Underreaction and Overreaction in Inference and Forecasting

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Motivation

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  - More underreaction when signals are strong.
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What drives variation in under/overreaction?

Are its determinants domain specific or common across domains?

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- Unifying framework to study both inference and forecasting.
- Map features across domains.
- Understand evidence through common psychological mechanism.

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- Memory and limited attention shape mental representations.
- Meta priors: pinned down by representative experiences with probelm.
- Attention weights: determined by top-down and bottom-up factors.

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Across Domains

- Inference and forecasting cue different mental representations.
- Prevalence of underreaction in inference, overreaction in forecasting.

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Within Domains

- Overreaction to weak signals and underreaction to strong signals.

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Within Domains

- Overreaction to weak signals and underreaction to strong signals.

  But with multiple features this is modulated by attention.
- More neglected features drive more variation in over/underreaction.
- Interaction of attended and neglected features can reverse comp static.

Outline

1. Common Framework

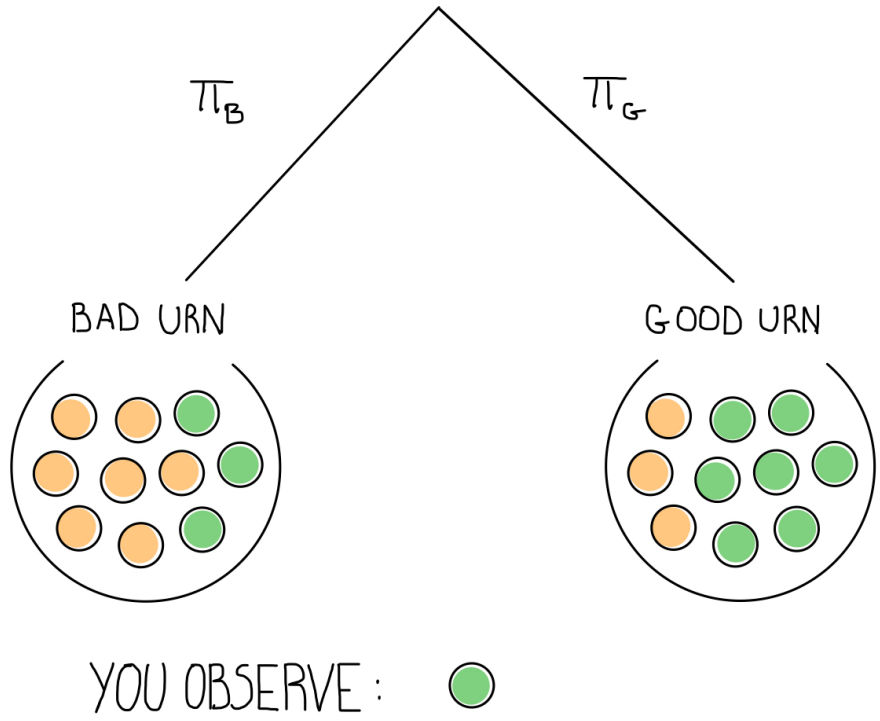
2. Mental Representations

3. Experiment

4. Manipulating Attention and Cognitive Defaults

Framework – Balls and Urns

- Standard inference problem: balls and urns experiment.



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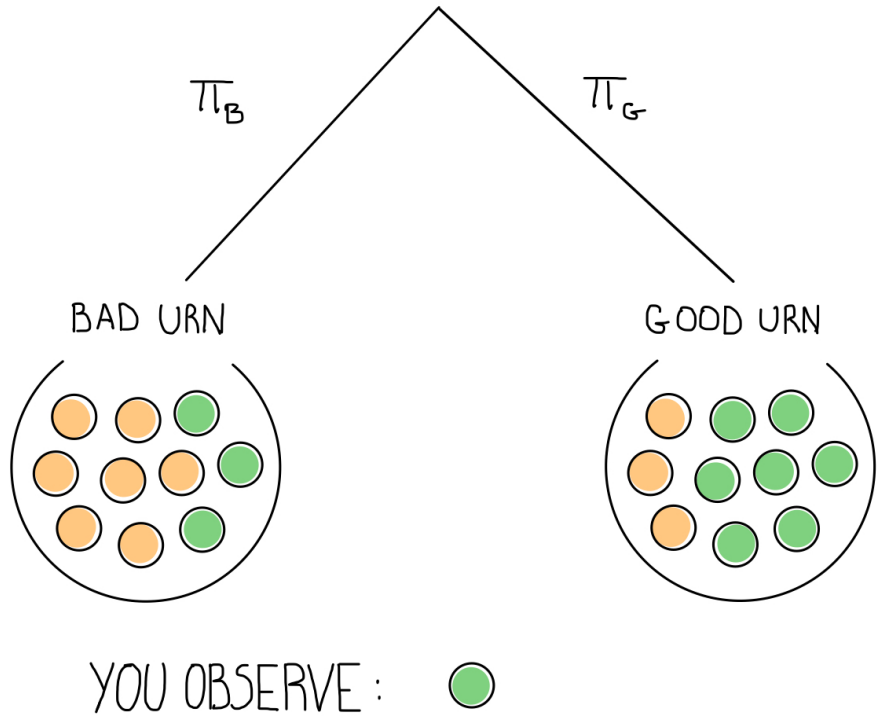

- Inference: how likely do you think the selected urn is G vs B?
- Signal strength = $\left(\frac{\pi_{\bullet|G}}{\pi_{\bullet|B}} \right)$

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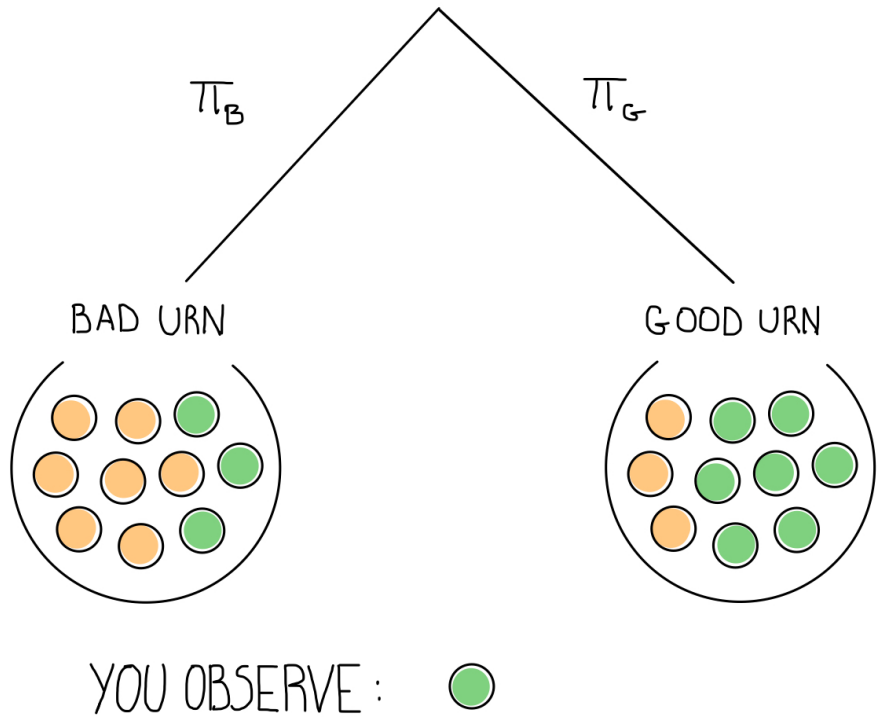
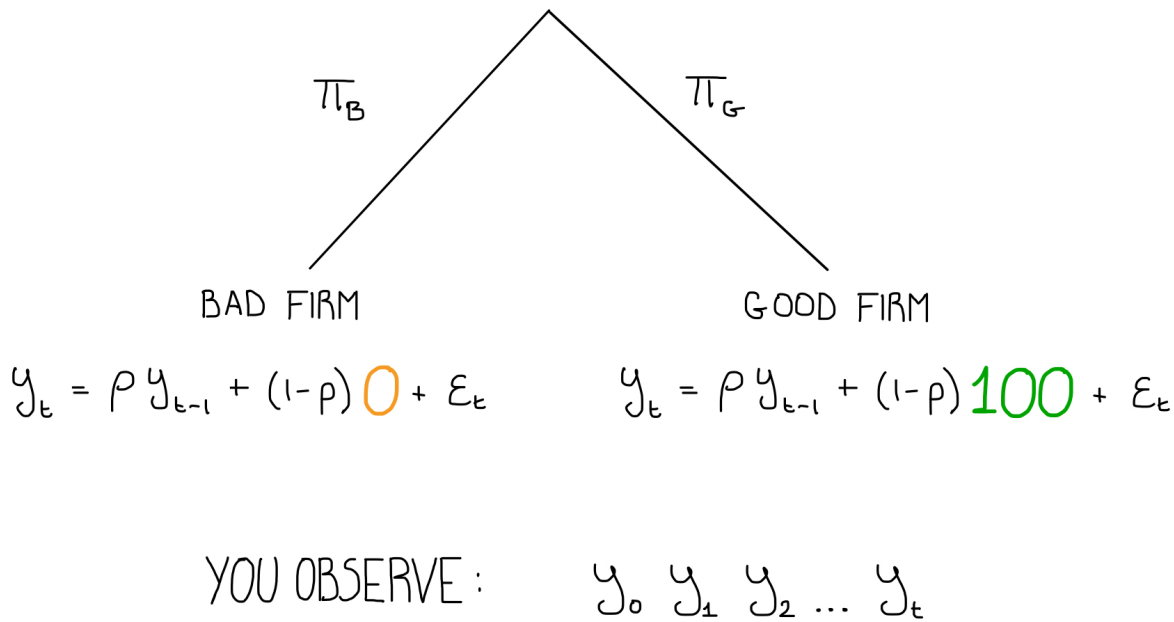


- Inference: how likely do you think the selected urn is Good?
- Forecasting: what do you expect the next ball to be?
- But signals are iid: no role for persistence or horizon.

Framework – Persistence and Horizon

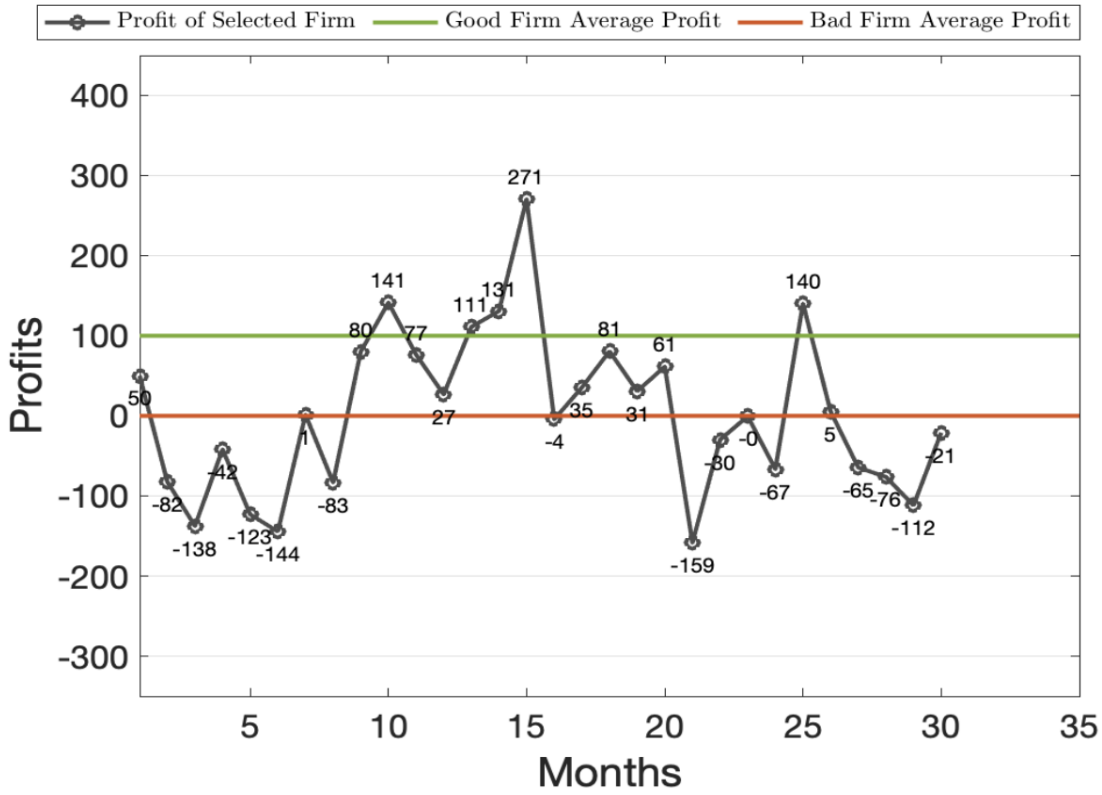
- Urns: just represent two data generating processes.
- Balls: draws from the DGPs.

- Let the two DGPs be AR(1)s with different means:



Inference and Forecasting with Persistence & Horizon

profit in current month =
(0.4) x (profit in previous month) + (0.6) x (firm's average profit)
+ unpredictable fluctuations



- Inference: how likely do you think the selected firm is G vs B?
- Forecasting: what do you expect profits to be in month $t + h$?

Inference and Forecasting with Persistence & Horizon

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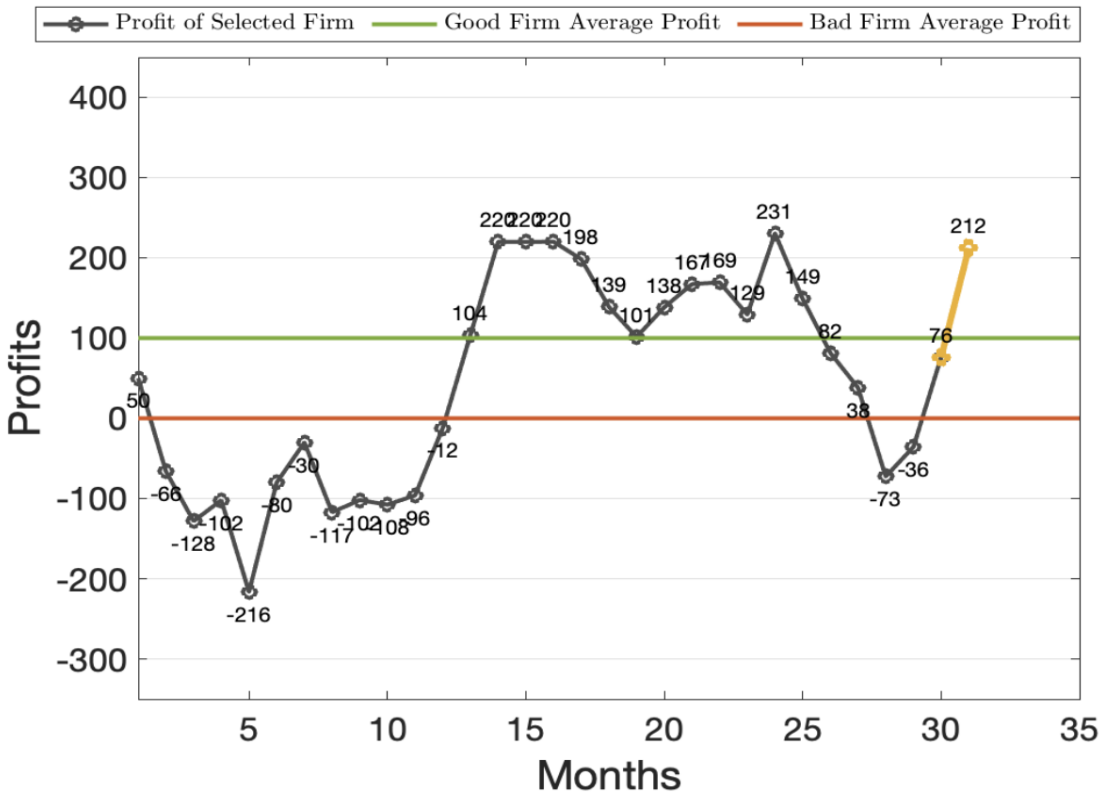
+ unpredictable fluctuations



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- Forecasting: what do you expect profits to be in month $t + h$?

Signal Strength in Inference and Forecasting

- Signal strength in inference:

$$\log\left(\frac{\pi_{y_t|G}}{\pi_{y_t|B}}\right) = \left(\epsilon_t + \frac{\mu_G - \mu_B}{\frac{2\sigma}{1-\rho}}\right)\left(\frac{\mu_G - \mu_B}{\frac{\sigma}{1-\rho}}\right)$$

- Signal strength in forecasting:

$$\mathrm{E}_t[y_{t+h}] - \mathrm{E}_{t-1}[y_{t+h}] = \rho^h \sigma \epsilon_t + (1-\rho^h)\left(\mathrm{E}_t[\mu] - \mathrm{E}_{t-1}[\mu]\right)$$

- Signal strength depends on multiple features which interact.

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- Signal strength depends on multiple features which interact.
- Opposite comparative static wrt ρ in inference and forecasting.
  - Increasing persistence decreases signal strength in inference.
  - Increasing persistence increases signal strength in forecasting.
- Signal strength in forecasting is decreasing in horizon.

Outline

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2. Mental Representations

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4. Manipulating Attention and Cognitive Defaults

Mental Representation and Limited Attention

- Feature vector:

$$\mathbf{x} = \{\rho, \epsilon_t, h, \mu_A - \mu_B, \sigma\}$$

- Mental representation:

$$\tilde{x}_k = \alpha_k x_k + (1 - \alpha_k)\mu_k$$

  - Vector of cognitive defaults: $\mu_k = \{\bar{\rho}, \bar{\epsilon}_t, \bar{h}, \mu_A - \mu_B, \sigma\}$
  - Vector of attention weights: $\alpha = \{\alpha_\rho, \alpha_{\epsilon_t}, \alpha_h, 1, 1\}$

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- Cognitive defaults determined by experiences in similar problems:

$$\mu_k = \sum_{m=1}^{M} w_k x_{k,m}, \qquad w_k \propto \left(\frac{P(x_{k,m}|q)}{P(x_{k,m}|\bar{q})} \right)^\theta$$

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- Allocate attention to minimize MSE s.t. attention budget.
- More attention to more valuable, easier to process, volatile features.

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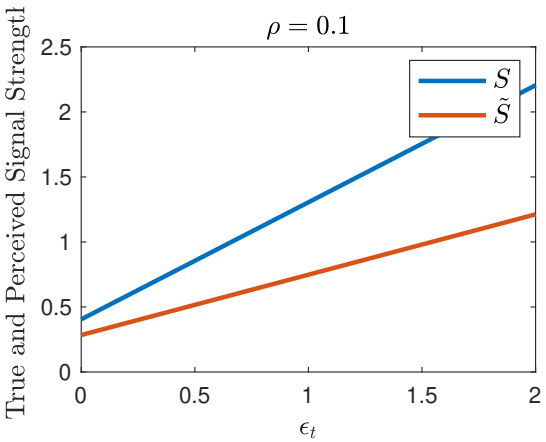
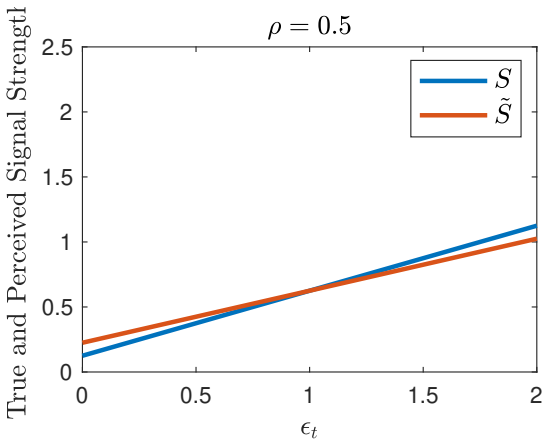
④ Interaction of features can reverse comparative static.

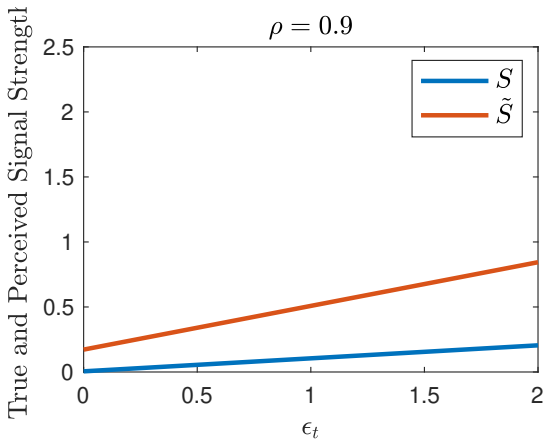
- Excess sensitivity is driven by **neglect**.

Insensitivity to $\rho \implies$ "Excess Sensitivity" to ϵ_t

$$S(\rho, \epsilon_t)_{\text{inference}} = \epsilon_t(1-\rho) + \frac{(1-\rho)^2}{2}$$







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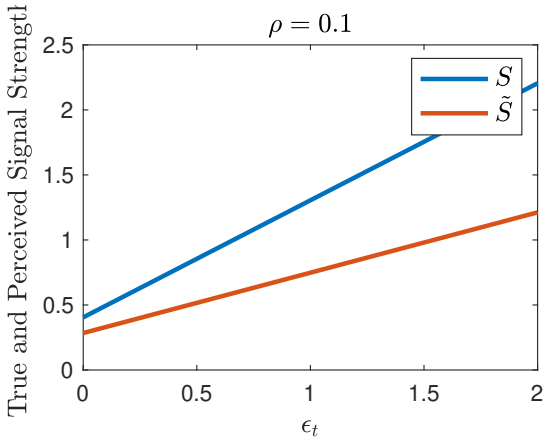
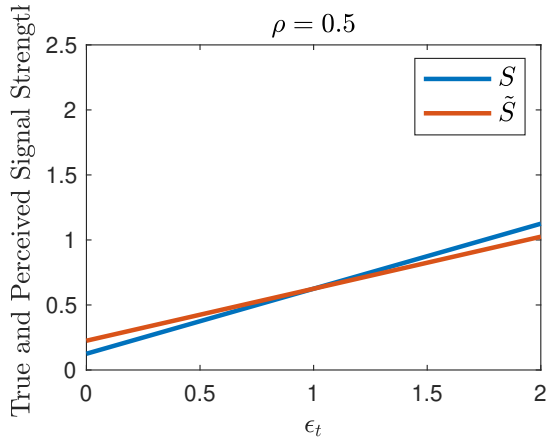
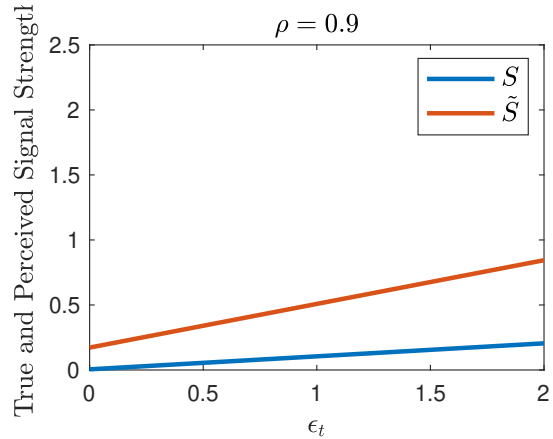
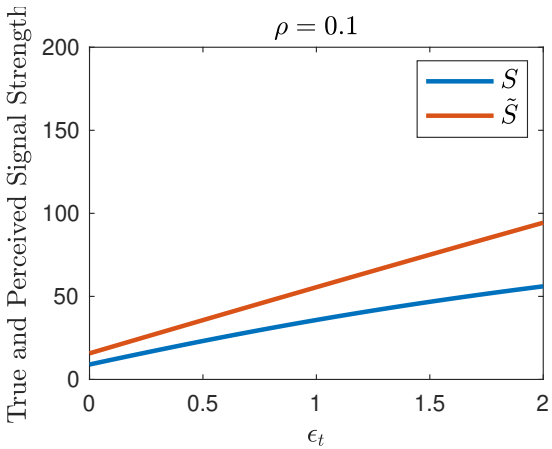
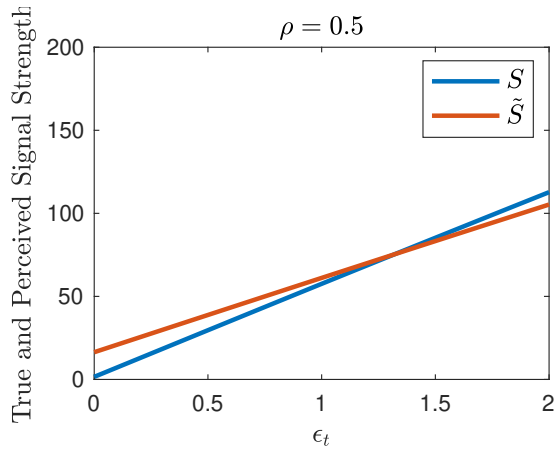


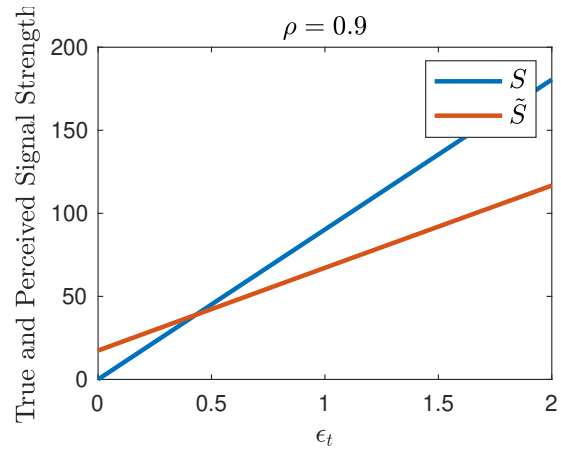




$$S(\rho, \epsilon_t)_{\text{forecasting}} = \rho\epsilon_t$$







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Experiment Setup (1)

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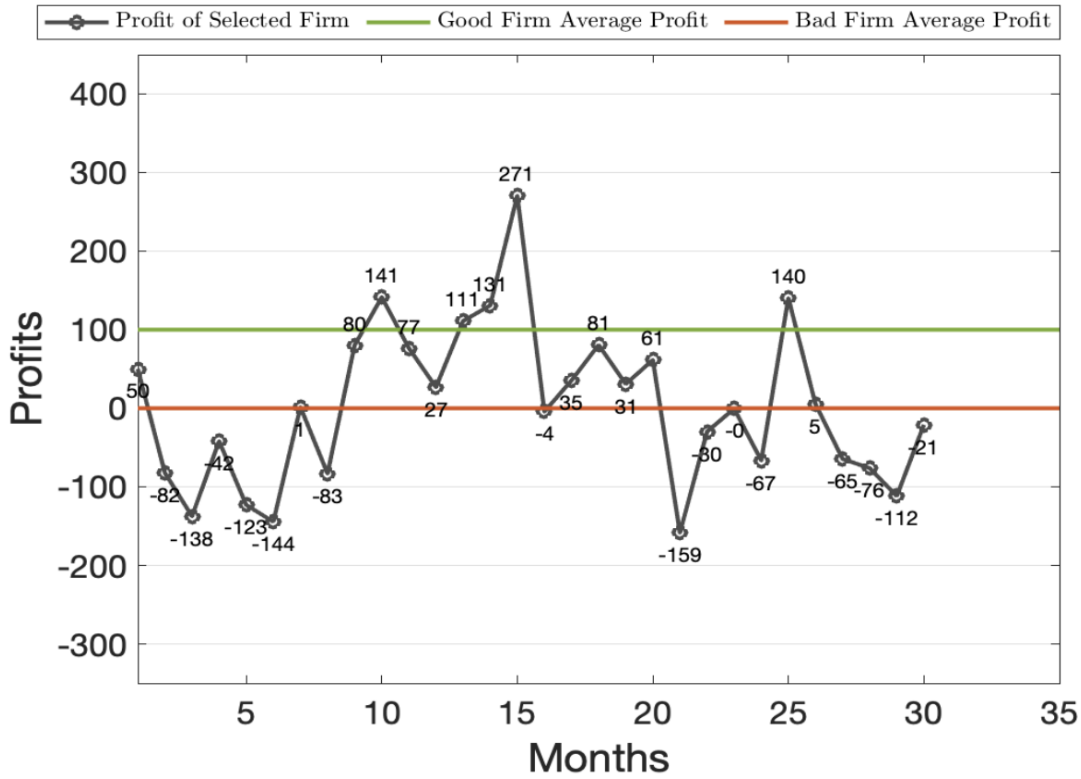

- Each participant answered either inference or forecasting questions.
- Inference: how likely do you think the firm is good or bad.
- Forecasting: what do you expect profits to be in month 32, 33, long run.

Experiment Setup (2)

- Participants were recruited on Prolific.
- Incentives: \$5 base fee, and \$10 potential bonus.
- Series of attention and comprehension checks.
- Each participant answers 12 rounds of questions.
- Variation:
  - Persistence: $\{0.1, 0.5, 0.9\}$
  - Shock size: $\{0.2\sigma, 0.8\sigma, 2\sigma\}$ and $\{0.6\sigma, 1.3\sigma, 2\sigma\}$
  - Horizon being forecasted: {month 32, long run profits}
- Over/under-reaction: actual revision relative to Bayesian revision.

Mental Representations and Attention (1)

	$\bar{\rho}$	$\bar{\epsilon}$	α_ρ	α_ϵ
Inference	**0.6**	medium shock	0	0.5
Forecasting	**0.9**	medium shock	0.4	0.8

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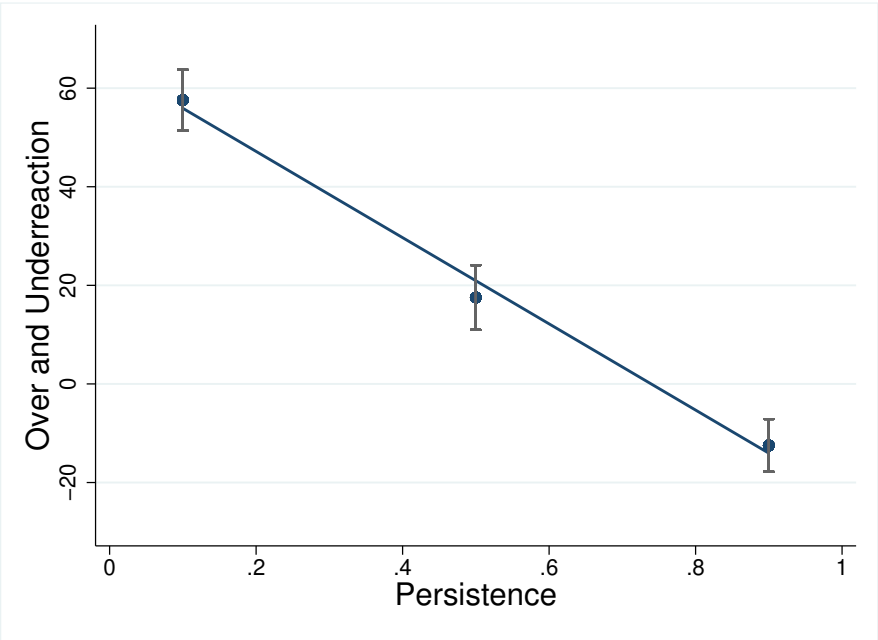
- We elicit what processes are more likely to come to mind.
- Provide two DGPs – coin flips or firm profits.
- *"are the scenarios that come to mind [in inference or forecasting] more similar to the coin or company scenario described above?"*
- Inference associated with coins, forecasting associated with firms.

① Inference and forecasting cue different mental representations.

Inference and Forecasting: variation in Persistence

- Greater persistence weakens signal strength in inference.
- Greater persistence strengthens signal strength in forecasting.

(a) Forecasting



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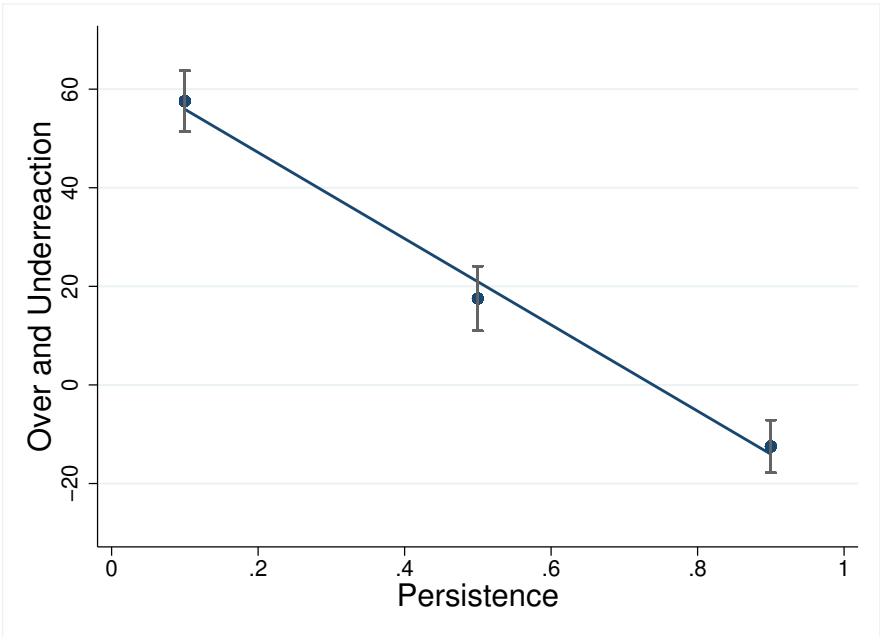
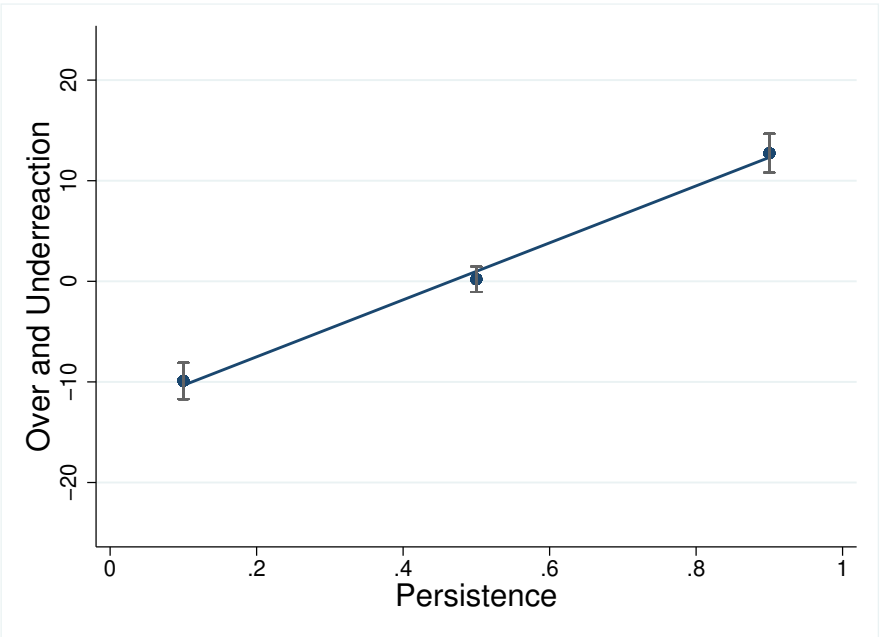


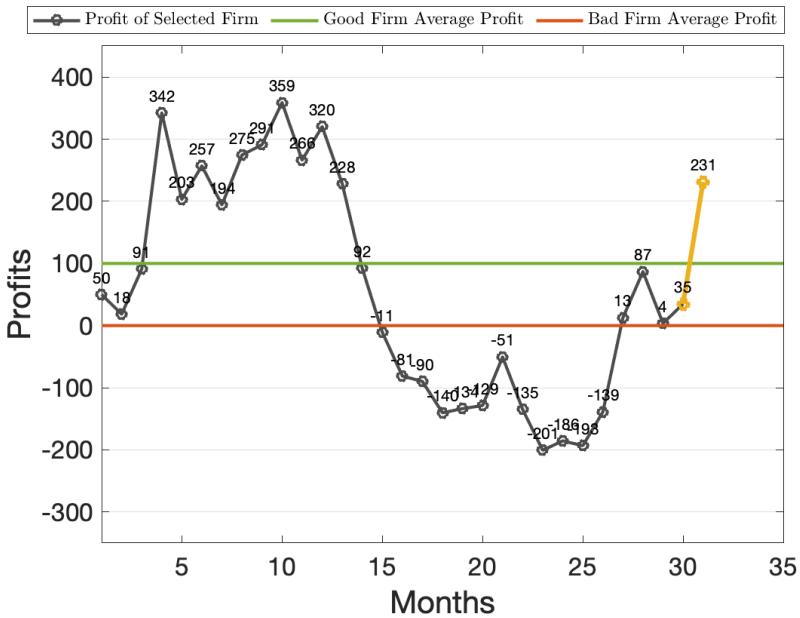
(b) Inference

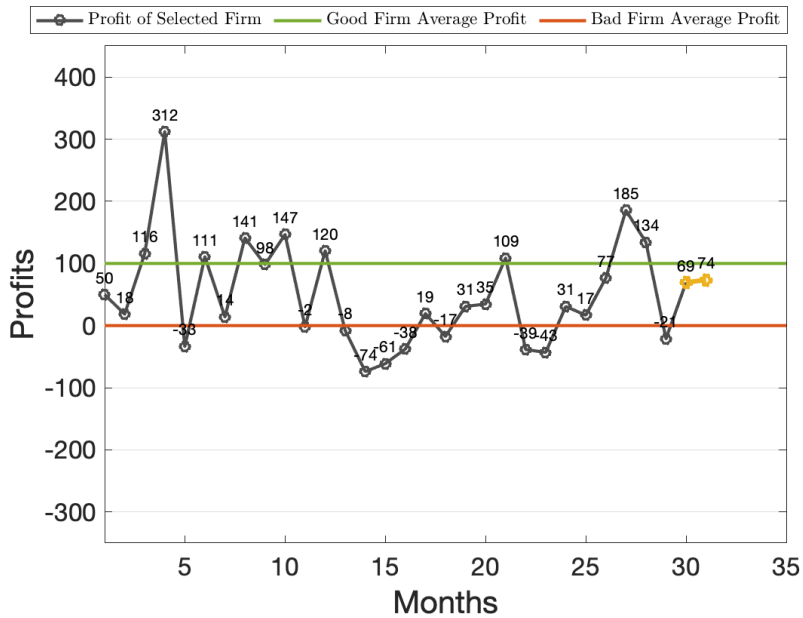


② Overreaction to weak signals and underreaction to strong signals.

Over/Underreaction Modulated by Attention (1)

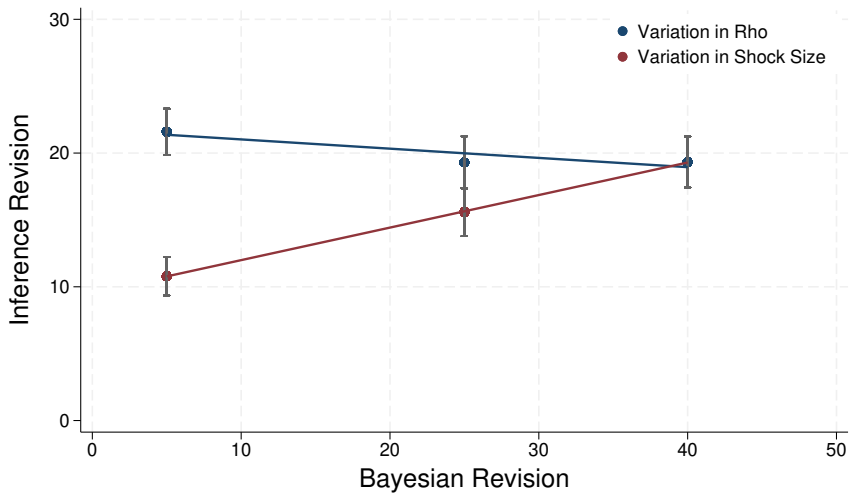
- Same signal strength:
  - Left: greater shock is discounted more due to higher persistence.
  - Right: smaller shock is discounted less due to lower persistence.

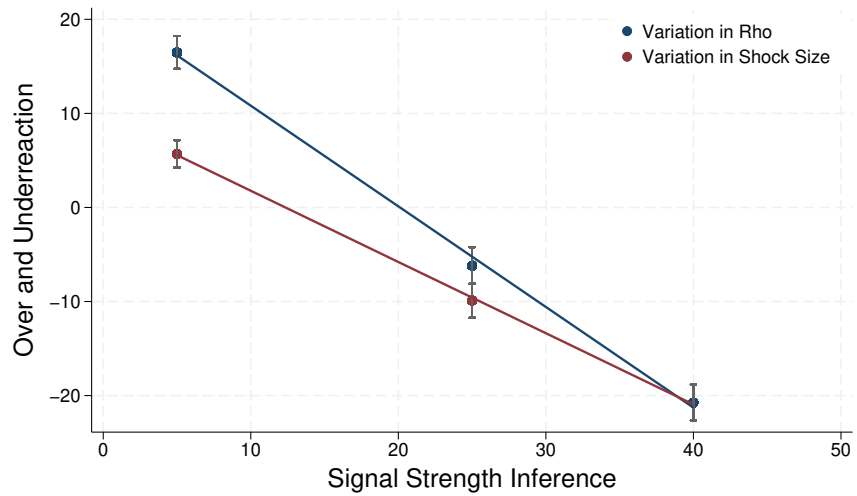




Over/Underreaction Modulated by Attention (2)

- Persistence neglected more than shock size.
- Persistence drives more variation in over/underreaction.





Over/Underreaction Modulated by Attention (3)

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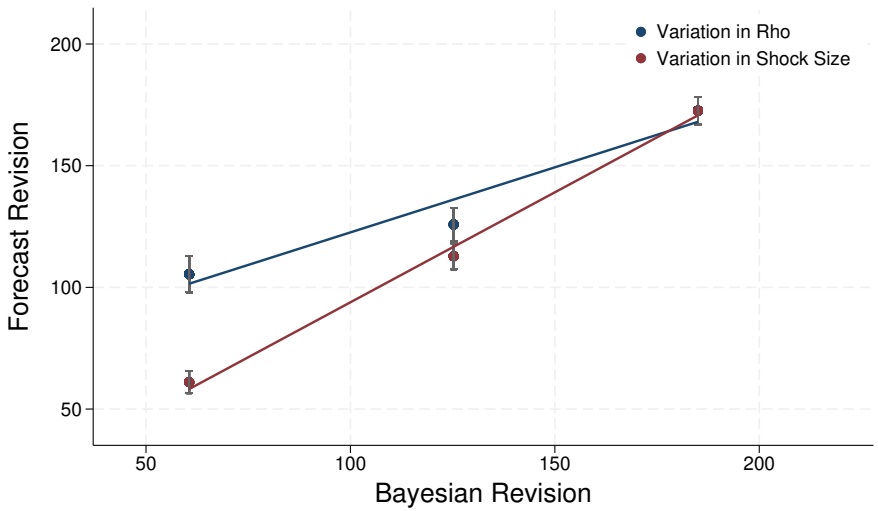
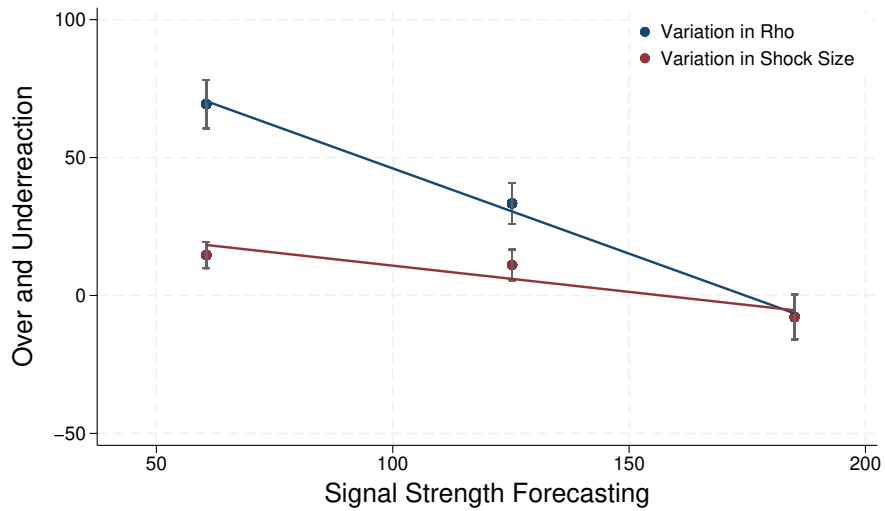




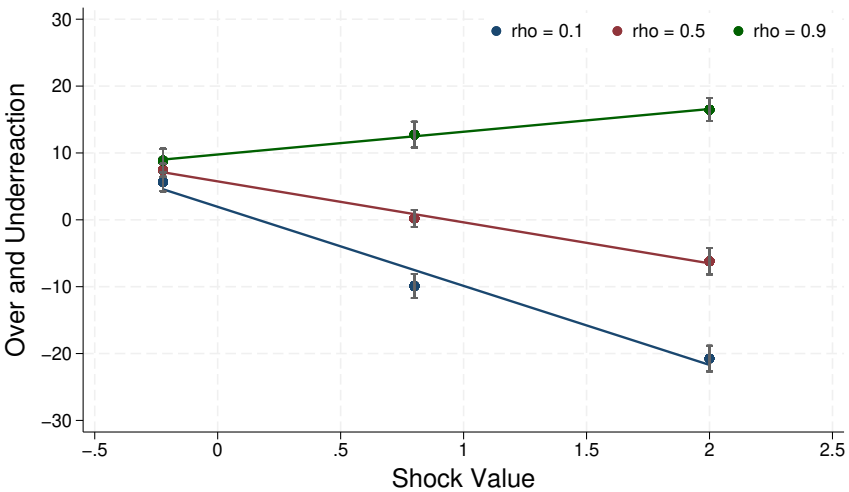
③ More neglected features $\Longrightarrow$ more variation in under/overreaction.

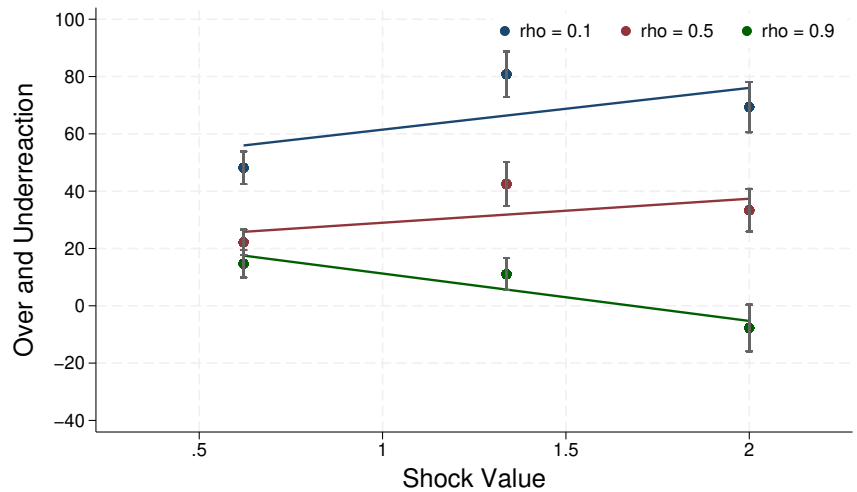
More Overreaction to Stronger Signals

$$S(x,y)_{\text{inference}} = (1-\rho)\epsilon_t + \frac{(1-\rho)^2}{2}$$

$$S(x,y)_{\text{forecasting}} = \rho\epsilon_t$$

- Neglecting ρ can make perceived signal strength overly sensitive to ϵ_t.





④ Interaction of neglected and attended to features can reverse comparative static $\Longrightarrow$ excess sensitivity symptomatic of insensitivity.

SPF

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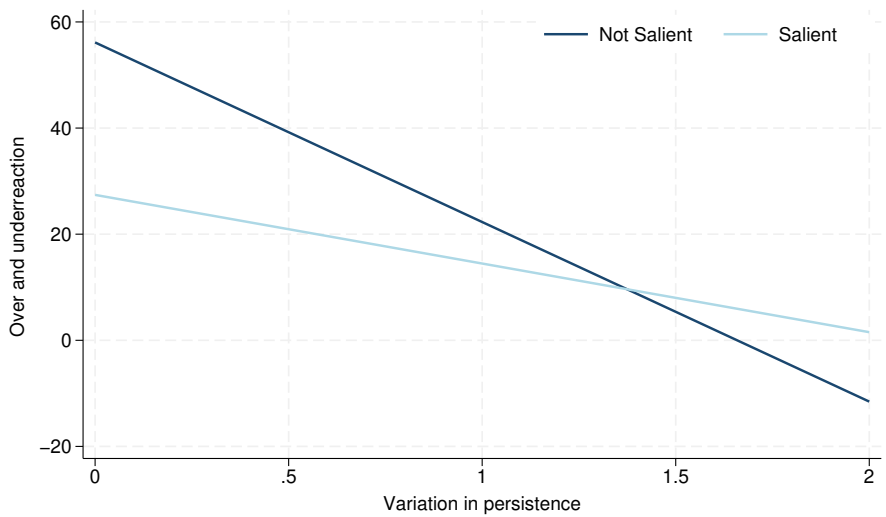
Manipulating Attention: Sensitivity

- Draw people's attention to variation in persistence:
  - Additional comprehension questions on persistence.
  - Describe a persistent and a transitory process they have encountered.
- Limited attention links sensitivities across features: $\alpha_\rho \uparrow \implies \alpha_\epsilon \downarrow$



Manipulating Attention: Sensitivity

- Draw people's attention to variation in persistence:
  - Additional comprehension questions on persistence.
  - Describe a persistent and a transitory process they have encountered.
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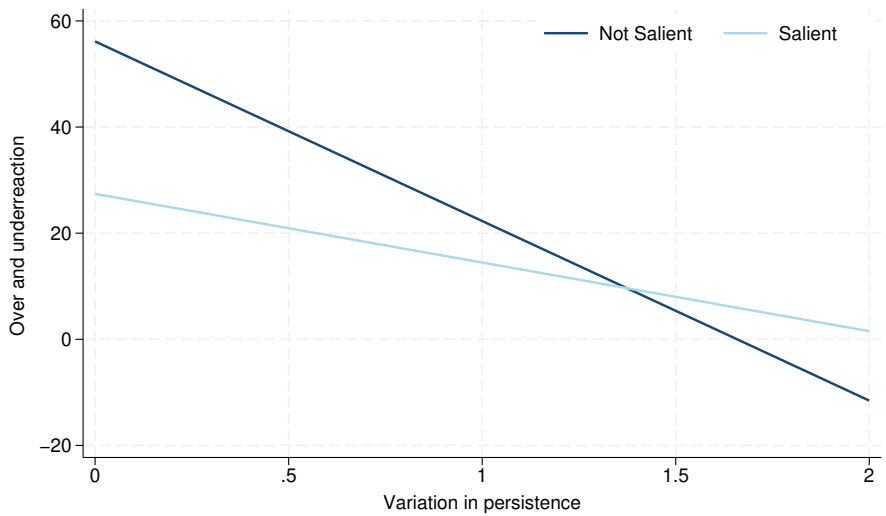
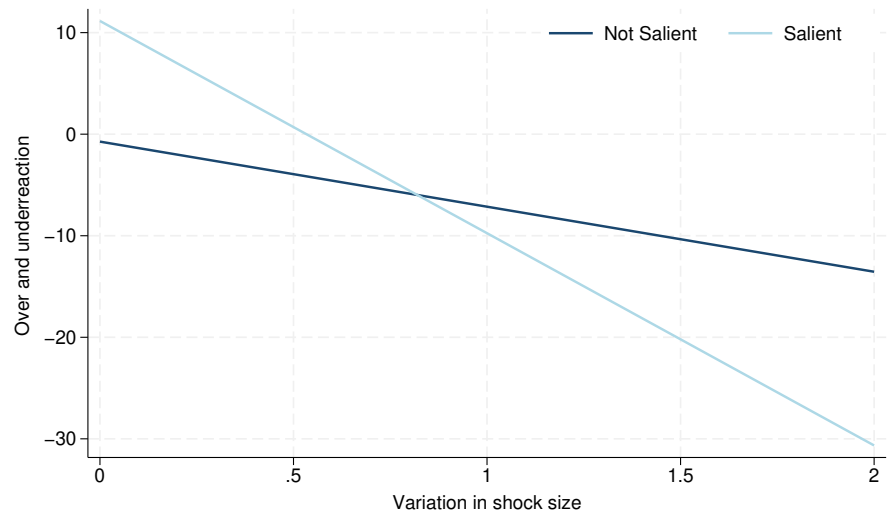




- **Limited attention links sensitivities across features.**

Manipulating Attention: Cognitive Default

- What do you expect profits to be in the long run, on average?

$$\mathrm{E}_t[y_{t+h}|y] = \rho^h y_t + (1-\rho^h)\mathrm{E}[\mu|y]$$

- When question is included in inference survey: $\bar{\rho} = 0.1$
- Frame as inference: what do you expect profits to be on average?

- When question is included in forecasting survey: $\bar{\rho} = 0.9$
- Frame as forecasting: what do you expect profits to be in the long run?

- **Inference and forecasting cue different mental representations.**

Conclusions

- What drives variation in under/overreaction? Domain specific?
- Memory and limited attention shape mental representations.

① Inference and forecasting cue different mental representations.

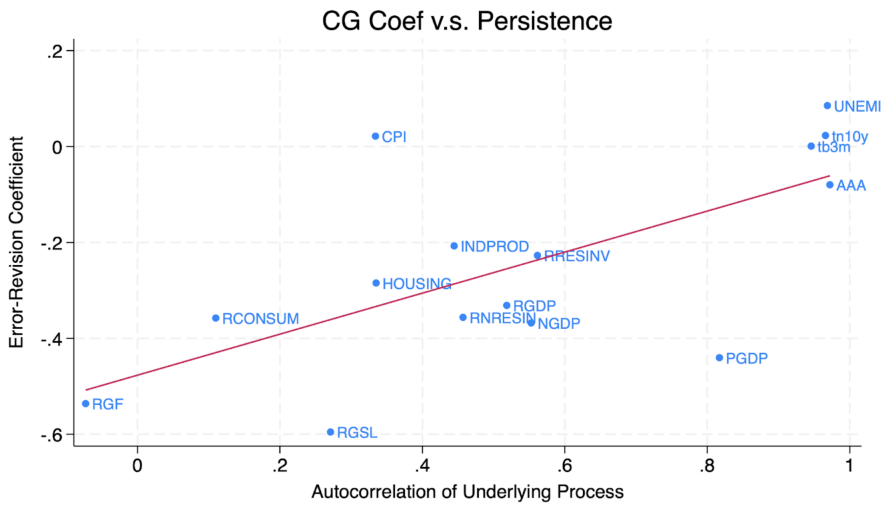
② Overreaction to weak signals and underreaction to strong signals is modulated by attention.

- More neglected features drive more variation in over/underreaction.
- Insensitivity to one feature can lead to excess sensitivity to another.

Appendix

SPF Data

- More overreaction when persistence is low (AKLMT).
- More variation in over/underreaction when ρ is further from default.



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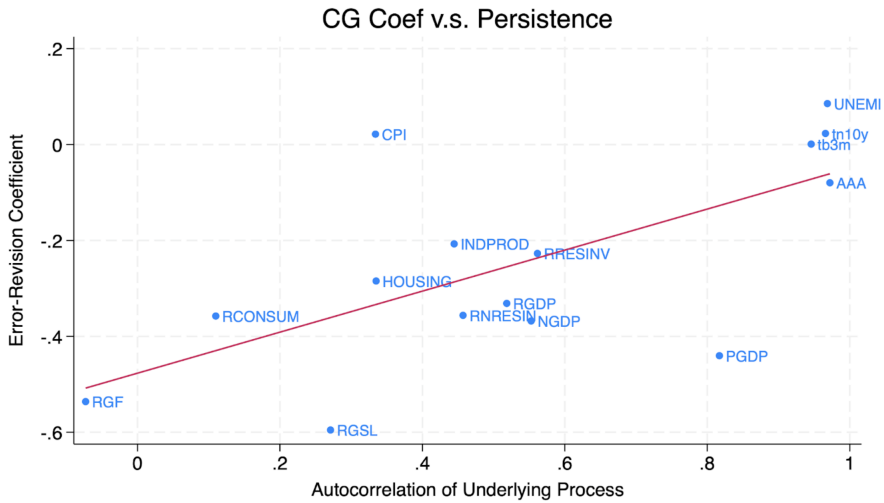

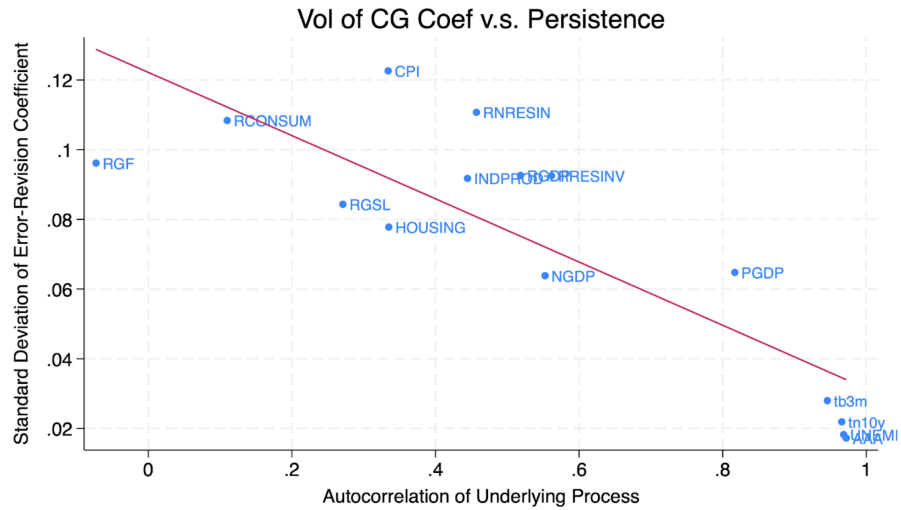

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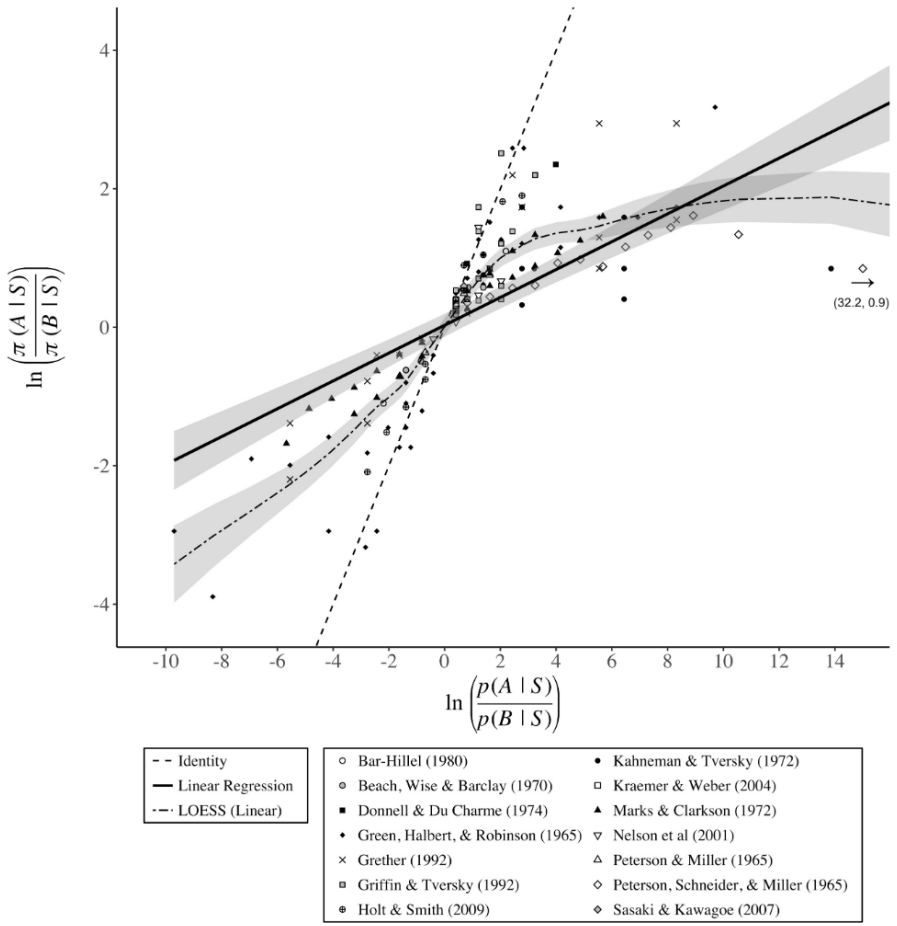
Benjamin Review

- Predominant underinference in inference problems.



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Limited Attention and Mental Representations (1)

- Feature vector: $\mathbf{x} = \{\rho, \epsilon_t, h, \mu_A - \mu_B, \sigma\}$
- True signal strength: $S(\mathbf{x})$
- Perceived signal strength: $S(\tilde{\mathbf{x}})$

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- A problem cues set of M prior experiences of solving it.
- Experience-based meta prior: $x_k \sim N(\tilde{\mu}_k, \tau_{0k}^{-1})$
- Weighted average of prior experiences: $\tilde{\mu}_k = \sum_{m=1}^{M} w_k x_{km}$
- Weights distorted by representativeness: $w_k \propto \left(\frac{P(x_m|q)}{P(x_m|\bar{q})} \right)^{\theta}$

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- Noisy estimate of a given feature: $\hat{x}_k | x_k \sim N(x_k, \tau_{sk}^{-1})$
- Bayesian updating, $\alpha_k = \frac{\tau_{sk}}{\tau_{sk}+\tau_{0k}}$: $\tilde{x}_k = \alpha_k \hat{x}_k + (1 - \alpha_k)\tilde{\mu}_k$

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- Attention increases precision of noisy estimate, τ_{sk}
- Allocate attention to minimize MSE st attention budget.
- More attention to more valuable, cheaper, volatile features.

Insensitivity vs. Underreaction

- True signal strength depends on objective features: $S(\rho, \epsilon_t)$
- Subjective signal strength depends on subjective features: $\tilde{S}(\tilde{\rho}, \tilde{\epsilon}_t)$
- Sensitivity vs. over/underreaction:
  - Sensitivity is about the slope: $\partial\tilde{S}/\partial x$ vs. $\partial\tilde{S}/\partial x$
  - Over/underreaction is about the level: $\tilde{S}$ vs. S
- Sensitivity at feature level vs. sensitivity at outcome level:
  - Limited attention $\implies$ insensitivity at feature level $(\partial\tilde{x}/\partial x = \alpha_x < 1)$
  - Insensitivity at feature level $\not\Longrightarrow$ insensitivity at outcome level.

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