The Expectations of Others

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Inflation, Inflation Expectations, and Policy: New Perspectives
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Introduction

- Personal experiences are important for consumers' inflation expectations.
  (Malmendier and Nagel (2016), D'Acunto et al. (2021, 2023), Bordalo et al. (2022, 2023), Pedemonte et al. (2023), Afrouzi et al. (2023). . .)

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- But we live in an inter-connected world and learn through social interaction
  - Share experiences with friends and family on grocery prices, rent, gas, ...
  - Use Twitter, Facebook, ...
- Festinger (1954) theory of social comparison: *"People evaluate their opinions and abilities by comparison respectively with the opinions and abilities of others"*
- Yet, the role of social networks for formation of inflation expectations is largely unknown
  - Lack of sufficiently dense data on individual inflation expectations for entire US.

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- **This paper**: shows relevance of social networks for formation of inflation expectations, both *empirically* and *theoretically*.

This Paper: Contributions

1. Create novel dataset of expectations and social connections merging two large datasets (Indirect Consumer Inflation Expectations + Facebook linkages):
   - Monthly frequency from March 2021 to July 2023: Over 1.9 million observations
   - Network connections at the county level
2. Establish empirically the importance of social networks for inflation expectations beyond the trade/economic network
   - Combine different empirical strategies, including IV to measure the influence of social network on inflation expectations
3. Macro implications of social networks from the lens of a monetary union NK model
   - Explore both cross-sectional and aggregate implications
   - Monetary policy implications

Preview of Main Results

Empirically:

1. Social networks have a positive effect on individual inflation expectations (intensive margin).
2. The effect of common demographic networks (gender/income/age/political affiliation) is stronger than the average effect.
3. Using IV, find effect of social network is strong, but lower than one

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Theoretically, social networks

1. generate incomplete risk-sharing
2. distort aggregate macro dynamics following local shocks, but not aggregate shocks

   $\rightarrow$ to minimize distortions, policy should internalize the social network and adjust weights to regional inflation rates accordingly

Related Literature

- Social network and learning
  - Banerjee (1992), Acemoglu et al. (2011), Golub and Sadler (2016): social learning in networks
  - Arifovic et al. (2013), Grimaud et al. (2023): social learning in NK framework
- Networks in macroeconomics and finance
  - Bailey et al. (2018a, 2018b, 2019), Burnside et al. (2016): social networks and the housing market
  - Baqaee and Farhi (2018), Rubbo (2020), Pasten et al. (2020): input-output linkages and shock transmission
- Formation of expectations
  - Malmendier and Nagel (2016), D'Acunto et al. (2021), Hajdini et al. (2022): empirically, role of individual characteristics and experiences for beliefs
  - Kahneman and Tversky (1972), da Silveira et al. (2020), Bordalo et al. (2022, 2023): use of heuristics in belief formation process, memory and recall

Empirical Tests of Effects of Social Networks

- Given data on inflation expectations of i that is socially connected to j with intensity ω_{ij}:

$$\pi_i^e = \alpha + \beta \sum_{j=1, j \neq i}^{N} \omega_{ij} \pi_j^e + \psi X_i + \varepsilon_i \quad (1)$$

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- Challenges:

1. Geographically thick data on ω_{ij} and π_i^e?
   - ★ Social Connectedness Index (Bailey et al., 2018) with county level connections – ω_{ij}
   - ★ ICIE: Inflation expectations of around 80.000 individuals every month from March 2021 to July 2023 (nearly 2 million in total) (Hajdini et al., 2024) – π_i
2. Common factors that affect both left and right had side of equation?
   - ★ Use many controls, robustness exercises, and IV strategy.
3. How to get around endogeneity problems, e.g. $\pi_i^e = f(\pi_j^e)$ but also $\pi_j^e = g(\pi_i^e)$?
   - ★ IV strategy.

Data: Social Connectedness Index (SCI)

Social Connectedness Index between counties c and k (Bailey et al., 2018):

$$SCI_{ck} = \frac{\text{FB Connections}_{ck}}{\text{FB Users}_c \times \text{FB Users}_k}, \quad (2)$$

- $\text{FB Connections}_{ck}$ - total Facebook friendship links between individuals in county c and k.
- FB Users_c - total Facebook users in county c.

Define bilateral social connectedness weights between county c and county k

$$\omega_{ck} = \frac{SCI_{ck}}{\sum_n SCI_{cn}} \quad (3)$$

Proxies how important is county k for an individual living in county c.

Data: Indirect Consumer Inflation Expectations (ICIE)

- Joint project between Morning Consult and the Federal Reserve Bank of Cleveland.
- Nationally representative sample
- Monthly 80,000 observations from March 2021 to July 2023 in the US
- Detailed information on demographic characteristics and zipcode where respondent is
- Aggregate information available online and updated weekly via CEBRA at https://cebra.org/indirect-consumer-inflation-expectations/

Data: Indirect Consumer Inflation Expectations (ICIE)

Q: [...] *Given your expectations about developments in prices of goods and services during the next 12 months, how would your income have to change to make you equally well-off relative to your current situation, such that you can buy the same amount of goods and services as today?* [...] *To make me equally well off, my income would have to*

- *Increase by ____ %*
- *Stay about the same*
- *Decrease by ____ %*

Evolution of ICIE over time

- Variations in individual prices must be reflected in variations in individual income holding individual consumption basket fixed
- Individual-level Laspeyres index; see Hajdini et al. (2024)
- Used to construct expectations of others at the county level:

$$\pi_{ct}^{e,others} = \sum_{k \neq c} \omega_{ck} \pi_{kt}^{e} \tag{4}$$

Steps of Empirical Analysis

1. Establish a positive correlation between own inflation expectations and expectations of others – does the network matter per se?
2. Rule out that the empirical measures of beliefs of others reflect "other factors" such as trade relationships or common price shocks transmitted through common consumption baskets
3. Construct exogenous expectations shocks to the inflation expectations of others
    - Establish the causal impact of social interaction on inflation expectations.

Step 1: Does the Network Matter?

$$\pi^e_{ict} = \alpha_0 + \gamma_t + \alpha_c + \alpha_1 \pi^e_{-ict} + \beta \sum_{k \neq c} \omega_{ck} \pi^e_{k,t} + \varepsilon_{ict}, \tag{5}$$

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

Note. Observations weighted by the number of answers each period; standard errors clustered at the county level.

County-level evidence

Step 2: Is it the Social Network or Something Else?

- **Rule out that $\hat{\beta}$ reflects "other factors" across counties in social network:**

$$\pi_i^e = \beta \times \text{inflation expectations of others} + \psi \times \text{other factors} \tag{6}$$

Other factors: common shocks; other common networks; common demographics...

- **Two approaches:**
  1. Directly account for other factors
  2. Enrich data structure and include county-time fixed effects (not today)

  → Effect of common demographics stronger than the average effect Results

Step 2.1: Directly Account for Demographic Factors

$$\pi^e_{ict} = \alpha_c + \gamma_t + \eta_{d(i),t} + \alpha_1 \pi^e_{-ict} + \beta \sum_{k \neq c} \omega_{ck} \pi^e_{k,t} + \varepsilon_{ict}$$

	(1)	(2)	(3)	(4)
Expectations of Others	0.051***	0.068***	0.058***	0.059***
	(0.017)	(0.019)	(0.020)	(0.020)
County Expectations	0.557***	0.542***	0.469***	0.454***
	(0.049)	(0.051)	(0.019)	(0.016)
Time FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Demographic FE	No	Yes	Yes	Yes
Demographic-Time FE	No	No	Yes	Yes
Combined Dem-Time FE	No	No	No	Yes
Observations	1,926,282	1,925,393	1,925,393	1,925,393
R-squared	0.017	0.033	0.036	0.049

Note. Observations weighted by the number of answers each period; standard errors clustered at the county level.

Step 2.1: Exclude Geographically Close Counties

$$\pi^e_{ict} = \gamma_t + \alpha_c + \alpha_1 \pi^e_{-ict} + \beta \sum_{|k-c|>r} \omega_{ck} \pi^e_{k,t} + \varepsilon_{ict} \quad (7)$$

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

Step 2.1: Directly Account for Common Retail Chains

- Could a hidden driver of inflation expectations co-movement be common retail chains ?
  - Uniform pricing strategies across locations (DellaVigna and Gentzkow, 2019)
  - Synchronized price adjustments in counties w/ common retail chains (Garcia-Lembergman (2020))
  - Salient prices important for how people form expectations (D'Acunto et al. (2021a, 2021b))
- Construct common retail chain weights, $\widetilde{\omega}_{ck}$, according to sale values of dominant county c retail chains in another county k

Step 2.1: Directly Account for Common Retail Chains

$$\pi^e_{ict} = \gamma_t + \alpha_c + \alpha_1 \pi^e_{-ict} + \beta_1 \underbrace{\sum_{k \neq c} \omega_{ck} \pi^e_{k,t}}_{\text{social network}} + \beta_2 \underbrace{\sum_{k \neq c} \widetilde{\omega}_{ck} \pi^e_{k,t}}_{\text{price network}} + \varepsilon_{ict} \tag{8}$$

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

Step 3: An Unbiased Estimate

- Goal: Exogenous inflationary shock at the **county level** with time variation.
  - Results not driven from the network speeding up learning about *common* shocks, but from idiosyncratic experiences becoming available over the network
- Cannot just use local prices.
  - Consumers tend to use local prices to form expectations (D'Acunto et al. (2023))
  - Local prices are affected by local demand (or expectations)

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  - Local prices are affected by local demand (or expectations)
- Exploit cross-sectional variation in car usage and national gas prices:

$$\pi^e_{idct} = \alpha_{c(i)} + \gamma_t + \psi^d \left[P_{gas,t} \times Comm_{c(i)} \right] + \varepsilon_{idct} \quad (9)$$

  - Heterogenous gas usage idea as in Hajdini et al. (2024).
  - Take into account gender-specificity of shift-share as in D'Acunto et al.(2021): Gender differences in influence of certain prices for inflation expectations.

SCI linkages uncorrelated with commuter shares

Step 3: An Unbiased Estimate

- Construct $Gas\_effect_{dct} = \hat{\psi}^{d}\,[P_{gas,t} \times Comm_c]$ $(\hat{\psi}^{M} = 3.958^{***},\ \hat{\psi}^{W} = 0.834^{**})$ Zoom in
  - Variation at the *gender, county*, and *time* level, in line with D'Acunto et al. (2021)
- Construct "gas price shock of others:" $\sum_{k \neq c} \omega_{ck}\, Gas\_effect_{dkt}$ with $d \in \{M, W\}$
- Estimate IV regressions at the individual level:

$$\pi^{e}_{idct} = \alpha_c + \alpha_t + \alpha_1 \pi^{e}_{-i,dct} + \beta \underbrace{\sum_{k \neq c} \omega_{ck} \pi^{e}_{dkt}}_{\text{IV: } \sum_{k \neq c} \omega_{ck}\, Gas\_effect_{dkt}} + \varepsilon_{idct} \tag{10}$$

Step 3: An Unbiased Estimate

	(1)	(2)	(3)	(4)
$\sum_{k \neq c} \omega_{ck} Gas\_effect_{c,d,t}$	1.980***	0.571***		
	(0.200)	(0.190)		
$\sum_{k \neq c} \omega_{ck} \pi^{e}_{d,k,t}$			0.359***	0.491***
			(0.047)	(0.088)
$\pi^{e}_{-i,d,c,t}$	0.532***	0.365***	0.593***	0.561***
	(0.023)	(0.012)	(0.029)	(0.040)
Sample	Men	Female	All	All
Time FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Regression	OLS	OLS	OLS	IV
F-Test	-	-	-	1459
Observations	882,338	1,028,341	1,910,679	1,910,679
R-squared	0.020	0.018	0.026	0.012

- Men react more strongly to gas prices *in their social network*, akin to D'Acunto et al. (2021) – differently relevant information.

Model

NK model of monetary union similar to Nakamura and Steinsson (2014).

Benigno and Benigno (2003); Galí and Monacelli (2008).

- 2 regions: home (H) with size n and foreign (F) with size $1-n$.
- Regions trade with each other; workers are immobile across regions.
- Consumers common utility preferences; firms rely on the same linear production function; subject to the same Calvo price rigidity. Details
- Standard Taylor rule:

$$\frac{R_t}{\bar{R}} = \left(\frac{\pi_{Ht}^{n}\pi_{Ft}^{1-n}}{\bar{\pi}}\right)^{r_\pi} \tag{11}$$

Socially Determined (Inflation) Expectations

Empirical results: others' inflation expectations matter!

$$\hat{c}_{it} = \mathbb{E}_{it}\hat{c}_{i,t+1} - (\hat{R}_t - \widetilde{\mathbb{E}}_{it}\hat{\Pi}_{i,t+1} - \hat{e}_{it}) \tag{12}$$

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$$\widetilde{\mathbb{E}}_{it}\hat{\Pi}_{i,t+1} = \Gamma_i \mathbb{E}_t\hat{\Pi}_{i,t+1} + (1 - \Gamma_i)\mathbb{E}_t\hat{\Pi}_{j,t+1} \tag{13}$$

Remarks:

- Micro-foundation: extension of the memory and belief model of Bordalo et al. (2023) Details
- $\Gamma_i = 1 \Rightarrow$ back to RE
- Reminiscent of the behavioral biases in Bianchi et al. (2023) and L'Huillier et al. (2023), applied in the cross-section.

Distortions due to Socially Determined Expectations

Corollary (Incomplete Risk-Sharing)

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

$$-\hat{c}_{Ht} + \hat{c}_{Ft} = \hat{x}_t - \underbrace{(2 - \Gamma_H - \Gamma_F)\hat{x}_t}_{\text{social network effect}} \tag{14}$$

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

- Similar to an uncovered interest parity shock in Itskhoki and Mukhin (2021) and Candian and De Leo (2023) that leads to modified risk-sharing condition.

Under-weighing local goods; over-weighing foreign goods

Aggregate Dynamics

$$\hat{\Pi}_t = \kappa_c \hat{c}_t + \beta \mathbb{E}_t \hat{\Pi}_{t+1} + \hat{u}_t \tag{15}$$

$$\hat{c}_t = \mathbb{E}_t \hat{c}_{t+1} - (\hat{R}_t - \mathbb{E}_t \hat{\Pi}_{t+1}) + \underbrace{[n(1-\Gamma_H) - (1-n)(1-\Gamma_F)] \mathbb{E}_t (\hat{x}_t - \hat{x}_{t+1})}_{\text{social network distortion: } \Delta * \mathbb{E}_t(\hat{x}_t - \hat{x}_{t+1})} + \hat{e}_t \tag{16}$$

- $\Delta = n(1-\Gamma_H) - (1-n)(1-\Gamma_F)$: effective belief asymmetry
- $\hat{u}_t$, $\hat{e}_t$: supply & demand shocks

Aggregate Dynamics

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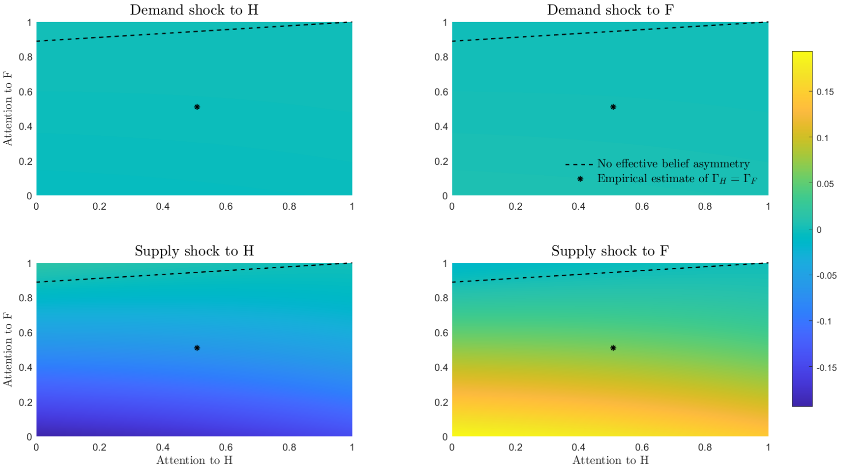
- $\Delta = n(1-\Gamma_H) - (1-n)(1-\Gamma_F)$: effective belief asymmetry
- $\hat{u}_t$, $\hat{e}_t$: supply & demand shocks

Proposition (Aggregate dynamics)

Socially determined expectations distort aggregate dynamics following a **regional shock** *iff there is* **effective belief asymmetry**. *Aggregate shocks do not lead to a distortion relative to RE.*

Inflation Impact: Socially Determined Inflation Expectations Relative to RE



Calibration as in Nakamura and Steinsson (2014), Similar outcome for output

Should Policy Place Regional Inflation Weights $\neq$ Economic Sizes?

$$\hat{R}_t = r_\pi \left[n\psi \hat{\Pi}_{Ht} + (1 - \psi n)\hat{\Pi}_{Ft} \right] \tag{17}$$

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

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Proposition

Let Phillips curve be almost flat in both regions. The additional optimal weight to the inflation rate of region H is

$$n(\psi^* - 1) \approx max\left(-n, -\frac{\Delta a}{r_\pi}\right) \tag{18}$$

a is the dependence of the current terms of trade on its past realization,
$\Delta = n(1 - \Gamma_H) - (1 - n)(1 - \Gamma_F) \neq 0$.

For our baseline calibration w/ $\Delta < 0$, $\psi^* = 1.26 \Rightarrow$

- Place weight 0.126 instead of $n = 0.1$ to region H.

Concluding Remarks

- Social networks are a relevant channel for how people form inflation expectations.
- Social networks positively affect individual inflation expectations.
    - Common demographic networks have stronger than average effects on inflation expectations.
- Social networks affect aggregate dynamics for inflation and output.
- To minimize deviations of dynamics from the RE benchmark, policy should internalize the social network and appropriately adjust weights assigned to regional inflation rates.

County Level OLS Results

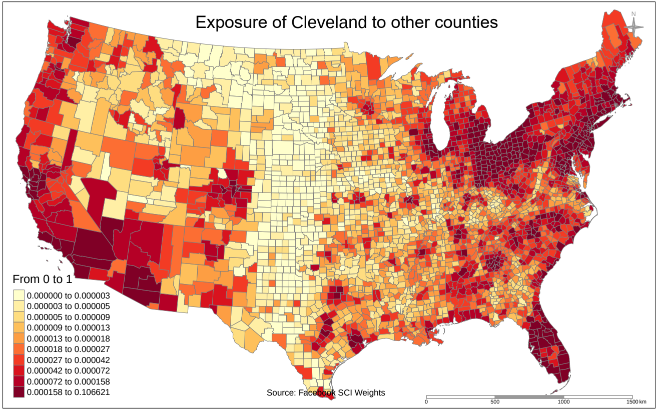
$$\pi^e_{ct} = \alpha_c + \gamma_t + \beta \sum_{k \neq c} \omega_{ck} \pi^e_{kt} + \varepsilon_{ct}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Expectations of Others	0.670***	0.306***	0.055***	0.318***	0.043**	0.035**	0.041**
	(0.018)	(0.018)	(0.020)	(0.017)	(0.018)	(0.018)	(0.018)
Average Expectations					0.997***		
					(0.036)		
Constant	2.172***	6.461***					
	(0.192)	(0.169)					
Sample	N>10	All	All	All	All	All	N>10
Weights	Yes	No	No	No	No	No	Yes
County FE	No	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	No	No	Yes	Yes
Observations	24,255	60,055	60,065	60,015	60,015	60,015	24,070
R-squared	0.151	0.009	0.026	0.150	0.167	0.167	0.441

Note. In column (1) and (7) we rely on counties with at least 10 observations ($N > 10$) and weight regressions by the number of answers in each period. Standard errors clustered at the county level.

Back to individual level evidence

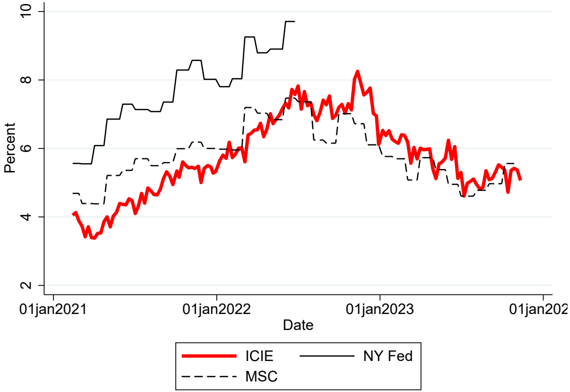
Bilateral Social Connectedness Weights: $\omega_{Cleveland,k}$



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.

Back to SCI data

Evolution of ICIE Over Time



- Weekly trimmed mean ICIE, NY Fed SCE mean and Michigan Survey of Consumers mean.
- ICIE highly correlated with both conventional measures of aggregate inflation.

Back to ICIE

Step 2.2: Introducing County-Time Fixed Effects

- Enrich data structure by adding a layer to the network – discriminate along demographic features – computing inflation expectations of a network with *shared demographic d*:

$$\pi^{e,others}_{dct} = \sum_{k \neq c} \omega_{ck} \pi^{e}_{dkt} \tag{19}$$

- Focus on gender (exogenous) and estimate:

$$\pi^{e}_{idct} = \alpha_c + \gamma_t + \phi_{ct} + \alpha_1 \pi^{e}_{-idct} + \beta \sum_{k \neq c} \omega_{ck} \pi^{e}_{dkt} + \varepsilon_{idct} \tag{20}$$

where

- π^{e}_{idct} – inflation expectation of individual i, with gender d, in county c, at time t
- π^{e}_{-idct} – average inflation expectation of everyone else in county c with gender d, at time t
- ϕ_{ct} – county-time fixed effects

Back

Step 2.2: Networks of Common Demographics Are Even More Important

$$\pi^e_{idct} = \alpha_c + \gamma_t + \phi_{ct} + \alpha_1 \pi^e_{-idct} + \beta \sum_{k \neq c} \omega_{ck} \pi^e_{dkt} + \varepsilon_{idct}$$

	(1)	(2)	(3)	(4)	(5)	(6)
$\sum_{k \neq c} \omega_{ck} \pi^e_{dkt}$	0.282***	0.334***	0.306***	0.359***	0.413***	0.777***
	(0.038)	(0.028)	(0.057)	(0.047)	(0.052)	(0.092)
π^e_{-idct}	0.684***	0.667***	0.610***	0.593***	0.535***	0.204***
	(0.040)	(0.029)	(0.043)	(0.029)	(0.015)	(0.056)
County FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes	Yes
State-Time FE	No	No	No	No	Yes	Yes
County-Time FE	No	No	No	No	No	Yes
Observations	1,910,679	1,910,679	1,910,679	1,910,679	1,910,679	1,910,679
R-squared	0.026	0.026	0.026	0.026	0.027	0.030

Note. Observations weighted by number of answers in a county each period; similar results when controlling by state-time FE; standard errors clustered at the county and time level. Control for other gender, All demographic factors

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Networks of Common Gender Amplify Inflation Expectations

Interference from the opposite gender

$$\pi^e_{idct} = \alpha_c + \gamma_t + \beta_1 \pi^e_{-jdct} + \beta_2 \sum_{k \neq c} \omega_{ck} \pi^e_{dkt} + \rho_1 \pi^e_{-j,-dct} + \rho_2 \sum_{k \neq c} \omega_{ck} \pi^e_{-dkt} + \varepsilon_{idct} \quad (21)$$

	(1)	(2)	(3)	(4)
$\sum_{k \neq c} \omega_{ck} \pi^e_{dkt}$	0.309***	0.275***	0.339***	0.204***
	(0.037)	(0.020)	(0.054)	(0.029)
$\sum_{k \neq c} \omega_{ck} \pi^e_{-dkt}$	-0.065***	-0.100**	-0.011	-0.148***
	(0.025)	(0.040)	(0.031)	(0.032)
π^e_{-jdct}	0.664***	0.653***	0.588***	0.566***
	(0.034)	(0.031)	(0.040)	(0.040)
$\pi^e_{-j,-dct}$	0.028***	0.021**	-0.045***	-0.065***
	(0.009)	(0.010)	(0.012)	(0.016)
Constant	Yes	No	No	No
County FE	No	No	Yes	Yes
Time FE	No	Yes	No	Yes
Observations	1,571,662	1,571,662	1,571,662	1,571,662
R-squared	0.025	0.025	0.025	0.026

Note. Observations weighted by number of answers in a county in each period; standard errors clustered at county-time level.

Main results for gender

Effects of Social Network Across all Demographics

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

Note. Observations are weighted by the number of answers in a county in each period; all specifications control for network and own county expectations. Standard errors are clustered at the county level and time level.

Results for gender

Measuring Gas Effect on County expectations

$$\pi^e_{idt} = \alpha_{c(i)} + \gamma_t + \psi^d \left[P_{gas,t} \times Comm_{c(i)}\right] + \varepsilon_{idt}$$

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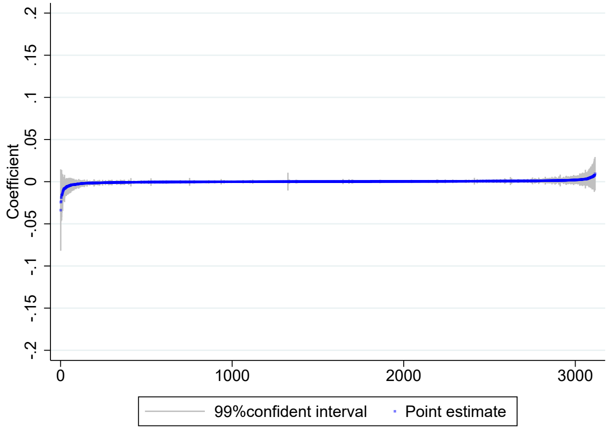
	(1)	(2)	(3)	(4)	(5)	(6)
$P_{gas,t}$	-0.874**	-1.060				
	(0.375)	(0.211)				
$Comm_{c(i)}$	-7.457***		-8.383***			
	(1.347)		(1.130)			
$P_{gas,t} \times Comm_{c(i)}$	3.171***	3.318***	3.310***	3.414***	3.958***	0.834**
	(0.513)	(0.386)	(0.444)	(0.407)	(0.475)	(0.379)
County FE	No	Yes	No	Yes	Yes	Yes
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

Bilateral SCI Weights and Own Car Commuting Shares



Back to Exogenous Variation

Theory of Belief Formation: Overview

- Benchmark model without social interaction following Bordalo et al. (2022, 2023):
  - When forming expectations, people use subjective probabilities.
  - Subjective probabilities depend on the number of successful "recalls" (draws) of experiences related to the respective "hypotheses" (events such as "high inflation" or "low inflation").
  - The probability of recall depends on the similarity of all relevant experiences in one's memory and the hypothesis evaluated.

- Model with social interaction:
  - Social interaction extends the set of experiences people may recall, affecting the recall probability.
  - **General mechanism:** Akin to a composition effect, when experiences recalled from the social network are more similar to the relevant hypothesis, they can amplify the recall probability and expectations.

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Theoretical Framework: Benchmark Without Social interactions

Setting similar to Bordalo et al. (2022, 2023)

- Set of personal experiences for individual i: E_i.
- $E_i = E_i^H \cup E_i^L \cup E_i^O$
  - H - high inflation; L - low inflation; O - irrelevant to inflation
- Similarity between u_i and $v_i \in E_i$: $S_i(u_i, v_i)$
  - S_i - *subjective* function, abstract from particular functional forms
  - Similarity between e_i and hypothesis k, $S_i(e_i, k)$, increases in shared features of e_i & k.
- Probability of recalling experiences related to hypothesis k

$$r_i(k) = \frac{\sum_{e \in E_i^k} S_i(e, k)}{\sum_{u \in E_i} S_i(u, k)} \in [0, 1] \tag{22}$$

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From Recall Probabilities to Expectations

2 regimes for inflation: high (H) with $\bar{\pi}^H$, or low (L) with $\bar{\pi}^L$

- Presence of regimes and $(\bar{\pi}^L, \bar{\pi}^H)$: common knowledge
- Given $r_i(k)$, i draws T_i experiences from memory database with replacement
- $R_i(k) =$ no. of successfully recalled experiences k-relevant: $R_i(k) \sim Bin(T_i, r_i(k))$
- Subjective probability that regime k will realize is $p_i(k) = \frac{R_i(k)}{R_i(H)+R_i(L)}$ and

$$\mathbb{E}_i[\pi] = p_i(H)\bar{\pi}^H + (1 - p_i(H))\bar{\pi}^L = p_i(H)(\bar{\pi}^H - \bar{\pi}^L) + \bar{\pi}^L$$

  - Distinct recall probabilities across individuals due to different experiences $=>$ heterogeneous probabilities assigned to H $=>$ heterogeneous inflation expectations
  - **Higher $r_i(H)$ leads to higher inflation expectations $\Rightarrow$ focus on recall probabilities.**

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Theoretical Framework with Social Interactions

- Individual i interacts with individuals $j \in \{1, 2, ..., i-1, i+1, ..., N_i\}$.
- Set of experiences i shares with i: $E_{j \to i} = E^H_{j \to i} \cup E^L_{j \to i} \cup E^O_{j \to i}$.
- Similarity between $e \in E^k_{j \to i}$ and k may depend on the share of common demographic characteristics, δ_{ij}.
- Individual i assigns weight γ_i to own experiences and $(1 - \gamma_i)$ to others' experiences.
- She assigns weight $\omega_{ij} \in [0, 1]$ to experiences shared by individual j s.t. $\sum_{j \neq i} \omega_{ij} = 1$.
- Probability of recalling experiences related to hypothesis k

$$\hat{r}_i(k) = \frac{\gamma_i \sum_{e \in E^k_i} S_i(e, k) + (1 - \gamma_i) \sum_j \omega_{ij} \sum_{e \in E^k_{j \to i}} S_i(e, k \mid \delta_{ij})}{\gamma_i \sum_{u \in E_i} S_i(u, k) + (1 - \gamma_i) \sum_j \omega_{ij} \sum_{u \in E_{j \to i}} S_i(u, k \mid \delta_{ij})} \tag{23}$$

- Next: summarize similarity of *all own* experiences as $\mathbf{S}_i$, *k-relevant own* experiences as $\mathbf{S}^k_i$, *all network* experiences as $\mathbf{S}_{\delta_{i.}}$, *k-relevant network* experiences as $\mathbf{S}^k_{\delta_{i.}}$. Back

Role of Social Networks

$$\hat{r}_i(k) = \underbrace{\frac{\gamma_i \mathbf{S}_i^k}{\gamma_i \mathbf{S}_i + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}}}_{\text{personal: interference}} + \underbrace{\frac{(1-\gamma_i)\mathbf{S}_{\delta_{i.}}^k}{\gamma_i \mathbf{S}_i + (1-\gamma_i)\mathbf{S}_{\delta_{i.}}}}_{\text{network: amplification}} \quad (24)$$

- There is a network effect on $\hat{r}_i(k)$ if $\gamma_i < 1$.
  - Prerequisite: individuals are attentive to networks.
- $k-$**irrelevant** experiences shared on the network interfere w/ both the individual and network components.
  - On net: **interference** $(\partial \hat{r}_i(k)/\partial \mathbf{S}_{\delta_{i.}} < 0)$.
- $k-$**relevant** experiences shared on the network interfere w/ individual component and amplify the network component.
  - On net: **amplification** $(\partial \hat{r}_i(k)/\partial \mathbf{S}_{\delta_{i.}}^k > 0)$.

Important: As long as $\gamma_i < 1$, there is a positive link between i's beliefs and network's beliefs.

Role of Demographics

Recall: Shared common demographics affect the similarity function.

- Example of binary shared demographic: $\delta_{ij} \in \{0, 1\}$.
- An additional set of k-relevant experiences $\{e\}$ is shared on the network of i.
- The effect of common demographic networks on expectations is stronger than the average effect if

$$\underbrace{\frac{\partial \mathbf{S}^{k}_{\delta_{i.}=1}}{\partial e}}_{\text{common demog. marginal relevance}} > \underbrace{\frac{\partial \mathbf{S}^{k}_{\delta_{i.}=0}}{\partial e}}_{\text{other demog. marginal relevance}}$$

  for any k-relevant experience e. Positive composition effect.

- **Intuition**: Common demographic share experiences that are easier to recall, becoming more relevant (similar history of events, consumption bundle, etc)

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Households

Standard problem: max utility wrt consumption, labor hours, risk-less one-period bonds

$$\max_{C_{Ht}, L_{Ht}, B_{Ht}/P_{Ht}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \zeta_{Ht} \left[\frac{C_{Ht}^{1-\gamma}}{1-\gamma} - \psi \frac{L_{Ht}^{1+\alpha}}{1+\alpha} \right] \tag{25}$$

$$B_{H,t+1} + P_{Ht} C_{Ht} = W_{Ht} L_{Ht} + B_{Ht} R_t + D_{Ht} \tag{26}$$

- C_{Ht} – consumption of HHs in region H
- L_{Ht} – labor hrs of workers in H
- B_{Ht} – nominal bond holdings of consumers in H
- W_{Ht} – nominal wage of workers in H
- P_{Ht} – price level in H
- R_t – nominal interest rate set by monetary authority
- D_{Ht} – nominal profits of firms in H distributed to consumers in H
- ζ_{Ht} – preference shock in H

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Households (cont'd)

- CES preferences across varieties produced in the H and F regions:

$$C_{Ht} = \left[\phi_H^{\frac{1}{\nu}} C_{H,H,t}^{\frac{\nu-1}{\nu}} + (1-\phi_H)^{\frac{1}{\nu}} C_{H,F,t}^{\frac{\nu-1}{\nu}} \right]^{\frac{\nu}{\nu-1}} \tag{27}$$

  - $C_{j,i,t}$ – consumption of goods produced in region i by consumers located in region j:

$$C_{i,j,t} = \left(\int_0^1 c_{i,j,t}(z)^{\frac{\eta_t - 1}{\eta_t}} dz \right)^{\frac{\eta_t}{\eta_t - 1}} \tag{28}$$

  - ϕ_H – preference for the local good
  - preferences for local goods   to relative economic sizes: $(1-n)(1-\phi_F) = n(1-\phi_H)$.

Households (cont'd)

- CES preferences across varieties produced in the H and F regions:

$$C_{Ht} = \left[\phi_H^{\frac{1}{\nu}} C_{H,H,t}^{\frac{\nu-1}{\nu}} + (1-\phi_H)^{\frac{1}{\nu}} C_{H,F,t}^{\frac{\nu-1}{\nu}} \right]^{\frac{\nu}{\nu-1}} \tag{27}$$

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  - ϕ_H – preference for the local good
  - preferences for local goods to relative economic sizes: $(1-n)(1-\phi_F) = n(1-\phi_H)$.

- Implied price index in H

$$P_{Ht} = \left(\phi_H p_{Ht}^{1-\nu} + (1-\phi_H) p_{Ft}^{1-\nu} \right)^{\frac{1}{1-\nu}} \tag{29}$$

  - p_{Ht} – price of the good produced in H

Firms

Continuum of firms in the home region that produce tradable varieties and face demand coming from all regions.

- Demand for goods produced in H:

$$Y_{Ht} = nC_{H,H,t} + (1-n)C_{F,H,t} \tag{30}$$

- Production function linear in labor: $Y_{Ht}(z) = L_{Ht}(z)$.
- Common real marginal costs across firms within H: $mc_{Ht} = \frac{W_{Ht}}{P_{Ht}}$
- Calvo (1983) price rigidity:

$$\max_{p_{Ht}(z)} \mathbb{E}_t \sum_{j=0}^{\infty} (\theta\beta)^{t+j} Q_{t,t+j} \left[p_{Ht}(z) y_{H,t+j}(z) - mc_{H,t+j} L_{t+j}(z) \right] \tag{31}$$

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

- Note: Problem of households and firms in the F region is similar.

Distortions due to Socially Determined Expectations

$$\widetilde{\mathbb{E}}_{it}\hat{\Pi}_{i,t+1} = \Theta_i^{own} \underbrace{\mathbb{E}_t\hat{\pi}_{i,t+1}}_{\text{goods produced in } i} + \Theta_i^{other} \underbrace{\mathbb{E}_t\hat{\pi}_{j,t+1}}_{\text{goods produced in } j} \tag{32}$$

- $\Theta_i^{own} = \phi_i\Gamma_i + (1-\phi_i)(1-\Gamma_i)$; $\Theta_i^{other} = 1 - \Theta_i^{own}$

Proposition (Under-weighing local goods but over-weighing foreign goods)

Relative to RE, if there is home bias ($\phi_i > 0.5$), then social determination of inflation expectations will under-weigh the inflation expectations of local goods, but will over-weigh the inflation expectations of goods in the other region:

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

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Regional Dynamics

Consumption block:

$$\hat{c}_{Ht} = \mathbb{E}_t \hat{c}_{H,t+1} - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t \hat{\Pi}_{H,t+1}) + \frac{1}{\gamma}\hat{e}_{Ht} - \underbrace{\frac{1-\Gamma_H}{\gamma}\mathbb{E}_t(\hat{x}_{t+1} - \hat{x}_t)}_{\text{social network distortion}} \tag{33}$$

$$\hat{c}_{Ft} = \hat{c}_{Ht} + \frac{1}{\gamma}\hat{x}_t - \frac{1}{\gamma}(\hat{e}_{Ht} - \hat{e}_{Ft}) + \underbrace{\frac{(\Gamma_H + \Gamma_F - 2)}{\gamma}\hat{x}_t}_{\text{social network distortion}} \tag{34}$$

Inflation block:

$$\hat{\Pi}_{Ht} = \kappa(\alpha+\gamma)\hat{c}_{Ht} + \beta\mathbb{E}_t\hat{\Pi}_{H,t+1} + \kappa(1-\phi_H)\chi\hat{x}_t + \hat{u}_{Ht} - \frac{\kappa\alpha(1-\phi_H)}{\gamma}(\hat{e}_{Ht} - \hat{e}_{Ft}) + \underbrace{\kappa(1-\phi_H)\widetilde{\chi}\hat{x}_t}_{\text{social network distortion}} \tag{35}$$

$$\hat{\Pi}_{Ft} = \kappa(\alpha+\gamma)\hat{c}_{Ft} + \beta\mathbb{E}_t\hat{\Pi}_{F,t+1} - \kappa(1-\phi_F)\chi\hat{x}_t + \hat{u}_{Ft} + \frac{\kappa\alpha(1-\phi_F)}{\gamma}(\hat{e}_{Ht} - \hat{e}_{Ft}) - \underbrace{\kappa(1-\phi_F)\widetilde{\chi}\hat{x}_t}_{\text{social network distortion}} \tag{36}$$

Terms of trade and policy rule block:

$$\hat{x}_t = \hat{x}_{t-1} + \hat{\Pi}_{Ht} - \hat{\Pi}_{Ft} \tag{37}$$

$$\hat{R}_t = r_\pi(n\hat{\Pi}_{Ht} + (1-n)\hat{\Pi}_{Ft}) \tag{38}$$

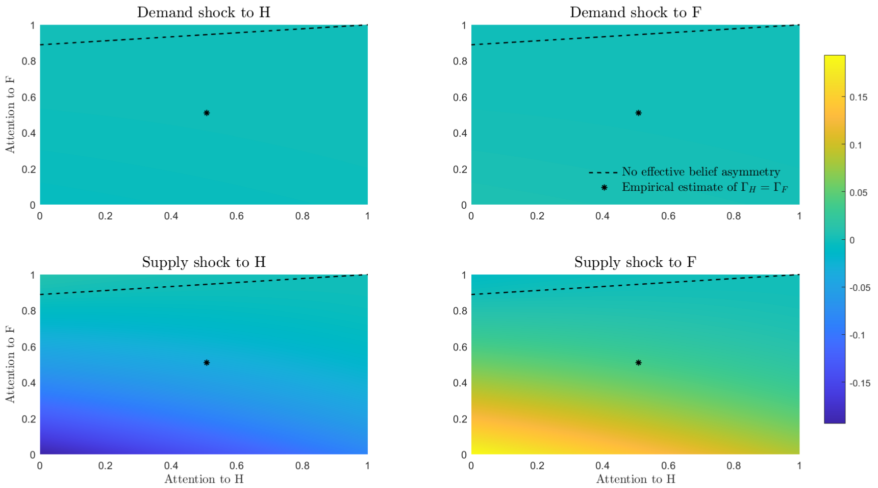
Calibration as in Nakamura and Steinsson (2014)

Parameter		Value
Discount factor	β	0.99
Inverse Frisch elasticity of labor supply	α	1
Varieties elasticity of substitution	ν	2
Calvo parameter	θ	0.75
Size of home region	n	0.1
Local good preference in home region	ϕ_H	0.69
Local good preference in foreign region	ϕ_F	0.9656
Feedback to inflation	r_π	1.5
Standard deviation of shocks	$\sigma_e = \sigma_u = \sigma$	1
Attention to H and F	$\Gamma_H = \Gamma_F$	0.509

Impact of a one-time shock relative to RE intuition

- demand shock in H: 0.11% lower output; 0.18% lower inflation
- supply shock in H: 3.7% lower output; 6.2% lower inflation

Output Impact: Socially Determined Inflation Expectations Relative to RE



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Intuition

- Terms of trade are given by $\hat{x}_t = \hat{x}_{t-1} + \hat{\Pi}_{Ht} - \hat{\Pi}_{Ft}$.
- The MSV solution for the terms of trade:

$$\hat{x}_t = a\hat{x}_{t-1} + B \underbrace{\hat{s}_t}_{\text{vector of shocks}}, \qquad a > 0 \tag{39}$$

- Recall the equilibrium condition for consumption

$$\hat{c}_t = \mathbb{E}_t \hat{c}_{t+1} - \frac{1}{\gamma}(\hat{R}_t - \mathbb{E}_t \hat{\Pi}_{t+1}) + \frac{\Delta(1-a)}{\gamma}\hat{x}_t + \frac{1}{\gamma}\hat{e}_t \tag{40}$$

- For our baseline calibration $\Delta < 0$
- Terms of trade: > 0 if supply shock to H; < 0 is supply shock to F
- $\Rightarrow$ term in red: < 0 if supply shock to H; > 0 is supply shock to F
- Similar implications for aggregate inflation from a PC logic