Monetary Policy & Anchored Expectations An Endogenous Gain Learning Model

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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

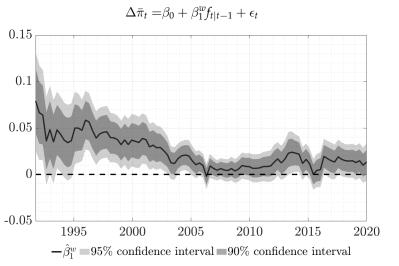
Individual SPF forecasts: for 1991-Q4 onward, estimate rolling regression

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

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)

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)

Reputation

Barro (1986), Cho & Matsui (1995)

Structure of talk

- 1. Model of anchoring expectations
- 2. Quantification of learning channel
- 3. Solving the Ramsey problem
- 4. Implementing optimal policy
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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 $y_t \equiv (\pi, x, i)'$

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

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

$$s_t = h s_{t-1} + \epsilon_t \qquad \epsilon_t \sim \mathcal{N}(\mathbf{0}, \Sigma)$$
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• Postulate linear functional relationship instead of (6):

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

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• 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:

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

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

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



1. Decreasing gain:

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

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Model summary

• New Keynesian core: IS and Phillips curves

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

Structure of talk

- 1. Model of anchoring expectations
- 2. Quantification of learning channel
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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

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 - Calibrate parameters of New Keynesian core to literature
 - Calibrate variances of disturbances to match moments
 - Estimate $\hat{\gamma}$ to match moments

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 - 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 $\mathbf{g}(\cdot)$

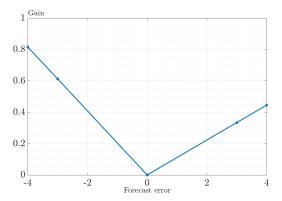
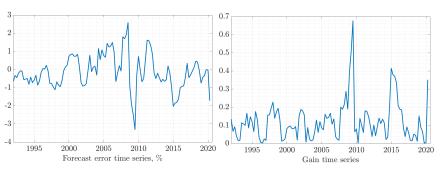


Figure: Gain as a function of forecast errors in inflation in %

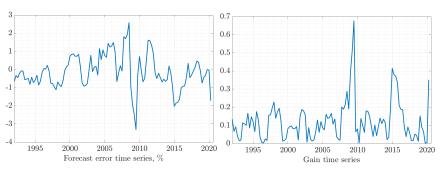
Forecast errors in the data

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



Forecast errors in the data

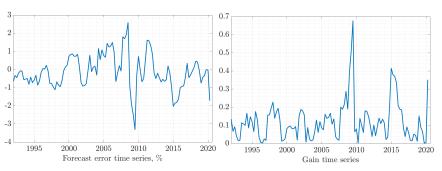
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Mean gain ≈ 0.12

Forecast errors in the data

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

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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

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Postpone current tradeoff to future as long as gain > 0

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Lemma

The discretion and commitment solutions of the Ramsey problem coincide.

▶ Why no commitment?

Corollary

Optimal policy under adaptive learning is time-consistent.

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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

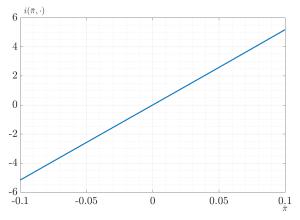


Figure: Policy function: $i(\bar{\pi}, \text{ all other states at their means})$

Optimal policy - responding to unanchoring

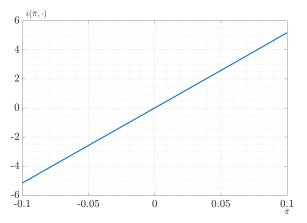


Figure: Policy function: $i(\bar{\pi}, \text{ all other states at their means})$

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

Unanchoring causes volatility

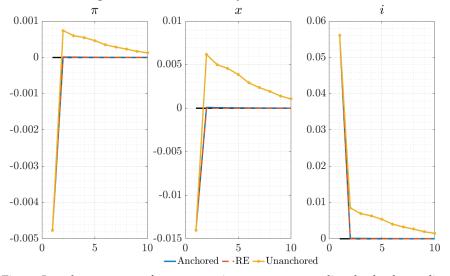


Figure: Impulse responses after a contractionary monetary policy shock when policy follows a Taylor rule

Why so volatile? Term structure of expectations

IS- and Phillips curve:

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

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Why oscillatory? Intertemporal anticipation effects

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Additional channel of policy

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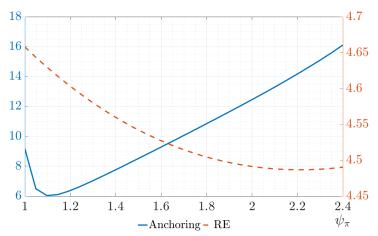
- Additional channel of policy
- Only if policy reaction function internalized

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Optimal Taylor-coefficient on inflation

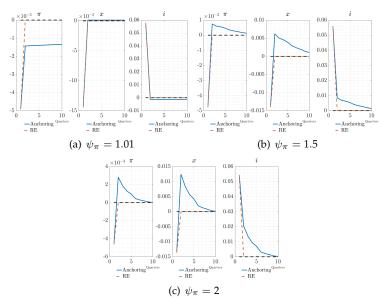
Figure: Central bank loss as a function of ψ_{π}



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

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

Respond but not too much



Conclusion

First theory of monetary policy for potentially unanchored expectations

Estimation of unanchoring in the data

- 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 frontloads aggressive interest rate response to suppress potential unanchoring
- Taylor rule less aggressive than under rational expectations

Future work

- \hookrightarrow Other applications: currency crises



Breakeven inflation



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



Correcting the TIPS from liquidity risk

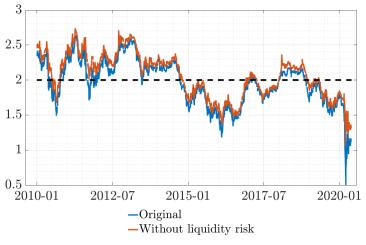


Figure: Market-based inflation expectations, 10 year, %



Further evidence

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

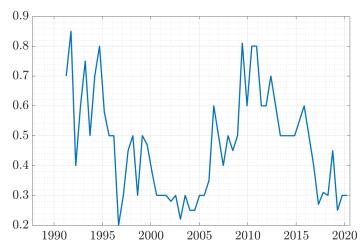
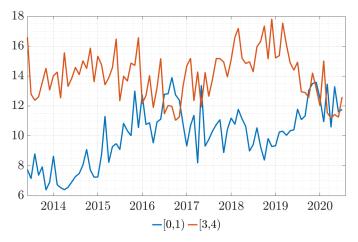




Figure: New York Fed Survey of Consumers: Percent of respondents indicating 3-year ahead inflation will be in a particular range





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

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

