The Inflation Expectations of Others *

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

August 20, 2026

Abstract

Using a dataset that combines inflation expectations with social-network connections, we show that expectations within an individual's network positively influence personal beliefs. A one-percentage-point increase in the expectations of an exposed individual's social network raises that person's expectations by 0.549 percentage points relative to someone unexposed to social networks. In a monetary-union New Keynesian model, socially determined inflation expectations generate imperfect risk sharing and distort both regional and aggregate dynamics. To limit the resulting welfare losses, monetary policy should assign substantially greater weight to inflation in regions whose residents are more socially connected across the entire monetary union.

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. Much of this work highlights deviations from full-information rational expectations (FIRE) and how they arise from individual heuristics and memory-based processes. In this paper, we add a complementary view of such deviations in the formation of inflation expectations that is reflective of a central insight from social psychology, pioneered by Festinger (1954): the formation of beliefs takes place in a social context of interaction with others.

Our analysis shows accordingly, 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. Specifically, we first establish that social networks affect individual inflation expectations using an instrumental variable approach. We do so by building an instrument that exploits time variation at the county level and using a new dataset that links inflation expectations of 1.3 million consumers with a measure of social connectedness. We find that the inflation expectations of an individual that is exposed to a 1 percentage point increase in the inflation expectations of his social network are 0.549 percentage points higher relative to an individual that is isolated from social networks. In other words, an individual exposed to the 75th percentile of network expectations holds beliefs about 1.05 percentage points higher than an individual at the 25th percentile. Second, we embed these findings in a monetary-union New-Keynesian model to show their macroeconomic relevance: Socially determined expectations distort, relative to a FIRE setup, the transmission of local shocks to both regional and aggregate variables, and weaken risk-sharing across regions. A key policy implication is that central banks should place greater

[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. (2023), among many others; and specifically, for recent work on the formation of inflation expectations, Gennaioli et al. (2024).

weight on the inflation dynamics of a more socially connected region to mitigate welfare losses, if that region's relative social centrality exceeds its relative economic centrality.

Empirically, pinning down the causal effects of social networks on individual inflation expectations is challenging. First, such analysis necessitates a dataset that combines geographically dense data on individual inflation expectations with a map of the social network. Second, measures of others' beliefs may simply capture factors that are common across individuals which happen to be connected through social networks. Then, whenever sufficiently common, such factors may create spurious co-movement in individual inflation expectations and inflation expectations of others – rather than reflect genuine social determination. Examples of such factors may trivially coincide with common regional or aggregate shocks. They may also include common networks such as local trade networks, or homophily in social networks, or shared commuting patterns, which can induce co-movement in expectations. The peer-effects literature has extensively discussed such threats to identification (see, e.g., Manski (1993); Sacerdote (2001); Duflo and Saez (2003); Bramoulle et al. (2009); Goldsmith-Pinkham and Imbens (2013)).

Our analysis aims to overcome these two challenges. To address the first challenge, we construct a detailed dataset that merges data on 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] Analyzing these data at a monthly frequency and at the county level yields sufficiently thick data for our purpose, with over 1.3 million observations from March 2021 to July 2023. 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. Based on the SCI, we construct social network weights $\omega_{c,k}$ that measure the relative social importance of county k to county c.

[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.

Central to our empirical analysis is exploiting these two data sources to construct a monthly measure of *inflation expectations of others* as follows. Thanks to the thickness of our data, we compute average monthly inflation expectations for U.S. counties. Then, we construct the inflation expectations of others relevant for an individual in a given county c by taking the weighted average of the average expectations in other counties, using $\omega_{c,k}$ for any $k \neq c$ as weights. In this calculation, the SCI-based weights give greater importance to counties that are more strongly connected to an individual's own county through the social network.

Using this dataset, we employ an instrumental-variable approach to address the second challenge, aiming to identify the effect of inflation expectations of others on an individual's own expectations. We proceed in two steps. In a first step, we use a shift-share approach to build our instrument: We regress individual inflation expectations on the interaction of county-level commuting shares by car and the national gas price while filtering out any common time variation or county-specific fixed effects. We then use the regression results to generate *local, county-specific* shocks in inflation expectations as the component of inflation expectations predicted by the interaction of county-level commuting shares and the national gas price. Because we account for common time variation with a time fixed effect, our identification exploits cross-county differences in the exposure to the national shock. We conclude the first step by aggregating these local inflation expectations shocks across all other counties, using the social network weights for each county.

In a second step, we estimate the effect of the inflation expectations of others on individual inflation expectations. We use the resulting aggregated measure of local inflation expectations shocks from the first step as an instrumental variable (IV) for the inflation expectations of others, and control for a county's direct exposure to changes in the national gas price in our IV regression. Our identification strategy thus allows us to exploit exogenous variation in expectations not related to the network nor to the type of relationship individuals have. We formally derive key identifying assumptions underlying our instrument and validate them. Moreover, the inclusion of the own-exposure measure takes care of the concern that identification is the by-product of similar commuting patterns that generate correlated exposure and hence expectations across counties. We further probe this concern through a battery of complementary robustness checks.

Implementing this approach, we provide evidence that inflation expectations in the social network influence individuals' own expectations: The estimation results indicate that inflation expectations within an individual's social network have a positive and statistically significant impact on their own expectations. Our preferred coefficient estimate is 0.549 and is economically meaningful: The estimate implies that an individual exposed to the 75th percentile of inflation expectations in their social network holds inflation expectations that are 1.05 percentage points higher than those of a comparable individual exposed to the 25th percentile of expectations in their social network.

Our analysis is robust to concerns about common regional shocks – potentially correlated with car-commuting shares – across regions connected through social networks. Such shocks could arise, for example, from spatial correlation in inflation expectations not fully captured by the baseline specification or from common shocks to economically similar counties. As we show, our results remain unchanged when we exclude nearby counties from the network or explicitly control for inflation expectations in geographically proximate counties. A related concern is that common characteristics of respondents, including those in geographically distant counties, may spuriously drive our findings. These characteristics may be associated with similar commuting shares or other forms of cross-county similarity. Although our own-county exposure control directly accounts for the role of commuting shares in a county's exposure to national gas-price changes, we also show that taking into account inflation expectations in counties with similar commuting shares leaves our coefficient of interest unchanged. Likewise, results remain robust when we take into account inflation expectations in similar counties in terms of income, population, debt, and other economic characteristics. Our coefficient of interest remains essentially unchanged. If omitted common factors were driving the estimated effect, adding these controls should instead attenuate the coefficient toward zero. Its remarkable stability across these exercises therefore suggests reassuring evidence against such omitted-variable bias.

It is equally important to interpret our findings cleanly: Our identification strategy exploits cross-sectional differences that result from heterogeneous exposure to a shock due to different social networks. This heterogeneity in exposure implies that our empirical finding measures a *relative* spillover effect, as other general equilibrium effects likely influence the size of the cross-sectional effect. To be able to interpret our finding at the aggregate level, we take a structural approach as in Nakamura and Steinsson (2018): We use a general equilibrium model that incorporates the reduced-form variation, map the social network effect to a model parameter, and explore its aggregate implications. Our model analysis highlights the theoretical relevance of socially determined inflation expectations in a monetary policy context.

Specifically, our analysis does 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 FIRE benchmark.

Several theoretical results arise, all tracing back to the result that, under home bias, households will under-weight the inflation expectations of locally-produced goods and over-weight the inflation expectations of goods produced in the other region (relative to the absence of social networks). As a consequence of this deviation from FIRE in relative inflation expectations and, hence, relative prices, perfect risk sharing breaks down. Likewise, regional inflation and output dynamics deviate from their FIRE counterparts following local shocks, but not common aggregate shocks. At the aggregate level, inflation and output dynamics are also distorted by socially determined inflation expectations, but only if the relative weights consumers place on the other region's inflation do not align with the regions' relative economic sizes.

Finally, our analysis highlights a novel policy implication: to minimize welfare losses arising from socially determined inflation expectations, monetary policy should weigh the inflation rate of a region more than what is implied by its relative economic size if that region's relative social centrality exceeds its relative economic centrality. 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).

Calibration of the model reveals that socially determined inflation expectations can play a quantitatively important role in shaping aggregate outcomes. 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 foreign supply shock on aggregate output and inflation is about 5.4% and 2.8% higher compared to the FIRE benchmark, respectively. Second, in terms of the weight on the regional inflation rates, policy should increase the weight assigned to the inflation rate of the economically smaller region by 23.1% to account for its high relative social centrality compared to its relative economic centrality.

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. (2023) 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, increasing 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 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. Our key result that social networks matter for how consumers form expectations about inflation complements the finding in papers such as Carroll (2003) and Chahrour et al. (2025) that consumers’ aggregate inflation expectations are affected by news reports.

Finally, we also contribute to a recent literature that discusses the relationship between cross-sectional estimates and aggregate effects. Chodorow-Reich (2020) discuss the challenges of inferring aggregate effects from cross-sectional estimates of local shocks, as spillover effects can affect the control group, for instance,

[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).

through trade linkages between regions. Our paper provides insights about the mechanisms underlying these spillovers and highlights a previously unexplored source: spillovers arising from beliefs. Then, to interpret our empirical findings and derive aggregate implications in the presence of these spillovers, we follow the structural approach of Nakamura and Steinsson (2014) and Nakamura and Steinsson (2018), embedding our estimates into a general equilibrium framework.

2 Empirical Analysis

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

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

relating inflation expectations π_i^e of some individual/region i 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 learning literature, and we show in Online Appendix D how they can be microfounded 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 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 dataset that merges data on 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 strategy we apply to overcome them.

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 con-

[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.

sumers with a map of their social network. In this section, we describe our approach to obtain a dataset with those characteristics.

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 3. Additionally, as consumers report the equivalent of their anticipated growth rate of their own Laspeyres index and not of their perceived aggregate price level index, using this measure can reduce concerns about using a measure heavily influenced by public signals and less relevant for the consumer's actions. 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 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 1.3 million monthly observations for the period from March 2021 to July 2023.

Data on social connections at the county level come from the Social Connectedness Index Database (SCI). The SCI was first proposed by Bailey et al. (2018a) and measures the social connectedness between different regions of the United States as of April 2016, based on Facebook friendship connections. Specifically, the SCI measures the relative probability that two representative individuals across two US counties are friends with each other on Facebook. That is,

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

where FB Connections$_{i,j}$ denotes the total number of Facebook friendship connections between individuals in counties i and j and FB Users$_i$, FB Users$_j$ denote the number of users in location j. Intuitively, if $SCI_{i,j}$ is twice as large as $SCI_{i,l}$, a given

Facebook user in location i is about twice as likely to be connected with a given Facebook user in location j than with a given Facebook user in location l.

In our analysis, we normalize the SCI by county so weights add up to unity, that is, $\omega_{c,k} = \frac{SCI_{c,k}}{\sum\limits_{k \neq c} SCI_{c,k}}$.[5] 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, but instead in common patterns of social connections.[6] 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 connectedness properties of the measure, we provide examples of the connectedness weights as applicable to our analysis (see Online Appendix A). We observe three distinct patterns. First, as

[5] We exclude the local SCI_{ii}, to remove its influence in the outcome, so we can focus on the cross-sectional difference of exposure to other counties.

[6] 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.

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 robustness exercises will take into consideration those geographic patterns, as we discuss in the subsequent sections.

Finally, we use data on the share of households that use gasoline more intensively for commuting from the American Community Survey of 2019. In this survey, respondents are asked whether they use a private vehicle to commute. Additionally, we use US regular gas price at the monthly frequency from the US Energy Information Administration.

2.2 Empirical Challenges and Identification Strategy

Identifying the effect of social networks on inflation expectations entails a challenge: Measures of others' beliefs may simply capture factors that are common across counties which happen to be connected through social networks. Then, whenever such factors are sufficiently common, they may create spurious co-movement in individual inflation expectations and inflation expectations of others – rather than reflect genuine social influence. This section points out several such factors and presents our identification strategy – designed to address these issues – which is based on an instrumental-variable (IV) approach complemented by a carefully chosen set of controls and robustness checks.

Several factors are likely to constitute such a challenge to identification in our context, and have also been discussed extensively in the peer-effects literature (see, e.g., Manski (1993); Sacerdote (2001); Duflo and Saez (2003); Bramoulle et al. (2009); Goldsmith-Pinkham and Imbens (2013)). First, common shocks may create co-movement in own outcomes and peer outcomes, in our setting embodied by own and others' inflation expectations. Such common shocks may occur at the aggregate level, or at more disaggregated but influential local levels, for example capturing region-specific price movements. These common shocks can lead to a classic correlated effects problem emphasized in the peer-effects literature, for example in Manski (1993), and subsequently addressed in empirical designs that exploit random assignment or randomized information (e.g., Sacerdote (2001); Duflo and Saez (2003)).

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. Common price co-movement may then lead people in the social network to form similar inflation expectations, but not reflect true influence of expectations of others. Third, homophily in social networks – we are friends with similar people – may induce common price movements because similar friends share similar consumption baskets which may lead to co-movement in attached inflation expectations. In other words, inflation expectations move together simply because those who we are connected to react similarly to the same shocks. Homophily may likewise manifest in correlated commuting patterns and, consequently, in similar exposure to gas-price fluctuations, which could generate common movements in experienced inflation and inflation expectations.

Our main approach to address these challenges relies on an instrumental-variable strategy. The approach takes two steps (which we describe formally below). In a first step, we use a shift-share approach to build our instrument: We regress inflation expectations on the interaction of county-level commuting shares by car and the national gas price while filtering out any common time variation or county-specific fixed effects. We then use the regression results to generate *local, county-specific* shocks in inflation expectations as the component of inflation expectations predicted by the county-specific exposure. As we account for common time variation with a time fixed effect, our approach exploits cross-county differences in car commuting shares for identification. The first step concludes by aggregating these local inflation expectations shocks across all other counties, county by county, using the social network weights for each county. In a second step, the resulting aggregated measure serves as an instrument for inflation expectations in the social network, allowing us to exploit exogenous variation in expectations not related to the network nor to the type of relationship individuals have. Importantly, we additionally control in our estimation for a county's direct exposure to changes in the national gas price, so the instrument acts on the residualized expectations, after controlling for common time trend and direct exposure. Thus, our identification strategy relies not on the instrument alone, but on combining the network-weighted shock with the direct-exposure control. The identifying variation consequently reflects exposure through a county's social network over and above its own exposure, mitigating the concern that similar commuting patterns and hence, similar, derivative exposure to gas prices, mechanically generate the estimated effect. As we show below, we complement our baseline instrumental-variable specification with a series of robustness exercises designed to address alternative explanations involving spatially correlated shocks or common shocks across economically similar regions that might likewise imply correlated inflation expectations.

Before formally presenting the details of the identification scheme and its assumptions, we note that the peer-effects literature has emphasized additional challenges. The most prominent is the reflection problem (Manski (1993)), namely the difficulty of distinguishing simultaneity of influence from true causal spillovers. In our context, this simultaneity concern is addressed by instrumenting "expectations of others" with shocks originating *solely* in *other* counties, which by construction cannot be driven by contemporaneous shifts in *own-county* expectations. Another concern is measurement error in networks (Sacerdote, 2001; Bramoulle et al., 2009)), which in our case would bias estimates toward zero; the use of well-validated SCI data mitigates this risk. Finally, network endogeneity—the possibility that individuals sort into networks based on unobserved traits—is less relevant in our context, as residential sorting will be absorbed by our subsequent use of appropriate county fixed effects (see Goldsmith-Pinkham and Imbens (2013)).

Formally, how does our identification approach proceed? As the below summarizes, we are interested in pinning down an unbiased estimate for β in the following regression:

$$\pi = \beta \underbrace{(\Omega \times \pi)}_{\pi^x} + \varepsilon \tag{3}$$

where π is an $N \times 1$ vector of county-specific inflation expectations; Ω is the social network matrix whose diagonal is a 0-vector and whose elements in each row sum to 1; ε is a vector of error terms. In **Step 1**, our first-stage regression is given by

$$\pi^x = \theta \underbrace{(\hat{\gamma}_d \Omega (P \times Comm))}_{z} + \epsilon, \tag{4}$$

where π^x is the $N \times 1$ vector of the expectations of others; P is the national gas price in the fixed time period; $Comm$ is an $N \times 1$ vector of county-level commuting shares; $\hat{\gamma}_d$ is the OLS estimate of the effect of $P \times Comm$ on county-specific inflation expectations; ϵ is a vector of error terms. Our instrument, z, is given by the network's variation in inflation expectations due to the local exposure to gas prices. This shift-share approach based on the national gas price and local car-based commuting shares follows Hajdini et al. (2022a).

Then, in **Step 2**, the IV estimate of β is given by

$$\begin{aligned} \hat{\beta}^{IV} &= \left(z'\pi^x\right)^{-1}\left(z'\pi\right) = \left(z'\Omega\pi\right)^{-1}\left(z'\pi\right) = \left(z'\Omega\pi\right)^{-1}\left(z'(\beta\Omega\pi + \varepsilon)\right) \\ &= \beta + \left(z'\Omega\pi\right)^{-1}\left(z'\varepsilon\right), \end{aligned} \tag{5}$$

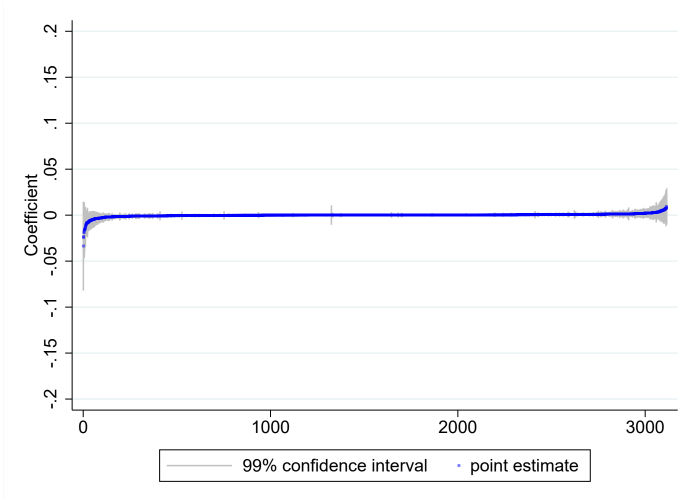
where $\hat{\beta}^{IV}$ uncovers the true β if $z'\varepsilon = 0$, that is, if

$$z'\varepsilon = \frac{\hat{\gamma}_d P}{N}\left[\sum_i \varepsilon_i \left(\sum_{j \neq i} \omega_{ij} Comm_j\right)\right] = 0. \tag{6}$$

Equation (6) is our central identifying assumption. Intuitively, we need to test whether the social network shares correlate with commuting shares, as in that case common shocks to the more exposed counties also imply higher transmission to the network. We formally test this condition by regression county's social network weights ω_{ij} on the connected respective commuter shares $Comm_j$, for all counties.

The central identifying assumption is clearly satisfied: The estimated coefficients are nearly 0 and not statistically different from zero for most counties, as Figure 1 illustrates with counties lined up on the horizontal axis and sorted in increasing order of their estimated coefficients. Likewise, a joint regression pooling all counties and including individual and time fixed effects yields a small coefficient that is not statistically different from zero. Taken together, these results imply that $\sum_{j \neq i} \omega_{ij} Comm_j / N \approx 0$. Hence, the central identifying assumption holds and the bias in the IV estimate is approximately absent. Intuitively, this finding also helps to rule out alternative channels. For instance, changes in gas prices could affect expectations through various aggregate or information channels, not just through heterogeneous exposure. However, the time fixed effects absorb any ag-

Figure 1: Correlation between SCI and Own Car Commuting Shares



Note: The figure shows coefficient and confidence interval of γ^i in regressions $\omega_{ij} = \alpha^i + \gamma^i \times Comm_j + \varepsilon^i_j$, 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.

gregate component of gas prices, as well as potential effects of public signals, and the absence of a systematic correlation between between social-network weights and our gas-use measure (Figure 1) rules out exposure-weighted effects.

A distinct concern is that the resulting network-weighted gas-price exposure – our instrument – may be correlated with an individual's own exposure to the national gas price if socially connected counties have similar commuting shares. More generally, homophily along dimensions beyond commuting shares can pose a concern when estimating network effects. Within our instrumental-variable approach, this would violate the exclusion restriction, since the instrument could affect the outcome through an individual's direct exposure rather than through network expectations. To address it, as noted above, we include a direct measure of individual exposure in our baseline specification, so that the instrument identifies the effect of network expectations conditional on own exposure to the national gas price. We retain this control in all specifications. We further estimate regressions that control for alternative measures of similarity, including similarity in commuting shares and in other demographic characteristics. Were the omission of such controls spuriously generating a positive relation between own and others' inflation expectations – the classic omitted-variable-bias case – including them should drive our main coefficient toward zero. Instead, the coefficient remains robust, as we report below, suggesting that this concern does not undermine our identification.

2.3 Results

Implementing the outlined approach then provides evidence of the effect of inflation expectations in the social network on individuals' own inflation expectations. In the first step, estimates show that exposure to gasoline prices indeed has a positive and highly significant effect on inflation expectations, generating the local variation in the network required to construct the instrumental variable. In the second step, the instrumental-variable estimation incorporating appropriate controls yields our main result: inflation expectations in the social network have a positive and statistically significant effect on individuals' own inflation expectations

In line with **Step 1**, we project individual inflation expectations on the county-level exposure to the national gas prices, including time fixed effects θ_t to filter out any common variation across counties:

$$\pi^e_{i,d,c,t} = \alpha_{c(i)} + \theta_t + \gamma_d \left(P_{gas,t} \times Comm_{c(i)} \right) + \varepsilon_{i,d,c,t}, \tag{7}$$

where $\pi^e_{i,d,c,t}$ denotes inflation expectations of individual i of gender d in county c in period t; $P_{gas,t}$ denotes the average national price of regular gas according to the US Energy Information Administration and $Comm_{c(i)}$ denotes the share of people who use their own car to commute according to the American Community Survey (ACS); $\alpha_{c(i)}$ denotes county fixed effects. The key coefficient of interest in this first stage is γ_d which gauges the validity of the exposure to gas prices in affecting inflation expectations. The specification notably allows for possible gender differences in this relationship through γ_d. This degree of freedom 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 1: 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	Women
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 $\pi^e_{i,c,t} = \alpha_{c(i)} + \theta_t + \gamma \left(P_{gas,t} \times Comm_{c(i)}\right) + \varepsilon_{i,c,t}$, 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 in county c 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 $\pi^e_{i,d,c,t} = \alpha_{c(i)} + \theta_t + \gamma_d \left(P_{gas,t} \times Comm_{c(i)}\right) + \varepsilon_{i,d,c,t}$, where $d \in (man, woman)$. 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 stage of the approach validate the crucial relationship between the exposure to gas prices and inflation expectations: The analysis shows a positive, highly statistically significant effect of the exposure measure on inflation expectations. This finding holds across specifications and is in line with the well-established impact of gas prices on inflation expectations. Specifically, as Table 1 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. Additionally, the findings from the first step show that salience of experiences in the network can amplify the transmission of information. According to Columns 5 and 6, men 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.

Given these estimates, we exploit county- and demographic-specific variation in the data to construct shocks to expectations at the county level as $Gas\_Effect_{d,c,t} = \hat{\gamma}_d \left(P_{gas,t} \times Comm_{c(i)} \right)$. We then aggregate these shocks up to summarize the changes in expectations within each county's network due to differential exposure to gasoline price movements, our subsequent instrument $z_{d,k,t}$, computed as

$$z_{d,c,t} = \sum_{k \neq c} \omega_{ck} Gas\_Effect_{d,k,t}. \tag{8}$$

In **Step 2**, we estimate the following main regression:

$$\pi^e_{i,d,c,t} = \alpha_{c(i)} + \theta_t + \beta \sum_{k \neq c} \omega_{c,k} \pi^e_{d,k,t} + \sum_{j \in \{m,w\}} \eta_j \left(P_{gas,t} \times Comm_{c(i)} \times \mathbf{1}_{d(i)=j} \right) + \varepsilon_{i,d,c,t}. \tag{9}$$

$\mathbf{1}_{d(i)=j}$ is a dummy variable set to 1 if individual i's gender d equals j, where $j \in \{\text{man (m), woman (w)}\}$. We use $z_{d,k,t}$, defined in equation (8), as our instrumental variable for $\sum_{k \neq c} \omega_{c,k} \pi^e_{d,k,t}$. Our main coefficient of interest is β.

When we estimate this specification, the main finding of the paper emerges: The coefficient estimate of the inflation expectations in the social network is positive, statistically significantly different from zero and larger than the coefficient estimate from a corresponding OLS specification. As Table 2 shows, relative to an OLS benchmark that takes into account fixed effects and comes out at 0.266 (Column (1)), the corresponding instrumental-variable approach estimates a coefficient of 0.549 (Column (2)). This result is economically meaningful. The estimated coefficient of 0.549 implies that an individual exposed to the 75th percentile of inflation expectations in their social network holds inflation expectations that are 1.05 percentage points higher than those of a comparable individual exposed to the 25th percentile of expectations in their social network. We take the estimated coefficient of 0.549 as our preferred measure of the social network effect, which serves as the key input for the subsequent model calibration.

After presenting our baseline estimate of the effect of network-weighted inflation expectations on individuals' own expectations, we examine whether the result could reflect alternative sources of correlated expectations. A natural concern

Table 2: Estimated Effect of Inflation Expectations in the Social Network on Own Expectations of Inflation

	(1)	(2)	(3)	(4)
$\sum_{k\neq c}\omega_{c,k}\pi^{e}_{d,k,t}$	0.266***	0.549***	0.548***	0.573***
	(0.056)	(0.093)	(0.094)	(0.112)
$P_{gas,t}\times Comm_{c(i)}\times \mathbf{1}_{d(i)=m}$	3.079***	3.093***	3.075***	3.083***
	(0.372)	(0.376)	(0.290)	(0.369)
$P_{gas,t}\times Comm_{c(i)}\times \mathbf{1}_{d(i)=w}$	3.762***	3.579***	3.562***	3.557***
	(0.338)	(0.342)	(0.265)	(0.340)
Counties	All	All	All	$> 200m$
Instrument	-	Baseline	Baseline	$> 200m$
Controls	No	No	Yes	No
Time FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Regression	OLS	IV	IV	IV
F-Test	-	621	583	2520
Observations	1,239,055	1,239,055	1,239,055	1,239,055
R-squared	0.021	0.008	0.008	0.008

Note: This table shows results from estimating our instrumental variable (IV) specification. Column (1) is an OLS benchmark. Column (2) instruments $\sum_{k\neq c}\omega_{c,k}\pi^{e}_{d,k,t}$ with the baseline gas instrument defined in (8). Column (3) repeats column (2) adding controls of similarity measures as defined in Table 4 of Appendix A (coefficients omitted). Column (4) constructs $\sum_{k\neq c}\omega_{c,k}\pi^{e}_{d,k,t}$ using only counties at least 200 miles away and instruments it with the corresponding $\geq$ 200-mile gas instrument. We weight by the observations in a county in each period. F-Test are from the first-stage regression. Standard errors clustered at the county level.

is spatially correlated shocks. Although Figure 1 shows that SCI weights are not systematically related to the car-commuting shares of connected counties, spatially correlated shocks that also covary with car-commuting shares could nevertheless affect our estimates. Column (3) of Table 2 adds a set of similarity-weighted controls described further below, including a proximity-weighted measure of inflation expectations in other counties. The coefficient remains virtually unchanged. Column (4) reconstructs both network-weighted inflation expectations and the instrument after excluding all counties within 200 miles of county c. The resulting estimate is again similar. Appendix Table 4 increases the exclusion threshold to 250 and 300 miles, with comparable results. These findings reduce the concern that spatially correlated shocks drive our estimates.

A separate concern is that geographically distant but economically or demographically similar counties may be exposed to common shocks or share characteristics that generate correlated inflation expectations. Beyond the baseline control for county c's direct exposure to the national gas-price shock, Column (3) therefore includes as additional controls measures of inflation expectations in counties with similar commuting shares, employment rates, average wages, education, household debt, and population. We also construct proximity weighted measures of network expectations. Table 4 in Appendix A contains their construction in the table note, and reports results from specifications that include these controls individually and jointly. In every case, the estimated social-network effect remains positive, statistically significant, and stable in magnitude.

Finally, we also assess whether spatial dependence affects statistical inference. Table 5 in Appendix A reports results obtained by clustering standard errors at more aggregate levels, including the state level, and by applying Conley (1999) standard errors that allow for spatial dependence. The coefficient remains statistically significant across these specifications.

Remark. In preparation for our modeling exercise, it is useful to highlight an important interpretation of our results: using an instrumental-variables approach, we can conclude, under certain assumptions, that an exogenous shock to the expectations of others that affects local inflation expectations—beyond the effects of exposure to tradable goods and trade linkages—implies a violation FIRE.

To illustrate this point, consider the following example with two regions, H and F, adapted from the model we develop in the following section. Regional inflation evolves according to $\Pi_{Ht} = \kappa mc_{Ht} + \beta \mathbb{E}_t \Pi_{H,t+1} + (1-\phi_H) a_H x_t$ and $\Pi_{Ft} = \kappa mc_{Ft} + \beta \mathbb{E}_t \Pi_{F,t+1} + (1-\phi_F) a_F x_t$, where mc_{it} denotes the exogenously given marginal cost in region i. Moreover, x_t denotes the terms of trade between the two regions, $(1-\phi_i) \in [0,1]$ denotes exposure to goods produced outside region i, and a_i is a region-specific constant. Consider a shock to inflation expectations in region F. Under FIRE, the only channel through which this shock feeds into expectations in region H is its effect on the terms of trade, the extent of which is captured by

$(1 - \phi_H)$. Therefore, if a shock to the expectations of others affects local inflation expectations after accounting for consumers' exposure to goods from region F, this implies a violation of FIRE.

Indeed, the findings in this section indicate that the estimated effect operates beyond exposure to tradable goods and trade linkages across regions—as evidenced by the stability of the main coefficient after controlling for spatially driven trade networks, local gasoline consumption shares, and similarities in consumption patterns, and after excluding nearby counties (Tables 3 and 4 in Appendix A; Figure 1). Building on this evidence, the next section develops a model in which expectation formation deviates from FIRE by incorporating the expectations of others.

3 Macroeconomic Implications

Our empirical findings establish a positive relationship between the inflation expectations of others and consumers' own inflation expectations, which can be interpreted as causal under certain assumptions. This result aligns with the social determination of beliefs documented 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 FIRE framework.

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.

3.1 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 (F) is symmetric to the home region.

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

$$\max_{C_{Ht}, L_{Ht}, B_{Ht}/P_{Ht}} \widetilde{\mathbb{E}}_{H0} \sum_{t=0}^{\infty} \beta^t \zeta_{Ht} \left[\frac{C_{Ht}^{1-\gamma}}{1-\gamma} - \psi \frac{L_{Ht}^{1+\alpha}}{1+\alpha} \right] \tag{10}$$

$$B_{Ht} + P_{Ht} C_{Ht} = W_{Ht} L_{Ht} + B_{H,t-1} R_{t-1} \zeta_{H,t-1} + D_{Ht} \tag{11}$$

where C_{Ht} is real consumption; P_{Ht} is the price level in the home region; L_{Ht} denotes labor hours at nominal wage rate W_{Ht} for consumers in the home region; B_{Ht} denotes risk-less nominal bond holdings of consumers in the home region that pay gross nominal interest R_t that is subject to an exogenous regional risk premium shock ζ_{Ht}; and D_{Ht} denotes the nominal profits of firms in the home region paid to consumers in that region. Finally, $\widetilde{\mathbb{E}}_{H0}$ is a generic expectations operator – defined in detail in the following section – that satisfies the law of iterative expectations and standard probability rules.

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

$$C_{Ht} = \left[\phi_H^{\frac{1}{\nu}} C_{H,H,t}^{\frac{\nu-1}{\nu}} + (1-\phi_H)^{\frac{1}{\nu}} C_{H,F,t}^{\frac{\nu-1}{\nu}} \right]^{\frac{\nu}{\nu-1}} \tag{12}$$

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,

$$P_{Ht} = \left(\phi_H p_{Ht}^{1-\nu} + (1-\phi_H) p_{Ft}^{1-\nu} \right)^{\frac{1}{1-\nu}} \tag{13}$$

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 a stochastic elasticity of substitution η_{Ht},

$$C_{i,j,t} = \left(\int_0^1 c_{i,j,t}(z)^{\frac{\eta_{Ht}-1}{\eta_{Ht}}} dz \right)^{\frac{\eta_{Ht}}{\eta_{Ht}-1}}. \tag{14}$$

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

$$Y_{Ht} = nC_{H,H,t} + (1-n)C_{F,H,t}. \tag{15}$$

Firms produce using a production function linear in local labor, $Y_{Ht}(z) = L_{Ht}(z)$. Firms within the region share the same real marginal cost (expressed in terms of domestic goods) which as in Galí and Monacelli (2008) equals the regional nominal wage divided by the price of the locally produced goods, that is, $mc_{Ht} = \frac{W_{Ht}}{p_{Ht}}$.

Firms' price-setting problem is subject to Calvo price rigidity, where in each period firms cannot re-adjust their price with probability θ, and they are subject to FIRE:[7]

$$\max_{p^*_{Ht}(z)} \mathbb{E}_t \sum_{j=0}^{\infty} (\theta\beta)^{t+j} Q_{t,t+j} \left[p^*_{Ht}(z) y_{H,t+j}(z) - mc_{H,t+j} L_{t+j}(z) \right], \tag{16}$$

where $Y_{H,t+j}(z) = \left(\frac{p^*_{Ht}(z)}{p_{H,t+j}}\right)^{-\eta_{Ht}} Y_{H,t+j}$ 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,

$$\frac{R_t}{\bar{R}} = \left(\frac{\pi^n_{Ht} \pi^{1-n}_{Ft}}{\bar{\pi}} \right)^{r_\pi}, \tag{17}$$

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

We describe the model in detail and derive the set of linear equilibrium condi-

[7] The generalized version of the model shown in Online Appendix C also relaxes this assumption for firms.

tions in Online Appendix B.1. From hereafter, we focus on the linearized version of the model and note that variables with a hat denote the log deviation of those variables from their respective steady states.

3.2 Socially Determined Expectations

Our empirical analysis shows that, when forming expectations about the inflation rate of the price index for their own consumption basket, consumers take into account the expected inflation rate held by consumers in other regions. That is equivalent to saying that that consumers in county i place some weight Γ_i on their own expectations about their local, within-county, inflation and weight $1-\Gamma_i$ on others' expectations about inflation in other counties.

We incorporate this finding in a tractable way into the consumer's inflation expectations formation process by making two assumptions.[8] 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

$$\mathbb{E}_t \hat{\Pi}_{i,t+1} = \phi_i \mathbb{E}_t \hat{\pi}_{i,t+1} + (1-\phi_i)\mathbb{E}_t \hat{\pi}_{j,t+1}.$$[9]

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

$$\begin{aligned} \widetilde{\mathbb{E}}_{it} \hat{\Pi}_{i,t+1} &= \Gamma_i \mathbb{E}_t \hat{\Pi}_{i,t+1} + (1-\Gamma_i)\mathbb{E}_t \hat{\Pi}_{j,t+1} \\ &= \mathbb{E}_t \hat{\Pi}_{i,t+1} + (1-\Gamma_i)\left(\mathbb{E}_t \hat{\Pi}_{j,t+1} - \mathbb{E}_t \hat{\Pi}_{i,t+1}\right). \end{aligned} \tag{18}$$

The second line of equation (18) highlights the diagnosticity component of our expectations assumption but newly applied in the cross-section dimension, whereby consumers over-weight news about inflation in other counties. Our setting, there-

[8] In Online Appendix C we generalize the model and apply this assumption to all expectations in the model and find very similar conclusions to the ones we present in this section.

[9] Note that under FIRE, all consumers have the same expectations about the same variable, and that is why an i subscript in the expectations operator is absent.

fore, complements insightful work by L'Huillier et al. (2023), Bianchi et al. (2023), and Bianchi et al. (2024), where the assumption of diagnosticity is applied in the time series dimension. Additionally, in Online Appendix D we present a model to micro-found the expression for the formation process of expectations, based on Bordalo et al. (2023).

We note that learning about an individual's consumption basket does not feature in our setup. The motivation for this modeling choice comes from our empirical findings: the instrumental-variable results show that exogenous local shocks in other counties, which are fundamentally exogenous to an individual's local consumption prices, affect that individual's beliefs about their own consumption prices. Put differently, the fundamentals in an individual's county are not informed by the exogenous local shocks in other counties, and yet these shocks are shown to matter for that individual's beliefs.

Our two assumptions about expectations taken together then imply that

$$\widetilde{\mathbb{E}}_{it}\hat{\Pi}_{i,t+1} = \Theta_i^{own}\mathbb{E}_t\hat{\pi}_{i,t+1} + \Theta_i^{other}\mathbb{E}_t\hat{\pi}_{j,t+1}, \tag{19}$$

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, Proposition 1 shows, and make up the basis for all subsequent deviations from FIRE results.

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

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

Proof. Follows from equation (19). □

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 ($0 \leq \Gamma_i < 1$) leads to under-weighting, that is, $\Theta_i^{own} < \phi_i$, when there is home bias. The rationale for why home bias matters is as follows: absent home bias (or foreign bias), consumers' FIRE about future regional inflation equally weigh the inflation rate of home- versus foreign-produced goods, that is, $\mathbb{E}_t\hat{\Pi}_{j,t+1} = \mathbb{E}_t\hat{\Pi}_{i,t+1}$. As a result, in the absence of home bias, the beliefs of consumers in region j do not embed any information that is different from that of consumers in region i, and the socially determined expectations collapse to FIRE. By contrast, when there is home bias and an associated deviation from FIRE, a "diagnostic" weight on foreign inflation emerges whereby information from the other region is unusually informative. This re-weighting pushes overall expectations away from the true trade weights and reduces the relative weight on home inflation — in other words, respondents under-weight home inflation expectations while over-weighting the other region's inflation expectations.

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 Corollary 1 shows, socially determined consumers' inflation expectations imply 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 and the regions are subject to the same risk-premium shocks. Under socially determined inflation expectations, the risk-sharing condition is given by*

$$-\gamma\hat{c}_{Ht} + \gamma\hat{c}_{Ft} = \hat{x}_t - \underbrace{(2 - \Gamma_H - \Gamma_F)\hat{x}_t}_{\text{social network effect}}. \tag{20}$$

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 B.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.

3.3 Regional and Aggregate Dynamics

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

Consumption block:

$$\hat{C}_{Ht} = \mathbb{E}_t \hat{C}_{H,t+1} - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t \hat{\Pi}_{H,t+1}) + \frac{1}{\gamma}\hat{e}_{Ht} - \underbrace{\frac{1-\Gamma_H}{\gamma}\mathbb{E}_t(\hat{x}_{t+1} - \hat{x}_t)}_{\text{social network distortion}} \tag{21}$$

$$\hat{C}_{Ft} = \hat{C}_{Ht} + \frac{1}{\gamma}\hat{x}_t - \frac{1}{\gamma}(\hat{e}_{Ht} - \hat{e}_{Ft}) + \underbrace{\frac{(\Gamma_H + \Gamma_F - 2)}{\gamma}\hat{x}_t}_{\text{social network distortion}} \tag{22}$$

Inflation block:

$$\begin{aligned}\hat{\Pi}_{Ht} = {} & \kappa(\alpha+\gamma)\hat{C}_{Ht} + \beta\mathbb{E}_t\hat{\Pi}_{H,t+1} + \kappa(1-\phi_H)\chi\hat{x}_t + \hat{u}_{Ht} - (1-\phi_H)(\hat{u}_{Ht} - \hat{u}_{Ft}) \\ & - \frac{\kappa\hat{\chi}(1-\phi_H)}{\gamma}(\hat{e}_{Ht} - \hat{e}_{Ft}) - \underbrace{\kappa(1-\phi_H)\widetilde{\chi}\hat{x}_t}_{\text{social network distortion}}\end{aligned} \tag{23}$$

$$\begin{aligned}\hat{\Pi}_{Ft} = {} & \kappa(\alpha+\gamma)\hat{C}_{Ft} + \beta\mathbb{E}_t\hat{\Pi}_{F,t+1} - \kappa(1-\phi_F)\chi\hat{x}_t + \hat{u}_{Ft} + (1-\phi_F)(\hat{u}_{Ht} - \hat{u}_{Ft}) \\ & + \frac{\kappa\hat{\chi}(1-\phi_F)}{\gamma}(\hat{e}_{Ht} - \hat{e}_{Ft}) + \underbrace{\kappa(1-\phi_F)\widetilde{\chi}\hat{x}_t}_{\text{social network distortion}}\end{aligned} \tag{24}$$

Terms of trade and policy rule block:

$$\hat{x}_t = \hat{x}_{t-1} + \hat{\Pi}_{Ht} - \hat{\Pi}_{Ft} \tag{25}$$

$$\hat{R}_t = r_\pi(n\hat{\Pi}_{Ht} + (1-n)\hat{\Pi}_{Ft}) \tag{26}$$

where $\hat{e}_{it} \sim \mathcal{N}(0,\sigma^2_{ie})$ and $\hat{u}_{it} \sim \mathcal{N}(0,\sigma^2_{iu})$, with $i \in \{H,F\}$, denote iid regional demand and supply shocks, respectively.[10] Moreover, $\chi = \alpha(\phi_H + \phi_F)(1/\gamma - \nu)$, $\hat{\chi} = \gamma + \alpha(\phi_H + \phi_F)$, and $\widetilde{\chi} = \hat{\chi}(2 - \Gamma_H - \Gamma_F)/\gamma$.

Distortions in regional dynamics due to socially determined inflation expectations – relative to FIRE – show up clearly in several of these equations as they alter the sensitivity of regional dynamics to the terms of trade $\hat{x}_t$. The precise effect of socially determined inflation expectations on the propagation of aggregate and local shocks depends on how the real terms of trade are 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 socially determined inflation expectations in response to local shocks but not in response to aggregate shocks.*

Proof. As equations (21)-(26) 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 are, however, affected only when the local shocks differ across regions. When the economy is subject to aggregate shocks, the real terms of trade are not affected. See Appendix B.2 for details. □

We note that in the special case of no home bias in either region ($\phi_H = \phi_F = 0.5$), the result in Proposition 1 implies that shocks do not affect the terms of trade and, as a result, socially determined inflation expectations cannot distort regional dynamics away from FIRE.

What about the aggregate effect of shocks? The aggregate dynamics of output and inflation are described by the following set of equilibrium equations:[11]

$$\hat{Y}_t = \mathbb{E}_t \hat{Y}_{t+1} - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t \hat{\Pi}_{t+1}) - \underbrace{\frac{n(1-\Gamma_H) - (1-n)(1-\Gamma_F)}{\gamma} \mathbb{E}_t(\hat{x}_{t+1} - \hat{x}_t)}_{\text{social network distortion}} + \frac{1}{\gamma}\hat{e}_t \tag{27}$$

$$\hat{\Pi}_t = \kappa(\alpha + \gamma)\hat{Y}_t + \beta \mathbb{E}_t \hat{\Pi}_{t+1} + \hat{u}_t \tag{28}$$

[10]See Online Appendix B.1 for their link to the risk-premium and elasticity of substitution shocks, respectively.

[11]Note that market clearing implies that $\hat{Y}_t = \hat{C}_t$.

where $\hat{e}_t = n\hat{e}_{Ht} + (1-n)\hat{e}_{Ft}$ and $\hat{u}_t = n\hat{u}_{Ht} + (1-n)\hat{u}_{Ft}$ denote the aggregate demand and supply shocks, respectively. The distortion due to socially determined expectations again depends on the real terms of trade. Unlike the case of regional dynamics in Proposition 2, local shocks have an aggregate impact only when some asymmetries are present, as proven in Proposition 3.

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 (27). □

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, the expectations of others 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.[12]

Whether socially determined expectations induce an amplification or attenuation on the response of aggregate output and inflation to local shocks, relative to FIRE, depends on the sign of the interaction of the belief asymmetry Δ and the expected first-difference in the terms of trade. Therefore, for a given Δ, the propagation of socially determined expectations relative to FIRE differs depending on

[12] Our result in Proposition 3 can also be interpreted from the point of view of economic and social centrality. Specifically, the economic centrality of a region i coincides with its economic size, whereas its social centrality is determined by the weight that consumers in the other region place on region i's inflation when forming expectations. The condition under which socially determined expectations play a role for aggregate dynamics can then be re-arranged into

$$\underbrace{\frac{1-\Gamma_F}{1-\Gamma_H}}_{\text{social centrality of H relative to F}} \neq \underbrace{\frac{n}{1-n}}_{\text{economic centrality of H relative to F}} .$$

Socially determined expectations will then lead to distortions in aggregate dynamics if the relative social centrality of a region does not match its relative economic centrality.

whether the shock originates in the home or the foreign region. Our result then adds a novel nuance to the well-known fact that diagnostic expectations – in a time series context – amplify the response of macro dynamics to aggregate shocks (see, for instance, L'Huillier et al. (2023), Bianchi et al. (2023), and Bianchi et al. (2024)).

We also note that socially determined expectations induce excess persistence to the effects of local shocks on aggregate output and inflation. Under FIRE, the effect of idiosyncratic local shocks dies out after impact since aggregates do not depend on the past terms of trade. By contrast, socially determined expectations yield a link between current macro variables and the previous terms of trade and, consequently, induce a more persistent response to local shocks.[13]

Finally, given that socially determined inflation expectations distort aggregate dynamics away from FIRE, we consider their implications for optimal monetary policy. Specifically, we assume a more general Taylor policy rule, such that $\hat{R}_t = r_\pi \left(n\psi \hat{\Pi}_{Ht} + (1 - n\psi)\hat{\Pi}_{Ft} \right)$, where policy optimally chooses ψ to minimize distortions of aggregate dynamics away from what is implied by FIRE. We are able to pin down an intuitive analytical solution for ψ in the special case of a flat Phillips curve ($\kappa \approx 0$). In this case, monetary policy should adjust ψ away from 1 as long as the socially determined expectations affect aggregate dynamics. Importantly, the inflation rate of region i should be weighed more than what is implied by its relative size if and only if, when forming inflation expectations, consumers in the other region assign a sufficiently high weight on the inflation rate of region i. Put differently, the inflation rate of region i should be weighed more than what is implied by its relative size if the social centrality of region i relative to the other region outpaces its economic centrality relative to the other region (see footnote 12). We refer the reader to Online Appendix B.2 for a detailed welfare analysis.[14]

3.4 Quantitative Analysis

How large are the effects of socially determined inflation expectations on aggregate dynamics, relative to the FIRE benchmark? A simple calibration exercise shows

[13]We refer the reader to the proof of Lemma 1 in Appendix B.3 for a detailed description of the equilibrium laws of motion for aggregate output and inflation.

[14]We acknowledge that explaining how policymakers can measure social networks accurately is beyond the scope of this paper. However, we also note that the dataset on the social connectedness index provides one way in which policy makers can measure social networks.

that allowing for socially determined inflation expectations matters mainly when supply shocks hit the economy. This finding follows from a standard parameterization as in Nakamura and Steinsson (2014), reported in Table 6 in Appendix A. 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 $\nu = 2$.[15] 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 $r_\pi = 1.5$. All shocks are drawn from a standard normal distribution, that is, $\sigma_{He} = \sigma_{Fe} = \sigma_{Hu} = \sigma_{Fu} = 1$.

Setting $\Gamma_H = \Gamma_F = \Gamma$, expectations about regional inflation in equation (18) can be alternatively written as

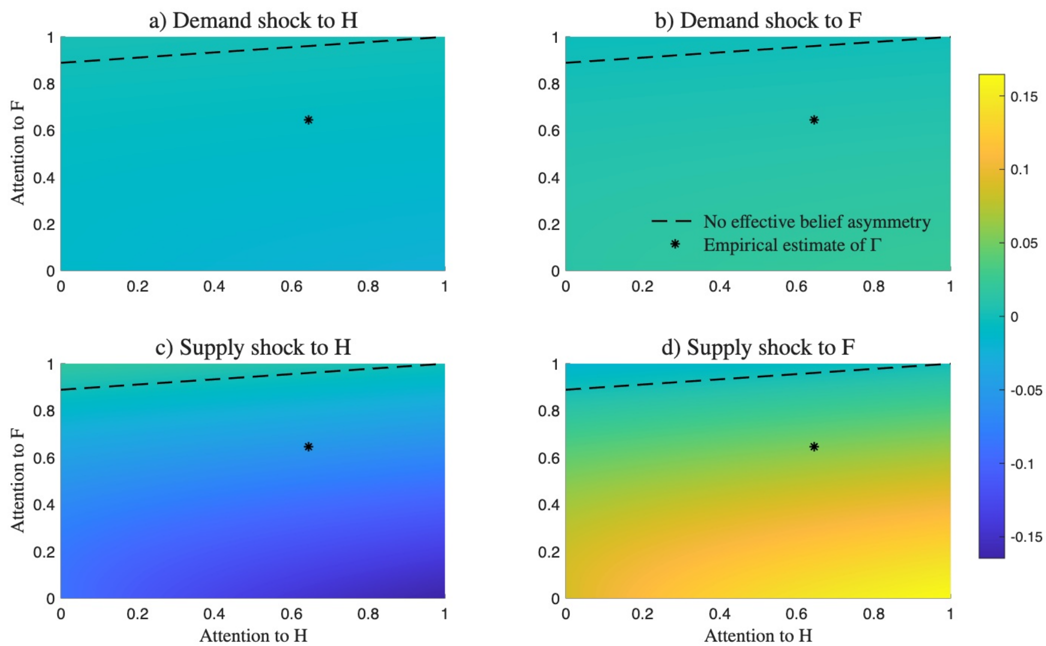
$$\widetilde{\mathbb{E}}_{it}\hat{\Pi}_{i,t+1} = \left(\frac{2\Gamma - 1}{\Gamma}\right)\mathbb{E}_t\hat{\Pi}_{i,t+1} + \left(\frac{1-\Gamma}{\Gamma}\right)\widetilde{\mathbb{E}}_{jt}\hat{\Pi}_{j,t+1}, \tag{29}$$

where $\frac{1-\Gamma}{\Gamma}$ captures the effect of a change in the expectations of region j on the expectations of region i, while holding constant $\mathbb{E}_t\hat{\Pi}_{i,t+1}$, that is, expectations of inflation in region i under FIRE. Hence, we map the effect of the expectations of others — consistent with the estimates of about 0.5 reported in the IV specifications in column (2) of Table 2 — to $\frac{1-\Gamma}{\Gamma}$, implying $\Gamma = \frac{1}{1+0.549} = 0.6456$. We find that the impact of a one-time home demand shock on aggregate output and inflation is 0.77% and 0.40% lower compared to FIRE, respectively. The impact of a one-time foreign demand shock on output and inflation is 0.77% and 0.40% higher compared to FIRE, respectively. On the other hand, the impact of a one-time home supply shock on output and inflation is about 5.39% and 2.82% lower compared to FIRE, respectively. By contrast, the impact of a one-time foreign supply shock on output and inflation is about 5.39% and 2.82% higher compared to FIRE, respectively.[16]

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

[16] We note that the sign of the impact of any of the four local shocks we consider on aggregate output and inflation is the same under FIRE and socially determined inflation expectations.

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

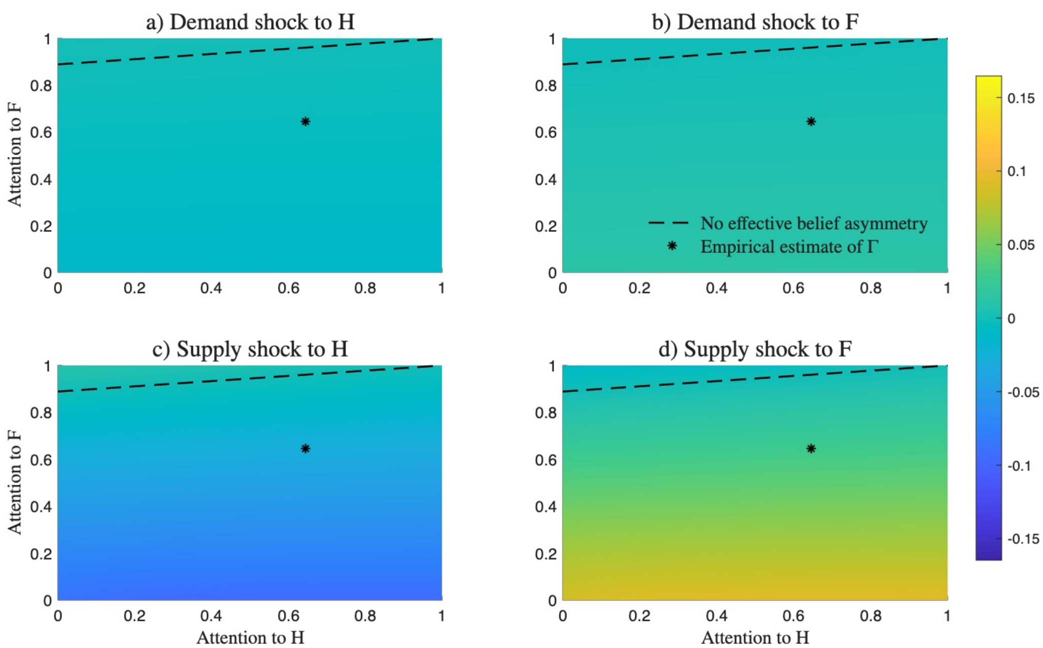


Note: Visualization of the effect of socially determined inflation expectations compared to FIRE for aggregate output, when the model is calibrated as in Table 6 in Appendix A. Star in black indicates the impact relative to FIRE when $\Gamma_H = \Gamma_F = \Gamma = \frac{1}{1+0.549} = 0.6456$, consistently with the empirical evidence reported in column (2) of Table 2. The dashed black line indicates the relationship between Γ_F and Γ_F for which there is no belief asymmetry ($\Delta = 0$).

More generally, Figures 2 and 3 plot the heat maps of the difference between the impact of various regional shocks on aggregate output and inflation for different parameterizations of socially determined inflation expectations parameters, Γ_H and Γ_F. The effect of socially determined inflation expectations is much more substantial in the case of local supply shocks compared to local demand 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 6 in Appendix A).[17] Moreover, the effects of socially de-

[17]We refer the reader to Lemma 1 in Appendix B.3 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 many others in related literature.

Figure 3: Impact of Socially Determined Inflation Expectations on Aggregate 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 6 in Appendix A. Star in black indicates the impact relative to FIRE when $\Gamma_H = \Gamma_F = \Gamma = \frac{1}{1+0.549} = 0.6456$, consistently with the empirical evidence reported in column (2) of Table 2. The dashed black line indicates the relationship between Γ_H and Γ_F for which there is no belief asymmetry ($\Delta = 0$).

termined expectations relative to FIRE increase as $\Gamma_H, \Gamma_F \to 0$, that is, when consumers focus all their attention on the other region's inflation when forming expectations.

Given the model calibration in Table 6 in Appendix A and $\Gamma_H = \Gamma_F = 0.6456$, we also compute the optimal adjustment to the weights assigned to home versus foreign inflation rates in the Taylor rule, so that welfare losses arising from socially determined expectations are minimized (see Online Appendix B.2 for details). Specifically, the optimal value of ψ is 1.231. This implies that the weight policy should assign to the inflation rate of the home region is 0.1231 instead of $n = 0.1$, whereas the weight it should assign to the inflation rate of the foreign region is 0.8769 instead of $1 - n = 0.9$. The optimal re-weighing gravitates toward the home region because that region's relative social centrality $\frac{1-\Gamma_F}{1-\Gamma_H} = 1$ is higher than its relative economic centrality $\frac{n}{1-n} \approx 0.1$.

Finally, we investigate the extent to which the higher estimate of the social network effect on inflation expectations has for our quantitative analysis. In particular, the estimate of 0.573 reported in column (4) of Table 2 implies a slightly lower value for $\Gamma_H = \Gamma_F = \frac{1}{1+0.573} = 0.6357$ and, as a result, a slightly bigger role of the socially determined inflation expectations for aggregate dynamics.[18] In terms of welfare, the optimal weight to be assigned to inflation in the home region is 0.1237, that is, negligibly higher compared to the baseline calibration of Γ_H and Γ_F.

4 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.

[18]Specifically, the impact of a home (foreign) demand shock on output and inflation is 0.79% and 0.41% lower (higher) compared to FIRE, respectively. On the other hand, the impact of a home (foreign) supply shock on output and inflation is 5.53% and 2.91% lower (higher) relative to FIRE, respectively.

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.

_ , Cosmin L Ilut, and Hikaru Saijo, "Smooth Diagnostic Expectations," Working Paper 32152, National Bureau of Economic Research February 2024.

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.

Bramoulle, Yann, Habiba Djebbari, and Bernard Fortin, "Identification of Peer Effects through Social Networks," *Journal of Econometrics*, 2009, *150* (1), 41–55.

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

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

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

Chahrour, Ryan, Adam Shapiro, and Dan Wilson, "News Selection and Household Inflation Expectations," Technical Report, National Bureau of Economic Research 2025.

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.

Chodorow-Reich, Gabriel, "Regional data in macroeconomics: Some advice for practitioners," *Journal of Economic Dynamics and Control*, 2020, *115*, 103875.

Coibion, Olivier, 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.

Conley, Timothy G, "GMM estimation with cross sectional dependence," *Journal of econometrics*, 1999, *92* (1), 1–45.

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.

Duflo, Esther and Emmanuel Saez, "The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment," *The Quarterly Journal of Economics*, 2003, *118* (3), 815–842.

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.

Galí, Jordi and Tommaso Monacelli, "Optimal monetary and fiscal policy in a currency union," *Journal of International Economics*, 2008, *76* (1), 116–132.

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.

Goldsmith-Pinkham, Paul and Guido W. Imbens, "Social Networks and the Identification of Peer Effects," *Journal of Business & Economic Statistics*, 2013, *31* (3), 253–264.

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.

L'Huillier, Jean-Paul, Sanjay R Singh, and Donghoon Yoo, "Incorporating Diagnostic Expectations into the New Keynesian Framework," *The Review of Economic Studies*, 10 2023, *91* (5), 3013–3046.

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.

_ and _ , "Identification in macroeconomics," *Journal of Economic Perspectives*, 2018, *32* (3), 59–86.

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.

Sacerdote, Bruce, "Peer Effects with Random Assignment: Results for Dartmouth Roommates," *The Quarterly Journal of Economics*, 2001, *116* (2), 681–704.

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

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

Appendix

A Additional Results

A.1 Tables

Table 3: Estimated Effect of Inflation Expectations in the Social Network on Own Expectations of Inflation

	(1)	(2)	(3)
$\sum_{k \neq c} \omega_{c,k} \pi^e_{d,k,t}$	0.573***	0.564***	0.570***
	(0.112)	(0.112)	(0.110)
$P_{gas,t} \times Comm_{c(i)} \times \mathbf{1}_{d(i)=m}$	3.083***	3.136***	3.102***
	(0.369)	(0.374)	(0.370)
$P_{gas,t} \times Comm_{c(i)} \times \mathbf{1}_{d(i)=w}$	3.557***	3.615***	3.579***
	(0.340)	(0.344)	(0.340)
Counties	$> 200m$	$> 250m$	$> 300m$
Time FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
F-Test	2520	3826	2675
Observations	1,239,055	1,239,055	1,239,055
R-squared	0.008	0.008	0.008

Note: This table shows results from estimating our main, instrumental variable (IV) specification. We constructs $\sum_{k \neq c} \omega_{c,k} \pi^e_{d,k,t}$ only using counties at least 200 miles (Column 1), 250 miles (Column 2) or 300m (Column 3) away. We weight by the observations in a county in each period. F-Test are from the first-stage regression. Standard errors clustered at the county level.

Table 4: Similarity-weighted inflation expectation controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\sum_{k\neq c}\omega_{c,k}\pi^e_{d,k,t}$	0.549***	0.549***	0.549***	0.550***	0.549***	0.547***	0.550***	0.549***	0.548***
	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)	(0.094)	(0.093)	(0.094)
$Inter_{m,c,t}$	3.093***	3.094***	3.093***	3.114***	3.052***	3.072***	3.115***	3.093***	3.075***
	(0.376)	(0.373)	(0.376)	(0.347)	(0.335)	(0.376)	(0.350)	(0.376)	(0.290)
$Inter_{w,c,t}$	3.579***	3.581***	3.579***	3.600***	3.539***	3.560***	3.601***	3.579***	3.562***
	(0.342)	(0.340)	(0.342)	(0.315)	(0.304)	(0.341)	(0.321)	(0.342)	(0.265)
$C^{Emp}_{d,c,t}$		0.180*							0.146
		(0.096)							(0.092)
$C^{AVGWage}_{d,c,t}$			-0.005						-0.007
			(0.033)						(0.032)
$C^{ed}_{d,c,t}$				0.017					0.019
				(0.027)					(0.026)
$C^{HHDebt}_{d,c,t}$					0.068				0.076
					(0.087)				(0.076)
$C^{PP}_{d,c,t}$						0.265***			0.260***
						(0.069)			(0.070)
$C^{Distance}_{d,c,t}$							-0.021		-0.023
							(0.017)		(0.017)
$C^{Commute}_{d,c,t}$								0.019	0.022
								(0.057)	(0.051)
Observations	1,239,055	1,239,055	1,239,055	1,239,055	1,239,055	1,239,055	1,239,055	1,239,055	1,239,055
R-squared	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
F (mean)	620.5	620	619.3	610.2	630	620.5	588.2	629.3	582.7

Note: This table shows results as Table 2, with additional controls $C^s_{d,c,t} = \sum_{k\neq c}\omega^{sim}_{c,k,0}\pi^e_{d,k,t}$. For all similarity measures other than physical distance, the weights are defined as $\omega^{sim}_{c,k,0} = (1/|X_{c,0} - X_{k,0}|) \,/\, \left(\sum_{j\neq c} 1/|X_{c,0} - X_{j,0}|\right)$ if $X_{c,0} \neq X_{k,0}$, and $\omega^{sim}_{c,k,0} = 1/C$ if $X_{c,0} = X_{k,0}$, where C is 1% of the first percentile of the variable's distance. The geographic-proximity control is constructed as $C^{Distance}_{d,c,t} = \sum_{k\neq c}\omega^{Distance}_{c,k}\pi^e_{d,k,t}$, where $\omega^{Distance}_{c,k} = d^{-1}_{ck} / \sum_{j\neq c} d^{-1}_{cj}$ and d_{ck} is the physical distance between counties c and k. The weights $\omega^{Emp}_{c,k}$ capture similarity in employment rates; $\omega^{AVGWage}_{c,k}$, similarity in average wages; $\omega^{ed}_{c,k}$, similarity in education; $\omega^{HHDebt}_{c,k}$, similarity in household debt; $\omega^{PP}_{c,k}$, similarity in population; $\omega^{Distance}_{c,k}$, geographic proximity; and $\omega^{Commute}_{c,k}$, similarity in commuting shares (gas usage). Each set of weights is used to construct a weighted average of inflation expectations in the other counties k. Column (1) is the baseline with no additional control, and Column (9) includes all controls jointly. See Appendix Section A.2 for details. Regressions are weighted by the number of responses in a county and period. The variable $Inter_{d,c,t} = P_{gas,t} \times Comm_{c(i)} \times \mathbf{1}_{d(i)=d}$ is the main control in our baseline specification. Standard errors are clustered at the county level.

Table 5: Estimated Effect of Inflation Expectations in the Social Network on Own Expectations of Inflation with Different Clusters

	(1)	(2)	(3)
$\sum_{k\neq c}\omega_{c,k}\pi^{e}_{d,k,t}$	0.549***	0.549***	0.549**
	(0.093)	(0.044)	(0.259)
$P_{gas,t}\times Comm_{c(i)}\times \mathbf{1}_{d(i)=m}$	0.3.093***	0.3.093***	0.3.093***
	(0.040)	(0.297)	(0.587)
$P_{gas,t}\times Comm_{c(i)}\times \mathbf{1}_{d(i)=w}$	3.579***	3.579***	3.579***
	(0.040)	(0.251)	(0.689)
Cluster	City	State	Conley
Time FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Regression	IV	IV	IV
Observations	1,239,055	1,239,055	1,239,055
R-squared	0.008	0.008	0.008

Note: This table shows results from estimating our main, instrumental variable (IV) specification. Standard errors are clustered according to row "Cluster", at the city level (Column 1) or at the state level (Column 2). Column 3 implements Conley (1999) standard errors. We report Conley standard errors using a Bartlett kernel and a 200 miles spatial cutoff. Results are robust to cutoffs of 100 and 300 miles.

Table 6: 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	σ_{shock}	1

A.2 Similarity Weights

We construct a variable that captures a county's exposure to inflation expectations in similar counties and add it as a control. We define similarity-weighted exposure to shocks in other counties as $C^s_{d,c,t} = \sum_{k \neq c} \omega^{sim}_{ck,0} \pi^e_{d,k,t}$. The weights are defined as $\omega^{sim}_{ck,0} = \frac{1/|X_{c,0}-X_{k,0}|}{\sum_k 1/|X_{c,0}-X_{k,0}|}$ if $X_{c,0} \neq X_{k,0}$, and $\omega^{sim}_{ck,0} = 1/C$ if $X_{c,0} = X_{k,0}$, where C is 1% of the 1st percentile of the variable's distance. Intuitively, the weights place a higher weight to inflation expectations in those counties that are similar in a set of characteristics X at 2007. We also compare social networks with geographical proximity networks. We construct proximity-weighted inflation expectations, where the weights are defined as

$$\omega^{distance}_{ck} = \frac{d_{ck}^{-1}}{\sum_k d_{ck}^{-1}},$$

with (d_{ck}) denoting the distance (in miles) between counties c and k.[19] We then include this proximity-based measure as a control in our main specification.

B Proofs

B.1 Proof of Corollary 1

Taking the first-order condition with respect to consumption in regions H and F, log-linearizing and combining them implies

$$\hat{c}_{Ht} - \hat{c}_{Ft} = -\frac{1}{\gamma}(\hat{\lambda}_{Ht} - \hat{\lambda}_{Ft}), \tag{B.1}$$

where λ_{it} is the marginal utility with respect to consumption for any region $i \in \{H, F\}$. Combining the two regions' log-linearized Euler equations and assuming that the law of one price holds in the long-run, that is, $\lim_{k\to\infty} \hat{P}_{H,t+k} = \lim_{k\to\infty} \hat{P}_{F,t+k}$,

[19] Distances are obtained from the National Bureau of Economic Research, compiled by Jean Roth (2014).

we have the following:

$$
\begin{aligned}
\hat{\lambda}_{Ht} - \hat{\lambda}_{Ft} &= \widetilde{\mathbb{E}}_{Ht}(\hat{\lambda}_{H,t+1} + \hat{R}_t - \hat{\Pi}_{H,t+1} + \hat{\zeta}_{Ht}) - \widetilde{\mathbb{E}}_{Ft}(\hat{\lambda}_{F,t+1} + \hat{R}_t - \hat{\Pi}_{F,t+1} + \hat{\zeta}_{Ft}) \\
&= \widetilde{\mathbb{E}}_{Ht}\sum_{k=0}^{\infty}(\hat{R}_{t+k} - \hat{\Pi}_{H,t+k+1} + \hat{\zeta}_{H,t+j}) - \widetilde{\mathbb{E}}_{Ft}\sum_{k=0}^{\infty}(\hat{R}_{t+k} - \hat{\Pi}_{F,t+k+1} + \hat{\zeta}_{F,t+j}) \\
&= \sum_{k=0}^{\infty}(\widetilde{\mathbb{E}}_{Ht}\hat{\Pi}_{H,t+k+1} - \widetilde{\mathbb{E}}_{Ft}\hat{\Pi}_{F,t+k+1}) + (\hat{\zeta}_{Ht} - \hat{\zeta}_{Ft}) \\
&= \mathbb{E}_t\sum_{k=0}^{\infty}\left[\Gamma_H\hat{\Pi}_{H,t+k+1} + (1-\Gamma_H)\hat{\Pi}_{F,t+k+1} - \Gamma_F\hat{\Pi}_{F,t+k+1} - (1-\Gamma_F)\hat{\Pi}_{H,t+k+1}\right] \\
&+ (\hat{\zeta}_{Ht} - \hat{\zeta}_{Ft}) \\
&= \mathbb{E}_t\sum_{k=0}^{\infty}(\Gamma_H + \Gamma_F - 1)(\hat{\Pi}_{H,t+k+1} - \Pi_{F,t+k+1}) - (\hat{\zeta}_{Ht} - \hat{\zeta}_{Ft}) \\
&= (\Gamma_H + \Gamma_F - 1)(\hat{P}_{Ht} - \hat{P}_{Ft}) - (\hat{\zeta}_{Ht} - \hat{\zeta}_{Ft}) \\
&= \hat{x}_t - (2 - \Gamma_H - \Gamma_F)\hat{x}_t - (\hat{\zeta}_{Ht} - \hat{\zeta}_{Ft}).
\end{aligned}
$$

In the absence of heterogenous regional risk-premium shocks, the following risk-sharing condition emerges

$$
-\gamma(\hat{c}_{Ht} - \hat{c}_{Ft}) = \hat{x}_t - (2 - \Gamma_H - \Gamma_F)\hat{x}_t.
$$

B.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

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

where $\hat{e}_{Ht} = -\hat{\zeta}_{Ht}$, $\hat{e}_{Ft} = -\hat{\zeta}_{Ft}$, $\chi = \alpha(\phi_H + \phi_F)(1/\gamma - \nu)$, $\hat{\chi} = \gamma + \alpha(\phi_H + \phi_F)$, and $\widetilde{\chi} = \frac{\hat{\chi}(2-\Gamma_H-\Gamma_F)}{\gamma}$. 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 $\Sigma = diag\left(\begin{bmatrix} \sigma^2_{He} & \sigma^2_{Fe} & \sigma^2_{Hu} & \sigma^2_{Fu} \end{bmatrix}\right)$. If both regions are shocked by the same innovations, that is, if $\hat{\zeta}_{Ht} = \hat{\zeta}_{Ft}$ 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 $\hat{\zeta}_{Ht} \neq \hat{\zeta}_{Ft}$ and/or $\hat{u}_{Ht} \neq \hat{u}_{Ft}$, the terms of trade are affected by local shocks, implying that the socially determined inflation expectations will impact regional dynamics.

B.3 Proof of Proposition 4

Before proving Proposition 4, we describe the minimum state variable (MSV) solution for aggregate output and inflation in Lemma 1 below.

Lemma 1 (MSV solution of the model)**.** *The equilibrium dynamics under EoO for ag-*

gregate output, inflation, and the terms of trade are described by the following equations:

$$\begin{aligned}\hat{Y}_t &= a_y \hat{x}_{t-1} + B_y \hat{s}_t;\\ \hat{\Pi}_t &= a_\pi \hat{x}_{t-1} + B_\pi \hat{s}_t;\\ \hat{x}_t &= a \hat{x}_{t-1} + B \hat{s}_t;\end{aligned} \tag{B.3}$$

where $a_y, a_\pi \in \mathbb{R}$; $\mid a \mid < 1$; $B_y, B_\pi, B \in \mathbb{R}^4$; *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* $\Sigma = diag\left(\begin{bmatrix} \sigma^2_{He} & \sigma^2_{Fe} & \sigma^2_{Hu} & \sigma^2_{Fu} \end{bmatrix}\right)$. *The MSV solution under FIRE is given by*

$$\begin{aligned}&\hat{Y}_t = \bar{B}_y \hat{s}_t; \quad \hat{\Pi}_t = \bar{B}_\pi \hat{s}_t;\\ &\hat{x}_t = \bar{a} \hat{x}_{t-1} + \bar{B} \hat{s}_t.\end{aligned} \tag{B.4}$$

Proof. We solve 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 (B.2), and re-organizing terms, a is the solution to the following quadratic equation

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

thus,

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

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

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

The solution for B is given by

$$B = \begin{bmatrix} \frac{\kappa(\alpha+\gamma+\hat{\chi}(\phi_H+\phi_F-2))}{\gamma} & -\frac{\kappa(\alpha+\gamma+\hat{\chi}(\phi_H+\phi_F-2))}{\gamma} & \phi_H+\phi_F-1 & 1-\phi_H-\phi_F \end{bmatrix}. \tag{B.6}$$

We now turn to output and inflation, and 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 guessed in equation (B.3) to the aggregate Euler equation and Phillips curve, we have the following two expressions for output and inflation:

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

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

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

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

$$\begin{bmatrix} B_y & B_\pi \end{bmatrix} = \begin{bmatrix} B_y & B_\pi \end{bmatrix} \underbrace{\begin{bmatrix} 0_{4\times4} & \kappa(\alpha+\gamma)I \\ -\frac{r_\pi}{\gamma}I & 0_{4\times4} \end{bmatrix}}_{\tilde{\Omega}} + \underbrace{\begin{bmatrix} \frac{(nr_\pi(1-\psi)+\gamma a_y+a_\pi+\Delta(1-a))B+B_e}{\gamma} & \beta a_\pi B + B_u \end{bmatrix}}_{D}$$

Therefore, in equilibrium,

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

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

$$\begin{bmatrix} \bar{B}_y & \bar{B}_\pi \end{bmatrix} = \begin{bmatrix} \frac{B_e}{\gamma} & B_u \end{bmatrix} (I - \widetilde{\Omega})^{-1}. \tag{B.10}$$

□

Knowing the model solution under FIRE and socially determined inflation expectations, we derive an analytic solution for welfare losses:

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

where $\delta = \frac{nr_\pi(1-\psi)+\gamma a_y + a_\pi + \Delta(1-a)}{\gamma}$. Note that a, B, and Σ do not depend on ψ, hence

$$\frac{\partial \mathbb{W}}{\partial \psi} = -\left(a_y \frac{\partial a_y}{\partial \psi} + a_\pi \frac{\partial a_\pi}{\partial \psi})\right)\mathbb{E}(x_t^2) - \left(\delta \frac{\partial \delta}{\partial \psi} + \beta^2 a_\pi \frac{\partial a_\pi}{\partial \psi}\right) B\Sigma B'. \tag{B.12}$$

As $\kappa \to 0$, we have $a_\pi \to 0$, $\gamma a_y \to a\Delta - nr_\pi(1-\psi)$, $\delta \to \frac{\Delta}{\gamma}$, and

$$\lim_{\kappa \to 0} \frac{\partial \mathbb{W}}{\partial \psi} = -a_y \frac{\partial a_y}{\partial \psi}\mathbb{E}(x_t^2) = -nr_\pi \frac{\Delta a - nr_\pi(1-\psi)}{\gamma^2}\mathbb{E}(x_t^2). \tag{B.13}$$

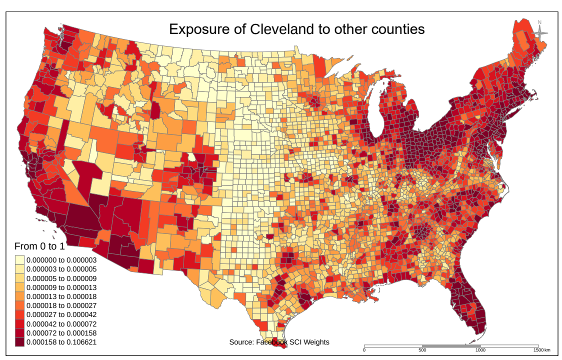
As $\kappa \to 0$, welfare is maximized for $\psi = \psi* \geq 0$ such that $n(\psi^* - 1) = \max\left(-n, -\frac{\Delta a}{r_\pi}\right)$.

Online Appendix

A Additional Figures

We consider the social connectedness of Cuyahoga County, where Cleveland, Ohio is located, with other counties across the United States. Figure 4 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.

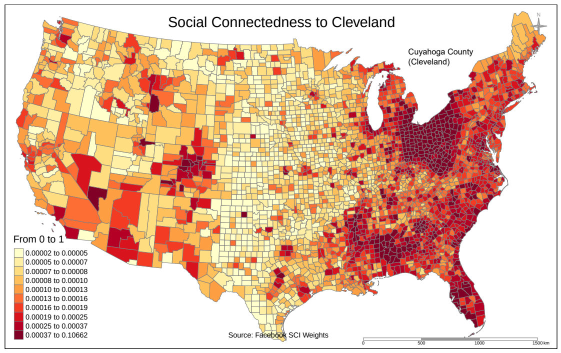
Figure 4: Social Connectedness of Cleveland to Other Counties ($\omega_{Cleveland,k}$)



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

In reverse, we also present the social connectedness of other counties to Cuyahoga County, Ohio. The heat map in Figure 5 shows the weights $\omega_{c,k}$ for $k = Cleveland$. Again, as in the illustration above, the three patterns also emerge in this case.

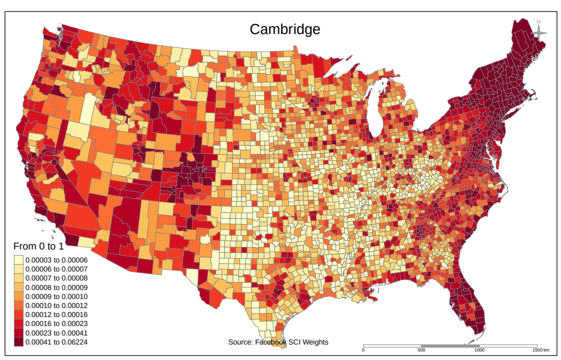
Figure 5: Social Connectedness of Each County to Cleveland ($\omega_{c,Cleveland}$)



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

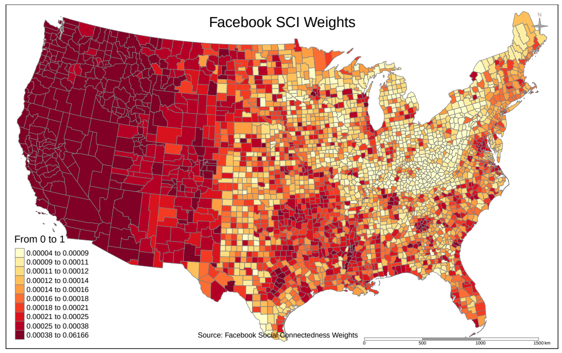
Below we show similar maps for other counties such as Cambridge, and Los Angeles.

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



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

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



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

B Model

B.1 Setup and Equilibrium Conditions

In this section we describe the model in detail for the home region H (the model for the foreign region F is symmetric to the home region) and derive the system of linear equations in equilibrium.

Households. Consumers maximize utility with respect to consumption C_{Ht}, labor hours L_{Ht}, and real bond holdings b_{Ht}, subject to their budget constraint:

$$\max_{C_{Ht},L_{Ht},b_{Ht}} \widetilde{\mathbb{E}}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_{Ht}^{1-\gamma}}{1-\gamma} - \psi \frac{L_{Ht}^{1+\alpha}}{1+\alpha} \right] \tag{B.1}$$

$$b_{Ht} + C_{Ht} = w_{Ht} L_{Ht} + \frac{b_{H,t-1} R_{t-1} \zeta_{H,t-1}}{\Pi_{Ht}} + d_{Ht}, \tag{B.2}$$

where the risk-less real bond holdings of consumers in $t-1$ pay gross nominal interest R_{t-1}; Π_{Ht} denotes the inflation rate in region H; labor hours are compensated at a real wage rate w_{Ht}; d_{Ht} are the real profits of firms in region H paid to consumers in that region; and ζ_{Ht} is a regional risk-premium shock such that

$log(\zeta_{Ht})$ is an iid normal shock with mean 0. $\widetilde{\mathbb{E}}_0$ is a generic expectations operator that satisfies the law of iterative expectations and standard probability rules. Letting λ_{Ht} be the Lagrangian, the first-order conditions with respect to consumption, labor hours, and bonds are given by

$$\begin{aligned} C_{Ht}^{-\gamma} &= \lambda_{Ht}, \\ \psi L_{Ht}^{\alpha} &= w_{Ht}\lambda_{Ht}, \\ \lambda_{Ht} &= \beta\widetilde{\mathbb{E}}_{Ht}\frac{R_t\zeta_{Ht}\lambda_{H,t+1}}{\Pi_{H,t+1}}. \end{aligned} \tag{B.3}$$

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

$$C_{Ht} = \left[\phi_H^{\frac{1}{\nu}} C_{H,H,t}^{\frac{\nu-1}{\nu}} + (1-\phi_H)^{\frac{1}{\nu}} C_{H,F,t}^{\frac{\nu-1}{\nu}}\right]^{\frac{\nu}{\nu-1}}, \tag{B.4}$$

where $C_{j,i,t}$ is region j's consumption of goods produced in region i. Moreover, $C_{j,i,t}$ is a CES aggregate of a continuum of varieties z with a stochastic elasticity of substitution η_{Ht}, such that $log(\eta_{Ht})$ is an iid normal shock with mean 0:

$$C_{i,j,t} = \left(\int_0^1 c_{i,j,t}(z)^{\frac{\eta_{Ht}-1}{\eta_{Ht}}} dz\right)^{\frac{\eta_{Ht}}{\eta_{Ht}-1}}.$$

The price index of the home region is defined by the CES preferences,

$$P_{Ht} = \left(\phi_H p_{Ht}^{1-\nu} + (1-\phi_H) p_{Ft}^{1-\nu}\right)^{\frac{1}{1-\nu}}, \tag{B.5}$$

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. Consumers in the home region optimally choose their demand for home-produced versus foreign-produced consumption by maximizing $P_{Ht}C_{Ht} - p_{Ht}C_{H,H,t} - p_{Ft}C_{H,F,t}$ with respect to $C_{H,H,t}$

and $C_{H,F,t}$ given (B.4), which in turn implies the following demand schedules

$$C_{H,H,t} = \phi_H \left(\frac{p_{Ht}}{P_{Ht}}\right)^{-\nu} C_{Ht} \tag{B.6}$$

$$C_{H,F,t} = (1-\phi_H) \left(\frac{p_{Ft}}{P_{Ht}}\right)^{-\nu} C_{Ht} \tag{B.7}$$

We assume that preferences for local goods are proportional to the sizes of the regional economies, so that, $(1-n)(1-\phi_F) = n(1-\phi_H)$.

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

$$Y_{Ht} = nC_{H,H,t} + (1-n)C_{F,H,t} \tag{B.8}$$

Firms produce using a production function linear in local labor, $Y_{Ht}(z) = L_{Ht}(z)$. The real marginal cost, expressed relative to the price of domestically produced goods, is given by $mc_{Ht} = \frac{w_{Ht}P_{Ht}}{p_{Ht}}$. Firms' price-setting problem is subject to Calvo price rigidity, where in each period firms cannot re-adjust their price with probability θ. Firms' have FIRE expectations and maximize their expected discounted stream of profits with respect to price $p^*_{Ht}(z)$:

$$\max_{p^*_{Ht}(z)} \mathbb{E}_t \sum_{j=0}^{\infty} (\theta\beta)^{t+j} Q_{t,t+j} \left[\frac{p^*_{Ht}(z)}{p_{H,t+j}} Y_{H,t+j}(z) - mc_{H,t+j} L_{t+j}(z)\right], \tag{B.9}$$

where $Y_{H,t+j}(z) = \left(\frac{p^*_{Ht}}{p_{H,t+j}}\right)^{-\eta_{Ht}} Y_{H,t+j}$ and $Q_{t,t+j}$ is a stochastic discount factor. The first-order condition with respect to the symmetric price decision p^*_{Ht} is given by

$$\mathbb{E}_t \sum_{j=0}^{\infty} (\beta\theta)^j Q_{t,t+j} p_{H,t+j} Y_{H,t+j} (\eta_{H,t+j} mc_{H,t+j} p_{H,t+j} - (\eta_{H,t+j} - 1) p^*_{Ht}) = 0.$$

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

Taylor rule,

$$\frac{R_t}{\bar{R}} = \left(\frac{\pi_{Ht}^{n} \pi_{Ft}^{1-n}}{\bar{\pi}} \right)^{r_\pi}, \tag{B.10}$$

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

Aggregates. Aggregate output in the economy is given by

$$Y_t = Y_{Ht} + Y_{Ft}. \tag{B.11}$$

Steady state equilibrium. We assume that the following conditions hold in steady state: $\bar{C}_H = \bar{C}_F = \bar{C}$; $\bar{p}_H = \bar{p}_F = \bar{P}_H = \bar{P}_F$; $\bar{\pi} = 1$. We now derive the steady-state equilibrium of the model.

$$\begin{aligned}
\bar{C}_{HH} &= \phi_H \bar{C}_H; \qquad \bar{C}_{HF} = (1-\phi_H)\bar{C}_H && \text{(B.12)}\\
\bar{C}_{FF} &= \phi_F \bar{C}_F; \qquad \bar{C}_{FH} = (1-\phi_F)\bar{C}_F && \text{(B.13)}\\
\bar{mc}_H &= \bar{mc}_F = \frac{\bar{\eta}-1}{\bar{\eta}} && \text{(B.14)}\\
\bar{Y}_H &= n\bar{C}; \qquad \bar{Y}_F = (1-n)\bar{C}; \qquad \bar{Y} = \bar{C} && \text{(B.15)}\\
\bar{R} &= 1/\beta; \qquad \bar{Y}_H^{\alpha} = \bar{w}_H \bar{C}_H^{\gamma} && \text{(B.16)}
\end{aligned}$$

Log-linearized model. We now log-linearize the model around the steady-state equilibrium and start with the household equilibrium conditions:

$$\begin{aligned}
\hat{C}_{Ht} &= \widetilde{\mathbb{E}}_{Ht}\hat{C}_{H,t+1} - \frac{1}{\gamma}\left(\hat{R}_t - \widetilde{\mathbb{E}}_{Ht}\hat{\Pi}_{H,t+1}\right) - \frac{1}{\gamma}\hat{\zeta}_{Ht} && \text{(B.17)}\\
\hat{Y}_{Ht} &= \hat{w}_{Ht} - \gamma \hat{C}_{Ht} && \text{(B.18)}\\
\hat{C}_{H,H,t} &= -\nu(\hat{p}_{Ht} - \hat{P}_{Ht}) + \hat{C}_{Ht} && \text{(B.19)}\\
\hat{C}_{H,F,t} &= -\nu(\hat{p}_{Ft} - \hat{P}_{Ht}) + \hat{C}_{Ht} && \text{(B.20)}\\
\hat{P}_{Ht} &= \phi_H \hat{p}_{Ht} + (1-\phi_H)\hat{p}_{Ft}. && \text{(B.21)}
\end{aligned}$$

Next, we move to the firms' equilibrium conditions:

$$\hat{Y}_{Ht} = \phi_H \hat{C}_{H,H,t} + (1-\phi_H)\hat{C}_{F,H,t} \tag{B.22}$$

$$\hat{mc}_{Ht} = \hat{w}_{Ht} - (\hat{p}_{Ht} - \hat{P}_{Ht}) = \alpha \hat{Y}_{Ht} + \left(\gamma - \frac{1}{\nu}\right)\hat{C}_{Ht} + \frac{1}{\nu}\hat{C}_{H,H,t} \tag{B.23}$$

Turning to the price optimal decision $\hat{p}^*_{Ht}$:

$$\begin{aligned}
&\bar{Y}_H(\bar{\eta}_H - 1)\mathbb{E}_t \sum_{j=0}^{\infty} (\beta\theta)^j \left(\hat{Q}_{t,t+j} + \hat{Y}_{H,t+j} + \hat{p}^*_{Ht}\right) + \bar{Y}_H \bar{\eta}_H \mathbb{E}_t \sum_{j=0}^{\infty} (\beta\theta)^j \hat{\eta}_{H,t+j} \\
=&\bar{Y}_H(\bar{\eta}_H - 1)\mathbb{E}_t \sum_{j=0}^{\infty} (\beta\theta)^j \left(\hat{Q}_{t,t+j} + \hat{Y}_{H,t+j} + \hat{p}_{H,t+j} + \hat{\eta}_{H,t+j} + \hat{mc}_{H,t+j}\right),
\end{aligned}$$

which implies that

$$\begin{aligned}
\frac{p^*_{Ht} - p_{Ht}}{1-\beta\theta} &= \mathbb{E}_t \sum_{j=0}^{\infty} (\beta\theta)^j \left[(p_{H,t+j} - p_{Ht}) - \frac{1}{\bar{\eta}_H - 1}\hat{\eta}_{H,t+j} + \hat{mc}_{H,t+j}\right] \\
&= \mathbb{E}_t \sum_{j=0}^{\infty} (\beta\theta)^j \left[\hat{\pi}_{H,t+1+j} - \frac{1}{\bar{\eta}_H - 1}\hat{\eta}_{H,t+j} + \hat{mc}_{H,t+j}\right].
\end{aligned}$$

Setting $\hat{\pi}_{Ht} = \frac{\theta}{1-\theta}(\hat{p}^*_{Ht} - \hat{p}_{Ht})$, $\kappa = \frac{(1-\theta)(1-\beta\theta)}{\theta}$, and $\hat{u}_{Ht} = -\frac{1}{\bar{\eta}_H - 1}\hat{\eta}_{Ht}$, one can show that the inflation rate of goods produced in region H is given by

$$\hat{\pi}_{Ht} = \kappa \hat{mc}_{Ht} + \beta \mathbb{E}_t \hat{\pi}_{H,t+1} + \hat{u}_{Ht}. \tag{B.24}$$

Using the fact that $\hat{P}_{Ht} = \phi_H \hat{p}_{Ht} + (1-\phi_H)\hat{p}_{Ft}$, it is easy to see that the inflation rate in region H is given by

$$\hat{\Pi}_{Ht} = \phi_H \hat{\pi}_{Ht} + (1-\phi_H)\hat{\pi}_{Ft}. \tag{B.25}$$

Similar equations can be easily derived for the foreign economy. Finally, aggregate output and interest rates are given by:

$$\hat{Y}_t = n\hat{Y}_{Ht} + (1-n)\hat{Y}_{Ft} \tag{B.26}$$

$$\hat{R}_t = r_\pi(n\hat{\Pi}_{Ht} + (1-n)\hat{\Pi}_{Ft}) \tag{B.27}$$

Regional equilibrium dynamics. We derive linear equations that describe consumption and inflation in each one of the regions. It is useful to note that the expected difference between future inflation in H and F under FIRE is given by

$$\mathbb{E}_t(\hat{\Pi}_{H,t+1} - \hat{\Pi}_{F,t+1}) = \mathbb{E}_t(\hat{x}_{t+1} - \hat{x}_t).$$

We start with the consumption: applying our definition of socially determined inflation expectations and setting $\hat{\zeta}_{it} = -\hat{e}_{it}$ for any $i \in \{H, F\}$, the Euler equation in the home region becomes

$$\hat{C}_{Ht} = \mathbb{E}_t\hat{C}_{H,t+1} - \frac{1}{\gamma}\left(\hat{R}_t - \mathbb{E}_t\hat{\Pi}_{H,t+1}\right) + \frac{1}{\gamma}\hat{e}_{Ht} - \frac{1-\Gamma_H}{\gamma}\mathbb{E}_t(\hat{x}_{t+1} - \hat{x}_t). \tag{B.28}$$

We then use the risk-sharing condition to derive consumption in the foreign region:

$$\hat{C}_{Ft} = \hat{C}_{Ht} + \frac{1}{\gamma}\hat{x}_t - \frac{1}{\gamma}(\hat{e}_{Ht} - \hat{e}_{Ft}) + \frac{\Gamma_H + \Gamma_F - 2}{\gamma}\hat{x}_t. \tag{B.29}$$

Before we derive the regional Phillips curves, it is useful to note the following relationships between prices

$$\hat{p}_{Ht} - \hat{P}_{Ht} = \frac{1-\phi_H}{\phi_H + \phi_F - 1}\hat{x}_t; \qquad \hat{p}_{Ft} - \hat{P}_{Ht} = -\frac{\phi_H}{\phi_H + \phi_F - 1}\hat{x}_t \tag{B.30}$$

$$\hat{p}_{Ht} - \hat{P}_{Ft} = \frac{\phi_F}{\phi_H + \phi_F - 1}\hat{x}_t; \qquad \hat{p}_{Ft} - \hat{P}_{Ft} = -\frac{1-\phi_F}{\phi_H + \phi_F - 1}\hat{x}_t, \tag{B.31}$$

and the links between consumptions

$$\hat{C}_{H,H,t} = \hat{C}_{Ht} - \frac{\nu(1-\phi_H)}{\phi_H+\phi_F-1}\hat{x}_t; \qquad \hat{C}_{H,F,t} = \hat{C}_{Ht} + \frac{\nu\phi_H}{\phi_H+\phi_F-1}\hat{x}_t \quad \text{(B.32)}$$

$$\hat{C}_{F,H,t} = \hat{C}_{Ft} - \frac{\nu\phi_F}{\phi_H+\phi_F-1}\hat{x}_t; \qquad \hat{C}_{F,F,t} = \hat{C}_{Ft} + \frac{\nu(1-\phi_F)}{\phi_H+\phi_F-1}\hat{x}_t. \quad \text{(B.33)}$$

The Phillips curve in the home region is given by

$$\begin{aligned}
\hat{\Pi}_{Ht} &= \kappa\alpha(\phi_H\hat{Y}_{Ht} + (1-\phi_H)\hat{Y}_{Ft}) + \kappa\gamma(\phi_H\hat{C}_{Ht} + (1-\phi_H)\hat{C}_{Ft}) - \frac{\kappa(1-\phi_H)}{\phi_H+\phi_F-1}(\phi_H-(1-\phi_F))\hat{x}_t \\
&\quad + \beta\mathbb{E}_t\hat{\Pi}_{H,t+1} + (1-\phi_H)(\hat{u}_{Ft}-\hat{u}_{Ft}) + \hat{u}_{Ht} \\
&= \kappa(\alpha+\gamma)\hat{C}_{Ht} + \kappa(1-\phi_H)\left(\gamma+\alpha(\phi_H+\phi_F)\right))\left(\hat{C}_{Ft}-\hat{C}_{Ht}\right) - \kappa(1-\phi_H)[\alpha\nu(\phi_H+\phi_F)+1]\hat{x}_t \\
&\quad + \beta\mathbb{E}_t\hat{\Pi}_{H,t+1} + (1-\phi_H)(\hat{u}_{Ft}-\hat{u}_{Ht}) + \hat{u}_{Ht} \\
&= \kappa(\alpha+\gamma)\hat{C}_{Ht} + \kappa(1-\phi_H)(\chi-\widetilde{\chi})\hat{x}_t + \beta\mathbb{E}_t\hat{\Pi}_{H,t+1} \\
&\quad - \frac{\kappa(1-\phi_H)\hat{\chi}}{\gamma}(\hat{e}_{Ht}-\hat{e}_{Ft}) - (1-\phi_H)(\hat{u}_{Ht}-\hat{u}_{Ft}) + \hat{u}_{Ht},
\end{aligned} \tag{B.34}$$

where $\chi = \alpha(\phi_H+\phi_F)(1/\gamma-\nu)$, $\hat{\chi} = \gamma+\alpha(\phi_H+\phi_F)$ and $\widetilde{\chi} = \frac{(\gamma+\alpha(\phi_H+\phi_F))(2-\Gamma_H-\Gamma_F)}{\gamma}$.
Following a similar procedure, the Phillips curve in the foregin region is given by

$$\begin{aligned}
\hat{\Pi}_{Ft} &= \kappa\alpha(\phi_F\hat{Y}_{Ft} + (1-\phi_F)\hat{Y}_{Ht}) + \kappa\gamma(\phi_F\hat{C}_{Ft} + (1-\phi_F)\hat{C}_{Ht}) + \frac{\kappa(1-\phi_F)}{\phi_H+\phi_F-1}(\phi_H-(1-\phi_F))\hat{x}_t \\
&\quad + \beta\mathbb{E}_t\hat{\Pi}_{F,t+1} - (1-\phi_F)(\hat{u}_{Ft}-\hat{u}_{Ft}) + \hat{u}_{Ft} \\
&= \kappa(\alpha+\gamma)\hat{C}_{Ft} - \kappa(1-\phi_F)\left(\gamma+\alpha(\phi_H+\phi_F)\right))\left(\hat{C}_{Ft}-\hat{C}_{Ht}\right) + \kappa(1-\phi_H)[\alpha\nu(\phi_H+\phi_F)+1]\hat{x}_t \\
&\quad + \beta\mathbb{E}_t\hat{\Pi}_{F,t+1} - (1-\phi_F)(\hat{u}_{Ft}-\hat{u}_{Ft}) + \hat{u}_{Ft} \\
&= \kappa(\alpha+\gamma)\hat{C}_{Ft} - \kappa(1-\phi_F)(\chi-\widetilde{\chi})\hat{x}_t + \beta\mathbb{E}_t\hat{\Pi}_{F,t+1} \\
&\quad + \frac{\kappa(1-\phi_F)\hat{\chi}}{\gamma}(\hat{e}_{Ht}-\hat{e}_{Ft}) + (1-\phi_F)(\hat{u}_{Ht}-\hat{u}_{Ft}) + \hat{u}_{Ft}
\end{aligned} \tag{B.35}$$

Aggregate equilibrium dynamics. We now move on to derive aggregate output and inflation.

$$
\begin{aligned}
\hat{C}_t &= n\hat{C}_{Ht} + (1-n)\hat{C}_{Ft} = \hat{C}_{Ht} + \frac{(1-n)(\Gamma_H+\Gamma_F-1)}{\gamma}\hat{x}_t - \frac{1-n}{\gamma}(\hat{e}_{Ht}-\hat{e}_{Ft}) \\
&= \mathbb{E}_t\hat{C}_{H,t+1} - \frac{1}{\gamma}(\hat{R}_t + (1-\Gamma_H)\mathbb{E}_t(\hat{x}_{t+1}-\hat{x}_t)) - \frac{1}{\gamma}\mathbb{E}_t\hat{\Pi}_{H,t+1} + \frac{1}{\gamma}\hat{e}_{Ht} \\
&+ \frac{(1-n)(\Gamma_H+\Gamma_F-1)}{\gamma}\hat{x}_t - \frac{1-n}{\gamma}(\hat{e}_{Ht}-\hat{e}_{Ft}) \\
&= \mathbb{E}_t\hat{C}_{t+1} - \frac{n(1-\Gamma_H)-(1-n)(1-\Gamma_F)}{\gamma}(\mathbb{E}_t\hat{x}_{t+1}-\hat{x}_t) - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t\hat{\Pi}_{t+1}) \\
&+ \frac{1}{\gamma}(n\hat{e}_{Ht} + (1-n)\hat{e}_{Ft}),
\end{aligned}
\tag{B.36}
$$

where we have made use of two equivalences: $\mathbb{E}_t\hat{\Pi}_{H,t+1} = \mathbb{E}_t\hat{\Pi}_{t+1} + (1-n)\mathbb{E}_t(\hat{x}_{t+1} - \hat{x}_t)$ and $\mathbb{E}_t\hat{C}_{H,t+1} = \mathbb{E}_t\hat{C}_{t+1} - \frac{(1-n)(\Gamma_H+\Gamma_F-1)}{\gamma}\mathbb{E}_t\hat{x}_{t+1}$. Imposing market clearing, that is, $\hat{C}_t = \hat{Y}_t$ and letting the aggregate demand shock be $e_t = n\hat{e}_{Ht} + (1-n)\hat{e}_{Ft}$, we have the following equilibrium expression for output:

$$
\hat{Y}_t = \mathbb{E}_t\hat{Y}_{t+1} - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t\hat{\Pi}_{t+1}) - \frac{n(1-\Gamma_H)-(1-n)(1-\Gamma_F)}{\gamma}\mathbb{E}_t(\hat{x}_{t+1}-\hat{x}_t) + \frac{1}{\gamma}\hat{e}_t.
\tag{B.37}
$$

Next, we derive the Phillips curve for aggregate inflation, defined as $\hat{\Pi}_t = n\hat{\Pi}_{Ht} + (1-n)\hat{\Pi}_{Ft}$, after noting that $n(1-\phi_H) = (1-n)(1-\phi_F)$:

$$
\hat{\Pi}_t = \kappa(\alpha+\gamma)\hat{Y}_t + \beta\mathbb{E}_t\hat{\Pi}_{t+1} + \hat{u}_t,
\tag{B.38}
$$

where $\hat{u}_t = n\hat{u}_{Ht} + (1-n)\hat{u}_{Ft}$.

B.2 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:

$$\begin{aligned}\hat{R}_t &= r_\pi(n\psi\hat{\Pi}_{Ht} + (1-\psi n)\hat{\Pi}_{Ft}) \\ &= r_\pi\hat{\pi}_t + nr_\pi(1-\psi)(\hat{x}_t - \hat{x}_{t-1})\end{aligned} \tag{B.39}$$

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 assigned 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 so that $a > 0$. 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*

$$n(\psi^* - 1) \approx max\left(-n, -\frac{\Delta a}{r_\pi}\right) \tag{B.40}$$

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 B.3. □

Proposition 4 shows that monetary policy should optimally respond to the terms of trade as long as there is effective belief asymmetry ($\Delta \neq 0$).[20] 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 if and only if $(1-n)(1-\Gamma_F) > n(1-\Gamma_H)$, that is, if the weight placed on the inflation rate of region H by consumers in region F, $1-\Gamma_F$, is sufficiently high. By contrast, if $(1-n)(1-\Gamma_F) < n(1-\Gamma_H)$ then the inflation rate of region F should be weighed by more than $1-n$.[21]

C Generalizing the Social Network Effect

In this section, we apply the assumption of socially determined expectations to consumers' expectations about consumption and firms' inflation expectations, such that

$$\widetilde{\mathbb{E}}_{Ht}\hat{C}_{H,t+1} = \mathbb{E}_t\hat{C}_{H,t+1} + (1-\Gamma_H)(\mathbb{E}_t\hat{C}_{F,t+1} - \mathbb{E}_t\hat{C}_{H,t+1}), \tag{C.1}$$

where $\mathbb{E}_t\hat{C}_{F,t+1} - \mathbb{E}_t\hat{C}_{H,t+1} = \frac{\Gamma_H+\Gamma_F-1}{\gamma}\mathbb{E}_t\hat{x}_{t+1}$. It is easy to see that generalizing the application of socially determined expectations to future consumption does not affect the Backus-Smith condition. Hence, the Euler equation in the home region becomes

$$\hat{C}_{Ht} = \mathbb{E}_t\hat{C}_{H,t+1} - \frac{1}{\gamma}\left(\hat{R}_t - \mathbb{E}_t\hat{\Pi}_{H,t+1}\right) + \frac{1}{\gamma}\hat{e}_{Ht} + \frac{1-\Gamma_H}{\gamma}\mathbb{E}_t\left[(\Gamma_H+\Gamma_F-2)\hat{x}_{t+1} + \hat{x}_t\right]. \tag{C.2}$$

[20] If $\Delta = 0$, then policy responds the most to the inflation rate of the region with the biggest economic size.

[21] Interpreted differently, when $\Delta < 0$, that is, the social centrality of region H relative to region F exceeds the economic centrality of of H relative to F, then it is optimal for policy to respond more to the inflation rate of region H. By contrast, when the social centrality of region H relative to region F is lower than the economic centrality of of H relative to F ($\Delta > 0$), then it is optimal to respond less to the inflation rate of region H.

The Phillips curves for the home and foreign inflation are also affected as follows:

$$\begin{aligned}\hat{\Pi}_{Ht} = {} & \kappa(\alpha+\gamma)\hat{C}_{Ht} + \kappa(1-\phi_H)(\chi-\widetilde{\chi})\hat{x}_t - \beta(1-\Gamma_H)\mathbb{E}_t(\hat{x}_{t+1}-\hat{x}_t) + \beta\mathbb{E}_t\hat{\Pi}_{H,t+1} \\ & - \frac{\kappa(1-\phi_H)\hat{\chi}}{\gamma}(\hat{e}_{Ht}-\hat{e}_{Ft}) - (1-\phi_H)(\hat{u}_{Ht}-\hat{u}_{Ft}) + \hat{u}_{Ht}\end{aligned} \tag{C.3}$$

$$\begin{aligned}\hat{\Pi}_{Ft} = {} & \kappa(\alpha+\gamma)\hat{C}_{Ft} - \kappa(1-\phi_F)(\chi-\widetilde{\chi})\hat{x}_t + \beta(1-\Gamma_F)\mathbb{E}_t(\hat{x}_{t+1}-\hat{x}_t) + \beta\mathbb{E}_t\hat{\Pi}_{F,t+1} \\ & + \frac{\kappa(1-\phi_F)\hat{\chi}}{\gamma}(\hat{e}_{Ht}-\hat{e}_{Ft}) + (1-\phi_F)(\hat{u}_{Ht}-\hat{u}_{Ft}) + \hat{u}_{Ft}\end{aligned} \tag{C.4}$$

Proposition 5. *[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 consumption:

$$\begin{aligned}\hat{C}_t &= n\hat{C}_{Ht} + (1-n)\hat{C}_{Ft} = \hat{C}_{Ht} + \frac{(1-n)(\Gamma_H+\Gamma_F-1)}{\gamma}\hat{x}_t - \frac{1-n}{\gamma}(\hat{e}_{Ht}-\hat{e}_{Ft}) \\ &= \mathbb{E}_t\hat{C}_{H,t+1} - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t\hat{\Pi}_{H,t+1}) + \frac{1-\Gamma_H}{\gamma}\mathbb{E}_t(\hat{x}_t + (\Gamma_h+\Gamma_F-2)\hat{x}_{t+1}) + \frac{1}{\gamma}\hat{e}_{Ht} \\ &\quad + \frac{(1-n)(\Gamma_H+\Gamma_F-1)}{\gamma}\hat{x}_t - \frac{1-n}{\gamma}(\hat{e}_{Ht}-\hat{e}_{Ft}) \\ &= \mathbb{E}_t\hat{C}_{t+1} - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t\hat{\Pi}_{t+1}) + \frac{1}{\gamma}\hat{e}_t \\ &\quad - \left[\frac{n(1-\Gamma_H)-(1-n)(1-\Gamma_F)}{\gamma}(\mathbb{E}_t\hat{x}_{t+1}-\hat{x}_t) - (1-\Gamma_H)(\Gamma_H+\Gamma_F-1)\mathbb{E}_t\hat{x}_{t+1}\right]\end{aligned} \tag{C.5}$$

Applying market clearing we have that aggregate output is described by

$$\hat{Y}_t = \mathbb{E}_t\hat{Y}_{t+1} - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t\hat{\Pi}_{t+1}) + \frac{1}{\gamma}\hat{e}_t$$
$$- \left[\frac{n(1-\Gamma_H)-(1-n)(1-\Gamma_F)}{\gamma}(\mathbb{E}_t\hat{x}_{t+1} - \hat{x}_t) - (1-\Gamma_H)(\Gamma_H+\Gamma_F-1)\mathbb{E}_t\hat{x}_{t+1}\right]. \tag{C.6}$$

Finally, the aggregate Phillips curve is given by:

$$\hat{\Pi}_t = \kappa(\alpha+\gamma)\hat{Y}_t + \beta\mathbb{E}_t\hat{\Pi}_{t+1} + \hat{u}_t - \beta\left[n(1-\Gamma_H)-(1-n)(1-\Gamma_F)\right]\mathbb{E}_t(\hat{x}_{t+1}-\hat{x}_t). \tag{C.7}$$

Thus, socially determined inflation expectations would have an effect on aggregate dynamics if $n(1-\Gamma_H)-(1-n)(1-\Gamma_F)\neq 0$ and/or $(1-\Gamma_H)(1-\Gamma_F-\Gamma_H)\neq 0$. □

Corollary 2 shows socially determined expectations can distort the dynamics away from FIRE even when both regions are symmetric to one another, that is, if $n=0.5$ and $\Gamma_H=\Gamma_F=\Gamma\neq 1$, as long as $\Gamma\neq 0.5$.

Corollary 2. *[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 $\Gamma\neq 0.5$.

Proof. Follows from Proposition 5. □

D Microfoundations for the Formation of Inflation Expectations in the Presence of Social Networks

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.

D.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.[22]

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

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

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

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

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

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

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

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

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 (D.2). Proposition 6 formalizes this positive relationship between inflation and the recall probability of events linked to the hypothesis of high inflation.

Proposition 6. *Individual inflation expectations π_i^e are increasing in the recall probability of the high-inflation regime.*

Proof. 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. □

D.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, $E_{j \to i}^H$, low inflation experiences, $E_{j \to i}^L$, and experiences irrelevant to high or low inflation, $E_{j \to i}^O$.

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 $e \in E_{j \to i}^k$ 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.[23]

[23] 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

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:

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

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 personal and network component as follows:

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

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 expe-

network formation process.

riences; 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 7 formalizes this analysis.

Proposition 7. *Consider individual i's recall probability of hypothesis k in equation (D.4). Then, the following statements are true:*

1. *The social network has an effect on the recall probability of individual i if and only if individual i allocates attention to experiences shared by others, that is, if and only if* $\gamma_i \in (0,1)$.
2. *Suppose that i assigns some weight to the experiences shared by others, that is,* $\gamma_i \in (0,1)$. *Then,*
$$\frac{\partial \hat{r}_i(k)}{\partial \mathbf{S}_{\delta_{i.}}^{k}} > 0 \text{ and } \frac{\partial \hat{r}_i(k)}{\partial \mathbf{S}_{\delta_{i.}}^{K\setminus k}} < 0 \tag{D.5}$$
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. Consider individual j's recall probability of hypothesis k

$$\hat{r}_i(k) = \frac{\gamma_i \mathbf{S}_i^k + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}^k}{\gamma_i \mathbf{S}_i + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}} \tag{D.6}$$

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

$$\frac{\partial \hat{r}_i(k)}{\partial \mathbf{S}_{\delta_{i.}}^k} = (1-\gamma_i)\frac{\gamma_i \mathbf{S}_i^{K\backslash k} + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}^{K\backslash k}}{\gamma_i \mathbf{S}_i + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}} \geq 0 \tag{D.7}$$

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

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 6, 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 3 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 3. *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 6 and 7. □

D.3 Testable Implications for Inflation Expectations

How predictions of the model map into a fairly generally defined empirical environment? Following Proposition 7, 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:

$$\pi_i^e = \alpha + \beta \times \sum_{j=1}^{N} \omega_{ij} \pi_j^e + \varepsilon_i \tag{D.8}$$

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 7).