HOW DO PEOPLE UPDATE BELIEFS?

EVIDENCE FROM THE LABORATORY

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Motivation

- Empirical structural learning models assume Bayesian learning and homogeneity in learning because:
    - Observational data only provide information on choice *but not on belief*
    - Parsimonious structure (Ching, Erdem, and Keane, 2013, 2017; Ching, Hermosilla, and Liu, 2019)
- Misspecification of belief updating rules may lead to biased estimates of preference parameters and misleading counterfactual predictions.
- Our research question: How do people update their beliefs?

Research Questions and Contribution

- Research Questions:
  1. How do people update their belief distribution?
  2. How do people differ from each other in learning ?
  3. Do people change their belief updating rule dynamically and how?

- Research Approach: Collect belief data in an incentive-compatible way in a dynamic learning environment in a laboratory.
  - Collect belief distribution data (both **first** and **second** moments) → Q1
  - Rich data set to allow for heterogeneity in belief updating rules → Q2
  - A dynamic environment where agents receive information signals sequentially → Q3

Belief Updating Experiments Literature (Skip)

- The existing literature often ignores (a) belief variance, (b) heterogeneity, and (c) how people may change their updating rule over time.
  - Many consider learning about a variable with binary outcomes — Grether (1980), El-Gamal and Grether (1995), Holt and Smith (2009), Coutts (2019): Variance cannot be separated from mean.
  - Most consider only homogenous agents — El-Gamal and Grether (1995) do allow for heterogeneity, but in a static setting where subjects receive information only once.
  - Hossain and Okui (2020) collect belief data in a static setting with multiple sources of information, but do not directly elicit variance or consumer heterogeneity.
  - Jindal and Aribarg (2021) collect belief data in the context of price search, but do not study unobserved consumer heterogeneity or potential dynamic change in belief updating rules.
  - Houser, Keane and McCabe (2004) use a lab experiment to study forward-looking human capital accumulation decisions.

Experimental Design

#1 #2 #3 #4 #5 #6 #7

For each house, a subject faces 7 periods.

In each period, a subject consults a different expert about their estimate about the selling price of this house (i.e., how much this house is worth).

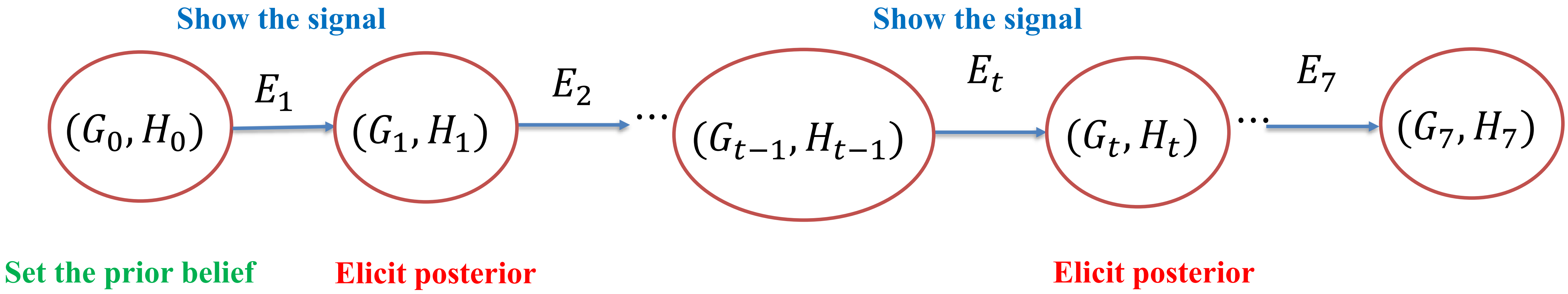
- These 7 expert estimates follow iid $N(S, \sigma_r^2)$.

In each period, a subject needs to come up with a new guess (posterior mean) and report the certainty level (posterior variance) of your new guess.

At the end of 7 periods, the actual selling price S will be revealed.

Experimental Design: Main Task

- Subjects guess the selling price of a house, S, as they receive more information:
  - Initial prior: house price distribution in the neighbourhood, $S \sim N(E_0, \sigma_0^2)$
  - Noisy signals: Independent price estimates from different people, $E_t \sim N(S, \sigma_\epsilon^2)$
- Elicit beliefs using the *Binarized Scoring Rule* (Hossain and Okui, 2013)
  - *Best guess* of the house price, G_t → posterior mean
  - *Certainty level* about the reported best guess, H_t → posterior variance



Posterior Variance and Certainty Level

- **Do regular people understand the concept of "variance"?**
- **Report how certain they are about their best guess:**

$$\textit{Certainty Level}, H_t \equiv Prob(S \in [G_t - 25, G_t + 25])$$

relationship between the standard deviation σ_t and the certainty level H_t has a one-to-one mapping:

$$H = \left(\Phi(\frac{25}{\sigma}) - 0.5\right) * 2 = \Phi(\frac{25}{\sigma}) * 2 - 1, \tag{5}$$

Experimental Design:
Posterior mean and certainty level elicitation (skip)

- Subjects report their *best guess* (G_t) of the house price (S) in period t
- Apply the Binarized Scoring Rule (BSR) to ensure it is incentive compatible for subjects to report truthfully without any assumption on risk-preference or functional form of utility
  - $Score_t = (G_t - S)^2$
  - Randomly draw a number K from uniform distribution on [0, 5000]
  - If $Score_t < K$, subject earns some reward and otherwise, no reward
  - Subjects were aware that it is optimal for them to report their beliefs truthfully
- For certainty level (H_t), we use the score $(\mathbb{I}(S \in [G_t - 25, G_t + 25]) - H_t)^2$ and K is drawn from a uniform distribution on $[0,1]$.

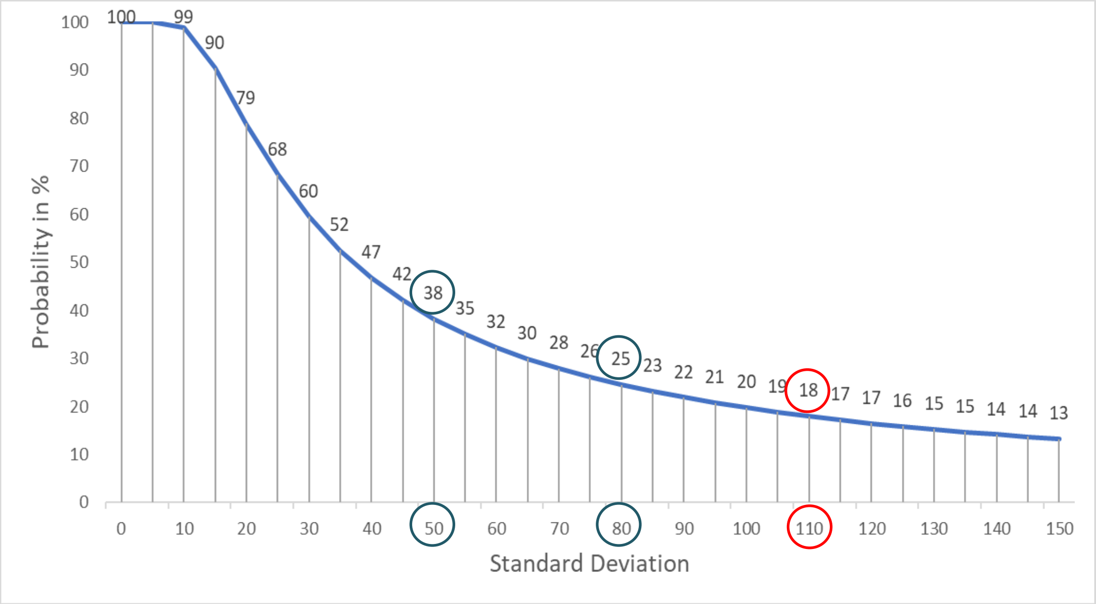
Experiment Procedure

Individual decision-making experiment at the Toronto Experimental Economics Lab (TEEL), programmed in *z-Tree* with the following steps (simplified):

1. Statistical Concepts.
2. Experimental Instructions Video.
3. Comprehension Test.
4. Main Experiment: 4 practice houses + 8 paid houses; each with 7 signals/periods.
5. Payment: Paid for one best guess and one certainty level for each "paid" house

Parameter Choice

- Initial prior: True house price, S, drawn from a normal distribution
  - Mean $E_0 \in \{660, 750, 830, 940\}$
  - S.D. $\sigma_0 = 110 \Leftrightarrow \mathrm{H}_0 = 18\%$



- Signals E_t generated from $N(S, \sigma_\epsilon^2)$
- $\sigma_\epsilon = 50 \Leftrightarrow H_\epsilon = 38\%$ (high precision)
- $\sigma_\epsilon = 80 \Leftrightarrow H_\epsilon = 25\%$ (low precision)
- 4 paid houses with high precision signals and the other four with low precision signals; for each house of this set of four, we assign the subject with a different initial prior.

Data

- Final sample includes 104 University of Toronto students:
  - 40 males, 64 females, average age 20.5
- Data on 8 houses from each subject with 7 signals/periods for each house:
  - Subscripts: i for individual, j for house, t for signal/period.
  - G_{j0} is the initial prior mean.
  - σ_0 is the initial prior standard deviation; H_0 is the initial prior certainty level.
  - V_j is the house j's true value
  - E_{jt} is the signal received
  - $\sigma_{j,\epsilon}$ is the signal distribution standard deviation; $H_{j,\epsilon}$ is the signal certainty level
  - G_{ijt} is the reported best guess
  - H_{ijt} is the reported certainty level

Experimental Design

Reported by Subjects

Econometric Specification for Posterior Mean

$$G_t = G_{t-1} + \frac{\tau_\epsilon}{\tau_{t-1} + \tau_\epsilon}(E_t - G_{t-1}) = G_{t-1} + \frac{\tau_\epsilon}{\tau_0 + t\tau_\epsilon}(E_t - G_{t-1})$$

$$\Updownarrow \tag{7}$$

$$G_t - G_{t-1} = \beta_t \cdot (E_t - G_{t-1})$$

$$G_{ij,t} - G_{ij,t-1} = \mathbb{1}(H_{j,l}) \cdot \beta_{t,l} \cdot x_{ijt} + \mathbb{1}(H_{j,h}) \cdot \beta_{t,h} \cdot x_{ijt} + u_{G,ijt}, \tag{8}$$

where $x_{ijt} = E_{ijt} - G_{ij,t-1}$, $H_{j,l} = 25\%$ corresponds to low precision signals, $H_{j,h} = 38\%$ corresponds to high precision signals, and $u_{G,ijt}$ are independent and identically normally distributed error terms, $\mathbb{1}(H_{j,h})$ (resp. $\mathbb{1}(H_{j,l})$) is a dummy variable for decisions under low (resp. high) precision signal environment, $\beta_{t,l}$ (resp. $\beta_{t,h}$) captures the effect of x_{ijt} on the updating of posterior mean under the low (resp. high) precision signal environment.

Econometric Specification for Posterior Certainty Level

As for the econometric model of posterior certainty level, we follow the specification of the posterior mean.

$$H_{ij,t} - H_{ij,t-1} = \mathbb{1}(H_{j,l}) \cdot \alpha_{t,l} + \mathbb{1}(H_{j,h}) \cdot \alpha_{t,h} + u_{H,ijt}, \tag{9}$$

where $u_{H,ijt}$ is independent and identically normally distributed error terms, $\hat{\alpha}_{t,l}$ (resp. $\hat{\alpha}_{t,h}$) is the estimated marginal change in certainty level as a function of updating step t.

If the estimated value $\hat{\alpha}_t$ is higher (resp. lower) than the derived Bayesian marginal effect α_t, it suggests that subjects tend to *overreact* or (resp. *underreact*) to signals when adjusting their certainty level adjustment at step t. The extent of over/underreaction is measured by $|\hat{\alpha}_t - \alpha_t|$, and we allow this deviation to vary across updating steps t nonparametrically.[4]

Model Selection

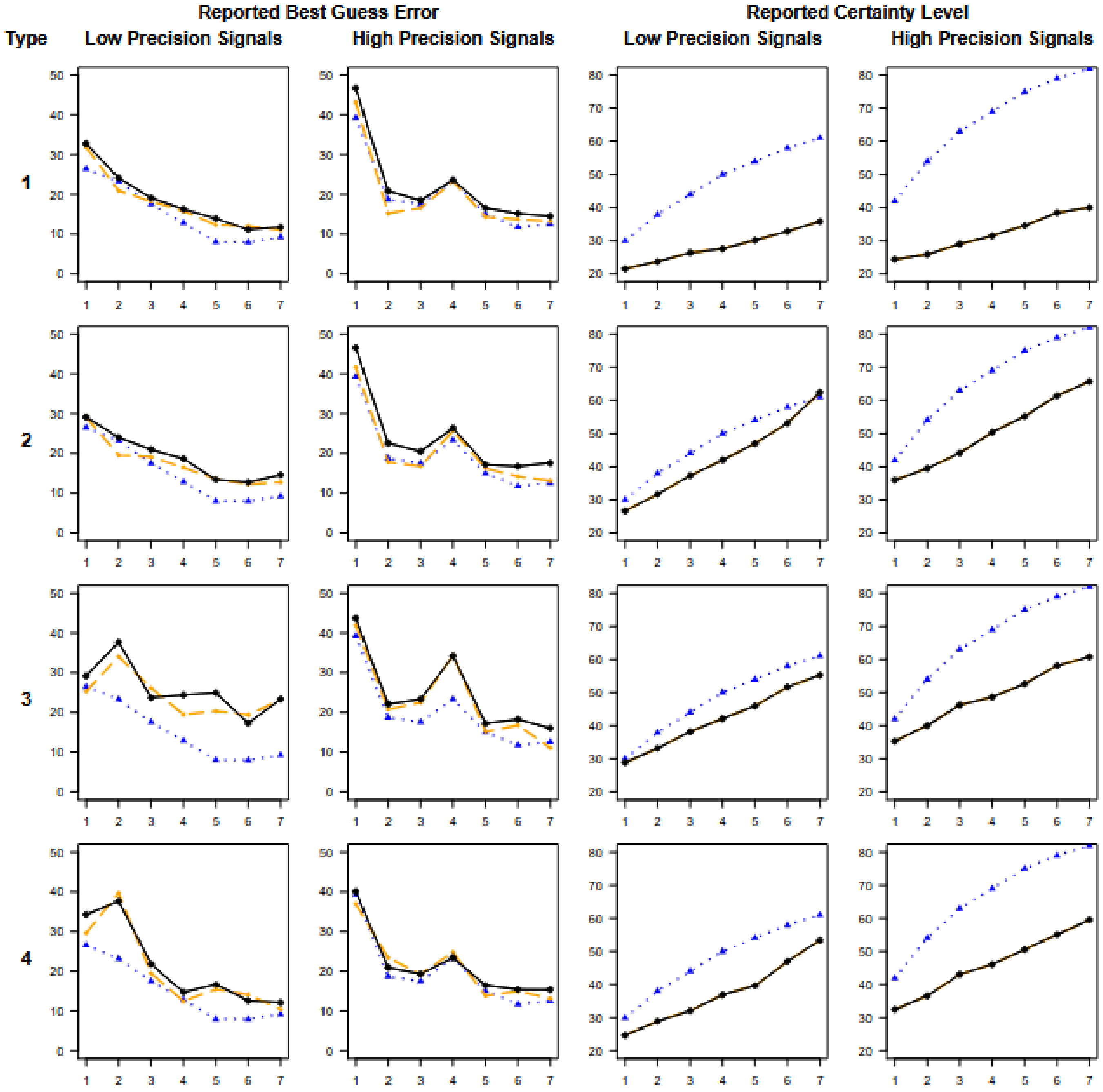
- Total number of obs = 104*8*7=5,824.
- Use finite mixture to allow for consumer heterogeneity.
  - Bayesian Information Criteria suggests the optimal number of types is 5.
  - Type 1 (40.5%), 2 (29.7%), 3 (14.4%), 4 (10.6%), 5 (4.8%).

RESULT 1. Subjects are heterogeneous in their belief updating rules.

Types	Log-Likelihood	No. of Parameters	BIC
1	-45450	30	91181
2	-44854	59	90259
3	-44615	88	90053
4	-44426	117	89947
5	**-44278**	**146**	**89922**
6	-44180	175	89997

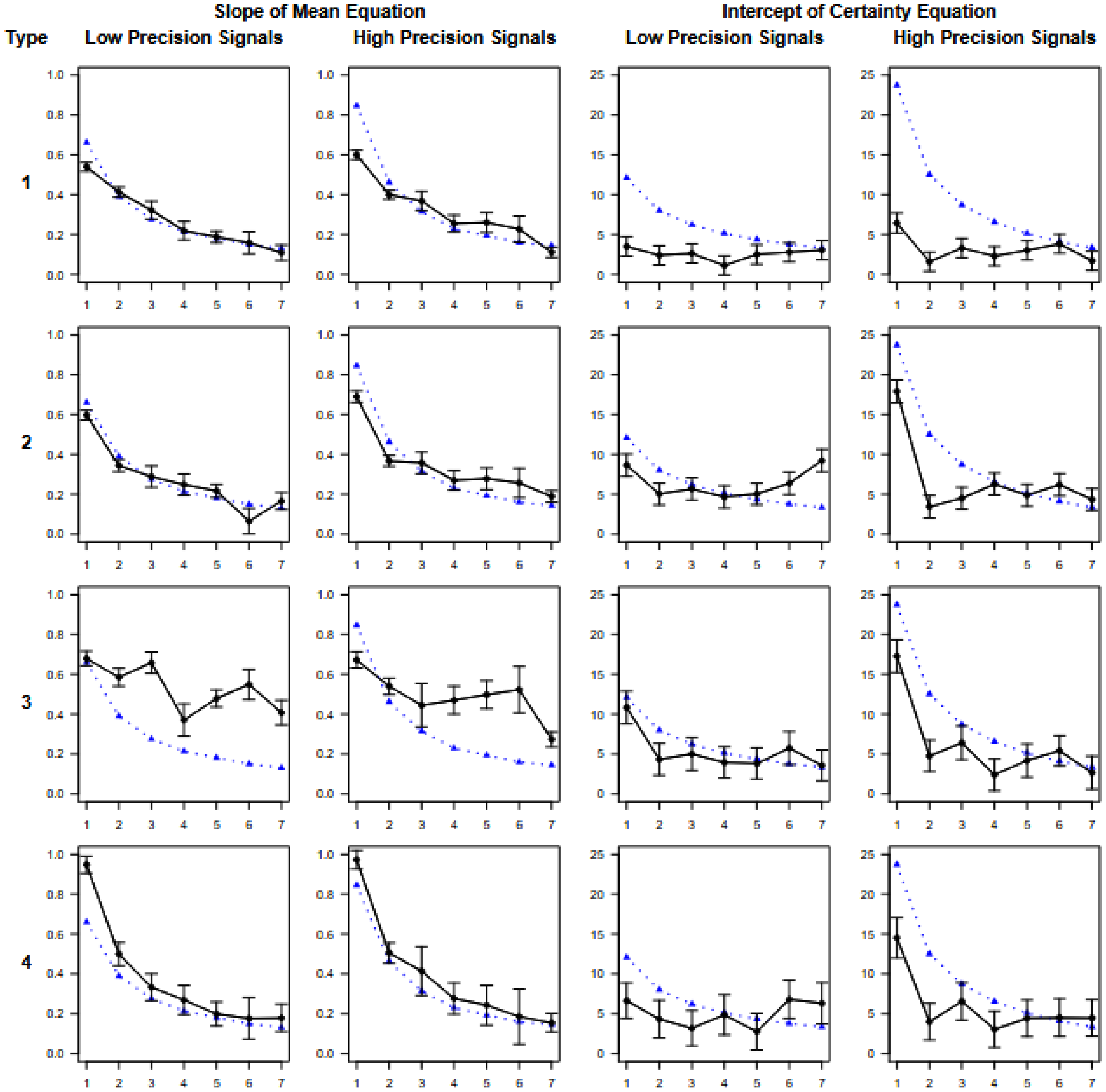
Notes: The preferred model is highlighted in bold.
The BIC is $-2LL + log(N)K$, where LL is the log-likelihood, N is the number of observations, and K is the number of parameters.

Figure 3: Absolute Best Guess Error $|G_{ijt} - S_j|$ and Reported Certainty Level H_{ijt}



Black Solid – Data
Orange – Fitted Value
Blue – Bayesian

Figure 4: The Effects of Signal on Posterior Mean and Certainty Level



Black – Estimates
Blue – Bayesian

Posterior Mean Equation

Type Probability	0.405***	0.297***	0.144***	0.106*	0.048**		
	(0.077)	(0.054)	(0.037)	(0.058)	(0.022)		
$\beta_{1,l}$	0.540***	0.597***	0.679	0.948***	0.823***	0.633***	0.66
	(0.011)	(0.013)	(0.019)	(0.022)	(0.034)	(0.009)	
$\beta_{2,l}$	0.413*	0.344***	0.585***	0.500***	0.757***	0.438***	0.391
	(0.013)	(0.016)	(0.023)	(0.030)	(0.039)	(0.010)	
$\beta_{3,l}$	0.322**	0.288	0.658***	0.333*	0.773***	0.435***	0.276
	(0.023)	(0.027)	(0.027)	(0.034)	(0.041)	(0.015)	
$\beta_{4,l}$	0.219	0.248	0.371***	0.269	0.604***	0.270***	0.214
	(0.024)	(0.027)	(0.041)	(0.037)	(0.071)	(0.018)	
$\beta_{5,l}$	0.188	0.217**	0.478***	0.199	0.724***	0.280***	0.181
	(0.015)	(0.017)	(0.022)	(0.031)	(0.036)	(0.011)	
$\beta_{6,l}$	0.158	0.065***	0.549***	0.177	0.872***	0.272***	0.15
	(0.028)	(0.033)	(0.039)	(0.054)	(0.056)	(0.020)	
$\beta_{7,l}$	0.109	0.166	0.408***	0.179	0.766***	0.210***	0.131
	(0.020)	(0.022)	(0.031)	(0.035)	(0.054)	(0.014)	
$\beta_{1,h}$	0.600***	0.690***	0.672***	0.973***	0.758**	0.684***	0.846
	(0.012)	(0.015)	(0.020)	(0.024)	(0.035)	(0.009)	
$\beta_{2,h}$	0.400***	0.367***	0.540***	0.505	0.852***	0.443**	0.462
	(0.012)	(0.014)	(0.021)	(0.026)	(0.032)	(0.009)	
$\beta_{3,h}$	0.369**	0.357	0.445**	0.414	0.465	0.377***	0.314
	(0.025)	(0.028)	(0.055)	(0.062)	(0.103)	(0.020)	
$\beta_{4,h}$	0.255	0.270	0.470***	0.276	0.765***	0.315***	0.23
	(0.021)	(0.025)	(0.036)	(0.040)	(0.062)	(0.016)	
$\beta_{5,h}$	0.260***	0.278***	0.498***	0.243	0.850***	0.355***	0.194
	(0.025)	(0.028)	(0.036)	(0.051)	(0.052)	(0.018)	
$\beta_{6,h}$	0.227**	0.257***	0.523***	0.186	0.944***	0.296***	0.16
	(0.034)	(0.037)	(0.059)	(0.071)	(0.116)	(0.026)	
$\beta_{7,h}$	0.111**	0.189***	0.273***	0.155	0.850***	0.212***	0.144
	(0.013)	(0.015)	(0.020)	(0.024)	(0.031)	(0.010)	

Posterior Certainty Level Equation

	Type 1	Type 2	Type 3	Type 4	Type 5	One Type	Bayes
Type Probability	0.405***	0.297***	0.144***	0.106*	0.048**		
	(0.077)	(0.054)	(0.037)	(0.058)	(0.022)		
$\alpha_{1,l}$	4.363***	9.999***	7.786***	11.008	7.985***	6.564***	12.08
	(0.627)	(0.712)	(1.128)	(1.007)	(1.576)	(0.394)	
$\alpha_{2,l}$	2.620***	6.794*	4.242***	7.121	3.426***	3.650***	7.998
	(0.601)	(0.724)	(1.085)	(1.023)	(1.569)	(0.395)	
$\alpha_{3,l}$	2.451***	6.650	3.551**	6.052	4.880	3.961***	6.205
	(0.570)	(0.707)	(1.043)	(1.068)	(1.569)	(0.395)	
$\alpha_{4,l}$	1.830***	5.954	5.172	5.323	2.521*	3.024***	5.115
	(0.575)	(0.723)	(1.008)	(1.056)	(1.576)	(0.395)	
$\alpha_{5,l}$	2.501***	6.608***	3.231	5.777	3.868	3.449**	4.357
	(0.582)	(0.712)	(0.990)	(1.107)	(1.540)	(0.393)	
$\alpha_{6,l}$	2.926	7.347***	6.289**	6.728***	9.309***	4.947***	3.788
	(0.562)	(0.695)	(1.016)	(1.062)	(1.581)	(0.394)	
$\alpha_{7,l}$	3.634	10.969***	6.600***	5.932**	-1.064***	5.005***	3.34
	(0.589)	(0.723)	(1.036)	(1.104)	(1.552)	(0.394)	
$\alpha_{1,h}$	7.170***	18.494***	15.932***	15.994***	16.659***	12.706***	23.72
	(0.597)	(0.691)	(0.987)	(1.092)	(1.484)	(0.394)	
$\alpha_{2,h}$	2.292***	5.462***	4.737***	7.409***	9.159**	3.078***	12.52
	(0.581)	(0.742)	(1.086)	(1.138)	(1.491)	(0.395)	
$\alpha_{3,h}$	3.089***	5.996***	6.048***	6.963	2.259***	4.350***	8.704
	(0.561)	(0.713)	(1.017)	(1.089)	(1.486)	(0.394)	
$\alpha_{4,h}$	2.587***	8.250**	3.703***	4.673	5.581	3.629***	6.547
	(0.575)	(0.753)	(1.057)	(1.154)	(1.561)	(0.394)	
$\alpha_{5,h}$	3.173***	6.816**	5.033	5.949	-0.373***	3.594***	5.122
	(0.571)	(0.759)	(1.007)	(1.140)	(1.528)	(0.393)	
$\alpha_{6,h}$	3.754	7.158***	4.298	6.973***	3.814	4.814*	4.102
	(0.563)	(0.684)	(1.038)	(1.048)	(1.517)	(0.393)	
$\alpha_{7,h}$	3.084	6.714***	5.520**	5.529**	3.777	2.882	3.338
	(0.607)	(0.777)	(1.049)	(1.077)	(1.589)	(0.392)	

Deviation From Bayesian Behavior

RESULT 2. Subjects' belief updating rules, regardless of their types, are all deviated from the Bayesian updating rule. But posterior certainty level deviates much more.

Posterior Mean Updating Rule

- **RESULT 3a**: The majority (80 percent) of the subjects with their mean belief updating rule roughly consistent with Bayesian.

- **RESULT 3b**: But around 20 percent of the subjects (types 3 and 5) who show significantly different mean updating behavior, violating the fundamental Bayesian mean belief updating rule of diminishing return of signals. These subjects significantly overreact to new information compared to Bayesian counterpart.

Posterior Certainty Level Updating Rule

- **RESULT 4a**: Majority of subjects show varied degrees of under-reaction at the beginning. In general, they increase their certainty level much slower than Bayesian.

- **RESULT 4b**: As they receive more signals, they tend to become more reactive to new signals. More specifically, their updating coefficient converges to their Bayesian counterpart, but their posterior certainty level remains far away from Bayesian's by period 7.

Belief Updating when Facing Surprising Signals

we augment Equations 8 and 9 with an indicator for whether the realized signal E_{jt} lies more than 1.5 standard deviations away from the prior mean.[7] We estimate the corresponding equations (13) and (14) and report results in Appendix C.

$$\begin{aligned} G_{ij,t} - G_{ij,t-1} = {} & \mathbb{1}(H_{j,l}) \cdot \beta_{t,l} \cdot x_{ijt} + \mathbb{1}(H_{j,h}) \cdot \beta_{t,h} \cdot x_{ijt} \\ & + \mathbb{1}(x_{ijt} > 1.5 \cdot \sigma(H_{ij,t-1})) \cdot \gamma_G \cdot x_{ijt} + u_{G,ijt}, \end{aligned} \tag{13}$$

$$\begin{aligned} H_{ij,t} - H_{ij,t-1} = {} & \mathbb{1}(H_{j,l}) \cdot \alpha_{t,l} + \mathbb{1}(H_{j,h}) \cdot \alpha_{t,h} \\ & + \mathbb{1}(x_{ijt} > 1.5 \cdot \sigma(H_{ij,t-1})) \cdot \gamma_H + u_{H,ijt}, \end{aligned} \tag{14}$$

where γ_G and γ_H capture the effect of surprising information on the mean and certainty level

Table A.1: Posterior Mean Equation: Controlling Surprising Effect

	Type 1	Type 2	Type 3	Type 4	Type 5	One Type	Bayes
Type Probability	0.419***	0.331***	0.135***	0.067***	0.048**		
	(0.079)	(0.073)	(0.036)	(0.025)	(0.022)		
$\beta_{1,l}$	0.537***	0.714***	0.608***	0.830***	0.725**	0.633***	0.66
	(0.012)	(0.013)	(0.020)	(0.029)	(0.033)	(0.009)	
$\beta_{2,l}$	0.400	0.458***	0.527***	0.640***	0.427	0.434***	0.391
	(0.013)	(0.019)	(0.025)	(0.038)	(0.048)	(0.011)	
$\beta_{3,l}$	0.326**	0.337**	0.609***	0.675***	0.496***	0.432***	0.276
	(0.024)	(0.024)	(0.034)	(0.040)	(0.064)	(0.016)	
$\beta_{4,l}$	0.226	0.272**	0.297*	0.586***	0.290	0.268***	0.214
	(0.024)	(0.025)	(0.044)	(0.062)	(0.070)	(0.018)	
$\beta_{5,l}$	0.216**	0.232**	0.467***	0.606***	0.344***	0.272***	0.181
	(0.018)	(0.021)	(0.031)	(0.038)	(0.054)	(0.013)	
$\beta_{6,l}$	0.160	0.134	0.503***	0.778***	0.320**	0.268***	0.15
	(0.029)	(0.032)	(0.047)	(0.052)	(0.080)	(0.021)	
$\beta_{7,l}$	0.135	0.205***	0.385***	0.612***	0.229	0.204***	0.131
	(0.021)	(0.024)	(0.039)	(0.049)	(0.063)	(0.016)	
$\beta_{1,h}$	0.590***	0.802***	0.609***	0.794*	0.758**	0.684***	0.846
	(0.013)	(0.014)	(0.022)	(0.031)	(0.037)	(0.009)	
$\beta_{2,h}$	0.406***	0.471	0.503	0.719***	0.450	0.437**	0.462
	(0.015)	(0.019)	(0.027)	(0.036)	(0.045)	(0.011)	
$\beta_{3,h}$	0.346	0.394***	0.404*	0.463*	0.543***	0.376***	0.314
	(0.024)	(0.031)	(0.052)	(0.090)	(0.076)	(0.020)	
$\beta_{4,h}$	0.258	0.324***	0.369***	0.626***	0.488***	0.312***	0.23
	(0.021)	(0.025)	(0.041)	(0.055)	(0.072)	(0.017)	
$\beta_{5,h}$	0.273***	0.264**	0.487***	0.709***	0.486***	0.351***	0.194
	(0.025)	(0.029)	(0.042)	(0.050)	(0.072)	(0.018)	
$\beta_{6,h}$	0.234**	0.306***	0.410***	0.840***	0.349*	0.292***	0.16
	(0.033)	(0.039)	(0.065)	(0.098)	(0.105)	(0.026)	
$\beta_{7,h}$	0.142	0.229***	0.283***	0.614***	0.255**	0.203***	0.144
	(0.017)	(0.020)	(0.030)	(0.037)	(0.050)	(0.013)	
γ_G	-0.025*	-0.070***	-0.006	0.109***	-0.056	0.009	0
	(0.013)	(0.015)	(0.022)	(0.028)	(0.037)	(0.009)	
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Table A.2: Posterior Certainty Level Equation: Controlling Surprising Effect

	Type 1	Type 2	Type 3	Type 4	Type 5	One Type	Bayes
Type	0.419***	0.331***	0.135***	0.067***	0.048**		
Probability	(0.079)	(0.073)	(0.036)	(0.025)	(0.022)		
$\alpha_{1,l}$	3.680***	8.226***	6.803***	6.481***	19.400***	6.564***	12.08
	(0.547)	(0.620)	(0.968)	(1.312)	(1.782)	(0.391)	
$\alpha_{2,l}$	2.392***	3.889***	7.169	2.217***	18.034***	4.191***	7.998
	(0.560)	(0.650)	(0.963)	(1.410)	(1.566)	(0.397)	
$\alpha_{3,l}$	2.586***	4.524***	7.773*	2.979**	12.471***	4.191***	6.205
	(0.552)	(0.626)	(0.952)	(1.426)	(1.569)	(0.393)	
$\alpha_{4,l}$	1.993***	4.034*	7.360**	1.497***	6.881	3.230***	5.115
	(0.549)	(0.637)	(0.969)	(1.386)	(1.594)	(0.393)	
$\alpha_{5,l}$	2.724***	4.581	6.657**	2.559	15.181***	4.259	4.357
	(0.576)	(0.641)	(1.043)	(1.422)	(1.546)	(0.401)	
$\alpha_{6,l}$	2.996	6.028***	8.652***	6.487*	16.581***	5.312***	3.788
	(0.551)	(0.643)	(0.986)	(1.385)	(1.631)	(0.393)	
$\alpha_{7,l}$	3.795	7.717***	11.052***	-1.077***	12.342***	5.792***	3.34
	(0.558)	(0.667)	(1.011)	(1.450)	(1.538)	(0.401)	
$\alpha_{1,h}$	6.701***	18.910***	12.708***	16.964***	16.526***	12.706***	23.72
	(0.585)	(0.654)	(0.972)	(1.503)	(1.674)	(0.391)	
$\alpha_{2,h}$	2.484***	3.019***	7.301***	5.924***	14.079	4.026***	12.52
	(0.567)	(0.653)	(1.002)	(1.357)	(1.763)	(0.407)	
$\alpha_{3,h}$	3.139***	3.992***	7.038*	0.964***	18.709***	4.449***	8.704
	(0.549)	(0.622)	(0.951)	(1.346)	(2.055)	(0.392)	
$\alpha_{4,h}$	2.672***	4.798***	7.499	3.238**	11.928***	4.200***	6.547
	(0.552)	(0.663)	(1.036)	(1.405)	(1.796)	(0.397)	
$\alpha_{5,h}$	3.171***	4.934	7.067**	-0.955***	16.925***	4.138**	5.122
	(0.558)	(0.647)	(0.983)	(1.434)	(1.905)	(0.395)	
$\alpha_{6,h}$	3.657	5.312*	9.147***	2.586	10.011***	5.110***	4.102
	(0.555)	(0.628)	(1.022)	(1.322)	(1.606)	(0.391)	
$\alpha_{7,h}$	3.424	5.057**	8.524***	2.575	5.015	4.450***	3.338
	(0.607)	(0.719)	(1.121)	(1.459)	(1.707)	(0.428)	
γ_H	-1.529***	-1.747***	-2.031***	-3.407***	-21.736***	-2.558***	0
	(0.521)	(0.444)	(0.670)	(1.168)	(0.989)	(0.289)	

Updating when facing surprising signals

- 19.5% signals are "surprising" signals according to our cutoffs.

- **RESULT 5a**: For posterior mean updating, most subjects underreact, while type 4 (a small group with 6.7%).

- **RESULT 5b**: In contrast, all participants consistently reduce their posterior certainty level in response to surprising signals, suggesting that they experience loss in confidence about their belief.

- Remark: These results are notable because whether a signal is surprising or not does not play a role in Bayesian belief updating.

Conclusion

- **Main Finding:** Individuals don't update beliefs like perfect Bayesians. We identify *five distinct, evolving types* of updaters, with most under-reacting to new information, especially in their posterior certainty.
- **Key Insights**
  - **Beyond Static Types:** People aren't just “conservative” or “over-reactors.” Their updating style (under/over/Bayesian) shifts dynamically over time.
  - **Posterior certainty level** deviates from Bayesian benchmark much more than **posterior mean**.
  - **The Surprise Effect:** Faced with surprising signals, people uniformly **under-react in certainty level**, becoming less confident than a Bayesian would predict.
- **Limitations & Future Work**
  - **Lab vs. Real World:** Findings from controlled experiments need validation in field settings.
  - **Beliefs vs. Actions:** Linking these dynamic belief updates to actual **choices and decisions**.