Talking Over Time - Dynamic Central Bank Communication

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[1]The views expressed are solely the views of the author and do not necessarily reflect the views of the European Central Bank or the Eurosystem.

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→ How to optimally deal with this tradeoff?
  - How to balance talking about today vs tomorrow?
  - How clearly to talk?

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    ... vs. static benchmark: treat present & future as correlated in cross section

Literature

1. **Global games**

   Morris and Shin (2002), Svensson (2006), Angeletos and Pavan (2007), Hellwig and Veldkamp (2009), Chahrour (2014).

   $\hookrightarrow$ Time dimension: Reis (2011), Gaballo (2016), Hansen and McMahon (2016).

2. **Bayesian persuasion**

   Kamenica and Gentzkow (2011), Inostroza and Pavan (2017), Goldstein and Leitner (2018), Herbert (2021).

A dynamic Bayesian persuasion game

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- Sender (central bank, CB) and receiver (financial market, FM)

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  $\hookrightarrow$ give FM info so FM takes action that maximizes CB's payoff

The economic environment

$$\theta_{t+1} = \rho\theta_t + \varepsilon_{t+1}$$

$$\varepsilon_{t+1} \sim \mathcal{N}(0, \sigma_\varepsilon^2) \qquad \sigma_\varepsilon^2 = 1 - \rho^2$$

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"Future output" "Current output"

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Financial market and central bank payoffs

$$\mathcal{L}_t^{FM}(I_t, \theta_{t+1}) = \mathbb{E}_t^{FM}(I_t - \theta_{t+1})^2$$

$$\mathcal{L}^{CB}(\{I_t, \theta_t\}_{t=0}^{\infty}) = \mathbb{E}_0^{CB} \sum_{t=0}^{\infty} \beta^t (I_t - b\theta_t)^2$$

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Financial market (FM) sets investment (I) to maximize future returns

Central bank (CB) wants investment to track current output, with weight b

$\beta \in (0, 1)$ CB's discount factor

Information structure

$$\mathcal{I}_t^{CB} = \{\theta_{t+1}, \theta_t, \dots, \theta_0\}, \qquad \mathcal{I}_t^{FM} = \{s_t, s_{t-1}, \dots, s_0\}$$

where $s_t \in S$ is a signal the CB sends the FM.

The central bank's signal

$$s_t = \theta_t + \frac{1}{\psi}\theta_{t+1} + v_t, \qquad v_t \sim \mathcal{N}(0, \sigma_v^2)$$

Two dimensions of communication

$$s_t = \theta_t + \frac{1}{\psi}\theta_{t+1} + v_t, \qquad v_t \sim \mathcal{N}(0, \sigma_v^2)$$

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▸ The static analogue

Perfect Bayesian equilibrium

Definition

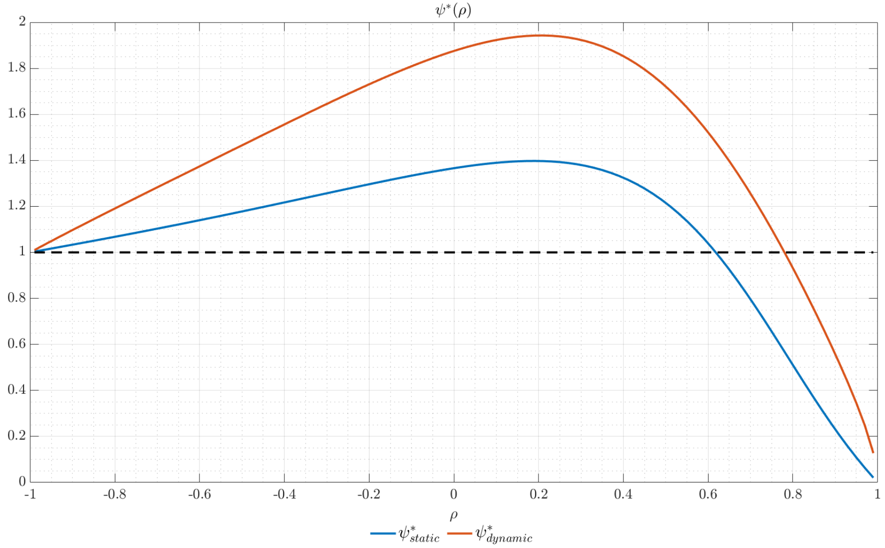
Let $\mu_X(x)$ be the probability distribution of a variable X induced by the FM's beliefs. A Perfect Bayesian Equilibrium is an action rule I_t, belief system μ and a communication policy (ψ^*, σ_v^*) such that

- $I_t = \arg\min \mathcal{L}_t^{FM}(I_t, \theta_{t+1}) \quad s.t. \quad \mathbb{E}_t^{FM}(\theta_{t+1}|s_t)$,
- $(\psi^*, \sigma_v^*) = \arg\min \mathcal{L}^{CB}(\{I_t, \theta_t\}_{t=0}^{\infty}) \quad s.t. \quad \mathbb{E}_t^{FM}(\theta_{t+1}|s_t)\ \forall t \geq 0 \quad$ *and*

  $s_t = \theta_t + \frac{1}{\psi}\theta_{t+1} + v_t \quad$ *with* $\quad v_t \sim \mathcal{N}(0, \sigma_v^2)$,
- *FM beliefs $\mathbb{E}_t^{FM}$ come from μ $\forall t$, and μ is consistent with Bayes' rule:*

$$\mu_{\Theta|S=s}(\theta) = \frac{\mu_{S|\Theta=\theta}(s)\mu_\Theta(\theta)}{\mu_S(s)}$$

OPTIMAL TARGETEDNESS


$\psi^*(\rho)$
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1
ρ
ψ^*_{static}
$\psi^*_{dynamic}$

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At time t, FM's beliefs on θ_t informed by

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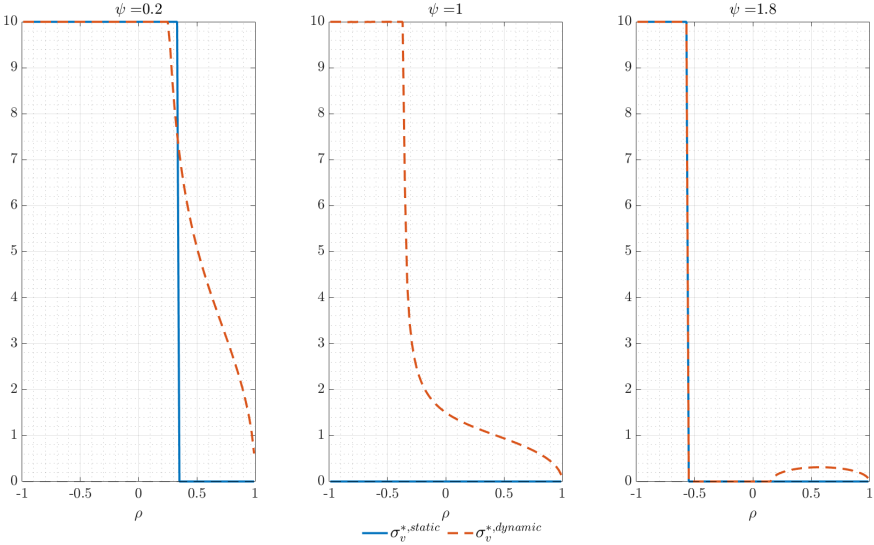
- Prior beliefs: $s_{t-1} = \theta_{t-1} + \frac{1}{\psi}\theta_t + v_{t-1}$

OPTIMAL PRECISION

Optimal precision - a cross-section



▸ 3D representation

Tightness of priors

$$\text{Prior variance:} \quad \pi(\theta_T) := \mathbb{E}[(\theta_T - \theta_{T|t-1})^2]$$
$$\text{Posterior variance:} \quad p(\theta_T, s_t) := \mathbb{E}[(\theta_T - \theta_{T|t})^2]$$

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Reduction in uncertainty (≈ mutual information):

$$I(\theta_T, s_t) := \pi(\theta_T) - p(\theta_T, s_t)$$

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↪ "Informativeness of the signal at time t about θ_T"

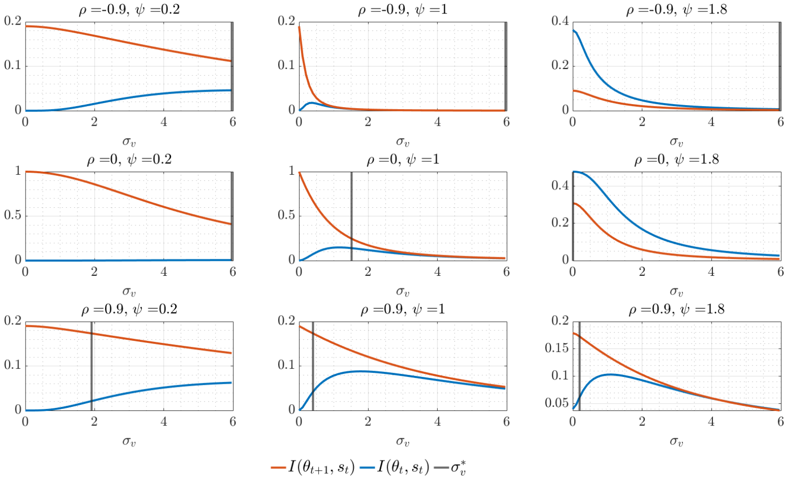

Figure: Informativeness $I(\theta_T, s_t)$ as a function of σ_v

Conclusion: CB pushes against priors

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     $\rightarrow$ ignores effect of current communication on future beliefs

Appendix

The static analogue

Fundamental: $(\theta_1, \theta_2) \sim \mathcal{N}(0, \mathbf{V}) \quad \text{with} \quad \mathbf{V} = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix},$

Payoffs:

$$\mathcal{L}^{FM}(I, \theta_2) = \mathbb{E}^{FM}(I - \theta_2)^2,$$
$$\mathcal{L}^{CB}(I, \theta_1) = \mathbb{E}^{CB}(I - b\theta_1)^2,$$

Info structure: $\mathcal{I}^{CB} = \{\theta_1, \theta_2\}, \quad \mathcal{I}^{FM} = \{s\},$

Signal: $s = \theta_1 + \frac{1}{\psi}\theta_2 + v, \qquad v \sim \mathcal{N}(0, \sigma_v^2).$

Return

Kalman filter

$$x_{t+1} = hx_t + \eta\epsilon_{t+1}$$
$$y_t = gx_t + v_t$$

$$x_t = \begin{bmatrix}\theta_{t+1}\\ \theta_t\end{bmatrix}, \quad y_t = s_t, \quad h = \begin{bmatrix}\rho & 0\\ 1 & 0\end{bmatrix}, \quad g = \begin{bmatrix}\frac{1}{\psi} & 1\end{bmatrix},$$
$$\eta = \begin{bmatrix}\sigma_\varepsilon & 0\\ 0 & 0\end{bmatrix}, \quad \epsilon_t = \begin{bmatrix}\varepsilon_t\\ 0\end{bmatrix}, \quad Q = \eta\eta' = \begin{bmatrix}\sigma_\varepsilon^2 & 0\\ 0 & 0\end{bmatrix}, \quad R = \sigma_v^2.$$

$$m_1 = \rho - \kappa_1(\frac{\rho}{\psi} + 1),$$
$$m_2 = m_4 = \kappa_1,$$
$$m_3 = \frac{\kappa_1}{\psi},$$

where κ_1 is the first element of the 2×1 Kalman gain and is given by

$$\kappa_1 = \frac{\rho p_4 + \frac{1}{\psi}p_1}{p_4 + \frac{1}{\psi^2}p_1 + 2\frac{\rho}{\psi}p_4 + \sigma_v^2}.$$

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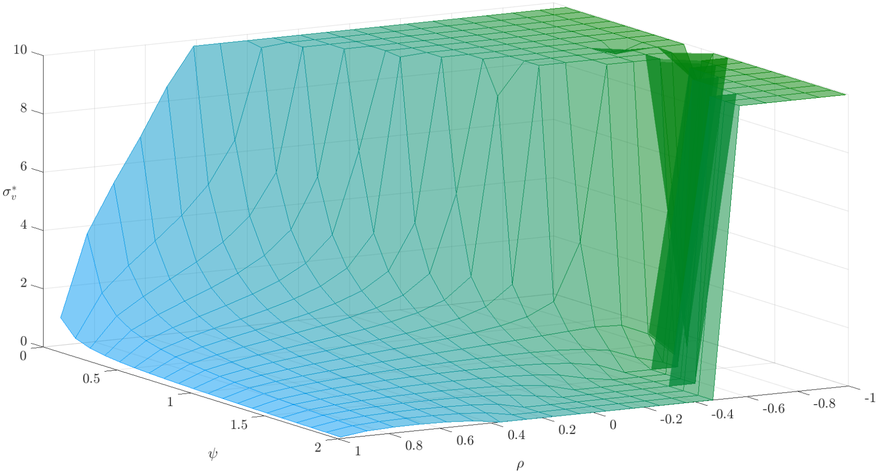

Figure: Optimal precision σ^*

◂ Return