# Adjustment Dynamics During a Strategic Estimation Task


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# Introduction

- Nominal inertia: ongoing question at the heart of monetary economics
- REE predicts the full adjustment of all prices on impact and no effects on real economic activity
- One hypothesis: price-setters have rational expectations but face adjustment costs
  - popular explanation in the literature
  - but limited direct evidence of such costs

# Introduction

- Part of broad issue in macro & finance: understanding how are expectations formed in strategic environments
- The REE modeling standard:
  - people are forward-looking & think through the consequences of their own actions and those of others
  - they incorporate optimally all information and make no systematic errors
  - they believe that all other agents behave in the same way

$\Rightarrow$ Subjective distributions = Objective distributions

# Introduction

- Alternative hypothesis: deviations from REE predictions occur because people economize on cognitive resources
  - used to acquire knowledge needed for decisions
  - and to think through the actions of others

- Compelling source of evidence: the lab

  Experiments can
  - minimize adjustment costs and vary incentives
  - control shocks and the info available to participants

- Several experiments on price-setting support cognitive frictions hypothesis: Fehr & Tyran (2001, 2008); Magnani, Gorry, Oprea (2016)

# Introduction

Q: How might cognitive limitations slow adjustment to a REE?

- Consider how people might come to hold RE to begin with
  - model-based inference
  - experience-based induction
- Also the two ways in which literature has relaxed REE
  - limits to inference or limits to accumulation of data
- Which one it is matters
  - *e.g.*, consequences of structural or policy changes that trigger transitions to new equilibria
  - *e.g.*, welfare effects of raising the inflation target

# Introduction

- Largely studied separately and often in very different contexts
  - level-k: one-shot static games, little opportunity to learn
  - adaptive learning: dynamic settings, abstracts from strategic considerations in the learning process

# Contribution - I

- We propose an experiment that gives people the opportunity to use either approach for the given forecasting task
- Both are useful for forecasting, neither is explicitly favored by the way we present the task
- We introduce regime changes : sharp approach to identifying how people transition to new equilibria
- Setting similar to that of an economic agent making the same kind of decision repeatedly, in a familiar context
    - consumer purchasing a staple good; firm updating the price of an existing product

# Contribution - II

- We estimate a series of models that nest the model-based and experience-based belief formation
- Consider main frameworks from macro: noisy forecasts, learning, inattentiveness to fundamentals
- Inside a level-k model (rather than RE!)
- 'Toolkit' for modeling bounded rationality in strategic settings

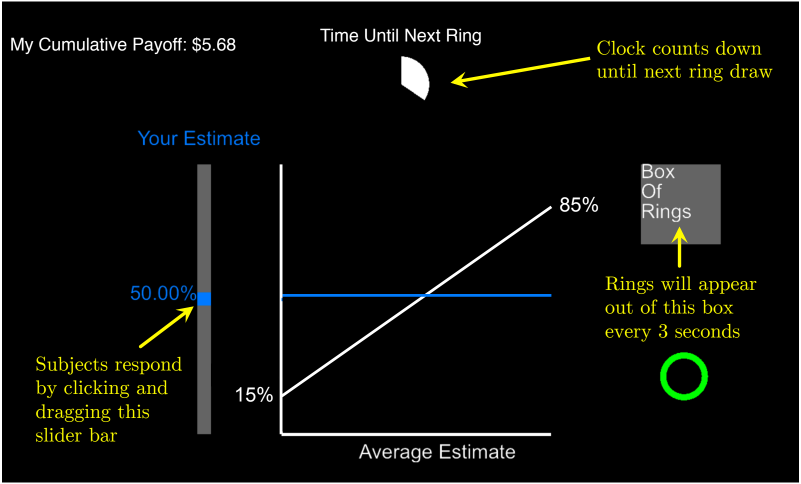
# The Experiment

- Simple probability estimation task in which individual payoff depends on both exogenous term and the group's forecast

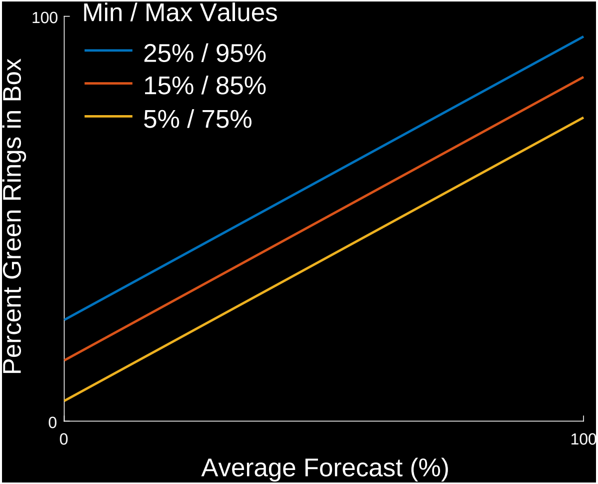
# The Experiment

- Subjects predict the percentage of green rings in virtual box with green + red rings
- Percentage depends in part on the group forecast: $p_t = z_t + \alpha \widehat{P}_t$
- Exogenous $z_1$ drawn from uniform on $Z = \{0.05, 0.15, 0.25\}$
- After each ring draw, 0.05 probability of an intercept shift
  - if no shift, $z_{t+1} = z_t$
  - if shift, $z_{t+1}$ is another independent draw from $Z$
- REE forecast: $p_t^{RE} = z_t \,/\, (1 - \alpha) \in \{0.17, 0.50, 0.83\}$

# The Experiment



# Best Response Functions

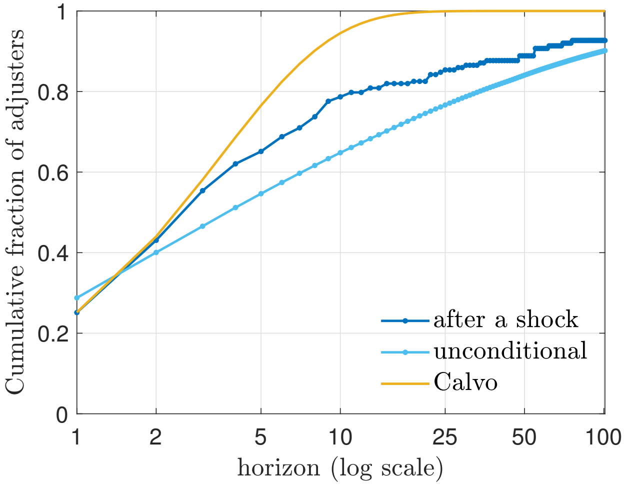



possible states and corresp. best response functions
(shown to subjects in the instructions)

# Patterns of Adjustment

- REE model: when the exogenous variable $z_t$ changes
  - all subjects adjust immediately to new equilibrium
  - there is no further adjustment after the initial response

# Cumulative Fraction of Adjusters

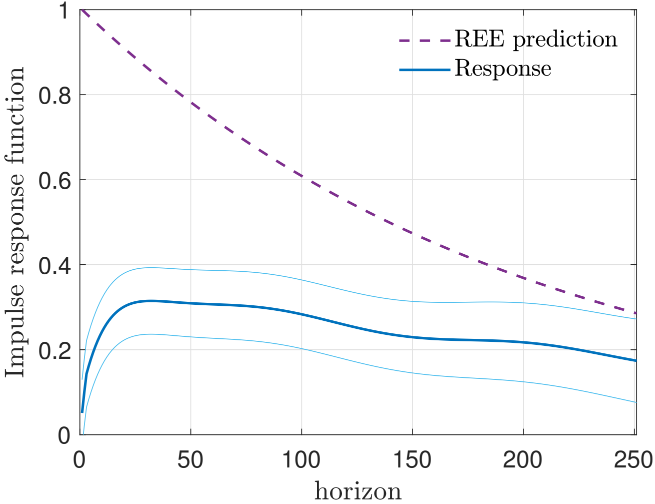



RE model predicts 100% on impact
(unconditional frequency of adjustment = 28%)

# Dynamics of Adjustment to Intercept Shift

- Consider the impulse response of the average forecast at time $t + h$ in response to a change in the fundamental $z_t$ at time $t$, relative to the expected change in the absence of such a change

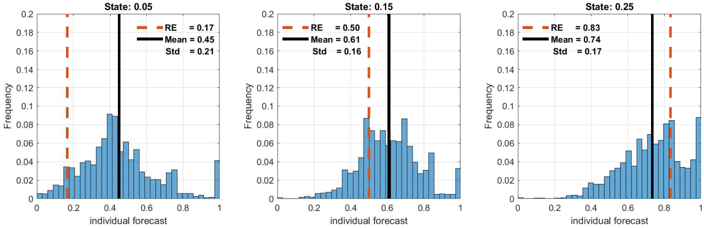
# Dynamics of Adjustment to Intercept Shift




very incomplete, sluggish adjustment

more so than in non-strategic settings

# Forecast Dispersion Conditional on Adjustment




dispersed distribution of forecasts *conditional* on adjustment

(vs. adjustment to optimum in macro models of sluggish adjustment)

# Summary

- Forecasts are noisy and biased
- Responses converge slowly to theoretical equilibria

# Modeling Adjustment

- Level-k: natural starting point for a model-based forecast
- Growing interest in macro in level-k classification of degree of strategic sophistication
  - dampening equilibrium forces and forward-looking behavior Garcia-Schmidt & Woodford, 2019; Farhi & Werning, 2019; Vimercati, Eichenbaum & Guerreiro, 2021)
- Absent: empirical guidance for macro applications relative to estimates from the games literature

# Stochastic Level-k

- To record forecast: exert effort
- Cost is linear in Shannon (1948) entropy reduction from a uniform default [$\Rightarrow$] Quantal Response Equilibria
- Estimate, for each subject:
    - best-fitting level $k_i$ and unit effort cost $\lambda_i$ (which determines noise in forecasts)

# Stochastic Level-k

| Level | Count | Frac |
|---|---|---|
| 0 | 6 | 0.11 |
| 1 | 18 | 0.32 |
| 2 | 14 | 0.25 |
| 3 | 1 | 0.02 |
| 4 | 1 | 0.02 |
| 5 | 3 | 0.05 |
| re | 14 | 0.25 |

# But...

- Even if subjects do not use a model-based approach, they can still perform well, and, at least in principle, approach the REE forecast, by monitoring the patterns in the data
- They observe a long series of ring draws and face a fundamental that only changes infrequently, which gives them ample opportunity to learn
- Moreover, even participants we labeled as strategic may act *as if* they produced forecasts that are strategic

# Adaptive Stochastic Level-k

- Suppose that non-strategic DMs watch the ring realizations and apply a constant-gain learning algorithm to form their forecast
- Higher levels in turn need to watch the rings, and run their own constant gain algorithm (with their own learning parameter), to simulate the level-0 forecasts
- Estimate, for each subject:
    - best-fitting level $k_i$, unit effort cost $\lambda_i$, and gain parameter $\gamma_i$ (which determines learning speed)

# Adaptive Stochastic Level-k

| Level | Count | Frac | Adaptive | Frac | Mean Lambda | Mean Gain |
|---|---|---|---|---|---|---|
| 0 | 29 | 0.51 | 27 | 0.47 | 0.06 | 0.03 |
| 1 | 19 | 0.33 | 14 | 0.25 | 0.03 | 0.03 |
| 2 | 7 | 0.12 | 4 | 0.07 | 0.05 | 0.09 |
| 3 | 1 | 0.02 | 1 | 0.02 | 0.04 | 0.16 |
| 5 | 1 | 0.02 | 1 | 0.02 | 0.01 | 0.07 |
| | | 1.00 | | 0.82 | | |

# But...

- Data shows substantial serial correlation in forecasts
- Moreover, thus far stochasticity is benign - randomness added on top of model forecast
- Consider alternative that allows errors to propagate:

$$m_{it}^{(0)} = (1 - \gamma_i)\ \hat{p}_{i,t-1}^{(0)} + \gamma_i\, s_{t-1}$$

instead of

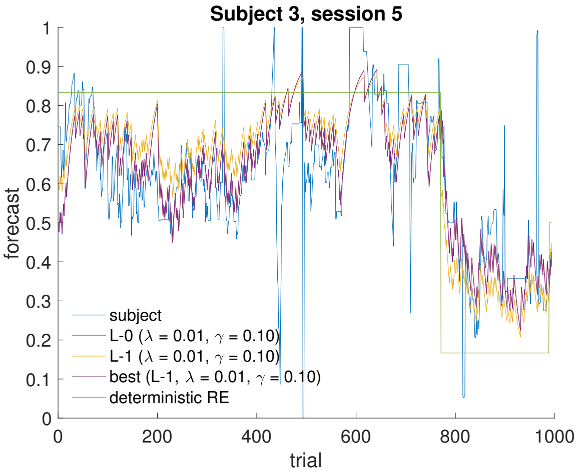
$$m_{it}^{(0)} = (1 - \gamma_i)\ m_{i,t-1}^{(0)} + \gamma_i\, s_{t-1}$$

# Adaptive Stochastic Level-k Revisited

| Level | Count | Frac | Mean Cost | Mean Gain |
|---|---|---|---|---|
| 0 | 52 | 0.91 | 0.01 | 0.08 |
| near re | 5 | 0.09 | 0.09 | - |

Even in setting where deductive reasoning is simple and people have all the information they need to compute the REE, people do a lot of statistical learning

# Adaptive Stochastic Level-k Revisited



# Conclusion

- We present results from a strategic estimation task in which participants have the option to use either model-based reasoning or empirical pattern recognition to form forecasts
- Adjustment in response to large, visible changes in the fundamental state is noisy and very sluggish
- Experience-based forecasting seems much more empirically-relevant than model-based forecasting
- Results consistent with evidence from neuroscience as descriptive model of what brain is actually doing
- In practice, complications regarding the environment and potentially ambiguous announcements of policy changes are likely to make learning and extrapolation of patterns even more appealing than in the controlled environment of the lab