# Expectations biases and their applications

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# Monetary Economics & Financial Economics

- Monetary economics:
  - Still largely dominated by rational/Bayesian expectations
    - Some bounded rationality (e.g. sticky information)
  - Applications: monetary policy, central banking doctrine
    - Managing expectations; Forecasting
    - ***Taking Lucas critique and commitment/credibility problems seriously***
- Financial Economics
  - Large fraction of behavioral studies
    - Welfare less central
  - Applications: statistical arbitrage, hedge funds
    - Identifying anticipation mistakes, taking advantage of them;
    - ***Taking "crowding" seriously; Taking overfitting seriously.***

# Expectations in financial economics

- Behavioral finance literature
  - Investors’ expectations can be wrong + mistakes have structure
    → leads to predictable returns
  - Sophisticated, investors can take advantage of this

- This talk: evidence from recent research on investor’s expectations

# Outline

1. Framework: Over- vs. Underreaction
2. A couple of examples: exploiting underreaction
3. Evidence from experimental data
4. Conclusion: applications to finance

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1. Framework: Over- vs underreaction

2. An example: the quality anomaly and underreaction

3. Evidence from experimental data

4. Conclusion: additional applications to finance

# Bayesian Updating: Central to Finance

Updated Beliefs = Prior Beliefs + News

***Very difficult to do this properly (especially if you are not a robot)***

Systematic Cognitive Mistakes :

- Non-Bayesian Updating
- Your “gut instinct” is misleading

# An old idea

- Dates back at least from Laplace (1825)

*The mind, like the sense of sight, has its illusions; and just as touch corrects those of the latter, so thought and calculation correct the former.* (Laplace, 1825, p. 91)

**The « Linda paradox»** ***(Kahneman&Tversky)***

*Linda is 31 years old, outspoken, and very bright. She majored in philosophy. As a student, she was deeply concerned with climate change and social justice.*

Which is more probable?

- Linda is a hedge fund manager.
- Linda is a hedge fund manager specialized in socially responsible strategies.

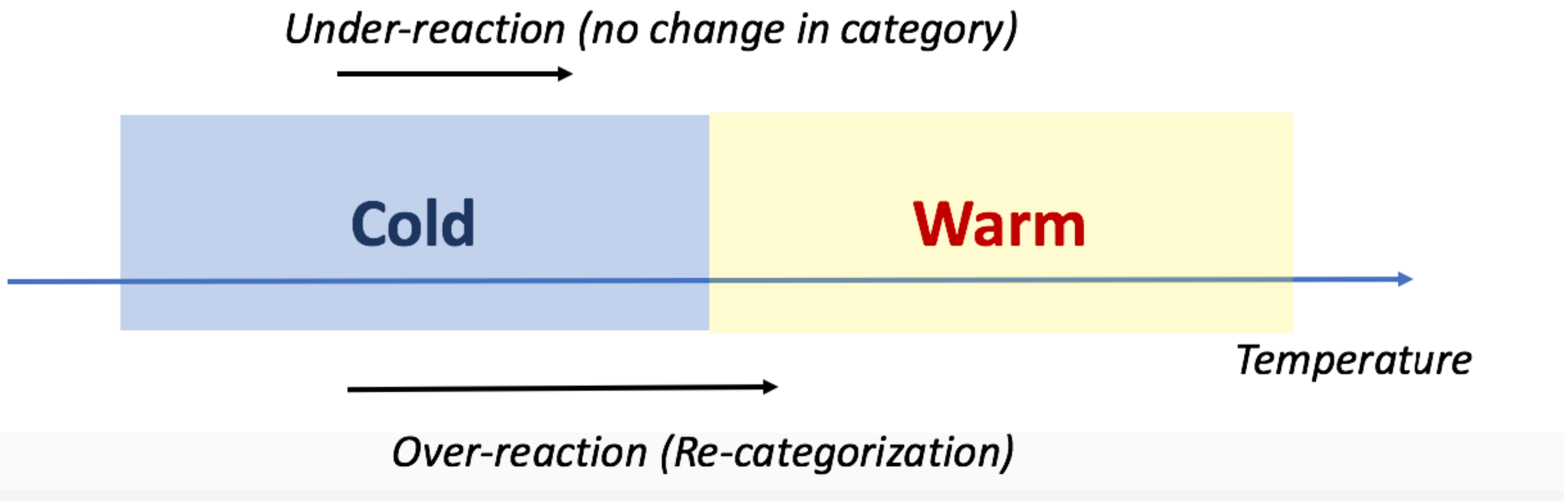
# Representativeness (cont.)

Assume that All of the families of 6 children in a city were surveyed.

- In exactly 72 families the order of birth for the children was: GBGBBG.
- What is your estimate of the number of families surveyed in which the exact order of births was BGBBBB?

# Representativeness can lead to both under and over-reaction

- in the short-term, we under-react to small changes (no re-categorization)
- When changes pass a threshold, we recategorize ($\rightarrow$ over-reaction)



# Failure to condition properly: even common in academic science…

- Two flaws common in many studies
  - Endogeneity
  - P-hacking

# Endogeneity as cognitive bias

- Ex: *"People who walk fast tend to be healthy. So to get healthy, make sure to walk fast"*

  - Pb: reverse causality
  - Modern empirical analysis tries to establish/reject causal link by:
    - Controlled experiments
    - Exogenous shocks (e.g. bus strike forcing people to walk more)

# P-hacking

- P-hacking in academia : 2 manifestations
  - Low successful replication rates
  - Poor performance out-of-sample
- Published papers: typically have to report p-value less than 0.05 (or equivalently, low confidence intervals in regressions)

# P-hacking

Two problems

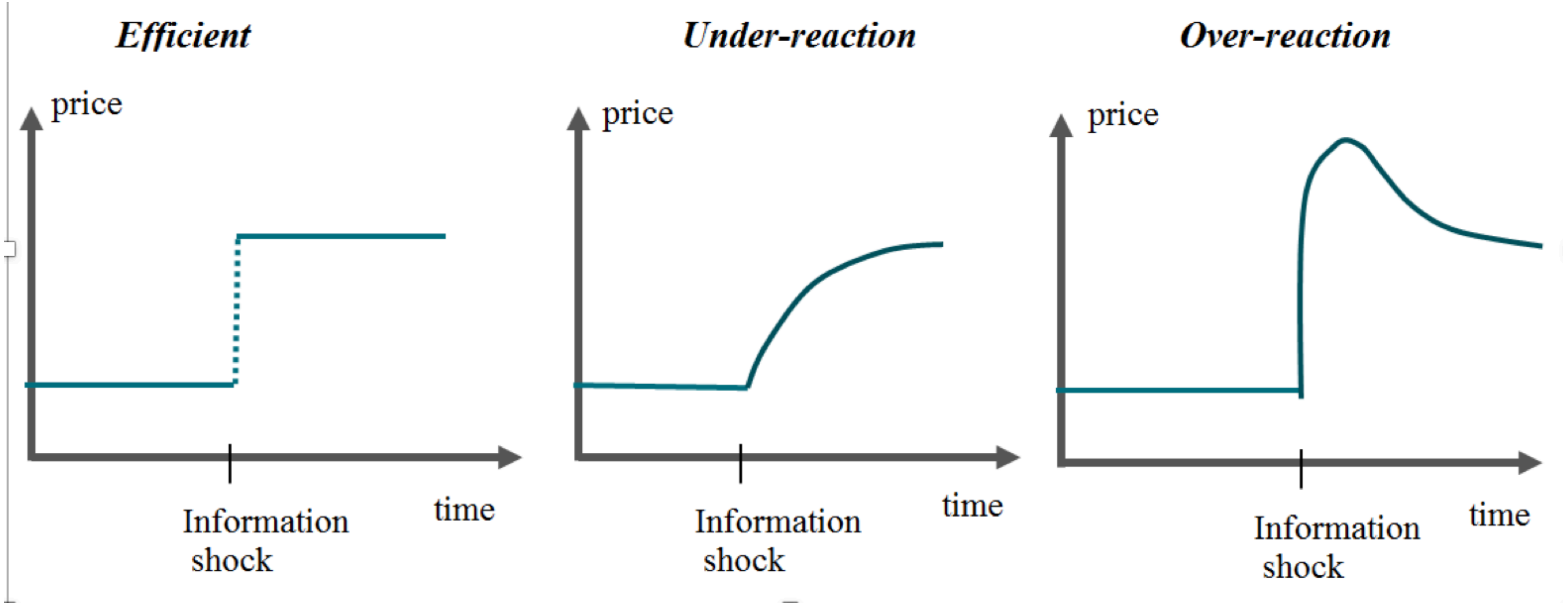
- **Selection-bias**: Likely to select spurious correlations in existing data (overfitting).
- **Perverse incentives in production**: Bias aggravated because researchers need to publish.

  → fishing for significant correlations: “overfitting”, “data mining”

→Bias : “real” statistical significance is much lower than in publications.

# Mispricing: Under-reaction vs. Over-reaction

- Markets are not perfectly efficient: they do not incorporate news immediately



# Outline

1. Framework: Over- vs underreaction
2. Some examples of strategies exploiting underreaction
3. Evidence from experimental data
4. Conclusion: additional applications to finance

# Quality anomaly

- Buy firms w/ high cash-flows
- Sell firm w/ low cash-flows

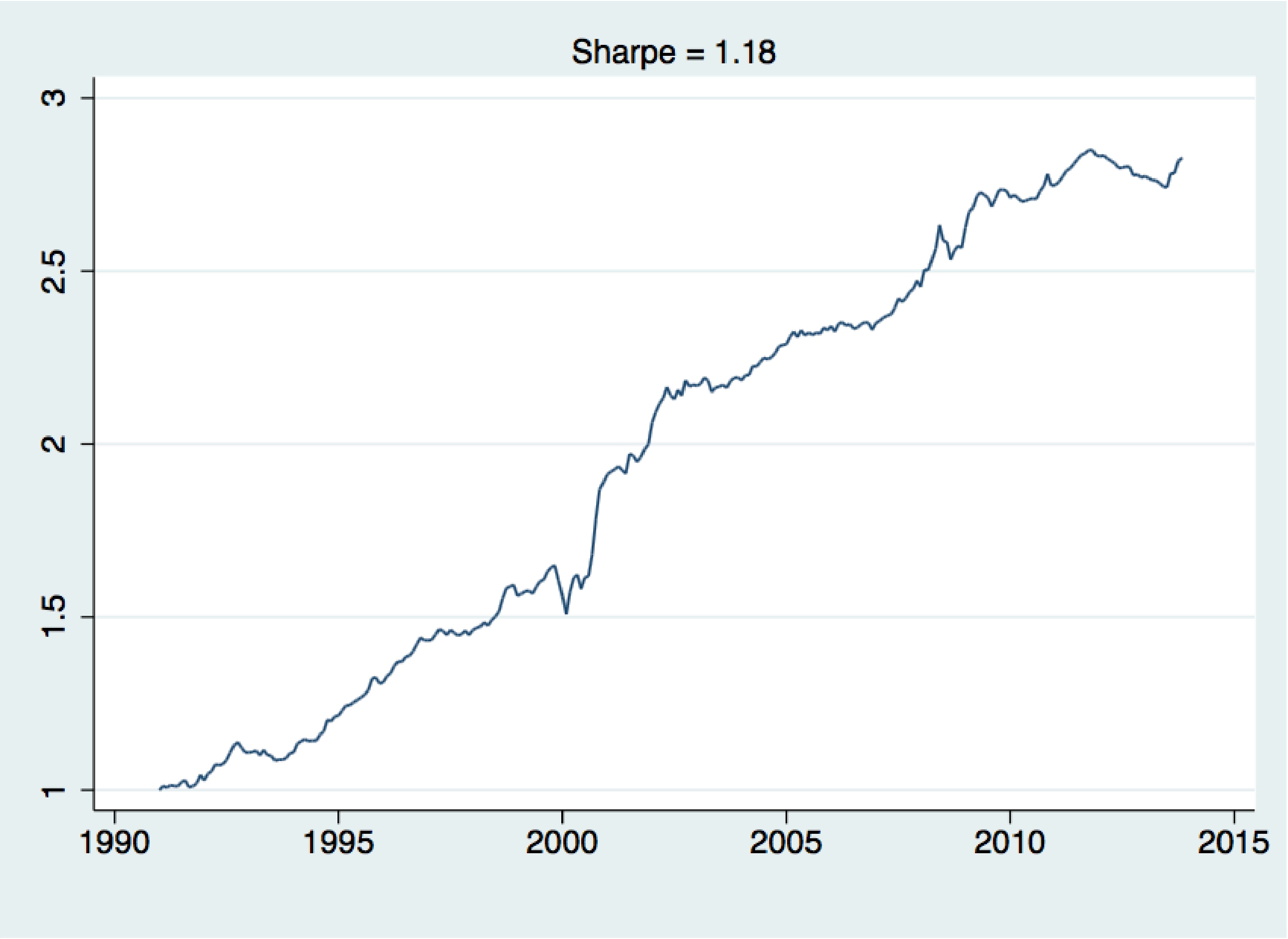
→ Uses public accounting info

→ profitable, both in and out of sample

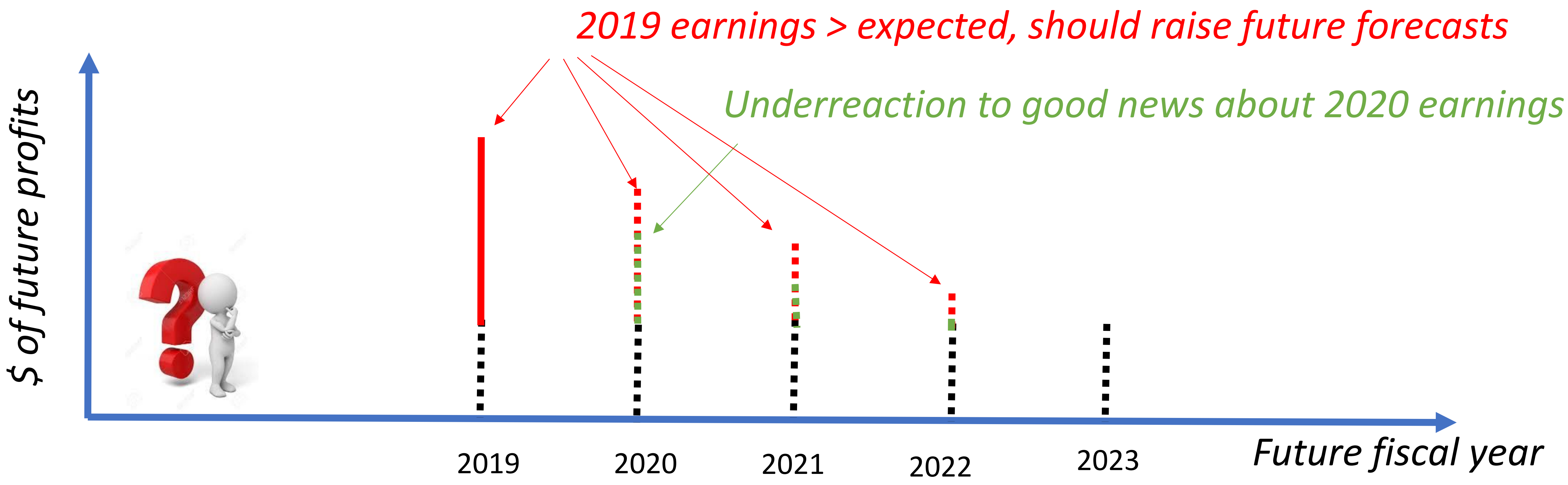
- Why does it work ?

Bouchaud, Krüger, Landier, Thesmar (JF, 2019) →

Figure 1: Cumulative Return of a Quality Anomaly



# Theory: investors underreact

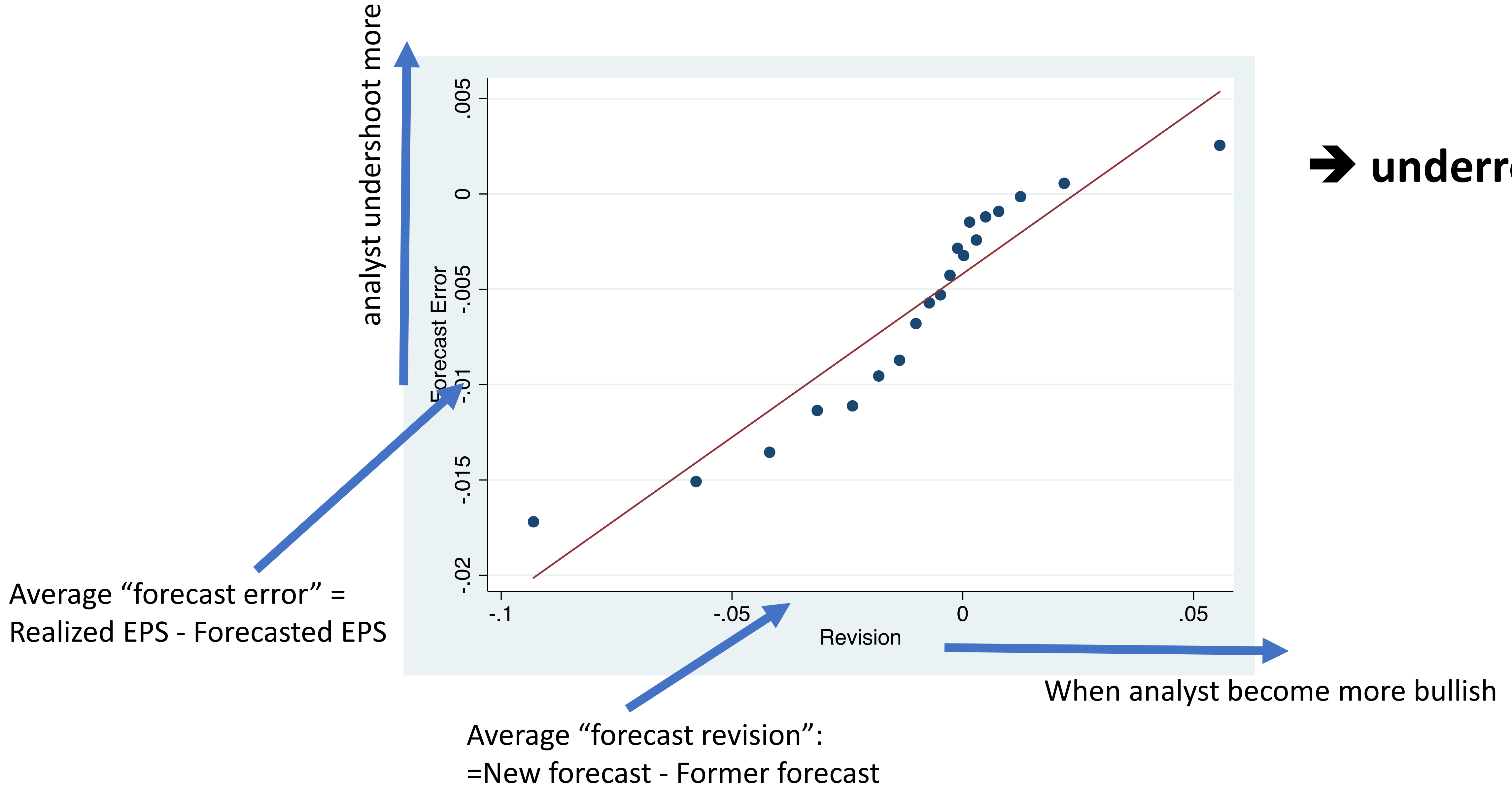



→ High profit firms → good news was just announced → but investors partially reacted

→ stock price will increase as investors realize

→ more pronounced for firms in which good news today have more long-term implications

# Evidence from 50k analyst EPS forecasts




➔ **underreaction!**

# Further tests

- In cross-section of firms, more underreaction by analysts

  → quality anomaly stronger

- In cross-section of firms, longer persistence of profits

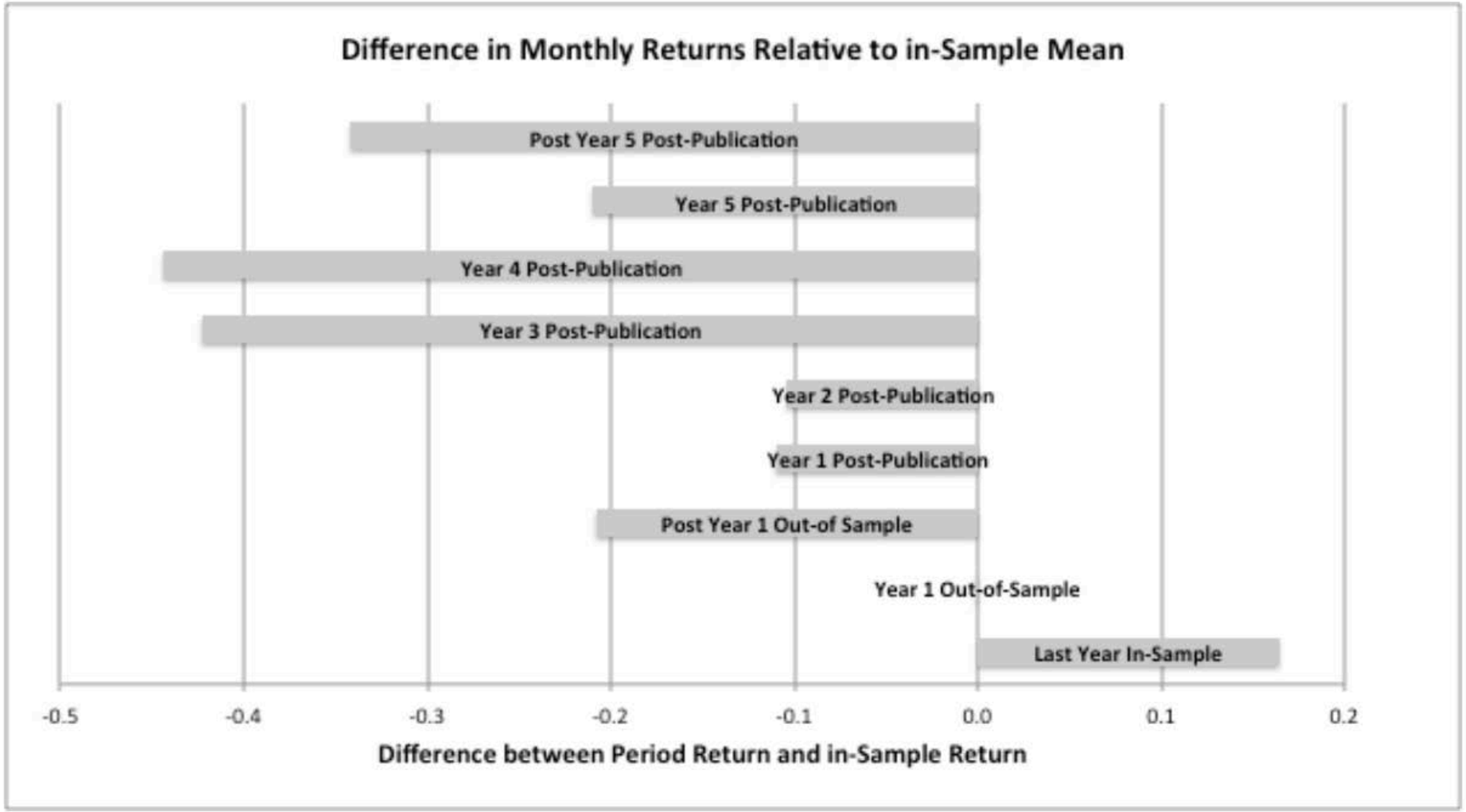
  → quality anomaly stronger

# Other strategies based on under-reaction

- Post-earnings announcement drift
- Diffusions of shock in the supply chain
- FX-shocks
- Mimic trades by well informed people etc.
- Typical "quant" investor approach:
  - Find data that are somewhat complex and plausible predictor
  - Back-test if that information predicts returns historically
  - Build robot that builds portfolio based on live information
  - Keep trading until things look too far away from back-test

# Alpha decay: p-hacking or crowding?

- Presence of arbitrageurs reduces anomalies → pricing anomalies not cast in stone



# More evidence from other data

- Other instances of underreaction
  - Professional forecasters (Coibion, Gorodnichenko, JPE 2015)
    - GDP growth, inflation, unemployment
- But also: overreaction/extrapolation
  - Analysts (Bordalo, Gennaioli, Laporta, Shleifer, JF forthcoming)
    - long horizon EPS forecast ("long-term growth")
  - CFOs: (Gennaioli, Ma, Shleifer, 2015)
  - Professional forecasters (Greenwood, Shleifer, 2017)
    - Stock returns

# *Forecasts of future stock-market performance tracks recent performance*

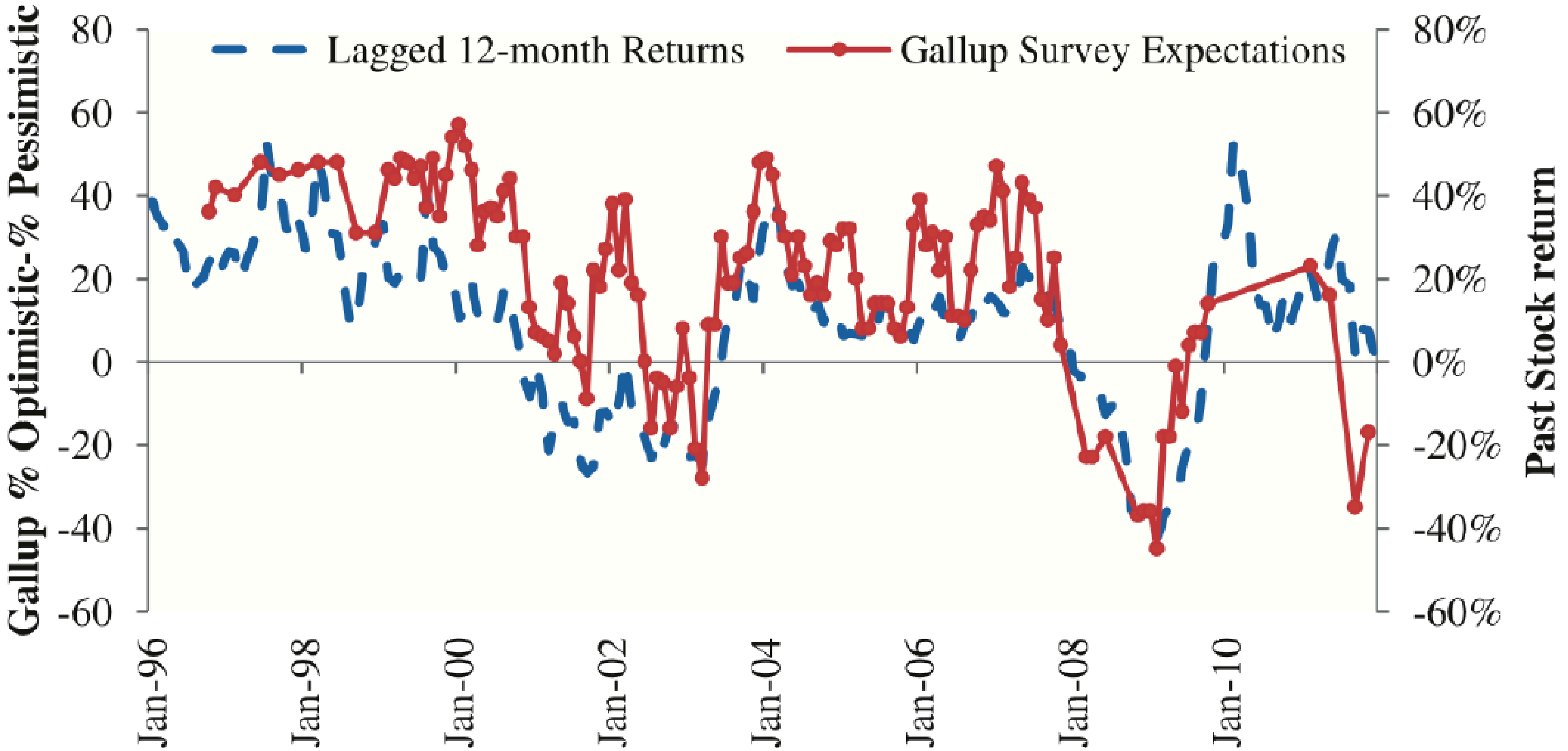
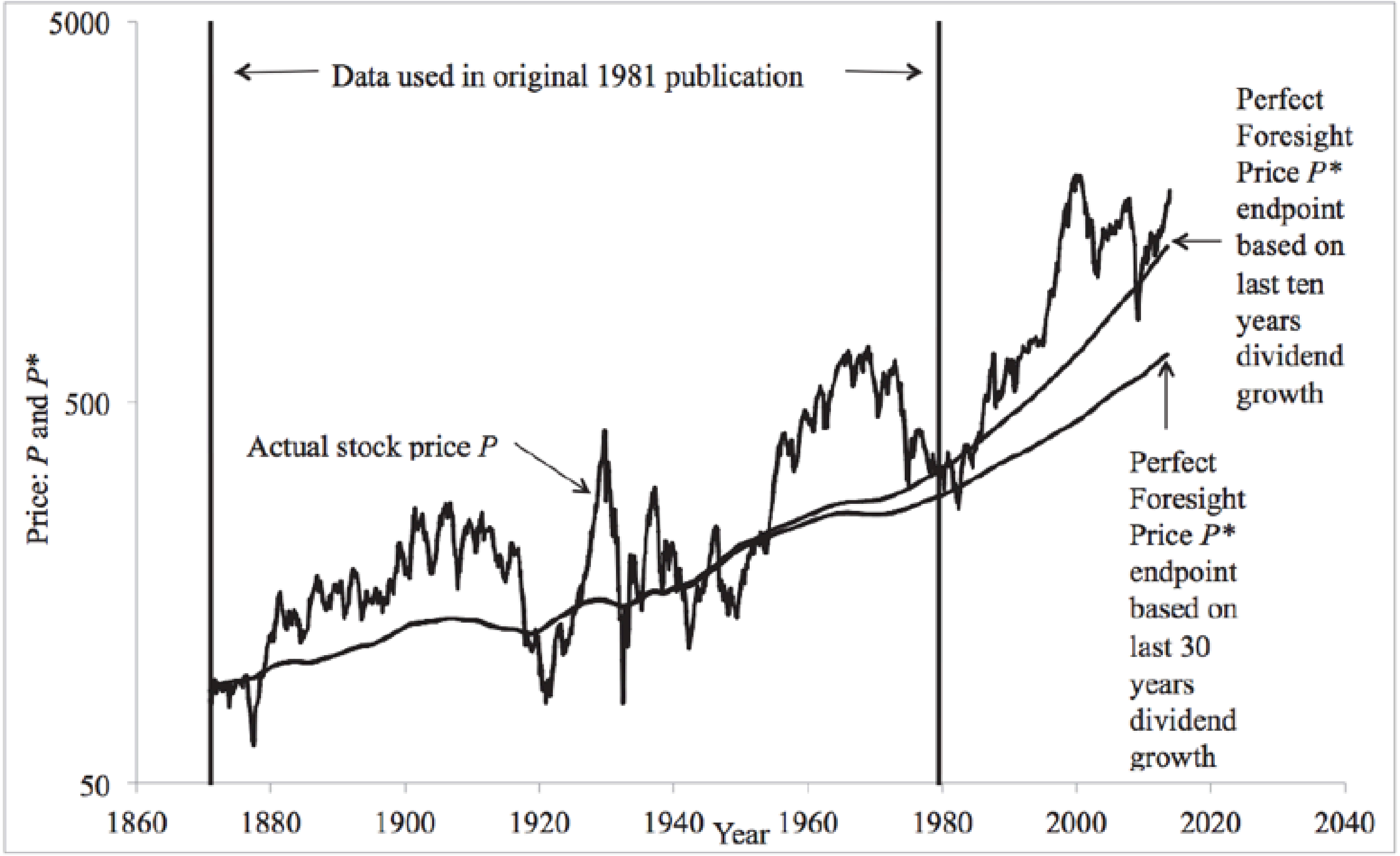



**Figure 6**
**The role of past stock market returns in explaining survey expectations**
The dashed line denotes the twelve-month rolling nominal return on the CRSP VW stock index. The solid line marked with circles denotes expectations from the Gallup survey (% optimistic – %pessimistic).

Greenwood shleifer, RFS 2014

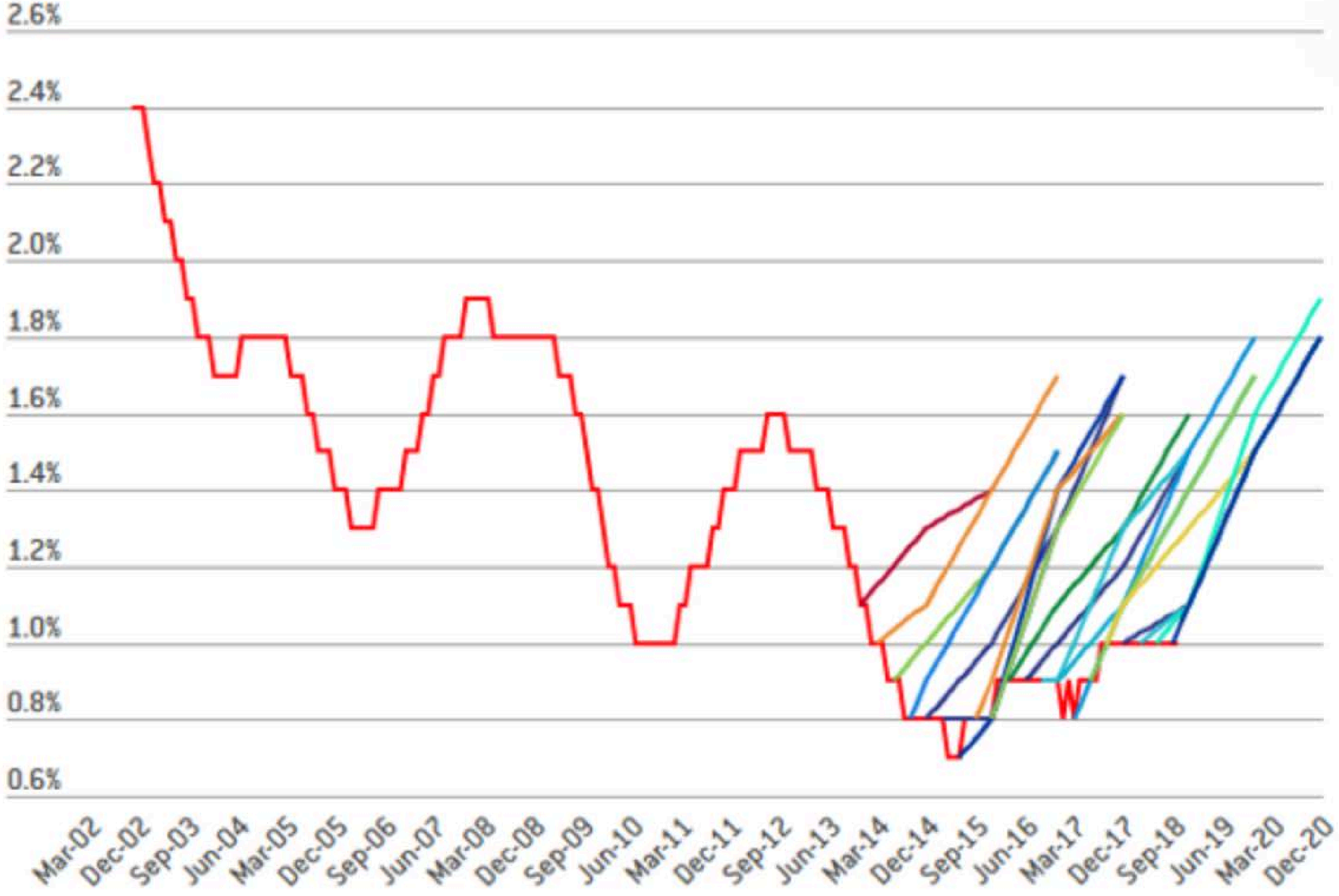
# Volatility puzzle (Shiller 1981)

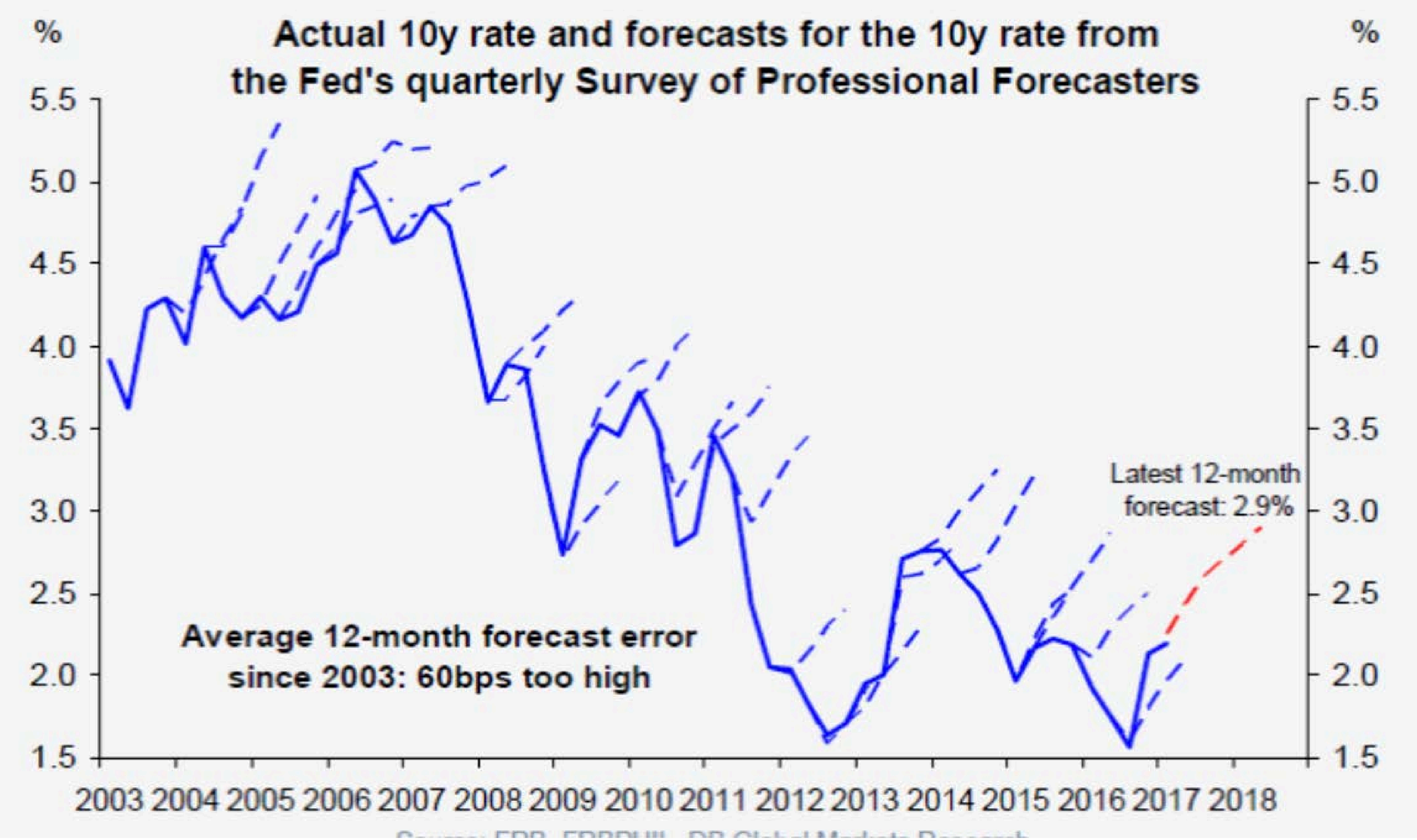


# Why/when under vs over reaction?

- Remains a bit of a mystery
  - Value, long-term reversal, sensitivity to salient news, bubbles
- Problem:
  - We don’t know information sets
  - We don’t all agree on underlying data generating process
    - Regime switches?
  - We don’t know in detail people’s incentives (e.g. career concern)

**Figure 1: ECB staff macroeconomic projections for euro-area core inflation**
*(moving 12 months average rate of change)*





Actual 10y rate and forecasts for the 10y rate from
the Fed's quarterly Survey of Professional Forecasters
%
%
5.5
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
Latest 12-month forecast: 2.9%
Average 12-month forecast error since 2003: 60bps too high
2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018

# Proposed solution: Experiment

- Canonical experiment: ask people to predict stable AR(1)
    - Can perfectly control their information set
    - Can control the data generating process
    - Can incentivize them

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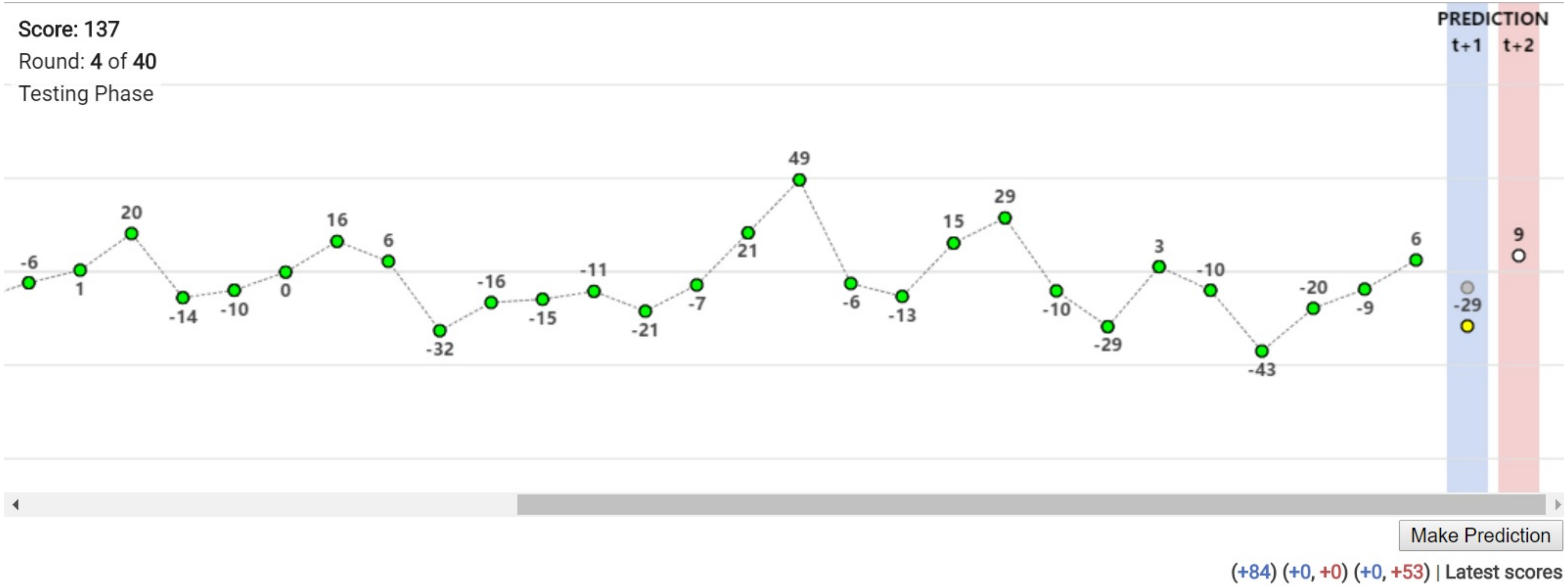
# Experiment (Landier, Ma, Thesmar, WP 2019)

Each participant is shown an AR1 process for $t = 1, ..., 40$

$$x_{t+1} = \rho x_t + 20\epsilon_{t+1} \text{ , where } \epsilon \sim \mathcal{N}(0, 1)$$

- click to predict $x_{t+1}$ and $x_{t+2}$
- then $x_{t+1}$ is realized; two new forecasts are asked
- iterate 40 times; score keeps track of forecast accuracy

- 1,500 participants had to forecast a “process” using this screen



# Result #0 : Classic expectation formation models do poorly

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

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

Full-information rational: $F_t x_{t+1} = E_t x_{t+1}$

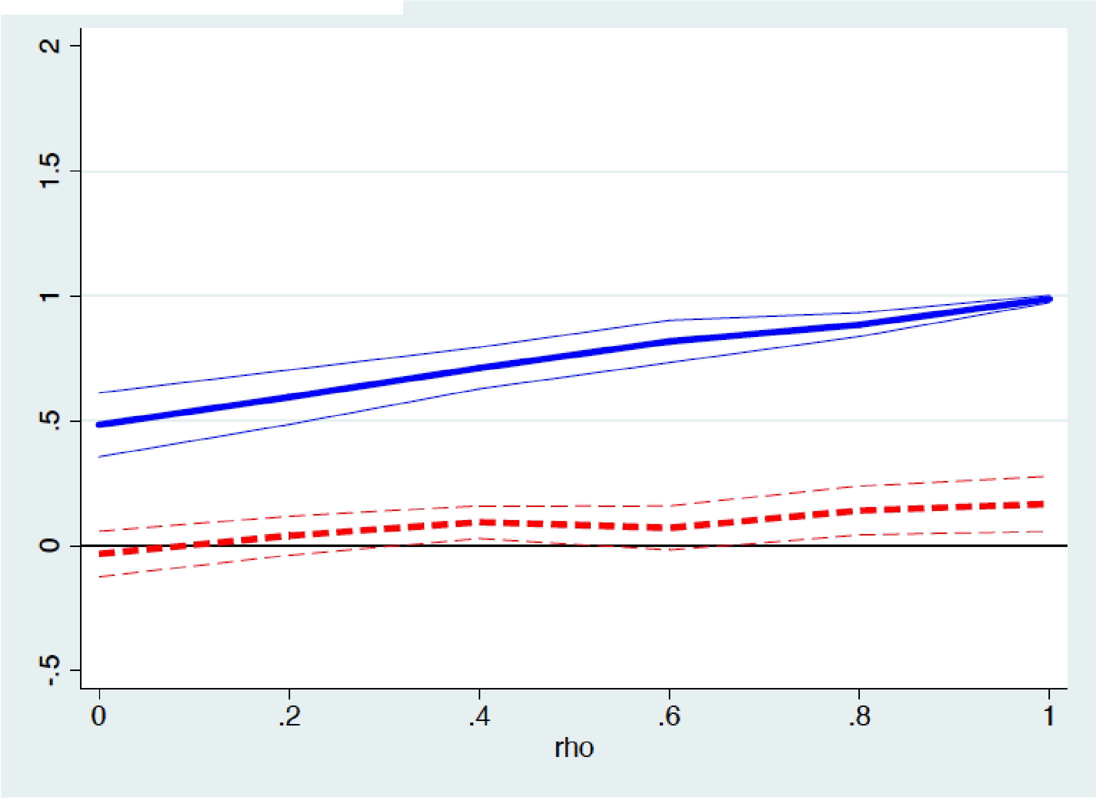
Least-square learning: $F_t x_{t+1} = \widehat{E}_t x_{t+1}$

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

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

# Traditional extrapolation does not fit

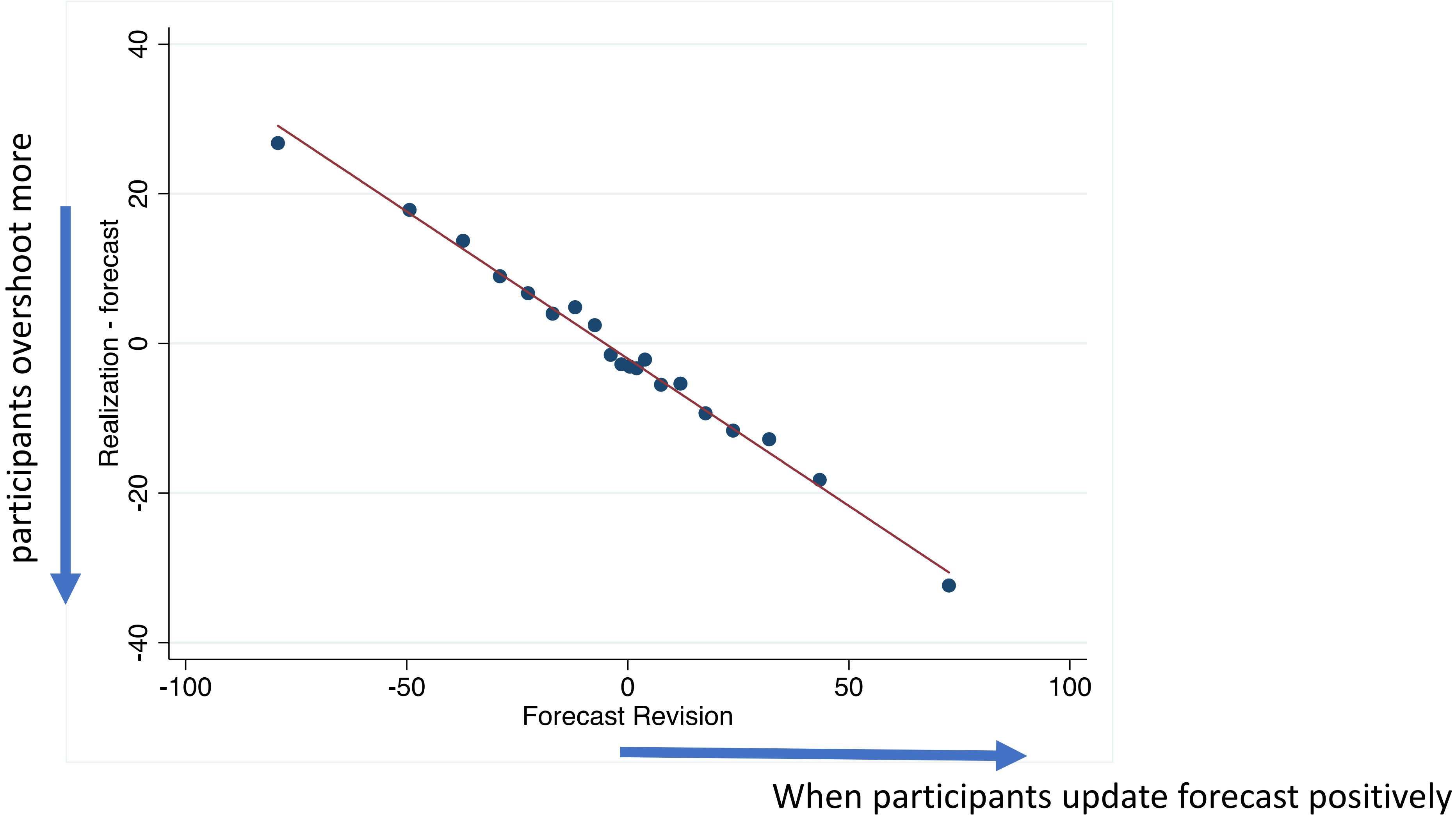
Extrapolative: $F_t x_{t+1} = x_t + \gamma(x_t - x_{t-1})$



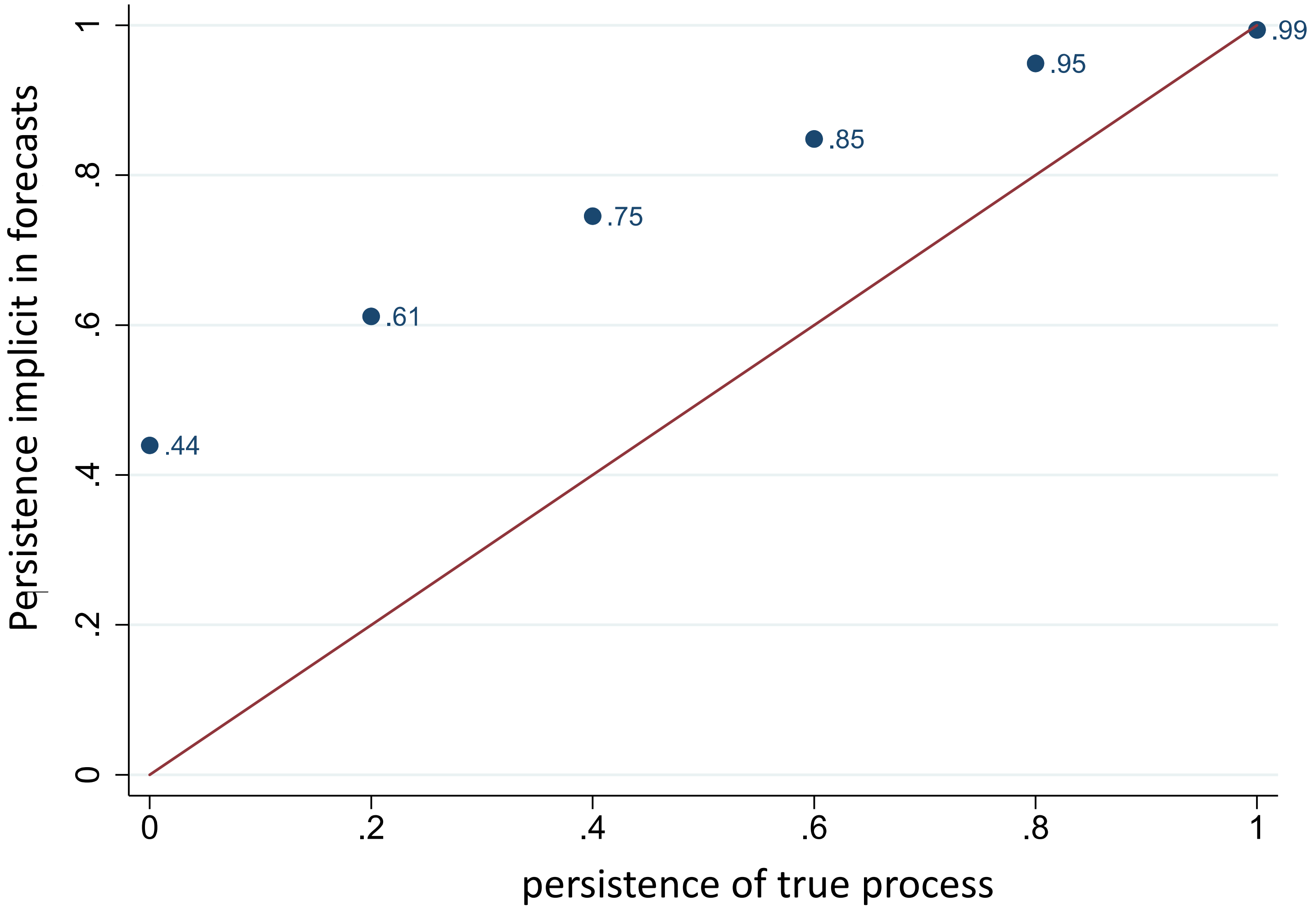

Extrapolative expectations

$$F_t x_{t+1} = a + {\color{blue}b} x_t + {\color{red}c}(x_t - x_{t-1})$$

# Result #1: there is (mostly) overreaction



# Result #2: persistence and overreaction

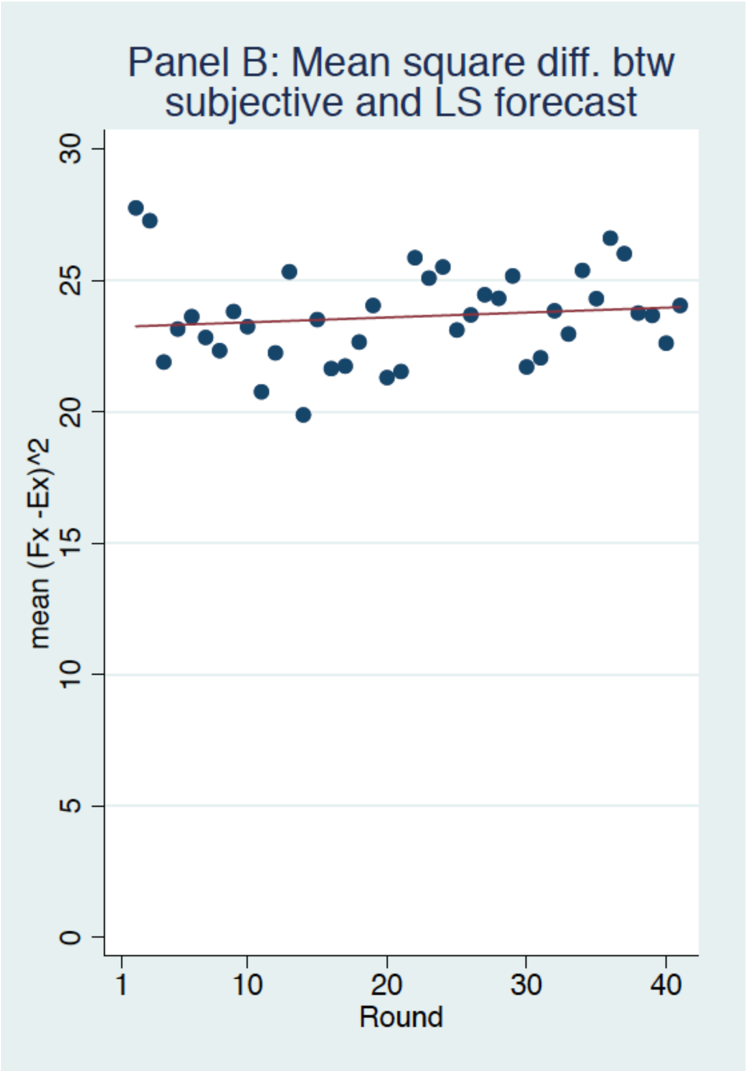



➔ participants overestimate the predictability of noisy processes

➔ leads them to overreact to recent realization

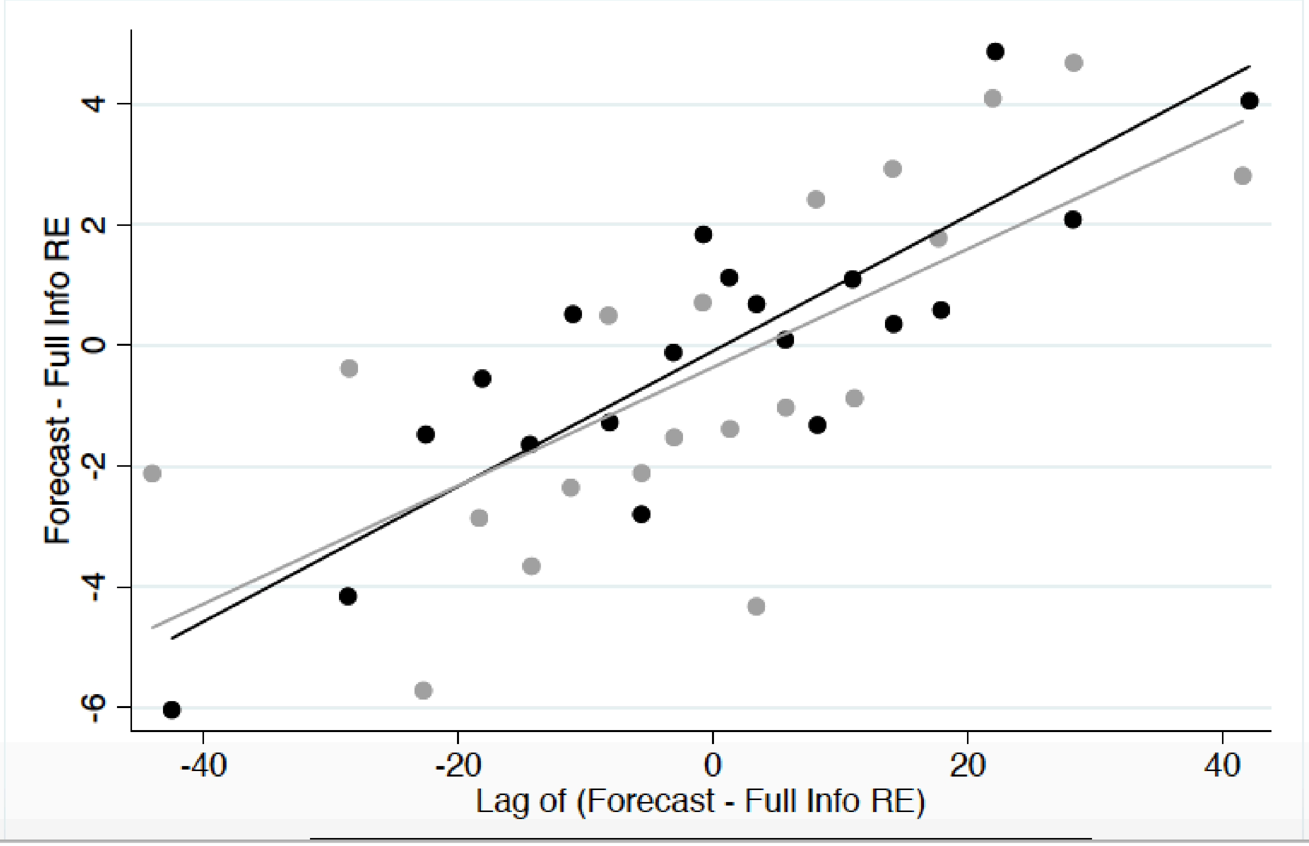
➔ participants understand noisy processes are noisier, but do not adjust enough

# Result #3: people do not learn over time

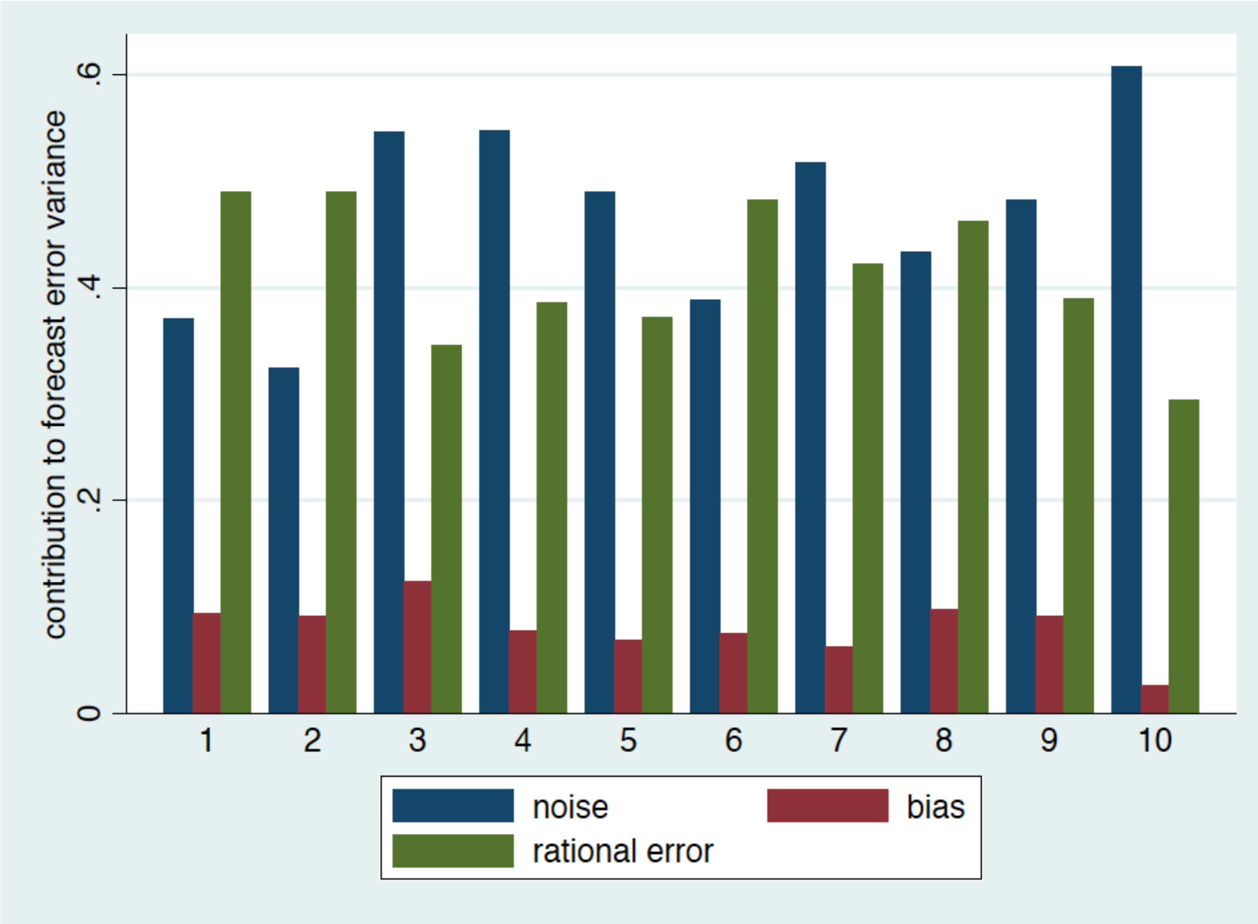


# Result #4: Mistakes persist

$F_t x_{t+1} - E_t x_{t+1}$ conditional on its lag :



# Result #5:individual noise is large




noise ~ 40% of forecast error

Consensus bias is highly predictable but small

# What model can fit this?

- We find that a **bounded memory** model (a la Malmendier&Nagel 2015) with *hyperbolic decay* can fit quite well
  - Need last observation to be overweighted

- But it is dominated by simple forward-extrapolation model:

$$F_t(x_{t+1}) = E_t(x_{t+1}) + \theta\underbrace{(x_t - E_{t-1}(x_t))}_{\text{(rational) surprise}}$$

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# Conclusion: why understand forecast errors?

- How people update beliefs:
  - Key object in models of individual choice
  - Highly active research field
  - Still somewhat unsettled: over-reaction vs. under-reaction
- Bayesian updating (including sticky information models) is not sufficient
- Methodological issues:
  - Agents might also evolve: get more help from computers
  - Practice in asset management: Pricing anomalies evolve as they become known