Overreaction and Working Memory

Hassan Afrouzi
Columbia

Spencer Kwon
Harvard

Augustin Landier
HEC Paris

Yueran Ma
Chicago Booth

David Thesmar
MIT

NYU Stern Class

Motivation

- Expectations are central to economic analyses
- Recent expectations research finds biases in survey forecasts
  - many find overreaction; some find underreaction
- Why?

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Today: randomized experiment to measure biases precisely

Preview

- Our experiment: stark setting where participants forecast an AR1
  - finding #1: significant overreaction
  - finding #2: stronger for transitory processes
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- We build a new model of expectations formation
  - costly retrieval $\rightarrow$ recency bias
  - additional prediction: overreaction $\nearrow$ horizon
  - model matches the data well

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One step towards a unified understanding of expectation biases

Literature

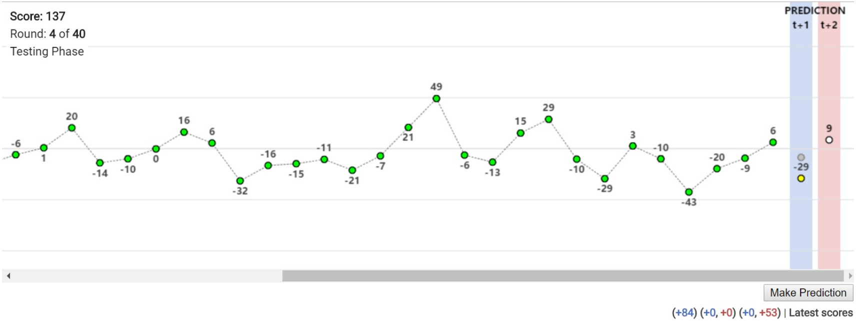
Connects to 3 main branches of research on expectations:

1. **Survey forecasts:** De Bondt and Thaler (1990), Greenwood and Shleifer (2014), Gennaioli, Ma and Shleifer (2016), Bordalo et al. (2019, 2020b), Bouchaud et al. (2019), Barrero (2020), Wang (2019)
2. **Forecasting experiments:** Hey (1994), Reimers and Harvey (2011), Beshears et al. (2013), Frydman and Nave (2016)
3. **Models of expectations formation:** Bordalo, Gennaioli and Shleifer (2018, 2020a), Nagel and Xu (2019), Wachter and Kahana (2020), da Silveira, Sung and Woodford (2020)

Roadmap

Experiment Design

- Forecast AR1 process ($x_{t+1} = \rho x_t + \epsilon_{t+1}$):
  - shown 40 past realizations
  - make 40 forecasts at different horizons (baseline: $t+1$ and $t+2$)
  - compensation $\nearrow$ accuracy of forecast
  - no hidden private information
- Randomly assigned into different conditions:
  - test 1 (main): vary ρ from 0 to 1
  - test 2: different forecast horizons (1, 2, 5)
  - test 3: explain DGP (stable AR1 vs. stable random process)
- Participants:
  - Amazon MTurk (Test 1, 2), MIT EECS undergrad (Test 3)



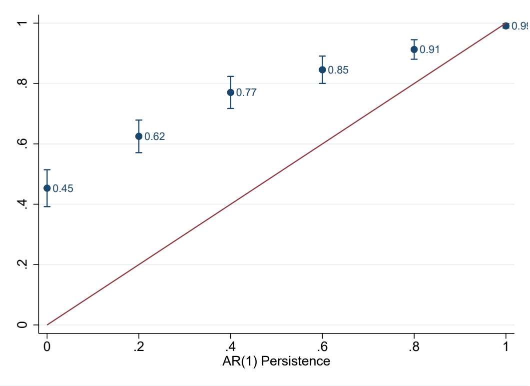
- Click to predict x_{t+1} and x_{t+2}
- Then x_{t+1} is realized; new forecasts are asked; iterate 40 times

Basic fact: overreaction & persistence

We measure bias as implied persistence in forecasts:

$$F_t x_{t+1} = \rho^s x_t + u_t$$

ρ^s compared to ρ:



Basic fact: overreaction & persistence

Robustness:

- Different subgroups & demographics
- First half vs. second half of experiment
- Use in-sample least-square learning as benchmark
- Explicitly provide linear AR1 prior

Do existing models match this fact?

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Existing models

- **Backward-looking models**
  - Extrapolative (Metzler, 1941)

$$F_t x_{t+1} - x_t = \gamma(x_t - x_{t-1})$$

  - Adaptive (Nerlove, 1958)

$$F_t x_{t+1} = (1-\lambda)x_t + \lambda F_{t-1} x_t$$

- **Forward-looking models**
  - Rational expectations: $F_t x_{t+1} = E_t x_{t+1}$
  - Diagnostic (Bordalo, Gennaioli and Shleifer, 2018)

$$F_t x_{t+1} = E_t x_{t+1} + \gamma(E_t x_{t+1} - E_{t-1} x_{t+1})$$

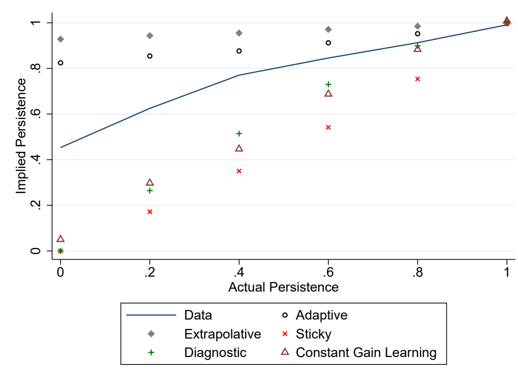
  - Sticky (Coibion and Gorodnichenko, 2015)

$$F_t x_{t+1} = E_t x_{t+1} + \lambda\left(F_{t-1} x_{t+1} - E_t x_{t+1}\right)$$

  - Constant gain learning (Nagel and Xu, 2019)

Existing models fail to match the data

- Estimate each model to fit *all* forecast data
- Plot ρ^s in model against ρ



Existing models fail to match the data

- Data: ρ^s adapts to ρ, but insufficiently
  - "kernel of truth"
- Backward-looking models do not adapt enough to ρ
  - ρ^s too high for low persistence series
- Forward-looking models adapt too much
  - ρ^s too low for low persistence series
  - e.g., diagnostic expectations (Bordalo, Gennaioli and Shleifer, 2018) $=$ RE when $\rho = 0$

Model: setup

- AR1 process: $x_{t+1} = (1-\rho)\mu + \rho x_t + \epsilon_{t+1}$. Forecast $F_t x_{t+h}$.
  - needs to estimate μ (true $\mu = 0$); knows ρ (for simplicity)
  - observes x_t and costly utilization of past x_{t-k} in working memory
  - what is "on top of the mind"
- Minimizes forecast-error, *subject to cost of retrieval* $C_t(S_t)$:

$$\min_{S_t} \mathbb{E}\left[\underbrace{\min_{F_t x_{t+h}} \mathbb{E}\left[(F_t x_{t+h} - x_{t+h})^2 | S_t\right]}_{\text{benefit}=(1-\rho^h)^2 var(\mu|S_t)} + \underbrace{C_t(S_t)}_{\text{cost}}\right]$$

  - S_t: retrieved information set (past observations, etc)
  - $C_t(S_t) = \omega[\exp(2\log(2)\cdot\gamma\cdot\mathbb{I}(S_t,\mu|x_t)) - 1]/\gamma$

Model: solution

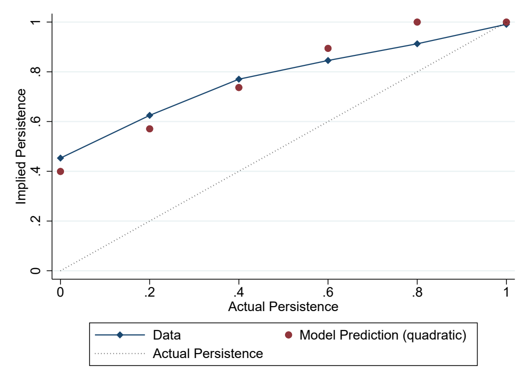
$$F_t x_{t+h} = \underbrace{\rho^h x_t}_{\text{rational}} + \underbrace{G(\rho^h) x_t}_{\text{overreaction}} + \epsilon_t$$

- $G > 0$ measures overreaction and is decreasing in ρ^h:
  - $G(0) > 0$: overreaction when $\rho = 0$
  - $G(1) = 0$: rational when $\rho = 1$

- Intuition: relies "too much" on x_t to infer μ
  - natural way to generate more overreaction for low persistence & long forecast horizon (later)

Model fit

- Estimate our model's retrieval cost function to fit *all* forecast data
- Plot ρ^s in model against ρ



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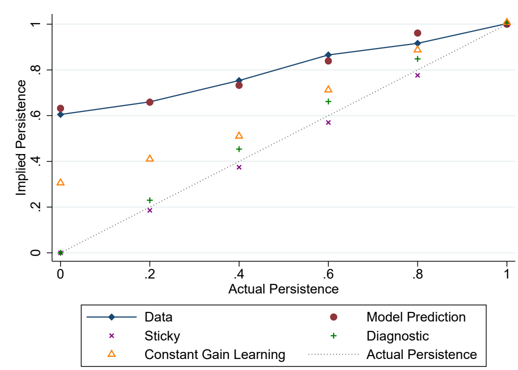
Forecast horizon

- Model: more overreaction at longer horizons (overreaction ↑ in ρ^h)
  - consistent with the data
  - Giglio and Kelly (2018), Wang (2019), d'Arienzo (2020)

ρ^s implied by $F_t x_{t+2}$ vs. ρ



Forecast horizon

- Model: more overreaction at longer horizons (overreaction $\uparrow$ in ρ^h)
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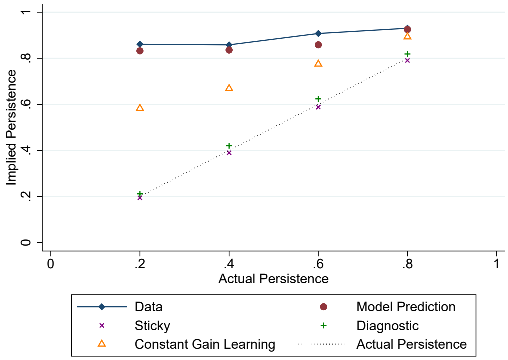
  - Giglio and Kelly (2018), Wang (2019), d'Arienzo (2020)

ρ^s implied by $F_t x_{t+5}$ vs. ρ



Conclusion

- Key fact: more overreaction for less persistent processes
  - demonstrate clearly through randomized experiments
  - robust & echo suggestive evidence in field data
  - existing expectations models do not fit very well
- Model of expectations with costly utilization of past info
  - recent observation comes to mind more easily
  - model fits data very closely
- Additional implications
  - more overreaction for long horizon
  - imperfect use of past info: overreaction;
    imperfect perception of recent info: underreaction

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Observations from Survey Data

Bordalo et al. (2020b): Overreaction in Macroeconomic Expectations

- 20 series from Survey of Professional Forecasters & Blue Chip
- Overreaction common, more pronounced when process less persistent
- Measuring overreaction:

$$\underbrace{x_{t+h} - F_t^i x_{t+h}}_{\text{Forecast Error}} = \alpha + \beta \underbrace{\left[F_t^i x_{t+h} - F_{t-1}^i x_{t+h}\right]}_{\text{Forecast Revision}} + e_{t+h}$$

- $\beta < 0$: overreaction (overshoot); $\beta > 0$: underreaction (insufficient adjustment)
- Forecast revision to measure information forecasters process
  - Difficult to observe their information sets
  - Limitation: Var(FR) ≈ 0 when $\rho \to 0$ & RE (or diagnostic)

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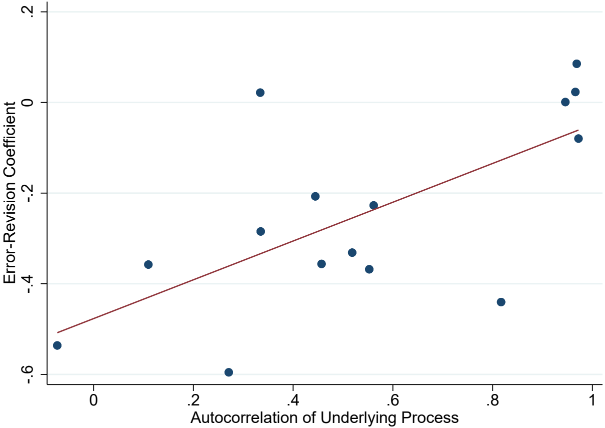
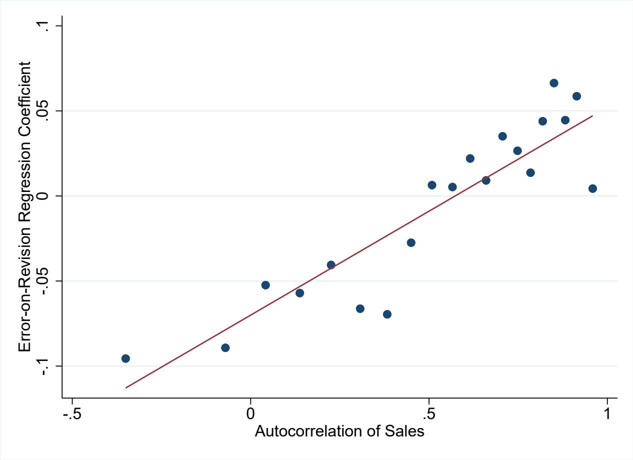
Observations from survey data

β in professional forecasts of different macro outcomes:



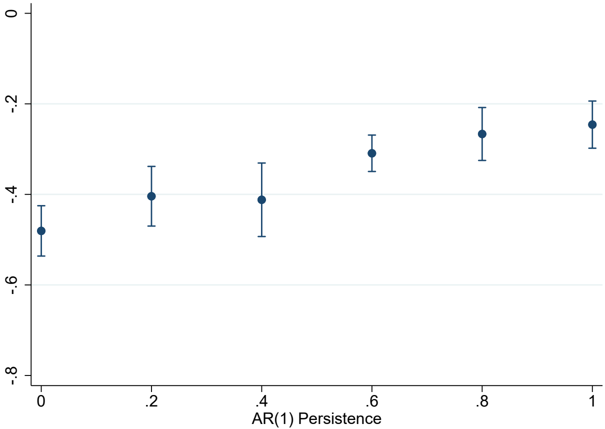
Observations from survey data

β in analyst forecasts of different stocks:

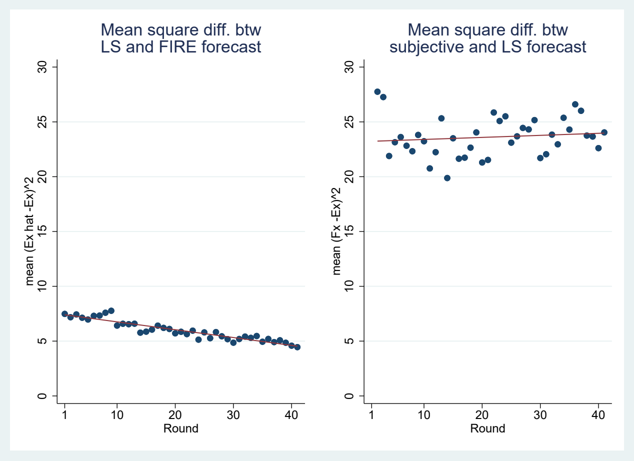


Experiment data

β in experiment forecasts:

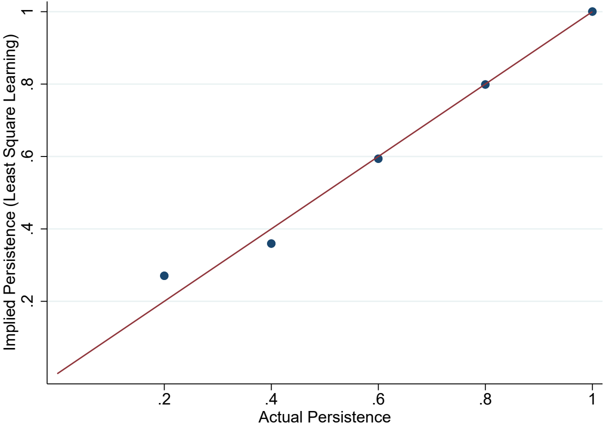


In-sample lease-square learning benchmark



In-sample lease-square learning benchmark

ρ^s implied by LS Learning vs ρ



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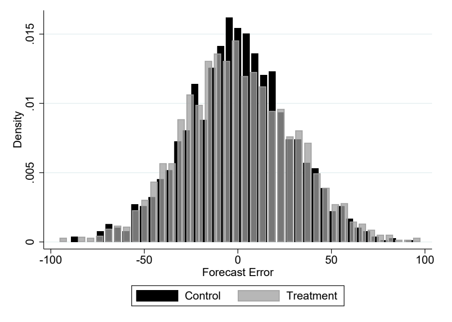
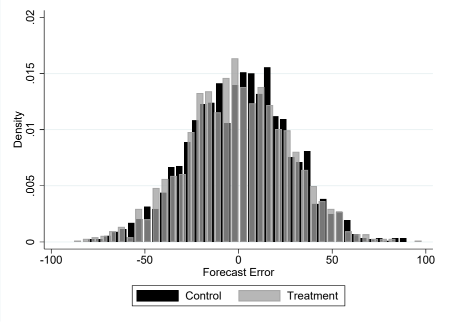
Providing info of stable AR1

Experiment with 204 MIT EECS students, random assignment

- Description: “stable random process” vs “stable AR1”
- ρ: 0.2, 0.6



$\rho = 0.2$



$\rho = 0.6$

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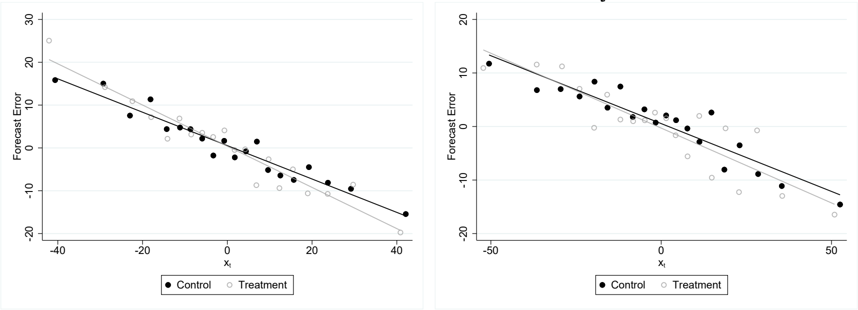
Providing info of stable AR1

Implied Persistence ρ^s

	Baseline Condition	Knows AR(1)	Test of difference (p-value)
$\rho = .2$	0.56	0.65	0.14
$\rho = .6$	0.86	0.88	0.71

Forecast Error Conditional on x_t



$\rho = 0.2$ $\rho = 0.6$

External validity

- A large literature on biases in high-stake settings
  - Malmendier and Tate (2005), Pope and Schweitzer (2011), Ben-David, Graham and Harvey (2013), Greenwood and Hanson (2015)
- Many important decisions made with discretion
- Imperfect utilization of past information is common
  - recency bias naturally generates overreaction

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