closed-form expression for β, we assume an extreme case where the network is constant and equal for everybody, with weights $\frac{1}{N-1}$, so

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

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 $\beta^{OLS,TFE}$:

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

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

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

Then,

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

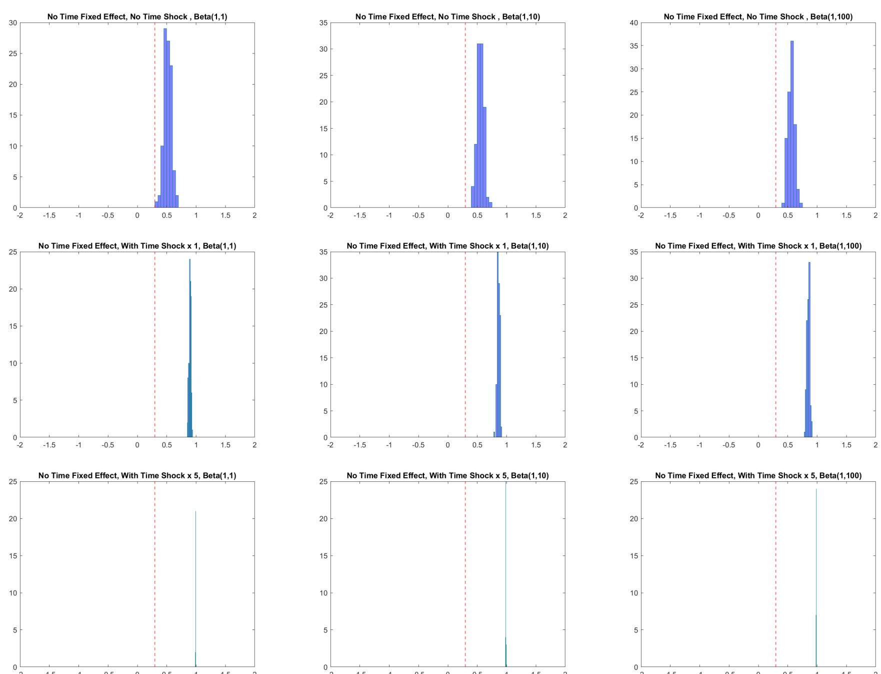
In this case $\beta^{OLS,TFE}$ is constant, negative and doesn't depend on the value of β.

The network structure in our case is not constant, so that case is a benchmark. To explore the potential biases from the inclusion of the time FE, we simulate data and a network structure. The network structure come from a Beta distribution with different parameters. In one case, the network will be drawn from a Beta(1,1) (uniform distribution), then a Beta(1,10) and finally a Beta(1,20), therefore the distribution will be moving more to an extreme value distribution, with less common nodes. The data-generating process comes from

$$\pi_t^e = (I - \beta\Omega)^{-1} \varepsilon_t$$

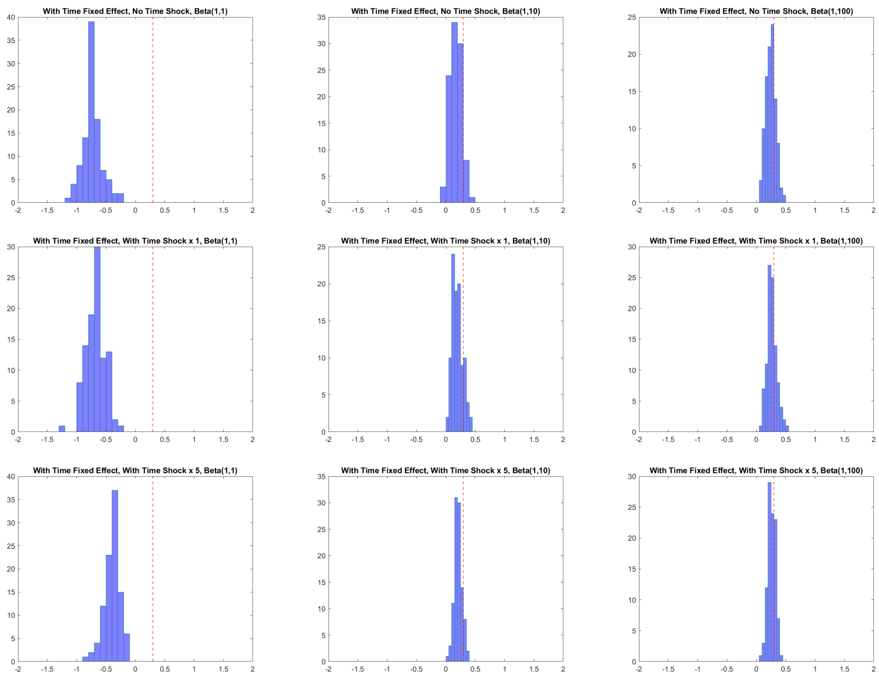
where $\boldsymbol{\varepsilon}_t = \left[\varepsilon_{1,t}, \varepsilon_{2,t}, ..., \varepsilon_{N,t}\right]'$ will have two forms, one where $\boldsymbol{\varepsilon^I}_t = \left[\varepsilon_{1t} \quad ... \quad \varepsilon_{Nt}\right]'$ denotes a set of county-specific i.i.d. shocks to inflation expectations 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 3 shows the results without time FE and Figure 4 shows the result with time FE.

Figure 3: Regression Results without Fixed Effects



Note: The figure shows the results of the regression (C.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 regressions do not include a time fixed effect.

Figure 4: Regression Results with Fixed Effects



Note: The figure shows the results of the regression (C.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 regressions 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.

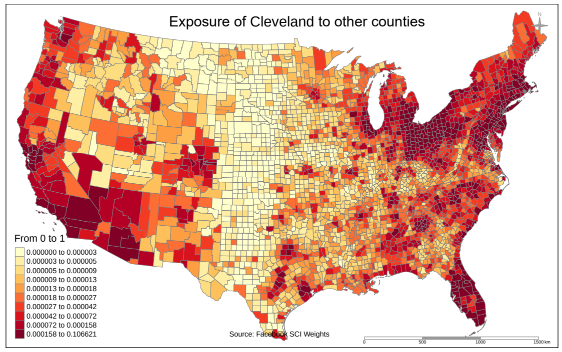
These results speak directly to the results in Tables 5 and 10. Column (5) of Table 5 is similar to Columns (2), (4) and (6) in Table 10: all regressions have time fixed effects, but in Columns (2), (4) and (6) of Table 10 we drop counties that are spatially close. By doing that, we are effectively moving 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 3.2, 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 3.3, 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.

D Additional Figures

D.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 5 illustrates this social connectedness through a heat map depicting the weights ($\omega_{c,k}$) for $c = Cleveland$. 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, geography plays a significant role, with Cleveland showing stronger connections to nearby counties. Second, we also observe robust social links with distant counties. For instance, individuals residing in Hillsborough, Florida (Tampa) and Clark County, Nevada (Las Vegas). Third, there is substantial heterogeneity in social connectedness. This is the kind of variability that we exploit in the paper.

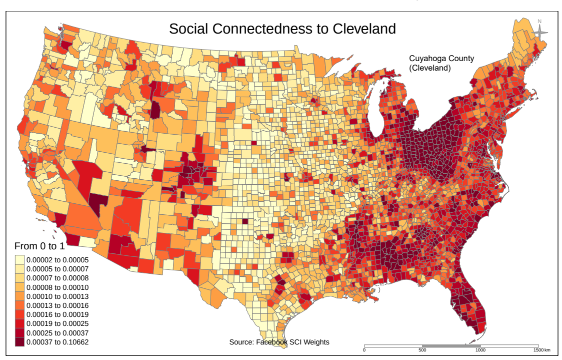
Figure 5: Social Connectedness of Cleveland to Other Counties ($\omega_{c=Cleveland,k}$)



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

In reverse, we also present the social connectedness of other counties to Cuyahoga County, Ohio. The heat map in Figure 6 shows the weights $\omega_{c,k}$ for $k = Cleveland$. Again, as in the illustration above, the three patterns also emerge in this case.

Figure 6: Social Connectedness of Each County to Cleveland ($\omega_{c,Cleveland}$)

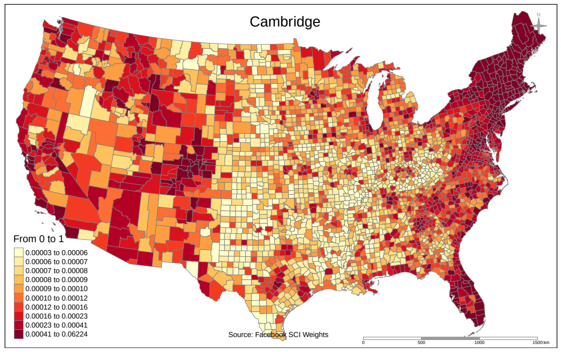


Note: The yellow-to-red color scale represents the degree to which counties are socially connected to Cleveland, based on $\omega_{c,Cleveland}$. Red indicates higher $\omega_{c,Cleveland}$. Source: Social Connectedness Index

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

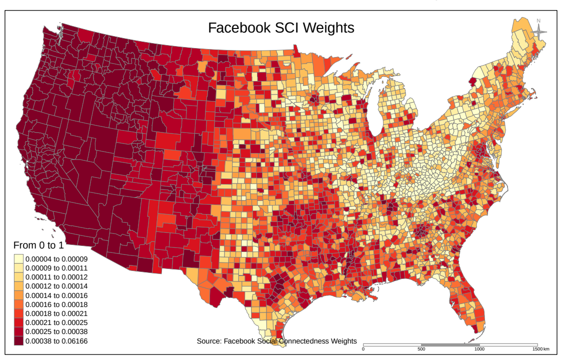
Angeles.

Figure 7: Social Connectedness of Each County to Cambridge ($\omega_{c,Cambridge}$)



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

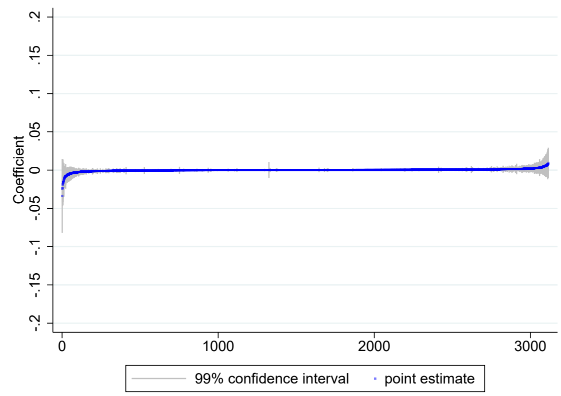
Figure 8: Social Connectedness of Each County to Los Angeles ($\omega_{c,LA}$)



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

D.2 Other Additional Figures

Figure 9: Correlation between SCI and Own Car Commuting Shares



Note: The figure shows coefficient and confidence interval of β^i in regressions $\omega_{ij} = \alpha^i + \beta^i \times Comm_j + \varepsilon^i_j$, where the dependent variables are the weights of a given county with the others ω_{ij} and the independent variable is the share of households that use their own car to commute in the other county $Comm_j$. The blue dots are the point estimates and the grey lines represent 99 percent confident intervals.

E Additional Evidence: County-Level Evidence

We find evidence for the importance of the social network for the expectations formation process at the county level. We estimate the following equation:

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

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 E.1 cluster standard errors at the county level.

Table 6 lists the different specifications and associated estimates of β across its columns.

Table 6: 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 (E.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.

F Other Additional Tables

Table 7: Individual Inflation Expectations and the Inflation Expectations of Others, Unweighted

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expectations of Others	0.248***	0.071***	0.339***	0.046**	0.027**	0.028**	0.024**	0.025**
	(0.008)	(0.012)	(0.012)	(0.018)	(0.011)	(0.011)	(0.011)	(0.011)
County Expectations	0.615***	0.594***	0.453***		0.406***	0.395***	0.387***	0.383***
	(0.010)	(0.012)	(0.008)		(0.011)	(0.010)	(0.009)	(0.008)
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	1,753,030	1,753,030	1,753,030	1,753,030	1,753,030	1,752,240	1,752,240	1,752,240
R-squared	0.024	0.024	0.027	0.023	0.027	0.042	0.043	0.048

Note. The table shows results of regression (3). The dependent $\pi^e_{i,c,t}$ is the inflation expectations of individual i from county c at time t. We use county-time units with more than 10 observations. Demographics FE are income, age, politics and gender at the individual level. Combined Dem-Time FE is a time FE interacted with the combination of demographic characteristics that an individual has. Standard errors are clustered at the county level.

Table 8: Individual Inflation Expectations and the Inflation Expectations of Others: Population Weights

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expectations of Others	0.250***	0.167***	0.341***	0.090***	0.047***	0.063***	0.053***	0.059***
	(0.050)	(0.038)	(0.057)	(0.033)	(0.018)	(0.019)	(0.019)	(0.021)
County Expectations	0.674***	0.655***	0.523***		0.475***	0.458***	0.419***	0.407***
	(0.044)	(0.036)	(0.043)		(0.030)	(0.027)	(0.017)	(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	1,926,282	1,926,282	1,926,282
R-squared	0.013	0.013	0.14	0.012	0.014	0.030	0.032	0.044

Note. The table shows results of regression (3). The dependent $\pi^e_{i,c,t}$ is the inflation expectations of individual i from county c at time t. We use county-time units with more than 10 observations. Demographics FE are income, age, politics and gender at the individual level. Combined Dem-Time FE is a time FE interacted with the combination of demographic characteristics that an individual has. Standard errors are clustered at the county level. We weight the regressions by the county population.

Table 9: Individual Inflation Expectations and the Inflation Expectations of Others: State Cluster

	(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***
	(0.041)	(0.049)	(0.071)	(0.060)	(0.022)	(0.024)	(0.024)	(0.022)
County Expectations	0.755***	0.732***	0.603***		0.557***	0.542***	0.469***	0.454***
	(0.048)	(0.044)	(0.060)		(0.055)	(0.056)	(0.025)	(0.020)
Constant	0.111	0.439	0.718***	6.338***	2.805***	2.763***	3.385***	3.493***
	(0.110)	(0.773)	(0.225)	(0.521)	(0.539)	(0.559)	(0.362)	(0.303)
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	1,936,032	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 (3), 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 state level.

We explore whether our main results are explained by proximity in space. In Table 10 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 Online Appendix C.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.[22]

Table 10: 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	1,926,282	1,926,282	1,926,282	1,926,282	1,926,282	1,926,282
R-squared	0.017	0.017	0.017	0.017	0.017	0.017

Note: The table shows the results of regression (3), 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.

[22]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 11: 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 (3), 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 12: 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 (3), 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 13: 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 (4), 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 14: 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 (4). 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 built from answers from individuals with the same income. $Inf - Income$ 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 15: 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 (4). The dependent variable $\pi^e_{i,d,c,t}$ is the inflation expectations of individual i, of age d from county c at time t. The network is built with answers from individuals of the same age group. $Inf - Age$ is the average of responses from respondents with the same age group in her 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 16: 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 (4), 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 17: 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 (4). The dependent variable $\pi^e_{i,d,c,t}$ is the inflation expectations of individual i of gender d in county c at time t. $Similarity - Network$ is the average inflation expectations of individuals of the same gender in other counties. $Dissimilarity - Network$ for the opposite gender. $Similarity - County$ is the average inflation expectations of respondents of the same gender in the same county. $Dissimilarity - County$ for the opposite gender. Columns (5) and (6) show regressions where the network is built removing counties closer than 200 miles and 250 miles, respectively. Observations are weighted by the number of responses in a county in each period. Standard errors are clustered at the county level.

Table 18: 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 (4). The dependent variable $\pi^e_{i,d,c,t}$ is inflation expectations of individual i of gender d in county c at time t. $Network - Dem$ is the average inflation expectations of individuals with the same demographic group in other counties. $OwnCountyDem$ is the average in the own county. 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 19: 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 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 $\pi^e_{i,d,c,t}$ is the inflation expectations of individual i, of gender d, in county c, at time t; $Gas\_effect_{c,t}$ is described in the text; $\pi^e_{d,k,t}$ is gender d inflation expectations in county k at time t; $Gas\_effect_{d,k,t}$ is described in the text. 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 20: 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: Column (1) shows results for Columns (5) and (6) of Table 3, in a single regression. We interact the coefficients with $I(Fem=1)$ that takes a value of 1 if the respondent is female and zero otherwise. Column (2) shows results for Columns (4) and (5) of Table 4, in a single regression, with the interaction with $I(Fem=1)$. Both regressions include time-fixed effects, and county-fixed effects, interacted with $I(Fem=1)$. We weigh by the number of respondents in a county-time. Standard errors are clustered at the county level.

G Generalizing the Social Network Effect

Arguably, not only inflation expectations can be socially determined. When we allow for a generalization to all variables, also on the firm side, an additional term arises. This term shows up as an additional distortion in the equilibrium conditions for home consumption, the expressions for home and foreign inflation rates change, but not the Backus-Smith condition. The additional terms appear as an additional distortion in the consumption Euler as follows:

$$\hat{c}_{Ht} = \mathbb{E}_t \hat{c}_{H,t+1} - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t \hat{\Pi}_{H,t+1}) + \frac{1-\rho_e}{\gamma}\hat{e}_{Ht} + \underbrace{\frac{1-\Gamma_H}{\gamma}\mathbb{E}_t\left[(\Gamma_H + \Gamma_F - 2)\hat{x}_{t+1} + \hat{x}_t\right]}_{\text{social network effect}} \tag{G.1}$$

while the dynamics of home and foreign inflation are additionally affected as follows:

$$\hat{\Pi}_{Ht} = \kappa(\alpha+\gamma)\hat{c}_{Ht} + \beta\mathbb{E}_t\hat{\Pi}_{H,t+1} + \kappa(1-\phi_H)\theta\hat{x}_t + \hat{u}_{Ht} - \frac{\kappa\alpha(1-\phi_H)}{\gamma}(\hat{e}_{Ht}-\hat{e}_{Ft}) + \underbrace{\kappa(1-\phi_H)\psi\hat{x}_t - \beta(1-\Gamma_H)\mathbb{E}_t(\hat{x}_{t+1}-\hat{x}_t)}_{\text{social network effect}} \tag{G.2}$$

$$\hat{\Pi}_{Ft} = \kappa(\alpha+\gamma)\hat{c}_{Ft} + \beta\mathbb{E}_t\hat{\Pi}_{F,t+1} - \kappa(1-\phi_F)\theta\hat{x}_t + \hat{u}_{Ft} + \frac{\kappa\alpha(1-\phi_F)}{\gamma}(\hat{e}_{Ht}-\hat{e}_{Ft}) - \underbrace{(\kappa(1-\phi_F)\psi\hat{x}_t - \beta(1-\Gamma_F)\mathbb{E}_t(\hat{x}_{t+1}-\hat{x}_t))}_{\text{social network effect}} \tag{G.3}$$

Proposition 7 (Generalized Network Effect)**.** *Expectations in the social network distort aggregate dynamics if and only if there is a local shock* and at least *one of the following two conditions holds:*

$$n(1-\Gamma_H) \neq (1-n)(1-\Gamma_F)$$

$$(1-\Gamma_H)(1-\Gamma_F-\Gamma_H) \neq 0$$

Proof. We aggregate regional dynamics to get aggregate inflation and consumption/output dynamics:

$$\hat{\Pi}_t = \kappa(\alpha+\gamma)\hat{c}_t + \beta\mathbb{E}_t\hat{\Pi}_{t+1} - \mathbb{E}_t\hat{\Pi}_{t+1}) - \underbrace{\beta(n(1-\Gamma_H) - (1-n)(1-\Gamma_F)\mathbb{E}_t(\hat{x}_{t+1}-\hat{x}_t)}_{\text{Social network effect}} + \hat{u}_t \tag{G.4}$$

$$\hat{c}_t = \mathbb{E}_t\hat{c}_{t+1} - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t\hat{\Pi}_{t+1}) + \hat{e}_t \underbrace{- \frac{1}{\gamma}[(n(1-\Gamma_H)-(1-n)(1-\Gamma_F))\mathbb{E}_t(\hat{x}_{t+1}-\hat{x}_t) + (1-\Gamma_H)(1-\Gamma_H-\Gamma_F)\mathbb{E}_t\hat{x}_{t+1}]}_{\text{Social network effect}} \tag{G.5}$$

□

Corollary 3 (Generalized Network Effect in a Symmetric Economy)**.** *Expectations in the social network distort the aggregate dynamics in a symmetric economy with $n = 0.5$ and $\Gamma_H = \Gamma_F = \Gamma \neq 1$ if and only if there is a local shock* and $\Gamma \neq 0.5$.