Problem set 7. 14.461 Fall 2012.

George-Marios Angeletos.

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References:

- Bergemann, Dirk, and Stephen Morris (2012), "Robust Predictions in Games with Incomplete Information," – Problem 1.
- Mackowiak, Bartosz, and Mirko Wiederhold (2009), Optimal Sticky Prices under Rational Inattention," – Problem 3.

1 Bergemann, Morris.

Following Bergemann, Morris approach of characterizing BNE over all information structures do the following exercises (notations are as in the class). Consider special case $\mu_{\theta} = 0$ and $\sigma_{\theta} = 1$.

1. Consider the model

$$\begin{pmatrix} \theta \\ a \\ A \\ B_{\theta} \end{pmatrix} \sim \mathcal{N} \left(\begin{pmatrix} \mu_{\theta} \\ \mu_{a} \\ \mu_{A} \\ \mu_{B_{\theta}} \end{pmatrix}, \begin{pmatrix} \sigma_{\theta}^{2} & * & * & * \\ \rho_{\theta a} \sigma_{a} & \sigma_{a}^{2} & * & * \\ \rho_{\theta A} \sigma_{A} & \rho_{Aa} \sigma_{A} \sigma_{a} & \sigma_{A}^{2} & * \\ \rho_{\theta B_{\theta}} \sigma_{B_{\theta}} & \rho_{AB_{\theta}} \sigma_{A} \sigma_{B_{\theta}} & \rho_{aB_{\theta}} \sigma_{a} \sigma_{B_{\theta}} & \sigma_{B_{\theta}}^{2} \end{pmatrix} \right)$$

where $B_{\theta} = \int_{I} \mathbb{E}_{i}[\theta] di$ is average first-order beliefs about fundamental. Best response for agent *i* is given by

$$a_i = (1 - r)\mathbb{E}_i[\theta] + r\mathbb{E}_i[A].$$

What information structure maximizes volatility $\mathbb{V}[A]$? noise generated volatility $\mathbb{V}[A|\theta]$? non-fundamental fraction of volatility $\mathbb{V}[A|\theta]/\mathbb{V}[A]$? volatility generated by higher-order beliefs $\mathbb{V}[A|\theta, B_{\theta}]$ for a fixed precision of information about fundamental, $\rho_{\theta B_{\theta}}$? Interpret.

Does this modification of the model allow to capture effect of higher-order beliefs independent of first-order beliefs?

- 2. Consider the following information structure. Each agent gets private signal $x_i = \theta + u + \epsilon_i$ and public signal $y = \theta + \zeta$ where ϵ_i , u and ζ are independently normally distributed with zero means and precisions τ_{ϵ} , τ_u and τ_{ζ} , respectively. Find $\mathbb{V}[A|\theta, B_{\theta}]$ in this model. How is your answer related to your finding in question 1. (for this question you may assume that $\theta \sim \mathcal{N}(0, \infty)$.)
- 3. Consider two period version of continuous population model. Suppose that $\theta_t = \theta + \epsilon_t, t = 1, 2$ where $\epsilon_t \sim \mathcal{N}(0, 1)$ are independent across periods. Consider the following version of correlated equilibrium. Best-response in first period is

$$a_1 = (1 - r)\mathbb{E}[\theta_1|a_1] + r\mathbb{E}[A_1|a_1],$$

best-response in second period is

$$a_2 = (1-r)\mathbb{E}[\theta_1|a_1, a_2] + r\mathbb{E}[A_2|a_1, a_2]$$

i = 1, 2. The model is

$$\begin{pmatrix} \theta_{1} \\ \theta_{2} \\ a_{1} \\ a_{2} \\ A_{1} \\ A_{2} \end{pmatrix} \sim \mathcal{N} \begin{pmatrix} \begin{pmatrix} 0 \\ 0 \\ \mu_{a_{1}} \\ \mu_{a_{2}} \\ \mu_{A_{1}} \\ \mu_{A_{2}} \end{pmatrix}, \begin{pmatrix} 2 & * & * & * & * & * & * & * \\ 1 & 2 & * & * & * & * & * & * \\ \rho_{\theta_{1}a_{1}}\sigma_{a_{1}}\sqrt{2} & \rho_{\theta_{1}a_{1}}\sigma_{a_{1}}\sqrt{2} & \sigma_{a_{1}}^{2} & * & * & * & * \\ \rho_{\theta_{1}a_{2}}\sigma_{a_{2}}\sqrt{2} & \rho_{\theta_{2}a_{2}}\sigma_{a_{2}}\sqrt{2} & \rho_{a_{1}a_{2}}\sigma_{a_{1}}\sigma_{a_{2}} & \sigma_{a_{2}}^{2} & * & * & * \\ \rho_{\theta_{1}A_{2}}\sigma_{A_{2}}\sqrt{2} & \rho_{\theta_{2}A_{2}}\sigma_{A_{2}}\sqrt{2} & \rho_{A_{1}a_{1}}\sigma_{A_{1}}\sigma_{A_{1}}\sigma_{A_{1}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A_{2}}\sigma_{A$$

Denote by $\rho_{b_{\theta}^{1}} = \mathbb{E}[\theta|a_{1}]$ and $\rho_{b_{\theta}^{2}} = \mathbb{E}[\theta|a_{1}, a_{2}]$. One could think of $\rho_{b_{\theta}^{2}\theta}/\rho_{b_{\theta}^{1}\theta}$ as speed of learning and $\rho_{A_{2}\theta}/\rho_{A_{1}\theta}$ as inertia. Explore what is the maximal intertia one could get given speed of learning. What is the dependence of level of strategic complementarity/substitutability r? How is this model related to BNE of game with signals?

2 Optimal Monetary Policy with Heterogeneous Information.

Show that in a standard New Keynesian model with only i.i.d. TFP shocks and heterogeneous information about shocks price stabilization is an optimal monetary policy (carried after observation of TFP shock).¹

3 Information Capacity Constratints.

Suppose agents have the following objective function:

$$\pi_{i} = -\mathbb{E}\left[k_{i} - \left((1-\xi)\theta + \xi K + \eta_{i}\right)\right]^{2}$$

where $\eta_i \sim N(0, \alpha_\eta)$ is an idiosyncratic shock that is not directly observable by the agents. The prior on θ is $N(\mu, \alpha_\mu)$ and, before choosing k_i agents observe private signals about θ and η_i :

$$x_i = \theta + \epsilon_i$$
$$s_i = \eta_i + \chi_i$$

where $\epsilon_i \sim N(0, \alpha_{\epsilon})$ and $\chi_i \sim N(0, \alpha_s)$.

1. Conjecture that the equilibrium decision rule is of the form:

$$k_i = \gamma_0 \mu + \gamma_1 x_i + \gamma_2 s_i$$

and solve for coefficients.

2. Now suppose the agent can choose the precision of the signals he receives subject to a capacity constraint:

$$\frac{1}{\alpha_x} + \frac{1}{\alpha_s} \ge \lambda.$$

Solve for the equilibrium α_x and α_s .

3. How does the degree of complementarity ξ affect α_x and α_s . Interpret.

¹Formulization is part of a problem.

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