

# Lecture 7

## Noisy information models and rational inattention: Foundations

Chen Lian<sup>1</sup>

<sup>1</sup>UC Berkeley and NBER

March 20, 2025

# Outline

- 1 Noisy-Information Models
- 2 Rational Inattention
- 3 Sparsity
- 4 Sticky Information
- 5 Imprecise Perceptual Judgments
- 6 Application: Narrow Thinking

# Overview: Lecture 1

- **Noisy-information models:** a basic model to capture imperfect knowledge
  - ▶ accommodate rational and behavioral interpretations
- **Rational inattention (Sims):** a behavioral foundation of the “noise”
  - ▶ limited cognitive capacity
- **Sparsity (Gabaix):** a close cousin of rational inattention
- **Imprecise Perceptual Judgments (Woodford):** an alternative foundation of noise
- **Foundations** for many applications (survey evidence, GE dampening, sentiments
  - ▶ today: narrow thinking (Lian, 2021)

# Formulation

- $\theta$  : an exogenous aggregate fundamental. For example:
  - ▶ TFP in RBC
  - ▶ monetary policy in NK
- Each household/firm  $i$ 's knowledge about  $\theta$  is captured by a noisy signal

$$s_i = \theta + \varepsilon_i$$

# Expectations under Noisy Signals

## Gaussian case:

$$\theta \sim \mathcal{N}(\mu, \sigma^2) \quad \text{and} \quad \varepsilon_i \sim \mathcal{N}(0, \sigma_\varepsilon^2),$$

where  $\varepsilon_i$  is i.i.d. and independent of  $x$ .

$$\begin{aligned} E_i[\theta] &= E[\theta | s_i] = \lambda s_i + (1 - \lambda) \mu \\ &= \lambda (\theta + \varepsilon_i) + (1 - \lambda) \mu, \end{aligned}$$

where

$$\lambda = \frac{\sigma^2}{\sigma^2 + \sigma_\varepsilon^2} \in [0, 1].$$

**Key prediction:** belief about  $\theta$  **under-reacts** to innovation in  $\theta$

“Heuristics” to think about conditional expectation:

- Run a predictive regression of  $\theta$  on  $s_i$
- Similar if you have multiple Gaussian signals

# Interpretation of Noisy Signals and Macro Implications

## First-generation (“70s”):

- Disperse information about the aggregate fundamental

## Lucas (1972) island model: an “impressionism” version

- Disperse information about money supply  $m_t$  on each island

$$p_{i,t} = E_{i,t}[m_t] \quad \text{and} \quad p_t = \lambda m_t,$$

where I log-linearize around the steady state so  $\mu_m = 0$ .

- Monetary policy has real effects

$$y_t = m_t - p_t = (1 - \lambda) m_t$$

- THE “micro-foundation” of the Phillips curve in 70s

# Interpretation of Noisy Signals and Macro Implications

## The “80s” critique:

- Public available statistics reveals the aggregate fundamental
- The sticky-price/NK paradigm becomes dominant

## The “00s” behavioral revival:

- Impossible for a human being to process all available info
- Noise captures cognitive limitation/rational inattention

## What do Noisy Signals Imply?

Imperfect knowledge about the **fundamental**: (“first-order uncertainty”)

$$\int E_i[\theta] di = \lambda \theta + (1 - \lambda) \mu$$

Imperfect knowledge about others' **information/signals**: (“higher-order uncertainty”)

$$\int \int E_i[s_j] dj di = \lambda \bar{s} + (1 - \lambda) \mu,$$

where  $\bar{s} = \int s_i di = \theta$ .

- When **noises are independent across agents**

Imperfect knowledge about others' **actions**:

$$\int \int E_i[x_j] dj di = \int E_i[\bar{x}] di = \lambda \bar{x} + (1 - \lambda) \mu_{\bar{x}},$$

where  $\bar{x} = \int x_i di$  is the aggregate action.

- Capture **frictions in strategic interactions** (key later)



Pause for Questions

# Outline

- 1 Noisy-Information Models
- 2 Rational Inattention**
- 3 Sparsity
- 4 Sticky Information
- 5 Imprecise Perceptual Judgments
- 6 Application: Narrow Thinking

# Overview

## Rational Inattention:

- Impossible for a human being to process all available info
- Limited cognitive capacity and optimally allocate attention
- Trade-off between
  - ▶ cost of attention
  - ▶ benefit of attention (better decisions)
- “Micro-foundation” of the noisy information approach

$$s_i = \theta + \varepsilon_i,$$

where the variance of  $\varepsilon_i \sim \mathcal{N}(0, \sigma_{\varepsilon}^2)$  is endogeneized

# Entropy

- Sims (03): Cost of attention determined by quantity of information
- Entropy: measure of **the quantity of information** in information theory
- How much information is required to describe  $\theta$  with probability density function  $p(\theta)$ ?

$$H(\theta) = -\mathbb{E}[\log_2(p(\theta))],$$

- ▶ Discrete:  $H(\theta) = -\sum_{\theta \in \Theta} \log_2(p(\theta)) p(\theta)$
- ▶ Continuous:  $H(\theta) = -\int_{\theta \in \Theta} \log_2(p(\theta)) p(\theta) d\theta$
- ▶ Note  $\log_2$  is concave. If  $\theta$  is more “dispersed,”  $H(\theta)$  is larger.

## Entropy: Examples

### Bernoulli:

- Flipping a fair coin. One bit of information.

$$H(\theta) = - \left( \frac{1}{2} \log_2 \left( \frac{1}{2} \right) + \frac{1}{2} \log_2 \left( \frac{1}{2} \right) \right) = 1$$

- Flipping a fair coin  $n$  times and  $\theta$  captures the # of heads.

$$H(\theta) = n$$

**Uniform:** Suppose  $\theta \in U[0, a]$

$$H(\theta) = - \int_0^a \log_2 \left( \frac{1}{a} \right) \frac{1}{a} d\theta = \log_2 a$$

# Entropy: Examples

## Normal Variables:

- If  $\theta \sim \mathcal{N}(\mu, \sigma^2)$

$$H(\theta) = \frac{1}{2} \log_2 (2\pi e \sigma^2)$$

- If  $\theta$  is an  $n \times 1$  vector of normal variables  $\theta \sim \mathcal{N}(\mu, \Sigma)$

$$H(\theta) = \frac{1}{2} \log_2 ((2\pi e)^n \det(\Sigma))$$

# Mutual Information

- **Measure:** How informative is a signal about the underlying random variable?
- **Mutual Information:** How much does observing one random variable reduce the entropy of the another?

$$I(\theta, s) = H(\theta) - H(\theta|s)$$

- **Conditional entropy:** The remaining amount of info in  $\theta$  given that the value of  $s$

$$H(\theta|s) = H(\theta, s) - H(s)$$

- **Symmetry** of mutual information:

$$I(\theta, s) = I(s, \theta) = H(\theta) + H(s) - H(\theta, s)$$

# Mutual Information: Examples

## Normal fundamentals and signals:

- Fundamental  $\theta \sim \mathcal{N}(\mu, \sigma^2)$
- Signal  $s = \theta + \varepsilon$ , where  $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$  and independent of  $\theta$

$$\begin{aligned} I(\theta, s) &= H(\theta) - H(\theta|s) \\ &= \frac{1}{2} \log_2 (2\pi e \sigma_\theta^2) - \frac{1}{2} \log_2 (2\pi e \sigma_{\theta|s}^2) \\ &= \frac{1}{2} \log_2 \left( 1 + \frac{\sigma_\theta^2}{\sigma_\varepsilon^2} \right) \end{aligned}$$



Pause for Questions

# Rational Inattention: the Entropy Approach

Rational Inattention: the Entropy Approach (Sims, 2003)

- **Bound on information flow** measured based on mutual information

$$I(\theta, s) \leq \kappa$$

- Equivalently, **cognitive costs of attention** proportional to mutual information

$$\eta I(\theta, s)$$

# A Simple Rational Inattention Problem

**Payoff:** A one-dimensional tracking problem.

$$-\frac{\omega}{2}\mathbb{E}\left[(a_i - \theta)^2\right] - \eta l(\theta, s_i),$$

where  $\theta \sim \mathcal{N}(\mu, \sigma^2)$ .

**Attention** to  $\theta$  can be captured by a Gaussian signal  $s_i$  about  $\theta$

$$s_i = \theta + \varepsilon_i,$$

where  $\varepsilon_i \sim \mathcal{N}(0, \sigma_\varepsilon^2)$  and independent of  $\theta$ .

- The Gaussian form of the signal can be proved as optimal
- Same formulation as noisy-information, but  $\sigma_\varepsilon^2$  is endogenously chosen

## An Equivalent Formulation

Given signal  $s_i$ , the **optimal action** is

$$a_i = E[\theta | s_i] = \lambda s_i + (1 - \lambda) \mu,$$

where  $\lambda = \frac{\sigma^2}{\sigma^2 + \sigma_\varepsilon^2}$  increases with the precision of the signal.

**Cognitive cost:**

$$I(\theta, s_i) = \frac{1}{2} \log_2 \left( \frac{1}{1 - \lambda} \right)$$

**Expected tracking error:**

$$\begin{aligned} \mathbb{E}[(a_i - \theta)^2] &= \mathbb{E}[(\lambda(\theta + \varepsilon_i) + (1 - \lambda)\mu - \theta)^2] \\ &= \frac{\sigma^2 \sigma_\varepsilon^2}{\sigma^2 + \sigma_\varepsilon^2} = (1 - \lambda) \sigma^2 \end{aligned}$$

## An Equivalent Formulation

$$\min_{\lambda} \frac{\omega}{2} \sigma^2 (1 - \lambda) + \frac{\eta}{2} \log_2 \left( \frac{1}{1 - \lambda} \right)$$

FOC:

$$\frac{\omega}{2} \sigma^2 = \frac{\eta}{2 \ln 2} \frac{1}{1 - \lambda^*}$$

Optimal attention:

$$\lambda^* = \begin{cases} 1 - \frac{\eta}{\ln 2} \frac{1}{\omega \sigma^2} & \omega \sigma^2 \geq \frac{\eta}{\ln 2} \\ 0 & \omega \sigma^2 < \frac{\eta}{\ln 2} \end{cases}$$

Under-appreciated point: “entropy” cost can generate **zero-attention corner solution**

- If benefits of tracking  $\omega \sigma^2$  is too small/cost  $\eta$  of attention is too large

Pause for Questions

# Optimal Price Setting under Rational Inattention

**Expected loss:** (Mackowiak & Wiederholt, 09)

$$-\frac{|\pi_{pp}|}{2} \mathbb{E} \left[ (p_{i,t} - p_{i,t}^*)^2 \right],$$

where  $p_{i,t}^* = \Delta_t - \frac{\pi_{pz}}{\pi_{pp}} z_{i,t}$ .

## Information choice:

- One signal about the aggregate component  $\Delta_t \sim \mathcal{N}(0, \sigma_\Delta^2)$

$$s_{1,i,t} = \Delta_t + \varepsilon_{i,t},$$

where  $\varepsilon_{i,t} \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ .

- One signal about the idiosyncratic component  $z_{i,t} \sim \mathcal{N}(0, \sigma_z^2)$

$$s_{2,i,t} = z_{i,t} + v_{i,t},$$

where  $v_{i,t} \sim \mathcal{N}(0, \sigma_v^2)$ .

- Implicit restriction: cannot have a signal directly about  $p_{i,t}^*$ 
  - ▶ otherwise optimal to have  $s_{i,t}^* = p_{i,t}^* + \varepsilon_{i,t}^*$

# Optimal Price Setting under Rational Inattention

Attention allocation:

$$\underbrace{\frac{1}{2} \log_2 \left( 1 + \frac{\sigma_{\Delta}^2}{\sigma_{\varepsilon}^2} \right)}_{\kappa_{\Delta}} + \underbrace{\frac{1}{2} \log_2 \left( 1 + \frac{\sigma_z^2}{\sigma_v^2} \right)}_{\kappa_z} \leq \kappa.$$

Expected loss:

$$-\frac{|\pi_{pp}|}{2} \left[ 2^{-2\kappa_{\Delta}} \sigma_{\Delta}^2 + \left( \frac{\pi_{pz}}{\pi_{pp}} \right)^2 2^{-2\kappa_z} \sigma_z^2 \right]$$



# Optimal Price Setting under Rational Inattention

- **Optimal Allocation of Attention:**

$$\kappa_{\Delta}^* = \begin{cases} \kappa & \text{if } \sigma_{\Delta}^2 / \left( \frac{\pi_{pz}}{\pi_{pp}} \sigma_z \right)^2 \geq 2^{2\kappa} \\ \frac{1}{2} \kappa + \frac{1}{4} \log_2 \left( \sigma_{\Delta}^2 / \left( \frac{\pi_{pz}}{\pi_{pp}} \sigma_z \right)^2 \right) & \text{if } \sigma_{\Delta}^2 / \left( \frac{\pi_{pz}}{\pi_{pp}} \sigma_z \right)^2 \in [2^{-2\kappa}, 2^{2\kappa}] \\ 0 & \text{if } \sigma_{\Delta}^2 / \left( \frac{\pi_{pz}}{\pi_{pp}} \sigma_z \right)^2 \leq 2^{-2\kappa} \end{cases}$$

- See paper for the detailed GE equilibrium
- Take-home lesson:
  - ▶ Variances of idiosyncratic shocks are larger so endogenous inattentive to the aggregate nominal shock
  - ▶ Micro-foundation of the Phillips curve
  - ▶ Monetary shocks have real effects

# Rational Inattention: Beyond Shannon

**Implicit assumptions** embedded in the Shannon cost:

- Each pair of states is equally difficult to distinguish
- 2 vs 2.00001; 2 vs 1000;

**Alternatives to the Shannon cost:**

- Hébert & Woodford (21, AER): “Neighborhood-Based Information Costs”
  - ▶ certain pairs of states are easy to distinguish, whereas others are difficult to distinguish
- Pomatto, Strack & Tamuz (23, AER). “Log-likelihood Ratio Cost”
  - ▶ axiom 1: the cost of generating two independent signals is the sum of their costs
  - ▶ axiom 2: generating a signal with probability half costs half its original cost

## Rational Inattention: Beyond Shannon

**Uniformly posterior separable (UPS) cost:**

$$C(\mu) = \mathbb{E}_{q \sim \mu} [H(q)] - H(p),$$

- Cost of acquiring information depends only on distribution of posterior beliefs  $q$  and the function  $H$  does not depend on prior.
- Nests Shannon, Hébert & Woodford, Pomatto, Strack & Tamuz
- Denti (22, AER); Caplin, Dean & Leahy (22, JPE): axioms for the UPS cost and the entropy cost
- Dean & Neligh (23, JPE): experimental evidence: some support of UPS but not entropy
- Hébert and Woodford (23, JET), Morris and Strack (2019), and Bloedel and Zhong (2021) provide conditions under which the ex ante cost of a sequential sampling procedure is posterior separable

# Rational Inattention: General Problems based on the Shannon Cost

## Fully general cost:

- Caplin & Dean (15, AER): Axioms for whether a dataset is consistent with a model of information acquisition that puts no restrictions on the cost of information.

## Static multidimensional rational Inattention:

- Koszegi and Matejka (2020, QJE)

## Dynamic rational inattention and learning:

- Maćkowiak, Matějka, & Wiederholt (18, JET); Afrouzi & Yang (21, with a nice toolbox!); Miao, Wu, & Young (22, ECMA)

## Beyond Linear-Quadratic-Gaussian:

- Matejka (2016); Jung, Kim, Matejka, Sims (19, Restud): leading to discrete actions

## Rational Inattention: Applications

- Matějka & McKay (15, AER): rational inattention as a foundation to discrete choice models
- Maćkowiak & Wiederholt (15, Restud): business cycle dynamics under rational inattention.
- Nieuwerburgh & Veldkamp (09, JF); Nieuwerburgh, & Veldkamp (10, Restud); Kacperczyk, Nieuwerburgh & Veldkamp (16, ECMA): portfolio choices

Pause for Questions

# Outline

- 1 Noisy-Information Models
- 2 Rational Inattention
- 3 Sparsity**
- 4 Sticky Information
- 5 Imprecise Perceptual Judgments
- 6 Application: Narrow Thinking

## Overview: Gabaix (2014)

### Sparsity:

- A vector  $m \in \mathbb{R}^{1,000,000}$  if it has a few non-zero elements

**Gabaix (2014):** A model of inattention that

- Handles multi-dimensional problems in a tractable way
- Generate the “sparsity” pattern



# An Unconstrained Sparsity Problem

- **Objective** (quadratic or quadratic approximation)

$$u(a, \vec{\theta}) \quad \text{with} \quad \vec{\theta} = (\theta_1, \dots, \theta_N)$$

- Rational, non-sparse, **optimal action**

$$a^r = \sum_{i=1}^N a_{\theta_i} \theta_i$$

- **Attention:**  $m_i \in [0, 1]$  (normalize  $\theta_i^d = 0$ )

$$\theta_i^s(\vec{m}) = m_i \theta_i$$

- ▶ no noise & deterministic inattention/belief

- **Sparse action** (optimal action given sparsely perceived fundamental):

$$a^s(\vec{m}) = \sum_{i=1}^N a_{\theta_i} \theta_i^s$$

# An Unconstrained Sparsity Problem

- **Optimal attention allocation:**

$$\max_{\vec{m}} u\left(a^s(\vec{m}), \vec{\theta}\right) - \mathcal{C}(\vec{m})$$

- **Loss:**  $L(\vec{m}) \equiv \mathbb{E}\left[u\left(a^s(\vec{m}), \vec{\theta}\right) - u\left(a^r, \vec{\theta}\right)\right]$

$$L(\vec{m}) = \frac{1}{2} \sum_{i,j \in \{1, \dots, N\}} (1 - m_i) \Lambda_{ij} (1 - m_j),$$

where  $\Lambda_{ij} = -\text{Cov}(\theta_i, \theta_j) a_{\theta_i} u_{aa} a_{\theta_j}$  and  $a_{\theta_i} = -u_{aa}^{-1} u_{a\theta_i}$ ,

- **Cost of attention:**

$$\mathcal{C}(\vec{m}) = \kappa \sum_{i=1}^N m_i^\alpha$$

- **Equivalent problem:**

$$\min_{\vec{m}} \frac{1}{2} \sum_{i,j \in \{1, \dots, N\}} (1 - m_i) \Lambda_{ij} (1 - m_j) + \kappa \sum_{i=1}^N m_i^\alpha$$

# The One-Dimensional Problem

**One-dimensional problem:**  $u(a, \theta) = -\frac{\omega}{2} (a_i - \theta)^2$

$$\min_m \frac{\omega}{2} (1 - m)^2 \sigma_\theta^2 + \kappa m^\alpha$$

**Optimal attention:**

$$m^* = \mathcal{A}_\alpha \left( \frac{\omega \sigma_\theta^2}{\kappa} \right),$$

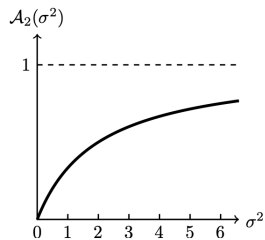
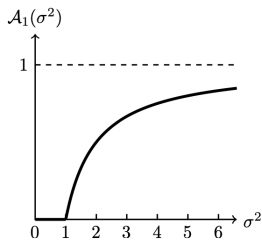
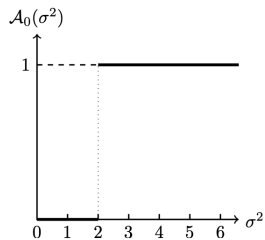
where  $\mathcal{A}_\alpha$  is the “attention function.”

Compared to the **entropy-based problem:**

$$\min_\lambda \frac{\omega}{2} \sigma^2 (1 - \lambda) + \frac{\eta}{2} \log_2 \left( \frac{1}{1 - \lambda} \right)$$

- Essentially just a change of the functional form

# The Attention Function and Sparsity (“ $\alpha \leq 1$ ”)



# Differences between Sparsity and Rational Inattention

## Deterministic vs Stochastic

- Sparsity: Decisions are deterministic
- Rational inattention: Decisions are stochastic
- Huge literature in decision theory on stochastic decisions
- Not that relevant for macro (law of large numbers)

## Simpler for multi-dimensional problems

- Independently distributed fundamentals: equally simple
- Correlated fundamentals: sparsity simpler
  - ▶ cost function separate:  $\mathcal{C}(\vec{m}) = \kappa \sum_{i=1}^N m_i^\alpha$

# Sparse Optimization with Constraints

$$\max u(\vec{c}) \quad \text{s.t.} \quad \vec{p} \cdot \vec{c} \leq w$$

- **Question:** how to maintain the budget with behavioral mistakes?
- **Solution:** MRS optimality holds with perceived prices

$$\frac{\partial u}{\partial c_i} / \frac{\partial u}{\partial c_j} = p_i^s / p_j^s$$

- **Sparse decision:**

$$u'(\vec{c}^s(\lambda)) = \lambda \vec{p}^s \quad \text{and} \quad \vec{p} \cdot \vec{c}^s(\lambda) = w$$

- Optimal attention part same
- Implications: asymmetric Slutsky Matrix

# Sparse Optimization with Constraints

Alternative: the “residual” decision approach

$$u(\vec{c}) + v(y) \quad \text{s.t.} \quad \vec{p} \cdot \vec{c} + y \leq w,$$

where  $v(y)$  is the “continuation” value.

- $\vec{c}$  made “behaviorally and  $y$  absorbs the changes

**Example** (Sims, 03): value from borrowing and saving.

**Open questions:** in practice, agents make decisions sequentially

- May have “hints” if “closer” to the constraint
- “Foundations” of those reduced-form approaches

Pause for Questions



# Outline

- 1 Noisy-Information Models
- 2 Rational Inattention
- 3 Sparsity
- 4 Sticky Information**
- 5 Imprecise Perceptual Judgments
- 6 Application: Narrow Thinking

## Overview: Mankiw & Reis (2002)

Concept of **sticky information**:

- Pricing decisions are not always based on current information
- Only a fraction of firm obtains new info each period
- Firms can always change their prices (no sticky “prices”)
- Key prediction: inertia to the inflation process

Comparison with the **sticky price** (Calvo) model:

- Though price is sticky, inflation is forward looking and “jumpy”

$$\pi_t = \kappa y_t + \beta E_t [\pi_{t+1}]$$

- Trouble explaining why inflation is so persistent
- Trouble explaining why shocks to monetary policy have a delayed and gradual effect on inflation (“hump-shape” response)

Differences between sticky-info and noisy-info more nuanced

- Especially in terms of macro implications

## Sticky Information

- In each period
  - ▶ a fraction  $\lambda$  of firm obtains new info and re-optimizes
  - ▶ the other firms continue to set prices based on outdated info
- Firm sets its price every period
  - ▶ can change prices even based on outdated info
  - ▶ e.g., anticipated news & steady-state inflation
- Connection with noisy-info/rational-inattention
  - ▶ a fraction  $\lambda$  of firm is “attentive” this period
  - ▶ the rest  $1 - \lambda$  of firm is “inattentive” this period
  - ▶ perfectly precise signals about the current shock if “attentive”
  - ▶ infinitely imprecise signals if “inattentive”

# Pricing Decisions under Sticky-info

- “Desired”/“Target” price:

$$p_t^* = p_t + \alpha y_t,$$

where  $p_t$  is nominal price and  $y_t$  is output gap.

- A firm that last updated its information  $k$  periods ago sets the price

$$p_t^k = E_{t-k} [p_t^*]$$

- The aggregate price level

$$p_t = \sum_{k=0}^{+\infty} \lambda (1 - \lambda)^k p_t^k$$

## Sticky Information PC

- From the previous slides

$$p_t = \sum_{k=0}^{+\infty} \lambda (1-\lambda)^k E_{t-k} [p_t + \alpha y_t]$$

- Take a first difference and collect terms

$$\pi_t = \frac{\alpha\lambda}{1-\lambda} y_t + \lambda \sum_{j=0}^{+\infty} (1-\lambda)^j E_{t-1-j} [\pi_t + \alpha \Delta y_t],$$

where  $\Delta y_t = y_t - y_{t-1}$

- ▶ Past expectations about current conditions

- Compared to NKPC

$$\pi_t = \frac{\alpha\lambda^2}{1-\lambda} y_t + E_t [\pi_{t+1}],$$

where  $\lambda$  is prob. of adjustment and the discount rate  $\beta = 1$ .

- ▶ Current expectations about future conditions

# A Sudden Permanent Drop in Agg. Demand $m_t = p_t + y_t$

- Key feature of sticky info: **inertia/hump-shape** in  $\pi_t$  response

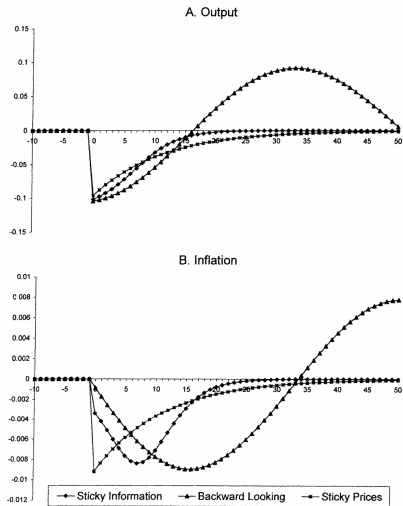


FIGURE I  
Dynamic Paths after a 10 Percent Fall in the Level of Aggregate Demand at Time 0

# Micro-foundation of Sticky Information

## Reis (2006): Inattentive Producers

- **Fixed cost** to acquire information
- Difference from RI:
  - ▶ cost does not depend on the “distance” between prior and posterior
- The producer optimally only **updates her info sporadically**
  - ▶ inattentive in between

## Alvarez et al. (2016): Monetary Shocks in Models with Inattentive Producers

- A general version of Reis (2006) beautifully solved

## Matejka (2016): Rationally Inattentive Seller: Sales and Discrete Pricing

- Entropy approach but beyond Gaussian
- Prices tend to remain constant for a period of time and then jump back and forth between a few given values

# Sticky Information v.s. Noisy Information

Differences more nuanced, especially in terms of macro implications

## First moments:

- Both: **average expectations under-reacts** to aggregate shock
  - ▶ initial underreaction

$$\frac{d\bar{E}_0[m_0]}{dm_0} = \lambda$$

- ▶ slow learning (soon)
- Both: generate inertia in inflation dynamics

## Second moments/disagreement: (Coibion & Gorodnichenko, 2012)

- Sticky info: more disagreement after a larger realization of shocks
- Noisy info: in a stationary environment
  - ▶ disagreement independent of the realization of shocks



Pause for Questions

# Outline

- 1 Noisy-Information Models
- 2 Rational Inattention
- 3 Sparsity
- 4 Sticky Information
- 5 Imprecise Perceptual Judgments
- 6 Application: Narrow Thinking

# Overview

A conceptual issue: what is the “noise” in rational inattention?

- Either attentive (the true value) or inattentive (the prior)
- What is the interpretation of the in-between (noise)?

**Woodford (20):** Modeling Imprecision in Perception, Valuation and Choice

- Imprecise perceptual judgments in psychophysics

# Psychophysics

Measure and model the relationship between

- Objective physical properties of environment
- The way these are subjectively perceived

**Finding:** the **stochasticity** of subjective judgments

- People unable to make completely accurate comparisons
  - ▶ which of two weights is heavier, which of two lights is brighter, etc
- But probability of a given response increases monotonically with increases in its relative magnitude
  - ▶ psychometric function

# Imprecise Perceptual Judgments

- Internal representation of a stimuli  $x$  summarized by

$$s \sim \mathcal{N}(m(x), v^2)$$

- ▶ “noisy” signal, but allowing mental coding to be in a “different space”

- As a result,

$$\text{Prob}["x_2 \text{ greater } x_1" | x_1, x_2] = \Phi\left(\frac{m(x_2) - m(x_1)}{\sqrt{2}v}\right)$$

- “Weber’s Law”

- ▶ discrimination threshold increases in proportion to the **relative difference** between two stimuli
  - ▶  $m(x)$  is the logarithm of  $x$

# Encoding and Decoding as Distinct Processes

**Encoding:** from the stimuli to the international representation

$$s \sim \mathcal{N}(m(x), v^2)$$

**Decoding:** inference based on the international representation  $s$ ,  $E[x|s]$

- Similar to inference based on a “noisy” signal

Why distinct process?

- Internal representation measurable with development of neuro-science
- Encoding/Decoding process can incorporate other cognitive features
  - ▶ Efficient coding theory (encoding)
  - ▶ Selective retrieval from memory (decoding)

## Application: Small-Stakes Risk Aversion

- Empirical studies documenting **small-stakes risk aversion**
- Rabin (00): based on expected utility theory, small-stakes risk aversion
  - ▶ leads to extraordinary risk aversion with respect to large gambles
- Standard explanation: loss aversion (Kahneman & Tversky, 79)
- Khaw, Li, & Woodford (21, Restud). Cognitive imprecision and small-stakes risk aversion.

# Cognitive Imprecision and Small-stakes Risk Aversion

- A choice between
  - ▶ money  $C > 0$  with certainty
  - ▶ a gamble that pays  $X$  with probability  $1/2$ , but has probability  $1/2$  of paying nothing
  - ▶  $C$  and  $X$  vary across trials
- Internal representation of  $C$  and  $X$

$$s = (s_C, s_X)$$



## Cognitive Imprecision and Small-stakes Risk Aversion

- If risk neutral, accept the game if and only if

$$E[X|s] > 2E[C|s]$$

- Probability of acceptance:

$$\Phi\left(\frac{\log(X/C) - \beta^{-1}\log 2}{\sqrt{2}\nu}\right),$$

where  $\beta$  increases with the precision of the signal.

- “Indifference” point:

$$X^{indiff}/C = 2^{1/\beta} > 2 \implies \text{Risk Aversion}$$

- Caveat: coding in the “log” space important
- Additional evidence: measured risk aversion
  - ▶ correlated with degree of randomness in responses
  - ▶ increases with cognitive loads of subjects in laboratory experiments

## Cognitive Imprecision and Small-stakes Risk Aversion

- If risk neutral, accept the game if and only if

$$E[X|s] > 2E[C|s]$$

- Probability of acceptance:

$$\Phi\left(\frac{\log(X/C) - \beta^{-1}\log 2}{\sqrt{2}\nu}\right),$$

where  $\beta$  increases with the precision of the signal.

- “Indifference” point:

$$X^{indiff}/C = 2^{1/\beta} > 2 \implies \text{Risk Aversion}$$

- Caveat: coding in the “log” space important
- Additional evidence: measured risk aversion
  - ▶ correlated with degree of randomness in responses
  - ▶ increases with cognitive loads of subjects in laboratory experiments

# Outline

- 1 Noisy-Information Models
- 2 Rational Inattention
- 3 Sparsity
- 4 Sticky Information
- 5 Imprecise Perceptual Judgments
- 6 Application: Narrow Thinking**

# A New Approach to Narrow Bracketing

Economic decisions are made disjointly (“**narrow bracketing**”)

- “We tend to make decisions as problems arise, even when we are specifically instructed to consider them jointly.”

— *Kahneman (2011)*

Existing model of narrow bracketing

- Directly **imposing each decision is made in isolation**

This paper: **narrow thinking** approach to narrow bracketing (Lian, 2021, Restud)

- Application: a “smooth” model of **mental accounting**
- Connect mental accounting with narrow bracketing

## Narrow Thinking (Lian, 2021)

**Definition:** Diff. decisions based on **diff. & non-nested information**

- When buying food, know food price, but not gasoline price & v.v.
- Psy foundation: bounded recall & “what you see is all there is”

**Rep.:** **Incomplete info**, common interest, game among multiple selves

- Each decision is made with imperfect perception of other decisions

**Essence:** Capture **difficulty in coordinating multiple decisions**

- As if each decision is made caring less about other decisions
- A smooth model of narrow bracketing

## Narrow Thinking $\implies$ Narrow Bracketing

A simple consumer theory example:

$$u(x_1, x_2, \vec{p}) = v(x_1, x_2) + w - p_1 x_1 - p_2 x_2$$

**Narrow thinker:** self  $i$  knows  $p_i$  & receives a noisy signal about other  $p_{-i}$

A smooth model of **narrow bracketing**

$$\frac{\partial x_i^{\text{Narrow}}}{\partial p_i} = \omega_i \frac{\partial x_i^{\text{Neglect}}}{\partial p_i} + (1 - \omega_i) \frac{\partial x_i^{\text{Standard}}}{\partial p_i}$$

- $x_i^{\text{Neglect}}(\vec{p})$  : completely neglecting the other decision

**Intuition.**

- $x_{-i}$  not as responsive to  $p_i$ .
- Indirect effect through  $x_{-i}$  dampened.
- Effectively cares less about the other decision

## Application: a Smooth Model of Mental Accounting

### Application: **mental accounting**

- Separable, non quasi-linear utility. Interaction from the budget.

$$\sum_{i=1}^N v_i(x_i) + h(w - \sum p_i x_i)$$

- A **smooth** model of mental accounting

$$\frac{\partial x_i^{\text{Narrow}}}{\partial p_i} = \omega_i \frac{\partial x_i^{\text{Explicit}}}{\partial p_i} + (1 - \omega_i) \frac{\partial x_i^{\text{Standard}}}{\partial p_i} \quad \forall i,$$

- $x_i^{\text{Explicit}}(\vec{p})$ : **explicit budget**, e.g. allocates \$100 to food
- **Intuition**: for  $x_i^{\text{Explicit}}(\vec{p})$ , each decision can be made in isolation

Narrow bracketing/mental accounting, by the same underlying friction

New predictions about what drives the **degree** of mental accounting

- Spending shares
- Cognitive limitations

## Related Literature

Difference from **rational inattention/sparsity**:

- Imperfect knowledge about the fundamental (e.g. prices)
- **Same information** for **all** decisions
  - ▶ Gabaix (2014); Koszegi & Matejka (2020)
  - ▶ When buy food/gasoline, always knows food but not gasoline price
- **Fully consider other decisions' influence** on current decision



Pause for Questions