Monetary Policy & Anchored Expectations An Endogenous Gain Learning Model

Laura Gáti

Boston College

TO DO April 15, 2020

Inflation that runs below its desired level can lead to an unwelcome fall in longer-term inflation expectations, which, in turn, can pull actual inflation even lower, resulting in an adverse cycle of ever-lower inflation and inflation expectations. [...] Well-anchored inflation expectations are critical[.]

Jerome Powell, Chairman of the Federal Reserve ¹ (Emphases added.)

¹"New Economic Challenges and the Fed's Monetary Policy Review," August 27, 2020.

Long-run expectations: capturing responsiveness to short-run conditions

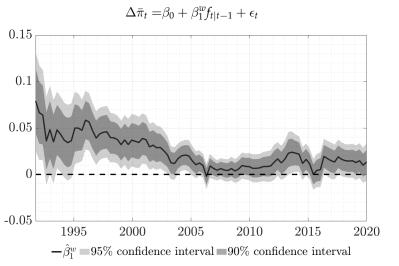
Individual SPF forecasts: for 1991-Q4 onward, estimate rolling regression

$$\Delta \bar{\pi}_t = \beta_0 + \beta_1^w f_{t|t-1} + \epsilon_t \tag{1}$$

where w indexes windows of 20 quarters length,

 $f_{t|t-1} \equiv \pi_t - \mathbb{E}_{t-1} \, \pi_t$ individual one-year-ahead forecast error

Time-varying responsiveness



This project

 How to conduct monetary policy in interaction with the anchoring expectation formation?

Preview of results

1. Estimation

- Larger mistakes unanchor more
- Overestimating inflation unanchors more than underestimating it (Hebden et al 2020)
- On average, people discount observations older than 8 quarters

2. Optimal policy

 Responds aggressively to inflation when unanchored, accommodates inflation when anchored

3. Taylor rule

Less aggressive on inflation than under rational expectations

Related literature

 Optimal monetary policy in the New Keynesian model Clarida, Gali & Gertler (1999), Woodford (2003)

• Adaptive learning

Evans & Honkapohja (2001, 2006), Sargent (1999), Primiceri (2006), Lubik & Matthes (2018), Bullard & Mitra (2002), Preston (2005, 2008), Ferrero (2007), Molnár & Santoro (2014), Mele et al (2019), Eusepi & Preston (2011), Milani (2007, 2014), Marcet & Nicolini (2003)

• Anchoring and the Phillips curve

Svensson (2015), Hooper et al (2019), Afrouzi & Yang (2020), Reis (2020), Hebden et al 2020, Gobbi et al (2019), Carvalho et al (2019)

Structure of talk

- 1. Model of anchoring expectations
- 2. Quantification of learning channel
- 3. Solving the Ramsey problem
- 4. Implementing optimal policy
- 5. Approximating optimal policy with a Taylor rule

Structure of talk

- 1. Model of anchoring expectations
- 2. Quantification of learning channel
- 3. Solving the Ramsey problem
- 4. Implementing optimal policy
- 5. Approximating optimal policy with a Taylor rule

Households: standard up to $\hat{\mathbb{E}}$

Maximize lifetime expected utility

$$\hat{\mathbb{E}}_t \sum_{T=t}^{\infty} \beta^{T-t} \left[U(C_T^i) - \int_0^1 v(h_T^i(j)) dj \right]$$
 (2)

Budget constraint

$$B_t^i \le (1 + i_{t-1})B_{t-1}^i + \int_0^1 w_t(j)h_t^i(j)dj + \Pi_t^i(j)dj - T_t - P_tC_t^i$$
 (3)

▶ Consumption, price level

Firms: standard up to $\hat{\mathbb{E}}$

Maximize present value of profits

$$\hat{\mathbb{E}}_{t} \sum_{T=t}^{\infty} \alpha^{T-t} Q_{t,T} \left[\Pi_{t}^{j}(p_{t}(j)) \right]$$
(4)

subject to demand

$$y_t(j) = Y_t \left(\frac{p_t(j)}{P_t}\right)^{-\theta} \tag{5}$$

▶ Profits, stochastic discount factor

Expectations: $\hat{\mathbb{E}}$ instead of \mathbb{E}

• Model implies mapping between exogenous states s_t and observables $y_t \equiv (\pi, x, i)'$

$$y_t = gs_t \tag{6}$$

Expectations: $\hat{\mathbb{E}}$ instead of \mathbb{E}

• Model implies mapping between exogenous states s_t and observables $y_t \equiv (\pi, x, i)'$

$$y_t = g s_t \tag{6}$$

Under rational expectations (RE), private sector knows model
 → knows (6)

$$\mathbb{E}_t \, y_{t+1} = g \, \mathbb{E} \, s_{t+1} \tag{7}$$

Expectations: $\hat{\mathbb{E}}$ instead of \mathbb{E}

• Model implies mapping between exogenous states s_t and observables $y_t \equiv (\pi, x, i)'$

$$y_t = gs_t \tag{6}$$

Under rational expectations (RE), private sector knows model

 → knows (6)

$$\mathbb{E}_t \, y_{t+1} = g \, \mathbb{E} \, s_{t+1} \tag{7}$$

• $\hat{\mathbb{E}}$: agents do not internalize that identical \to do not know aggregate model \to do not know (6)

• Agents know exogenous evolution of states

$$s_t = h s_{t-1} + \epsilon_t \qquad \epsilon_t \sim \mathcal{N}(\mathbf{0}, \Sigma)$$
 (8)

• Agents know exogenous evolution of states

$$s_t = h s_{t-1} + \epsilon_t \qquad \epsilon_t \sim \mathcal{N}(\mathbf{0}, \Sigma)$$
 (8)

• Postulate linear functional relationship instead of (6):

$$\hat{\mathbb{E}}_t y_{t+1} = a_{t-1} + b_{t-1} s_t \tag{9}$$

Agents know exogenous evolution of states

$$s_t = h s_{t-1} + \epsilon_t \qquad \quad \epsilon_t \sim \mathcal{N}(\mathbf{0}, \Sigma)$$
 (8)

• Postulate linear functional relationship instead of (6):

$$\hat{\mathbb{E}}_t y_{t+1} = a_{t-1} + b_{t-1} s_t \tag{9}$$

 $a \rightarrow$ concept of long-run expectations in the model

Agents know exogenous evolution of states

$$s_t = h s_{t-1} + \epsilon_t \qquad \epsilon_t \sim \mathcal{N}(\mathbf{0}, \Sigma)$$
 (8)

• Postulate linear functional relationship instead of (6):

$$\hat{\mathbb{E}}_t y_{t+1} = a_{t-1} + b_{t-1} s_t \tag{9}$$

 $a \rightarrow$ concept of long-run expectations in the model

• Estimate *a*, *b* using recursive least squares (RLS) using observed states and knowledge of (8)

Recursive least squares (RLS)

Observables are: $(\pi, x, i)'$

Assumption: learn only intercept of inflation:

$$a_{t-1} = (\bar{\pi}_{t-1}, 0, 0)', \quad b_{t-1} = g h \quad \forall t$$
 (10)

Recursive least squares (RLS)

Observables are: $(\pi, x, i)'$

Assumption: learn only intercept of inflation:

$$a_{t-1} = (\bar{\pi}_{t-1}, 0, 0)', \quad b_{t-1} = g h \quad \forall t$$
 (10)

 $\bar{\pi}_{t-1}$: long-run inflation expectations \rightarrow anchoring

Recursive least squares (RLS)

Observables are: $(\pi, x, i)'$

Assumption: learn only intercept of inflation:

$$a_{t-1} = (\bar{\pi}_{t-1}, 0, 0)', \quad b_{t-1} = g h \quad \forall t$$
 (10)

 $\bar{\pi}_{t-1}$: long-run inflation expectations \rightarrow anchoring

$$\rightarrow$$
 RLS

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k_t \underbrace{\left(\pi_t - (\bar{\pi}_{t-1} + b_1 s_{t-1})\right)}_{\equiv f_{t|t-1}, \text{ forecast error}}$$
(11)

 $k_t \in (0,1)$ gain b_1 first row of b



1. Decreasing gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \frac{1}{t} f_{t|t-1} \tag{12}$$

 $\bar{\pi}_t$ sample mean of full sample of forecast errors

1. Decreasing gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \frac{1}{t} f_{t|t-1} \tag{12}$$

 $\bar{\pi}_t$ sample mean of full sample of forecast errors

2. Constant gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k f_{t|t-1} \tag{13}$$

 $\bar{\pi}_t$ sample mean of most recent forecast errors only

1. Decreasing gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \frac{1}{t} f_{t|t-1} \tag{12}$$

 $\bar{\pi}_t$ sample mean of full sample of forecast errors

2. Constant gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k f_{t|t-1}$$

 $\bar{\pi}_t$ sample mean of most recent forecast errors only

3. Endogenous gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \mathbf{g}(f_{t|t-1}) f_{t|t-1}$$

(13)

(14)

1. Decreasing gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \frac{1}{t} f_{t|t-1} \tag{12}$$

Optimal monetary policy: Mele et al 2019

2. Constant gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k f_{t|t-1}$$

3. Endogenous gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \mathbf{g}(f_{t|t-1}) f_{t|t-1}$$
 (14)

(13)

1. Decreasing gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \frac{1}{t} f_{t|t-1} \tag{12}$$

Optimal monetary policy: Mele et al 2019

2. Constant gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k f_{t|t-1}$$

Optimal monetary policy: Molnár & Santoro 2014

3. Endogenous gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \mathbf{g}(f_{t|t-1}) f_{t|t-1}$$

15 / 37

(13)

(14)

1. Decreasing gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \frac{1}{t} f_{t|t-1} \tag{12}$$

Optimal monetary policy: Mele et al 2019

2. Constant gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k f_{t|t-1}$$

Optimal monetary policy: Molnár & Santoro 2014

3. Endogenous gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \mathbf{g}(f_{t|t-1}) f_{t|t-1}$$

(14)

(13)

Marcet & Nicolini 2003, Carvalho et al 2019

1. Decreasing gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \frac{1}{t} f_{t|t-1}$$
 (12)

Optimal monetary policy: Mele et al 2019

2. Constant gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k f_{t|t-1}$$

Optimal monetary policy: Molnár & Santoro 2014

3. Endogenous gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \mathbf{g}(f_{t|t-1}) f_{t|t-1}$$

Marcet & Nicolini 2003, Carvalho et al 2019 Optimal monetary policy: - (13)

(14)

Model summary

• New Keynesian core: IS and Phillips curves

$$x_{t} = -\sigma i_{t} + \hat{\mathbb{E}}_{t} \sum_{t=0}^{\infty} \beta^{T-t} ((1-\beta)x_{T+1} - \sigma(\beta i_{T+1} - \pi_{T+1}) + \sigma r_{T}^{n})$$
 (15)

$$\pi_t = \kappa x_t + \hat{\mathbb{E}}_t \sum_{T=1}^{\infty} (\alpha \beta)^{T-t} \left(\kappa \alpha \beta x_{T+1} + (1-\alpha) \beta \pi_{T+1} + u_T \right)$$
 (16)

Model summary

• New Keynesian core: IS and Phillips curves

$$x_{t} = -\sigma i_{t} + \hat{\mathbb{E}}_{t} \sum_{t=0}^{\infty} \beta^{T-t} \left((1 - \beta) x_{T+1} - \sigma(\beta i_{T+1} - \pi_{T+1}) + \sigma r_{T}^{n} \right)$$
 (15)

$$\pi_t = \kappa x_t + \hat{\mathbb{E}}_t \sum_{T=1}^{\infty} (\alpha \beta)^{T-t} \left(\kappa \alpha \beta x_{T+1} + (1-\alpha) \beta \pi_{T+1} + u_T \right)$$
 (16)

• Expectations:

$$\hat{\mathbb{E}}_t \pi_{t+1} = \bar{\pi}_{t-1} + b_1 s_t \tag{17}$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \mathbf{g}(f_{t|t-1}) f_{t|t-1}$$
 (18)

Model summary

• New Keynesian core: IS and Phillips curves

$$x_{t} = -\sigma i_{t} + \hat{\mathbb{E}}_{t} \sum_{t=0}^{\infty} \beta^{T-t} ((1-\beta)x_{T+1} - \sigma(\beta i_{T+1} - \pi_{T+1}) + \sigma r_{T}^{n})$$
 (15)

$$\pi_t = \kappa x_t + \hat{\mathbb{E}}_t \sum_{t=0}^{\infty} (\alpha \beta)^{T-t} \left(\kappa \alpha \beta x_{T+1} + (1-\alpha) \beta \pi_{T+1} + u_T \right)$$
 (16)

• Expectations:

$$\hat{\mathbb{E}}_t \pi_{t+1} = \bar{\pi}_{t-1} + b_1 s_t \tag{17}$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \mathbf{g}(f_{t|t-1}) f_{t|t-1}$$
 (18)

 \rightarrow How should $\{i_t\}$ be set?

Structure of talk

- 1. Model of anchoring expectations
- 2. Quantification of learning channel
- 3. Solving the Ramsey problem
- 4. Implementing optimal policy
- 5. Approximating optimal policy with a Taylor rule

Estimating form of gain function

$$\mathbf{g}(f_{t|t-1}) = \sum_{i} \gamma_i b_i (f_{t|t-1}) \tag{19}$$

- $b_i(f_{t|t-1})$ = piecewise linear basis
- γ_i = approximating coefficient at node i

Estimating form of gain function

$$\mathbf{g}(f_{t|t-1}) = \sum_{i} \gamma_i b_i (f_{t|t-1}) \tag{19}$$

- $b_i(f_{t|t-1})$ = piecewise linear basis
- γ_i = approximating coefficient at node i
- \hookrightarrow Estimate $\hat{\gamma}$ via simulated method of moments (Duffie & Singleton 1990, Lee & Ingram 1991, Smith 1993)
 - Calibrate parameters of New Keynesian core to literature
 - Calibrate variances of disturbances to match moments
 - Estimate $\hat{\gamma}$ to match moments

Estimating form of gain function

$$\mathbf{g}(f_{t|t-1}) = \sum_{i} \gamma_{i} b_{i}(f_{t|t-1})$$
(19)

- $b_i(f_{t|t-1})$ = piecewise linear basis
- γ_i = approximating coefficient at node i
- \hookrightarrow Estimate $\hat{\gamma}$ via simulated method of moments (Duffie & Singleton 1990, Lee & Ingram 1991, Smith 1993)
 - Calibrate parameters of New Keynesian core to literature
 - Calibrate variances of disturbances to match moments
 - Estimate $\hat{\gamma}$ to match moments
 - Moments: autocovariances of inflation, output gap, federal funds rate and 1-year ahead SPF inflation expectations at lags 0,...,4

Calibration - parameters from the literature

β	0.98	stochastic discount factor
$\overline{\sigma}$	1	intertemporal elasticity of substitution
α	0.5	Calvo probability of not adjusting prices
κ	0.0842	slope of the Phillips curve
$\overline{\psi_{\pi}}$	1.5	coefficient of inflation in Taylor rule
\bar{g}	0.145	initial value of the gain
λ_x	0.05	weight on the output gap in central bank loss

Main sources: Chari et al 2000, Woodford 2003, Nakamura & Steinsson 2008

Calibration - matching moments

ψ_x	0.3	coefficient of the output gap in Taylor rule
σ_r	0.01	standard deviation, natural rate shock
σ_i	0.01	standard deviation, monetary policy shock
σ_u	0.5	standard deviation, cost-push shock
$\hat{\gamma}_i$	(0.82; 0.61; 0; 0.33; 0.45)	coefficients in anchoring function

Estimated form for $\mathbf{g}(\cdot)$

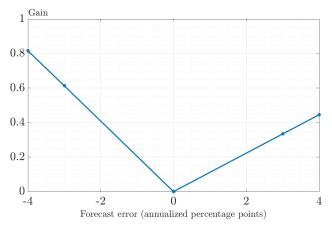
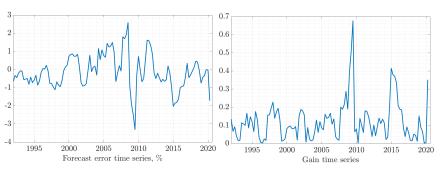


Figure: Gain as a function of forecast errors in inflation

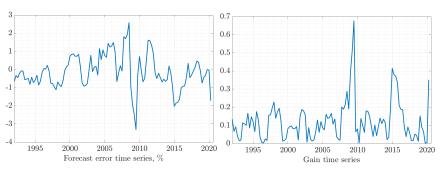
Forecast errors in the data

Figure: Time series of 1-year ahead forecast errors and implied gain in the SPF



Forecast errors in the data

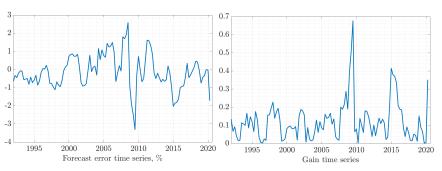
Figure: Time series of 1-year ahead forecast errors and implied gain in the SPF



Mean gain ≈ 0.12

Forecast errors in the data

Figure: Time series of 1-year ahead forecast errors and implied gain in the SPF



Mean gain ≈ 0.12 \rightarrow discount forecast errors older than 8 quarters

Structure of talk

- 1. Model of anchoring expectations
- 2. Quantification of learning channe
- 3. Solving the Ramsey problem
- 4. Implementing optimal policy
- 5. Approximating optimal policy with a Taylor rule

Ramsey problem

$$\min_{\{y_t, \bar{\pi}_{t-1}, k_t\}_{t=t_0}^{\infty}} \mathbb{E}_{t_0} \sum_{t=t_0}^{\infty} \beta^{t-t_0} (\pi_t^2 + \lambda_x x_t^2)$$

- s.t. model equations
- s.t. evolution of expectations

- \mathbb{E} is the central bank's (CB) expectation
- Assumption: CB observes private expectations and knows the model

Target criterion

Proposition

In the model with anchoring, monetary policy optimally brings about the following target relationship between inflation and the output gap

$$\begin{split} \pi_t &= -\frac{\lambda_x}{\kappa} x_t \\ &+ \frac{\lambda_x}{\kappa} \frac{(1-\alpha)\beta}{1-\alpha\beta} \bigg(k_t + f_{t|t-1} \mathbf{g}_{\pi,t} \bigg) \bigg(\mathbb{E}_t \sum_{i=1}^{\infty} x_{t+i} \prod_{j=0}^{t-1} (1 - k_{t+1+j} - f_{t+1+j|t+j} \mathbf{g}_{\bar{\pi},t+j}) \bigg) \end{split}$$

where $\mathbf{g}_{z,t} \equiv \frac{\partial \mathbf{g}}{\partial z}$ at t, and b_1 is the first row of b.



Responding to cost-push shocks

$$\pi_t = -\frac{\lambda_x}{\kappa} x_t + \frac{\lambda_x}{\kappa} \frac{(1-\alpha)\beta}{1-\alpha\beta} \left(k_t + f_{t|t-1} \mathbf{g}_{\pi,t} \right) \left(\mathbb{E}_t \sum_{i=1}^{\infty} x_{t+i} \prod_{j=0}^{i-1} (1 - k_{t+1+j} - f_{t+1+j|t+j} \mathbf{g}_{\bar{\pi},t+j}) \right)$$

Intratemporal tradeoffs in RE (discretion)

Postpone current tradeoff to future as long as gain >

Extent to which can postpone depends on not unanchoring too much in future

Responding to cost-push shocks

$$\pi_t = -\frac{\lambda_x}{\kappa} x_t + \frac{\lambda_x}{\kappa} \frac{(1-\alpha)\beta}{1-\alpha\beta} \left(k_t + f_{t|t-1} \mathbf{g}_{\pi,t} \right) \left(\mathbb{E}_t \sum_{i=1}^{\infty} x_{t+i} \prod_{j=0}^{i-1} (1 - k_{t+1+j} - f_{t+1+j|t+j} \mathbf{g}_{\bar{\pi},t+j}) \right)$$

Intratemporal tradeoffs in RE (discretion)

Postpone current tradeoff to future as long as gain > 0

Extent to which can postpone depends on not unanchoring too much in future

Responding to cost-push shocks

$$\pi_t = -\frac{\lambda_x}{\kappa} x_t + \frac{\lambda_x}{\kappa} \frac{(1-\alpha)\beta}{1-\alpha\beta} \left(k_t + f_{t|t-1} \mathbf{g}_{\pi,t} \right) \left(\mathbb{E}_t \sum_{i=1}^{\infty} x_{t+i} \prod_{j=0}^{i-1} (1 - k_{t+1+j} - f_{t+1+j|t+j} \mathbf{g}_{\bar{\pi},t+j}) \right)$$

Intratemporal tradeoffs in RE (discretion)

Postpone current tradeoff to future as long as gain > 0

Extent to which can postpone depends on not unanchoring too much in future

Lemma

The discretion and commitment solutions of the Ramsey problem coincide.

▶ Why no commitment?

Corollary

Optimal policy under adaptive learning is time-consistent.

Structure of talk

- 1. Model of anchoring expectations
- 2. Quantification of learning channel
- 3. Solving the Ramsey problem
- 4. Implementing optimal policy
- 5. Approximating optimal policy with a Taylor rule

Solution procedure

Solve system of model equations + target criterion

 \hookrightarrow solve using parameterized expectations (PEA)

 \hookrightarrow obtain a cubic spline approximation to optimal policy function

Optimal policy - responding to unanchoring

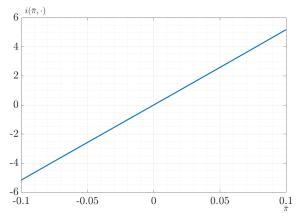


Figure: Policy function: $i(\bar{\pi}, \text{ all other states at their means})$

Optimal policy - responding to unanchoring

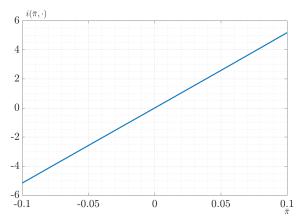


Figure: Policy function: $i(\bar{\pi}, \text{ all other states at their means})$

 \rightarrow For 5 bp drop in $\bar{\pi}$, lower *i* by 2.5 pp

Unanchoring causes volatility

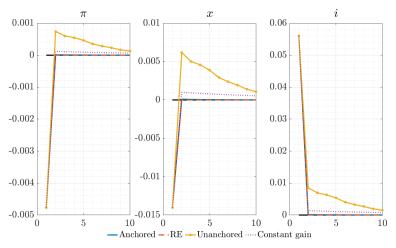


Figure: Impulse responses after a contractionary monetary policy shock when policy follows a Taylor rule

Volatility comes from endogenous gain

• Constant gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k f_{t|t-1} \tag{13}$$

• Endogenous gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \mathbf{g}(f_{t|t-1}) f_{t|t-1}$$
 (14)

Volatility comes from endogenous gain

• Constant gain:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k f_{t|t-1} \tag{13}$$

• Endogenous gain:

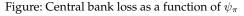
$$\bar{\pi}_t = \bar{\pi}_{t-1} + \mathbf{g}(f_{t|t-1}) f_{t|t-1}$$
 (14)

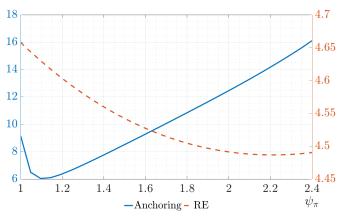
Shocks raise the gain → central bank needs to anchor

Structure of talk

- 1. Model of anchoring expectations
- 2. Quantification of learning channel
- 3. Solving the Ramsey problem
- 4. Implementing optimal policy
- 5. Approximating optimal policy with a Taylor rule

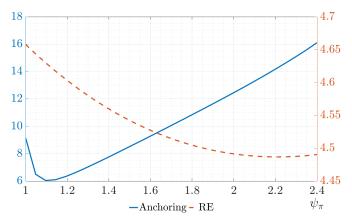
Optimal Taylor-coefficient on inflation





Optimal Taylor-coefficient on inflation

Figure: Central bank loss as a function of ψ_{π}



Anchoring-optimal coefficient: $\psi_{\pi}^{A} = 1.09$ RE-optimal coefficient: $\psi_{\pi}^{RE} = 2.21$

Respond but not too much

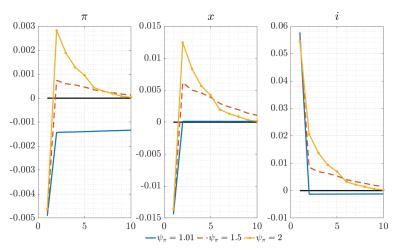


Figure: Impulse responses for unanchored expectations for various values of ψ_π

Why less aggressive? Future interest rate expectations

IS- and Phillips curve:

$$x_t = -\sigma i_t + \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} \beta^{T-t} \left((1-\beta) x_{T+1} - \sigma(\beta i_{T+1} - \pi_{T+1}) + \sigma r_T^n \right)$$

$$\pi_t = \kappa x_t + \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} (\alpha \beta)^{T-t} \left(\kappa \alpha \beta x_{T+1} + (1-\alpha) \beta \pi_{T+1} + u_T \right)$$

• Current interest rate *i*_t: one channel of policy

Why less aggressive? Future interest rate expectations

IS- and Phillips curve:

$$x_t = -\sigma i_t + \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} \beta^{T-t} \left((1-\beta) x_{T+1} - \sigma (\beta i_{T+1} - \pi_{T+1}) + \sigma r_T^n \right)$$

$$\pi_t = \kappa x_t + \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} (\alpha \beta)^{T-t} \left(\kappa \alpha \beta x_{T+1} + (1-\alpha) \beta \pi_{T+1} + u_T \right)$$

- Current interest rate *i*_t: one channel of policy
- Expected future interest rates: additional channel of policy

Why less aggressive? Future interest rate expectations

IS- and Phillips curve:

$$x_t = -\sigma i_t + \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} \beta^{T-t} \left((1-\beta) x_{T+1} - \sigma (\beta i_{T+1} - \pi_{T+1}) + \sigma r_T^n \right)$$

$$\pi_t = \kappa x_t + \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} (\alpha \beta)^{T-t} \left(\kappa \alpha \beta x_{T+1} + (1-\alpha) \beta \pi_{T+1} + u_T \right)$$

- Current interest rate *i*_t: one channel of policy
- Expected future interest rates: additional channel of policy
- Only if policy reaction function internalized

Conclusion

First theory of monetary policy for potentially unanchored expectations

Estimation of novel unanchoring channel

- Large and negative surprises unanchor more
- Estimated gain time series: on average, people only use the last 8 quarters
 of data

Monetary policy

- Expectations unanchoring makes smoothing shocks over time possible
- Optimal policy aggressive when unanchored, accommodates otherwise
- Taylor rule less aggressive than under rational expectations

Future work

- → How to anchor at zero-lower bound?
- \hookrightarrow Other applications: currency crises



Breakeven inflation



Figure: Market-based inflation expectations, various horizons, %



Correcting the TIPS from liquidity risk

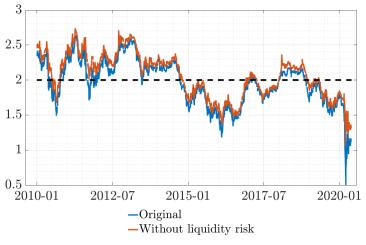


Figure: Market-based inflation expectations, 10 year, %



Further evidence

Figure: Livingston Survey of Firms: Interquartile range of 10-year ahead inflation expectations

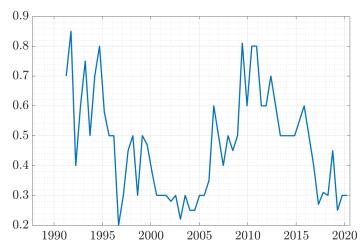
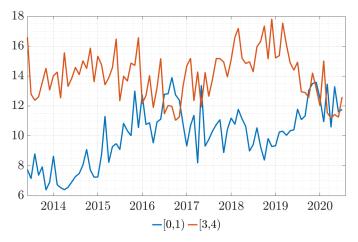




Figure: New York Fed Survey of Consumers: Percent of respondents indicating 3-year ahead inflation will be in a particular range





Oscillatory dynamics in adaptive learning

Consider a stylized adaptive learning model in two equations:

$$\pi_t = \beta f_t + u_t \tag{20}$$

$$f_t = f_{t-1} + k(\pi_t - f_{t-1}) \tag{21}$$

Solve for the time series of expectations f_t

$$f_t = \underbrace{\frac{1 - k^{-1}}{1 - k^{-1}\beta}}_{\approx 1} f_{t-1} + \frac{k^{-1}}{1 - k^{-1}\beta} u_t \tag{22}$$

Solve for forecast error $f_t \equiv \pi_t - f_{t-1}$:

$$f_t = \underbrace{-\frac{1-\beta}{1-k\beta}}_{\lim_{k\to 1}=-1} f_{t-1} + \frac{1}{1-k\beta} u_t$$
 (23)

Functional forms for g in the literature

• Smooth anchoring function (Gobbi et al, 2019)

$$p = h(y_{t-1}) = A + \frac{BCe^{-Dy_{t-1}}}{(Ce^{-Dy_{t-1}} + 1)^2}$$
 (24)

 $p \equiv Prob(\text{liquidity trap regime})$ y_{t-1} output gap

• Kinked anchoring function (Carvalho et al, 2019)

$$k_t = \begin{cases} \frac{1}{t} & \text{when } \theta_t < \bar{\theta} \\ k & \text{otherwise.} \end{cases}$$
 (25)

 θ_t criterion, $\bar{\theta}$ threshold value



Choices for criterion θ_t

• Carvalho et al. (2019)'s criterion

$$\theta_t^{CEMP} = \max |\Sigma^{-1}(\phi_{t-1} - T(\phi_{t-1}))|$$
 (26)

 Σ variance-covariance matrix of shocks $T(\phi)$ mapping from PLM to ALM

CUSUM-criterion

$$\omega_t = \omega_{t-1} + \kappa k_{t-1} (f_{t|t-1} f'_{t|t-1} - \omega_{t-1})$$
(27)

$$\theta_t^{CUSUM} = \theta_{t-1} + \kappa k_{t-1} (f'_{t|t-1} \omega_t^{-1} f_{t|t-1} - \theta_{t-1})$$
 (28)

 ω_t estimated forecast-error variance



Recursive least squares algorithm

$$\phi_t = \left(\phi'_{t-1} + k_t R_t^{-1} \begin{bmatrix} 1 \\ s_{t-1} \end{bmatrix} \left(y_t - \phi_{t-1} \begin{bmatrix} 1 \\ s_{t-1} \end{bmatrix} \right)' \right)' \tag{29}$$

$$R_t = R_{t-1} + k_t \begin{pmatrix} 1 \\ s_{t-1} \end{pmatrix} \begin{bmatrix} 1 & s_{t-1} \end{bmatrix} - R_{t-1}$$

$$(30)$$



Actual laws of motion

$$y_{t} = A_{1}f_{a,t} + A_{2}f_{b,t} + A_{3}s_{t}$$

$$s_{t} = hs_{t-1} + \epsilon_{t}$$
(31)

where

$$y_t \equiv \begin{pmatrix} \pi_t \\ x_t \\ i_t \end{pmatrix} \qquad s_t \equiv \begin{pmatrix} r_t^n \\ u_t \end{pmatrix} \tag{33}$$

and

$$f_{a,t} \equiv \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} (\alpha \beta)^{T-t} y_{T+1} \qquad f_{b,t} \equiv \hat{\mathbb{E}}_t \sum_{T=t}^{\infty} (\beta)^{T-t} y_{T+1}$$
 (34)

No commitment - no lagged multipliers

Simplified version of the model: planner chooses $\{\pi_t, x_t, f_t, k_t\}_{t=t_0}^{\infty}$ to minimize

$$\mathcal{L} = \mathbb{E}_{t_0} \sum_{t=t_0}^{\infty} \beta^{t-t_0} \left\{ \pi_t^2 + \lambda x_t^2 + \varphi_{1,t} (\pi_t - \kappa x_t - \beta f_t + u_t) + \varphi_{2,t} (f_t - f_{t-1} - k_t (\pi_t - f_{t-1})) + \varphi_{3,t} (k_t - \mathbf{g}(\pi_t - f_{t-1})) \right\}$$

$$2\pi_t + 2\frac{\lambda}{\kappa}x_t - \varphi_{2,t}(k_t + \mathbf{g}_{\pi}(\pi_t - f_{t-1})) = 0$$
 (35)

$$-2\beta \frac{\lambda}{\kappa} x_t + \varphi_{2,t} - \varphi_{2,t+1} (1 - k_{t+1} - \mathbf{g_f}(\pi_{t+1} - f_t)) = 0$$
 (36)



Target criterion system for anchoring function as changes of the gain

$$\varphi_{6,t} = -cf_{t|t-1}x_{t+1} + \left(1 + \frac{f_{t|t-1}}{f_{t+1|t}}(1 - k_{t+1}) - f_{t|t-1}\mathbf{g}_{\bar{\pi},t}\right)\varphi_{6,t+1} - \frac{f_{t|t-1}}{f_{t+1|t}}(1 - k_{t+1})\varphi_{6,t+2}$$
(37)

$$0 = 2\pi_t + 2\frac{\lambda_x}{\kappa} x_t - \left(\frac{k_t}{f_{t|t-1}} + \mathbf{g}_{\pi,t}\right) \varphi_{6,t} + \frac{k_t}{f_{t|t-1}} \varphi_{6,t+1}$$
(38)

 $\varphi_{6,t}$ Lagrange multiplier on anchoring function

The solution to (38) is given by:

$$\varphi_{6,t} = -2 \, \mathbb{E}_t \sum_{i=0}^{\infty} (\pi_{t+i} + \frac{\lambda_x}{\kappa} x_{t+i}) \prod_{j=0}^{i-1} \frac{\frac{k_{t+j}}{f_{t+j|t+j-1}}}{\frac{k_{t+j}}{f_{t+j|t+j-1}} + \mathbf{g}_{\pi,t+j}}$$
(39)



Details on households and firms

Consumption:

$$C_t^i = \left[\int_0^1 c_t^i(j)^{\frac{\theta - 1}{\theta}} dj \right]^{\frac{\sigma}{\theta - 1}} \tag{40}$$

 $\theta > 1$: elasticity of substitution between varieties

Aggregate price level:

$$P_t = \left[\int_0^1 p_t(j)^{1-\theta} dj \right]^{\frac{1}{\theta-1}} \tag{41}$$

Profits:

$$\Pi_t^j = p_t(j)y_t(j) - w_t(j)f^{-1}(y_t(j)/A_t)$$
(42)

Stochastic discount factor

$$Q_{t,T} = \beta^{T-t} \frac{P_t U_c(C_T)}{P_T U_c(C_t)}$$
(43)



Derivations

Household FOCs

$$\hat{C}_t^i = \hat{\mathbb{E}}_t^i \hat{C}_{t+1}^i - \sigma(\hat{i}_t - \hat{\mathbb{E}}_t^i \hat{\pi}_{t+1}) \tag{44}$$

$$\hat{\mathbb{E}}_t^i \sum_{s=0}^{\infty} \beta^s \hat{C}_t^i = \omega_t^i + \hat{\mathbb{E}}_t^i \sum_{s=0}^{\infty} \beta^s \hat{Y}_t^i$$
(45)

where 'hats' denote log-linear approximation and $\omega_t^i \equiv \frac{(1+i_{t-1})B_{t-1}^i}{P_tY^*}$.

- 1. Solve (44) backward to some date *t*, take expectations at *t*
- 2. Sub in (45)
- 3. Aggregate over households *i*
- \rightarrow Obtain (15)

