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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2. An example: the quality anomaly and underreaction

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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 (→ 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
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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)
Theory: investors underreact

- 2019 earnings > expected, should raise future forecasts
- Underreaction to good news about 2020 earnings

→ 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

Average “forecast error” = Realized EPS - Forecasted EPS

Average “forecast revision”:
= New forecast - Former forecast

⇒ 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 $\rightarrow$ 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

![Graph showing the relationship between past stock market returns and Gallup survey expectations.]

**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

Average 12-month forecast error since 2003: 60bps too high

Latest 12-month forecast: 2.9%
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 $t = 1, \ldots, 40$

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

- 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: \( F_t x_{t+1} = \hat{E}_t x_{t+1} \)

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
\[ F_t x_{t+1} = a + bx_t + c(x_t - x_{t-1}) \]
Result #1: there is (mostly) overreaction

When participants update forecast positively, participants overshoot more.
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 $\sim 40\%$ 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:

\[ F_t(x_{t+1}) = E_t(x_{t+1}) + \theta(x_t - E_{t-1}(x_t)) \]

(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