Overinference from Weak Signals and Underinference from Strong Signals

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How does new information change beliefs? Conflicting evidence in different environments...

1. Financial markets
   ▶ Excess volatility in aggregate valuations: Consistent with overreaction
   ▶ Post-earnings drift for individual stocks: Consistent with underreaction
   ▶ …

2. The lab
   ▶ Experimental evidence on conservatism ⇐⇒ Underreaction to signals
   ▶ Benjamin (2019) handbook chapter:
     “Stylized Fact 1: Underinference is by far the dominant direction of bias.”

Seek to reconcile evidence from both controlled experiments and observational data.
What drives over- vs. underinference?

- Depends on the strength of information
- Experiments overwhelmingly study strong signals
  - Benjamin (2019) meta-analysis: 500 experimental treatment blocks on inference from symmetric binary signal about binary state
  - None of these experiments features signal with $P(\text{high signal} | \text{high state}) < 0.6$
- Outside the lab, constant stream of weakly informative signals about future events
  - New poll about politician’s favorability...reelection
  - Daily index return...annual index return
  - But can find counterexamples: earnings are informative about firm’s fundamental value [Vuolteenaho 2002]

Underinference from strong signals, overinference from weak signals
What We Do

Systematic study of reaction to information of different strengths:

1. In the lab
   - Straightforward to vary signal strength given control of DGP
   - But concerns about external validity

2. In high-stakes observational data from betting & financial markets
   - No longer control DGP, so need ex ante empirical correlate of signal strength . . .
   - . . .and well-defined measures of over- vs. underinference
   - Simple theory to tie it together: Imprecision about signal strength
     - People have meta-prior on how much to update, don’t fully adjust to true signal strength
     - Provides useful language for interpreting results, and ties together empirical evidence
Contribution

Underinference:
- Dominant direction in balls-and-urns experiments (Benjamin 2019; Edwards 1968; Griffin & Tversky 1992; Enke & Graeber 2023)
  - But no prior work uses weak signals
  - One recent paper does, confirms patterns we find (Ba, Bohren, & Imas WP)
- Also: Neglect signal quantity or setting (Griffin & Tversky 1992; Massey & Wu 2005)

Overinference:
- More common in observational data (Bordalo et al. 2022; Bordalo et al. 2019)
  - Our argument: Environments with weakly informative signals
- Also common in forecasting experiments, varying horizon (Afrouzi et al. 2022; Fan et al. WP)
- Finance literature on overreaction and excess volatility (e.g. De Bondt and Thaler 1985)

We unite these strands: underinfer from strong signals and overinfer from weak signals:
- Strong: More common in lab. Weak: More common in forecast revisions.
- Other complementary mechanisms: Fan et al. WP; Kwon and Tang 2023

Combine experiment with betting + finance data for external validity (Levitt & List 2006)
- Use tools from Augenblick & Rabin (2021), Augenblick & Lazarus (WP)
- ID settings in which signals strong vs. weak by using time to resolution
Outline

1. Background
2. Theory
3. Experimental Evidence
4. Observational Data
5. Conclusions
Theory: Setup

- Person has prior $\pi_0 \equiv P(\theta = 1)$ about binary state $\theta \in \{0, 1\}$
- Sees binary signal $s \in \{s_L, s_H\}$, with $P(\theta = 1|s_H) > P(\theta = 1|s_L)$
- Consider misperception of signal strength in person’s subjective posterior $\hat{\pi}_1$:

$$\logit(\hat{\pi}_1) = \logit(\pi_0) + w \log \left( \frac{P(s|\theta = 1)}{P(s|\theta = 0)} \right)$$

  - $w = 1$: **Bayesian** ($\hat{\pi}_1 = \pi_1$)
  - $w > 1$: **Overinference**
  - $w < 1$: **Underinference**

Main question: How does $w$ depend on signal strength $S \equiv \left| \log \left( \frac{P(s|\theta = 1)}{P(s|\theta = 0)} \right) \right|$?
Misweighting via Imprecision

Cognitive imprecision:

- Longstanding idea (Weber 1834; Fechner 1860), recent applications to numerical values, probabilities, . . . (Woodford 2020; Khaw et al. 2021; Frydman & Jin 2022; Enke & Graeber 2023)
- We extend to imprecision about strength of information $S$
- Basic idea: Noisy representation of signal strength $\rightarrow$ shrinkage to “moderate” strength
  - Weak signals appear “too weak” relative to prior signal distribution $\rightarrow$ update too much
  - Consistent with inattention models (Gabaix 2019)
Misweighting via Imprecision

Cognitive imprecision:

1. Cognitive prior about signal strengths: $\log S \sim N(\mu_0, \sigma^2)$

+ 2. Signal of strength $S \rightarrow$ noisy cognitive representation $r$, with $r \sim N(\log S, \eta^2)$
   
   ▶ Easier to differentiate $S$ and $S + \epsilon$ when $S$ small

$\Rightarrow$ Posterior mean of perceived $S$ follows power law $k \cdot S^\beta$, with $\beta \equiv \frac{\sigma^2}{\sigma^2 + \eta^2} \in (0, 1)$

   ▶ Shrinkage to “moderate” signal strength

   ▶ **Switching point** $S^* \equiv k^{1/(1-\beta)}$ s.t. person underestimates $S$ iff $S > S^*$:

   $w > 1$ if $S < S^*$ (overweight weak signals + overinference)

   $w < 1$ if $S > S^*$ (underweight strong signals + underinference)
Over- and Underinference by Signal Strength: Theory

- \( y \)-axis: weight \( w(p) \) put on signal of precision \( p \) relative to Bayesian

- Compare: **Bayes** \((w = 1)\)
Over- and Underinference by Signal Strength: Theory

- y-axis: weight $w(p)$ put on signal of precision $p$ relative to Bayesian
- Compare: **Bayes ($w = 1$), constant underweight**
Over- and Underinference by Signal Strength: Theory

- y-axis: weight $w(p)$ put on signal of precision $p$ relative to Bayesian
- Compare: Bayes ($w = 1$), constant underweight, constant overweight
Over- and Underinference by Signal Strength: Theory

- y-axis: weight $w(p)$ put on signal of precision $p$ relative to Bayesian
- Compare: **Bayes ($w = 1$)**, constant underweight, constant overweight, **our model**
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Preregistered Experiment

- $n = 552$ U.S. adults recruited from Prolific (proliﬁc.co) in March 2021
- Standard bookbag-and-poker-chips setup: Card drawn from either green or purple deck (equally likely ex ante)
- Binary signal about deck: Card suit
- Green deck has share $p_1$ diamond ♦ cards & $1 - p_1$ spades ♠ (Purple: $p_2, 1 - p_2$)
- Baseline: Symmetric signals, precision $p \equiv p_1 = 1 - p_2$
- Elicit $\mathbb{P}(\text{deck} \mid \text{card drawn})$, compare answers as we vary $p$ (via deck composition)
- Answers incentivized (based on probability points), keep only if pass attention check (91%)
You draw a card from one of two modified decks of cards; a **Green** deck or a **Purple** deck.

The **Green** deck has **853 Diamonds** (♦) and **812 Spades** (♠).
The **Purple** deck has **812 Diamonds** (♦) and **853 Spades** (♠).

*The card you draw is a **Spade** (♠).*

What do you think is the percent chance that your **Spade** (♠) came from the **Green** deck vs. the **Purple** deck?

Please answer between 0 and 100 for each question and have your answers sum up to 100, where higher numbers mean you think that deck is more likely. Your answer may include decimals.

| Percent chance that your **Spade** (♠) came from the **Green** deck | 0 percent |
| Percent chance that your **Spade** (♠) came from the **Purple** deck | 0 percent |
| **Total** | 0 percent |

Vary deck size (small/large), suit (diamond/spade), signal strength (strong/weak)
Over- and Underinference by Signal Strength: Theory

- y-axis: weight $w(p)$ put on signal of precision $p$
- Compare **model (black curve)** to **Bayes ($w = 1$)**, constant overweight, constant underweight
Replicate previous experimental results with strong signals...
Over- and Underinference by Signal Strength: Main Results

- Replicate previous experimental results with strong signals...
- ...but strong evidence for underinference with weak signals
Recall: model predicts people perceive signal strength $S \equiv \log \left( \frac{P(s|\theta=1)}{P(s|\theta=0)} \right)$ as strength $\hat{S} = k \cdot S^\beta$

- Nonlinear least squares estimate: $k = 0.88$ (s.e. 0.02); $\beta = 0.76$ (s.e. 0.03)

- Switching point $S^*$ is such that $\hat{S}^* = S^*$, occurs when signal precision $P(s_H|\theta = 1) = 0.64$:
  - Signals with precision $> 0.64 \to \hat{S} < S$, i.e. underinference
  - Signals with precision $< 0.64 \to \hat{S} > S$, i.e. overinference

- Explains why hard to detect overinference when looking at signals with precision $\geq 0.6$
Heterogeneity and Learning

Lower score on cognitive reflection test (Frederick 2005): Infer more from weak signals and less from strong signals
Less task experience: Infer more from weak signals and less from strong signals
Additional Analysis and Robustness

In paper (and appendix):

- Additional heterogeneity analyses to speak to psychological channel: Heterogeneity by variance in signal weights, news consumption
- Excessive willingness to pay for weak signals, too little for strong signals
- Asymmetric signals
- Multiple signals
- Tests of potential alternative explanations
- Formal regression evidence on main results
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Evidence from Options & Betting Markets

- Experiment is tightly controlled, but unclear external validity
- Turn to high-stakes real-world setting: market-implied probabilities in betting markets and index options
- Challenges:
  1. No longer control DGP $\implies$ true signal informativeness is unknown, as is objectively correct belief period by period
  2. Interpretation as “beliefs”?  
- Develop & argue for proxy for signal informativeness based on time to resolution
  - Key feature of setting: Fix expiration date and observe implied beliefs over time within contract
Belief Movement and Uncertainty Reduction

For belief $\pi_t$ over binary state $\theta$ (“Bulls win”) realized at $T$:

- **Belief movement** (amount of updating): $m_{t,t+1} = (\Delta \text{belief})^2$

- **Uncertainty reduction** (signal informativeness): $r_{t,t+1} = \text{decrease in subjective variance from } t \text{ to } t + 1$

- **Result** (Augenblick & Rabin 2021): For a Bayesian, for any DGP, $E_t[m_{t,t+1}] = E_t[r_{t,t+1}]$.
  - Crucial features: Valid regardless of DGP, for any subset of data (as long as cut is ex ante)

**Our hypothesis:**

- Signals are weak $\implies E[m] > E[r]$ (overinference); signals strong $\implies E[m] < E[r]$ (underinf.)

- Sorting variable for signal strength: time to resolution
  - Ex ante known and observable
  - And signals are intuitively much more informative about payoffs closer to expiration

- To verify that (1) overinference $\iff E[m] > E[r]$, and (2) stronger signals closer to resolution: theory & simulations
Simulated Belief Streams

- Simulate one million “games” with two teams
  - One team scores in each of 27 periods (50/50), winner has most points at end

- **Movement** (sq. chg. in beliefs) & **uncertainty reduction**
  (drop in variance)

- **Our model**
  (calibrated from experiment):
  \( m > r \) early and \( m < r \) late
Data

1. Sports betting (Moskowitz 2021): Betfair
   - Large UK-based prediction exchange matching individual bettors on contracts over game outcome
   - Within-game binary bet prices for soccer, American football, baseball, basketball, hockey games

2. Index options:
   - Use risk-neutral beliefs over 5-percentage-point return ranges, keeping at-the-money $+/− 20$ ppt
   - Also translate RN beliefs to physical beliefs under hundreds of parameterizations for risk aversion $\phi_{t,j}$ (nearly identical results)
Betfair Data: NBA and NFL

Using implied probabilities from Betfair over the course of sports games:

Over course of game, $m$ and $r$ increase, and $m - r$ moves from $+$ to $-$. 
Over course of game, $m$ and $r$ increase, and $m - r$ moves from $+$ to $−$. 
Data

1. Sports betting (Moskowitz 2021): Betfair
   ▶ Large UK-based prediction exchange matching individual bettors on contracts over game outcome
   ▶ Within-game binary bet prices for soccer, American football, baseball, basketball, hockey games

2. Risk-neutral beliefs from index options:
   ▶ Use risk-neutral beliefs over 5-percentage-point return ranges, keeping at-the-money $+/- 20$ ppt
   ▶ Augenblick & Lazarus (2022) show how risk-neutral beliefs are informative about excess vol. . .
     less important for our analysis, because looking for relative over-/underreaction within a contract
   ▶ Also translate RN beliefs to physical beliefs under hundreds of parameterizations for risk aversion $\phi_{t,j}$ (nearly identical results)
As move closer to expiration, $m$ and $r$ increase, and $m - r$ moves from $+$ to $-$.
Regression evidence that $m$ increases less than one-for-one w/ informativeness: Appendix
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Conclusions

- Updating behavior differs by signal strength: overinference from weak signals & underinference from strong signals
- Robust & consistent evidence across domains: experiment, sports betting, financial markets
- In line with predictions of simple theoretical framework
- Reconciles disparate findings in experimental lit. & finance lit.
- Interesting open questions on how people form cognitive defaults in novel settings & what structure the noise in signal processing takes
Higher variance in signal weights: Infer more from weak signals, less from strong signals

- Suggests cognitive imprecision may be driving biases
- Though part of effect may be mechanical
## Effects on Overinference: Linear Regression Specification

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<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<tbody>
<tr>
<td></td>
<td>Main Effects</td>
<td>By CRT Score</td>
<td>By Round</td>
<td>By Noise</td>
<td>By News</td>
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<tr>
<td>Signal Strength</td>
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<td>-0.578</td>
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<td>Strength x CRT Score</td>
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<td>Strength x Round Number</td>
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<td>Strength x News Cons</td>
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<td>0.24</td>
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Standard errors in parentheses
## Effects on Overinference: Power Law Regression Specification

<table>
<thead>
<tr>
<th>DV: Weight on signal</th>
<th>(1) Main Effects</th>
<th>(2) By CRT Score</th>
<th>(3) By Round</th>
<th>(4) By SD</th>
<th>(5) By News</th>
</tr>
</thead>
<tbody>
<tr>
<td>Switching point $p^*$</td>
<td>0.644 (0.011)</td>
<td>0.624 (0.013)</td>
<td>0.628 (0.013)</td>
<td>0.702 (0.014)</td>
<td>0.628 (0.015)</td>
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<tr>
<td>Sensitivity $\beta$</td>
<td>0.761 (0.028)</td>
<td>0.741 (0.034)</td>
<td>0.745 (0.035)</td>
<td>0.803 (0.028)</td>
<td>0.745 (0.036)</td>
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<tr>
<td>$\beta_1 \times$ CRT Score</td>
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<td>0.024 (0.007)</td>
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<tr>
<td>$\beta_1 \times$ Round Number</td>
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<td>0.005 (0.002)</td>
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<td>$\beta_1 \times$ SD of Guesses</td>
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<td>-0.198 (0.044)</td>
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<tr>
<td>$\beta_1 \times$ News Cons</td>
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<td>0.054 (0.027)</td>
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<td>Observations</td>
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</table>

Standard errors in parentheses

The function estimated is $\frac{\logit(p^*)^{1-\beta}}{\logit(\pi_1)^{1-\beta}}$ for (1) and $\frac{\logit(p^*)^{1-\beta}-\beta_1 \text{Interaction}}{\logit(\pi_1)^{1-\beta}-\beta_1 \text{Interaction}}$ for each interaction from (2)-(5).
**Demand for Information**

- Mistaken demand for information often tracks inference biases (Ambuehl and Li 2018)

- If demand tracks misinference, people will:
  - Pay too much for weak signals
  - Pay too little for strong signals
  - Generally: have demand that is too insensitive to the quality of the information
Demand for Information

WTP bias similar to beliefs:
- Excess demand for weak signals
- Too little demand for strong signals

Effects even more severe for WTP:
- Explanation: Subjects also undervalue multiple signals.
- Run main treatment with 3 signals and see this effect.
Alternative Explanations

- Misperceptions of probabilities rather than signal strengths (*relative* probabilities)?
  - E.g. Maybe people overestimate probabilities that are $1/2 + \epsilon$ vs. $1/2 - \epsilon$.
  - Test using **asymmetric** signals, where one signal is close to uninformative
    - $P(s|\theta = 1) \gg 1/2$, but $P(s|\theta = 0) = 1/2 + / - \epsilon$.
    - Whether + or - $\epsilon$ would affect agent who misperceives probabilities, but not agents in our model
    - Find little effect of changing + to - $\epsilon$.

- Others: Aversion to 50%, # of cards, preference for one deck or color
  - No evidence these are driving results
  - E.g. 72 subjects see decks with $P(\text{Green}) = 1/2$ and 69 (96%) have posteriors of exactly 1/2
Effect of signal strength similar across groups, but switching point changes:
- Gray: 0.644
- Purple: 0.523
- Green: 0.507

Consistent with Griffin and Tversky (1992)
Signal in one state has likelihood far from 1/2:
  Vary $P(s|\theta = 1) = 0.65$ or 0.80

Signal in other state has likelihood close to 1/2:
  Vary $P(s|\theta = 0) = 0.495$ or 0.505

Estimate $\beta$ from power law model for each $P(s|\theta = 0)$

If effects due to probabilities, would expect significantly higher $\beta$ when $P(s|\theta = 0) = 0.505$

Instead: $\beta = 0.54$ when $P(s|\theta = 0) = 0.505$ and $\beta = 0.60$ when $P(s|\theta = 0) = 0.495$
  Difference small, in the opposite direction, and not statistically significant (p-value = 0.404)
Risk-Neutral Beliefs: Empirical Illustration

S&P 500 Option Prices and Risk-Neutral Beliefs as of July 1, 2005
Expiration Date: July 16, 2005

Call Option Prices

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<thead>
<tr>
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Risk-Neutral Beliefs

<table>
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<th>Terminal Index Value</th>
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Conditional Beliefs: 1175–1200 vs. 1200–1225

<table>
<thead>
<tr>
<th>Binary Probability</th>
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Risk-Neutral Beliefs: Empirical Illustration

S&P 500 Option Prices and Risk-Neutral Beliefs as of July 5, 2005
Expiration Date: July 16, 2005

Call Option Prices

Risk-Neutral Beliefs

Conditional Beliefs: 1175–1200 vs. 1200–1225
Risk-Neutral Beliefs: Empirical Illustration

S&P 500 Option Prices and Risk-Neutral Beliefs as of July 6, 2005
Expiration Date: July 16, 2005

Call Option Prices

Risk-Neutral Beliefs

Conditional Beliefs: 1175–1200 vs. 1200–1225
Risk-Neutral Beliefs: Empirical Illustration

S&P 500 Option Prices and Risk-Neutral Beliefs as of July 7, 2005
Expiration Date: July 16, 2005

Call Option Prices

Risk-Neutral Beliefs

Conditional Beliefs: 1175–1200 vs. 1200–1225
Formal Regression Framework

- Our hypothesis:
  - Signals are weak $\implies \mathbb{E}[m] > \mathbb{E}[r]$
  - Signals are strong $\implies \mathbb{E}[m] < \mathbb{E}[r]$

- Sorting variable for signal strength: time to resolution

- Cut market-implied belief streams into 24 time windows
  - Paper has results for alternative choices

- Regress average movement on average uncertainty reduction within each window
  - If used individual observations, would have severe attenuation bias
  - Bayesian: $\mathbb{E}_t[m_{t,t+1}] = \mathbb{E}_t[r_{t,t+1}] \implies$ should observe intercept of 0, slope of 1
  - Our theory: positive intercept, slope below 1
  - Results strongly align with our theoretical predictions
### Regressions of Movement on Uncertainty Reduction

<table>
<thead>
<tr>
<th>Dep Var: Movement</th>
<th>Soccer</th>
<th>Basketball</th>
<th>Baseball</th>
<th>Hockey</th>
<th>Football</th>
<th>Options</th>
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<tbody>
<tr>
<td>Uncert. Red.</td>
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<td>0.806</td>
<td>0.889</td>
<td>0.945</td>
<td>0.912</td>
<td>0.680</td>
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<tr>
<td></td>
<td>(0.005)</td>
<td>(0.008)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.027)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Constant</td>
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<td>0.976</td>
<td>0.995</td>
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<tr>
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<td>24</td>
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<tr>
<td>Events</td>
<td>6,584</td>
<td>5,176</td>
<td>3,927</td>
<td>4,123</td>
<td>1,390</td>
<td>955</td>
</tr>
<tr>
<td>Observations</td>
<td>4,589,289</td>
<td>867,567</td>
<td>166,346</td>
<td>109,751</td>
<td>86,193</td>
<td>58,864</td>
</tr>
<tr>
<td>p-val.: $\beta_1 = 1$</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
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<tr>
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<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
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</tbody>
</table>

Parentheses show bootstrapped standard errors with resampling clustered by stream.

Overreaction when signal informativeness is low...but decreases systematically as signal strength increases, with underreaction close to expiration.
### Regressions of Movement on Uncertainty Reduction

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Uncert. Red.</td>
<td>0.839</td>
<td>0.797</td>
<td>0.903</td>
<td>0.987</td>
<td>0.912</td>
<td>0.796</td>
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<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.027)</td>
<td>(0.054)</td>
<td>(0.063)</td>
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<tr>
<td>Constant</td>
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<td>0.0018</td>
<td>0.0024</td>
<td>0.0013</td>
<td>0.0015</td>
<td>0.0060</td>
<td>0.0054</td>
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<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0004)</td>
<td>(0.0009)</td>
<td>(0.0002)</td>
<td>(0.0005)</td>
<td>(0.0005)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.984</td>
<td>0.991</td>
<td>0.996</td>
<td>0.990</td>
<td>0.997</td>
<td>0.945</td>
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<td>58,864</td>
<td>58,864</td>
</tr>
<tr>
<td>$p$-val.: $\beta_1 = 1$</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>0.274</td>
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<td>&lt;0.001</td>
<td>&lt;0.001</td>
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- Overreaction when signal informativeness is low...but decreases systematically as signal strength increases, with underreaction close to expiration.
### Regressions of Movement on Uncertainty Reduction

<table>
<thead>
<tr>
<th>Dep Var: Movement</th>
<th>Soccer</th>
<th>Basketball</th>
<th>Baseball</th>
<th>Hockey</th>
<th>Football</th>
<th>Sports</th>
<th>Finance</th>
<th>Raw</th>
<th>Risk-Adj</th>
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<tbody>
<tr>
<td>Uncert. Red.</td>
<td>0.847</td>
<td>0.849</td>
<td>0.883</td>
<td>0.925</td>
<td>0.920</td>
<td>0.705</td>
<td>0.751</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.008)</td>
<td>(0.015)</td>
<td>(0.013)</td>
<td>(0.026)</td>
<td>(0.035)</td>
<td>(0.040)</td>
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</tr>
<tr>
<td>Constant</td>
<td>0.0014</td>
<td>0.0016</td>
<td>0.0027</td>
<td>0.0020</td>
<td>0.0015</td>
<td>0.0063</td>
<td>0.0058</td>
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<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0001)</td>
<td>(0.0002)</td>
<td>(0.0002)</td>
<td>(0.0001)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td></td>
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</tr>
<tr>
<td>$R^2$</td>
<td>0.955</td>
<td>0.974</td>
<td>0.993</td>
<td>0.975</td>
<td>0.982</td>
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<tr>
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<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>0.054</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
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</tr>
<tr>
<td>p-val.: $\beta_0 = 0$</td>
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<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>0.051</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td></td>
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